Global Currency Misalignments, Crash Sensitivity, and Moment Risk Premia

Huang, Huichou and MacDonald, Ronald and Zhao, Yang

Adam Smith Business School, University of Glasgow, Adam Smith Business School, University of Glasgow, Adam Smith Business School, University of Glasgow

23 July 2012

Global Currency Misalignments, Crash Sensitivity, and Moment Risk Premia*

Huichou Huang† Ronald MacDonald‡

This Version: November 23, 2013

Abstract

We show that the profitability of currency carry trades can be understood as the compensation for exchange rate misalignment risk based on the rare disastrous model of exchange rates (Farhi and Gabaix, 2008). It explains over 97% of the cross-sectional excess returns and dominates other candidate factors, including volatility and liquidity risk. Both currency carry and misalignment portfolios trade on the position-likelihood indicator (Huang and MacDonald, 2013) that explores the probability of the Uncovered Interest Rate Parity (UIP) to hold in the option pricing model. To examine the crash story of currency risk premia, we employ copula method to capture the tail sensitivity (CS) of currencies to the global market, and compute the moment risk premia by model-free approach using volatility risk premia as the proxy for downside insurance costs (DI). We find: (i) notable time-varying currency risk premia in pre-crisis and post-crisis periods with respect to both CS and DI; and (ii) the pay-off components of the strategy trading on skew risk premia mimic the behavior of currency carry trades. We further reveal and rationalize the differences in the performances of currency portfolios doubly sorted by CS and DI. We propose a novel trading strategy that makes a

*First Draft: July 23, 2012. The authors would like to thank George Jiang, Lucio Sarno, Stephen Taylor, and Dimitris Korobilis for helpful conversations and comments. Huang acknowledges financial support from Scottish Institute for Research in Economics. Any errors that remain are the responsibility of the authors.

†Corresponding author; Email: huichou.huang@exeter.oxon.org.

‡Department of Economics, Adam Smith Business School, University of Glasgow, Glasgow, G12 8QQ, United Kingdom.

trade-off of the time-variation in risk premia between low and high volatility regimes and is thereby almost immunized from risk reversals. It generates a sizable average excess return (6.69% per annum, the highest among several studied currency trading strategies over the sample period) and its alpha that cannot be explained by canonical risk factors, including hedge fund (Fung and Hsieh, 2001) and betting-against-beta (Frazzini and Pedersen, 2014) risk factors, and government policy uncertainty meausres (Baker, Bloom, and Davis, 2012). Unlike other currency trading strategies, its cumulative wealth is driven by both exchange rate and yield components. We also investigate the behavior of currency momentum that is shown subject to credit risk, similarly to its stock market version (Avramov, Chordia, Jostova, and Philipov, 2007): Winner currencies performance well when sovereign default probability is low and loser currencies provide the hedge against this type of risk when sovereign default probability hikes up. The changes in global sovereign CDS spreads contribute 59% of the variation to the factor that captures the common dynamics of the currency trading strategies. From asset allocation perspective, a crash-averse investor is better off by allocating about 40% of the wealth to currency-misalignment portfolio and about 35% to crash-sensitive portfolio in tranquil period while reallocating about 85% of portfolio holdings to downside-insurance-cost strategy during the financial turmoil.

JEL classification: F31, F37, G01, G12, G17.

Keywords: Exchange Rate Misalignments, Copula, Tail Dependence, Moment Risk Premia, Currency Investment Strategies.

1. Introduction

Meese and Rogoff (1983) highlight that it is difficult to find a theoretically-grounded factor that can beat random walk in forecasting short-run exchange rate movements. MacDonald and Taylor (1994) reveal that an unrestricted monetary model can outperform the random walk as long as the short-run data dynamics is properly processed. Recent literature emphasizes that the disconnection puzzle of exchange rates can be understood when the stochastic discount factor is near unity and/or the macroeconomic fundamentals are I(1) (e.g. Engel and West, 2005; Sarno and Sojli, 2009). Bacchetta and van Wincoop (2006, 2009) argue that the unstable relationship between the exchange rates and macroeconomic fundamentals can be attributable to the uncertainty in expectations of the structural parameter. Alternatively, Menkhoff, Sarno, Schmeling, and Schrimpf (2013) adopt the portfolio approach originally applied by Lustig, Roussanov, and Verdelhan (2011) to currency market, and they find that macroeconomic fundamentals have substantial predictive power on exchange rates from the cross-sectional perspective. The currency risk premia are the compensations for dynamic business cycle risk.

Huang and MacDonald (2013) show that the excess returns of currency carry trades can be understood from the perspective of sovereign credit premia and their results are robust to the alternative measure of sovereign default risk implied in government bonds. However, this is not a full story. Because sovereign risk of public debts is just a partial source of global imbalances and the dramatic increase in debt of private sector also plays a pivotal role. Moreover, even external imbalances are still a constituent of the currency risk premia, because other factors such as productivity shocks[1], deteriorations of terms of trade, etc. are also of paramount importance for exchange rate determination and risk premia (MacDonald, 2005). The devi-

[1]Balassa-Samuelson effect does not measure the total factor productivity for which real GDP per capita proxies.

ation from the equilibrium exchange rates determined by the macroeconomic fundamentals is an important predictor of exchange rates but omitted in the recent influential studies (Jordà and Taylor, 2012). Therefore, we reasonably conjecture that currency risk premia originate from their misalignments, as equilibrium exchange rates are the composite indicators of the competitiveness of the states and exchange rate misalignments reflect the sustainability of the states. We find currency misalignment risk explains over 97% of the cross-sectional excess returns of carry trades and both currency carry and misalignment portfolios trade on the position-unwinding likelihood indicator (Huang and MacDonald, 2013) that explores the probability of the Uncovered Interest Rate Parity (UIP) to hold in the option pricing model, so do other currency investment strategies studied in this paper.

We assess the currency risk premia comprehensively through evaluating misalignments, relying on the portfolio approach to exploit the cross-sectional information in a single integrated macroeconomic fundamental indicator by sorting portfolio on the basis of lagged exchange rate misalignments, instead of pure time-series testing on a set of factors mentioned above or those in a monetary exchange rate model[2] (see Engel, Mark, and West, 2007, for specification) individually. We contribute to this literature by showing that exchange rate misalignment is the composite fundamental source of currency risk premia and well explains both time series and cross section of the profitability of currency carry trades. By sorting currencies on the basis of exchange rate misalignment, we form five currency portfolios with monotonic average excess returns and a trading strategy (risk factor) that buys top 20% overpriced currencies funded by bottom 20% undervalued ones. High interest-rate currencies load positively on the misalignment (overvaluation) risk and tend to depreciate sharply during the turmoil periods, while low interest-rate currencies offer a hedge against the crash risk (negatively ex-

[2]The variables include differentials in real output/income level, in money supply (balances/circulations), and in money demand shock.

posed to misalignment risk). Given a certain macroeconomic fundamental and policy environment, global currency misalignments seem unable to go beyond a sustainable level, identifying the misalignment bound is conducive to timing the overvalued currency collapses and risk reversals during the crashes, which are rare but extreme events.

Recently, the rare disaster risk has also caught a lot attention in the literature (e.g. Rietz, 1988; Barro, 2006; Weitzman, 2007; Bollerslev and Todorov, 2011; Gabaix, 2012) that equity premium puzzle can be illuminated as a compensation for the risk of rare but extreme events. Farhi and Gabaix (2008) build a novel tractable model of exchange rates based on the previous work by Rietz (1988), Barro (2006), and Weitzman (2007) that representative agents attach a substantial weight, in their consumption and investment decisions, to the possibility of rare but extreme events, which are the major sources of the risk premia in asset prices. It is also stressed by Jurek (2007), Farhi and Gabaix (2008), Brunnermeier, Nagel, and Pedersen (2009), Chernov, Graveline, and Zviadadze (2012) that currency premia embody the crash risk. Given the fact that the comovements of high interest-rate currencies with the aggregate market conditional on high volatility regime is stronger than it is conditional on low volatility regime, and this phenomenon also exists in other asset classes, Lettau, Maggiori, and Weber (2013) utilize a Downside Risk CAPM (DR-CAPM) that is able to jointly price the cross section of currencies, equities, sovereign bonds, and commodities. Garleanu, Pedersen, and Poteshman (2009) broach a theoretical model that bridges the net hedging demand imbalances with option prices, which matches the empirical reality of the skewness and expensiveness of index option. In their analytical framework, the hedging demand of the investors for the unhedgeable risk drives up the position-protection costs. Jurek (2007) reveals the abnormal behavior of option prices that the downside protection costs are negatively related to the crash risk of the currencies, and the implied volatilities of the out-of-money options are not big enough to drive the excess returns of crash-neutral currency carry trades to zero for the crash story to become a resolution of forward premium anomaly.

Encouraged by these pioneering work, we employ copula methods to measure the crash sensitivity by tail dependence and use the moment (volatility and skew) risk premia as the proxy for downside insurance costs, as we are pondering that solely crash risk cannot explain the currency premia in an economic sense, provided that there is in fact a variety of financial derivatives, such as option, available for us to hedge against the downside risk. So, a currency that is sensitive to tail risk but cheap to insure may not offer a premium higher than that brought by a currency which is less crash-sensitive but expensive to hedge its position the investors take. Our another contribution is to provide an answer to this question. We find that skew risk premia as the proxy for crash risk premia explain the cross section of currency carry trade excess returns as well as the misalignment risk. Skew risk premia tell us the expected changes in probability for the UIP to hold because they contain valuable ex-ante information about the directions and magnitudes of the future movements of spot rates. Exchange rate misalignment drives skew risk premia but the reverse is not true, which conforms to the economic sense. The currency strategy trading on skew risk premia mimics both the exchange rate return and yield components of carry trades. We also notice considerable time-varying currency risk premia in pre-crisis and post-crisis periods with respect to both crash sensitivity and downside insurance cost. Accordingly, we propose a novel trading strategy that makes a trade-off in the time-variation of currency risk premia between low and high volatility regimes - investing in medium tail-sensitivity and high downside-protection-cost currencies funded by the low tail-sensitivity and medium downside-protection-cost ones. It is nearly immunized from risk reversals and generates sizeable returns that cannot be explained by canonical risk factors, hedge fund (Fung and Hsieh, 2001) and betting-against-beta risk factors (Frazzini and Pedersen, 2014), and measures of government economic policy uncertainty in both Europe and U.S. (Baker, Bloom, and Davis, 2012). Unlike currency carry trades, the profit of risk reversal trade-off strategy is not simply driven by interest rate differentials but also exchange rate returns.

We further investigate another popular currency trading strategy - momentum to check if its profitability is related to relevant explanations for its equity market version, e.g. the macroeconomic fundamentals (Chordia and Shivakumar, 2002; Liu and Zhang, 2008), individual (country-specific) characteristics (see Hong, Lim, and Stein, 2000, for analysis of firm-specific characteristics), transaction costs (Korajczyk and Sadka, 2004), funding liquidity risk (Asness, Moskowitz, and Pedersen, 2013), investors' underractions and delayed overractions (Chan, Jegadeesh, and Lakonishok, 1996; Hvidkjaer, 2006; Moskowitz, Ooi, and Pedersen, 2012), their heterogeneous beliefs (Verardo, 2009). Grinblatt and Han (2005) show that stock market momentum can be understood by the "Prospect Theory" (Kahneman and Tversky, 1979) and "Mental Accounting" (Thaler, 1980): Distinction in risk attitudes towards capital gain and capital loss drives the "Disposition Effect" (Shefrin and Statman, 1985) and generates predictable equilibrium prices (momentum) that converge to the fundamental values. The existing literature generally concentrates on the time series of currency momentum. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) instead focus on the cross section and assert that it is the "Limits to Arbitrage" (Shleifer and Vishny, 1997) preventing this trading strategy from being easily exploitable in currency market. Our empirical results suggest that the momentum in currency market is subject to credit risk as it is in stock market (Avramov, Chordia, Jostova, and Philipov, 2007). Winner currencies performance well when sovereign default probability is low and loser currencies provide the hedge against this type of risk when sovereign default probability rises. Currency momentum profits seem to depend on the market states as well (see Griffin, Ji, and Martin, 2003; Cooper, Gutierrez, and Hameed, 2004, for analysis of stock market).

The changes in global sovereign CDS spreads is the key contributor[3] to the factor that captures the common dynamics of the several studied currency trading strategies in our paper. We extract the common dynamic and static factors by the Forni, Hallin, Lippi, and Reichlin's (2005) one-sided methodology for the estimation of the Generalized Dynamic Factor Model. From the asset allocation perspective, a crash-averse investor would optimally allocate about 40% of the wealth to currency-misalignment portfolio and about 35% to crash-sensitive portfolio in tranquil period and dramatically reallocates his/her portfolio holdings to downside-insurance-cost strategy with a weight of about 85% in turmoil period.v

The rest of this paper is organized as follows: Section 2 introduces the ideas and two standard approaches (FEER and BEER) for computing the exchange rate misalignments. Section 3 describes the copula methods and measure of crash sensitivity by tail dependence. Section 4 shows the evaluation of downside insurance costs via moment risk premia, and compare the model-free (swap) method with option-implied method. Section 5 contains the information about the data set used in this paper, the currency trading strategies constructed by portfolio approach, monotonicity tests for portfolio excess returns and risk exposures, optimal asset allocations according to business cycles and risk reversal trade-off, standard empirical asset pricing procedures, and generalized dynamic factor model estimates. In Section 6, we discuss our empirical results. Conclusion is drawn in Section 7. The main findings of this paper are delegated to Appendix A. Appendix B contains the supplementary materials.

[3]It explains about 59% of the factor variation.

2. Global Currency Misalignments

In this section, we introduce two popular approaches that deal with the question of whether the Real Effective Exchange Rate (REER) of a country is consistent with its macroeconomic fundamentals. One approach defines the "Fundamental Equilibrium Exchange Rate" (FEER) as a REER that guarantees sustainable current account balance with desired net capital flows (external balance) which are set at full employment and low inflation levels (internal balance). Another approach directly resorts to econometric analysis of the REER behavior in a Vector Autoregressive (VAR) Model, consequently is called "Behavioral Equilibrium Exchange Rate" (BEER). It measures misalignments of REER as the deviations of actual REER from its equilibrium value in the long-run relationship identified by the cointegration method. Thereby, it requires the judge which macroeconomic fundamentals determine the exchange rate behavior.

2.1. Equilibrium Exchange Rate Determinations

Williamson (1983) first proposes the idea of FEER that the equilibrium exchange rate is calibrated to ensure the economy operating at both internal and external balances over the medium run, i.e. to bring the current account at full employment and desirable inflation levels into equality with the net capital account. It is essentially a flow equilibrium concept and requires parameter estimates and judgement of potential outputs for country concerned and its main trading partners. The calculation does not involve some crucial factors that actually influence the behavior of exchange rates. As long as the four key elements mentioned above are undisturbed, the equilibrium exchange rate remains unchanged. But it is unclear whether the REER is still in equilibrium in a behavioral sense. Nevertheless, one may favor this approach since the exchange rates are volatile and unpredictable (see Frankel and Rose, 1995; Kilian and Taylor, 2003) and the relationship between of exchange rates and macroeconomic fundamentals seems to be evolutive over time (Sarno and Valente, 2009).

Clark and MacDonald (1998) propose an alternative BEER assess of e-quilibrium exchange rates using a reduced-form estimation equation that decomposes the behavior of the REER into three horizons. Specifically, the equilibrium REER is given by:

$$\mathbb{E}_t[REER_{t+T}] = REER_t + (\mathbb{E}_t[\tilde{r}_{d,t}] - \mathbb{E}_t[\tilde{r}_{f,t}]) + \lambda_t \tag{1}$$

where $\mathbb{E}_t[\,\cdot\,]$ is the expectation operator. $\tilde{r}_{d,t}$, $\tilde{r}_{f,t}$ denotes real domestic, and foreign interest rate for T period, respectively. λ_t represents a measure of risk premium. $\mathbb{E}_t[REER_{t+T}]$ is interpreted as the long-run component of the REER and hence can be replaced by a set of expected macroeconomic fundamentals, $\mathbb{E}_t[Z^L_{t+T}]$. Then Equation (1) can rearranged as:

$$REER_t = \mathbb{E}_t[Z^L_{t+T}] - (\mathbb{E}_t[\tilde{r}_{d,t}] - \mathbb{E}_t[\tilde{r}_{f,t}]) - \lambda_t \tag{2}$$

Given that λ_t is time-varying, Equation (2) can be simplified by the im-position of rational expectations:

$$REER_t = Z^L_t - (\tilde{r}_{d,t} - \tilde{r}_{f,t}) \tag{3}$$

In practice, the REER can be written as a function of long and medium-term macroeconomic fundamentals (Z^L_t and Z^M_t) that maintain a permanent and relatively stable relationship with the REER, and short-term factors (Z^S_t) that impose transitory impacts on the REER. The actual REER can be explained exhaustively by this set of variables of three horizons.

$$REER_t = REER_t\left(Z^L_t, Z^M_t, Z^S_t\right) \tag{4}$$

Égert, Halpern, and MacDonald (2006), MacDonald and Dias (2007) i-dentify a standard set of variables for the estimation of equilibrium exchange rates, including real interest rates, real GDP per capita as the proxy for productivity, terms of trade, CPI-to-PPI ratio as the proxy for Balassa-Samuelson effect[4], government expenditures as the pecentage of GDP, net foreign asset as the pecentage of GDP, export plus import as the percentage of GDP as the proxy for economic openness. We also take the financial openness into account (see Chinn and Ito, 2006).

2.2. VAR Estimations

To estimate the relationships between the REER and relevant variables in Equation (4) is tantamount to estimate a reduced-form model:

$$REER_t = \beta_L Z_t^L + \beta_M Z_t^M + \beta_S Z_t^S + \varepsilon_t \tag{5}$$

where the random disturbance term $\varepsilon_t \sim \mathcal{N}(0,\, \sigma_\varepsilon^2)$, the Gaussian *i.i.d.* normal distribution. We distinguish the contemporary equilibrium REER as the long and medium-term component in Equation (5) from the observed REER. Then the current misalignment (CM_t) of REER can be computed as:

$$CM_t = REER_t - \beta_L Z_t^L - \beta_M Z_t^M = \beta_S Z_t^S + \varepsilon_t \tag{6}$$

It would also be natural to look at the total misalignment (TM_t) that can be decomposed into two components as follows:

$$\begin{aligned} TM_t &= REER_t - \beta_L \bar{Z}_t^L - \beta_M \bar{Z}_t^M \\ &= CM_t + [\beta_L (Z_t^L - \bar{Z}_t^L) + \beta_M (Z_t^M - \bar{Z}_t^M)] \end{aligned} \tag{7}$$

where $\bar{Z}_t^L$, $\bar{Z}_t^M$ denotes the long-run sustainable values of corresponding variables that are acquired by either Hodrick-Prescott filter, Beveridge-

[4]Real GDP per capita measures the total factor productivity, so it is preferable and when it is available, CPI-to-PPI ratio is not included.

Nelson decomposition, or unobserve component analysis. BEER approach decomposes the misalignment of REER into three components: deviations of the macroeconomic fundamentals from their long-run sustainable values, transitory effect of short-run factors, and random disturbances. Hence, it is more general for interpreting the cyclical movements of real exchange rates.

[**Insert Table A.1. about here**]

We calculate the current misalignments of 34 global currencies in our sample individually using the ragged quarterly and annual data from 1984 to 2012, and standard econometric procedures[5] for cointegration test, such as unit-root test, optimal lag selection, Johansen rank tests (both trace and maximum eigenvalue). Note that we do not include a risk premium term as one of the determinants of equilibrium exchange rates. Although we try to minimize the measurement errors of REER introduced in the estimations, they inevitably exist. However, we harness the REER misalignments just for sorting currencies into portfolios and the rank of our estimates of BEER misalignments is close to that provided by Cline's (2008) FEER estimates, which sets forth a symmetric matrix inversion method to evaluate a consistent set of REER realignment. Therefore, the effects of the measurement errors may be trivial. Table A.1. above indicates the average REER misalignments of 34 global currencies over the sample period. Overall, majority of currencies are underpriced against USD except for AUD, NZD, and TRY that are significantly overvalued. This is concordant with the fact that investment in global money market outside U.S. funded by USD yields an excess return about 2.39% in our the sample period.

[**Insert Table A.2. about here**]

We sort the currencies into five portfolios based on their interest rate

[5] Although Bayesian Time-Varying Parameter (TVP) VAR works better to acquire accurate estimates of REER misalignment, we cannot consider it owing to the limited observations for some series.

differentials (forward discounts), and estimated REER misalignments, respectively. Table A.2. presents the descriptive statistics of currency carry and misalignment portfolios. We can see consistency of monotonicity in average excess returns. Holding fundamentally overvalued currencies yields an average excess return of 5.35% per annum (p.a.) with a Sharpe ratio of 0.45 over the sample period while holding high interest-rate currencies is remunerated with an average annual excess return of 4.57% with a comparable Sharpe ratio of 0.43.

[**Insert Figure A.1. about here**]

We construct a REER misalignment strategy (HML_{ERM}) that consists of a long position in overpriced currencies and a short position in undervalued currencies. Figure A.1. above shows the remarkable comovement of it with currency carry trades (with a high correlation of 0.72). Della Corte, Ramadorai, and Sarno (2013) propose to decompose the cumulative excess returns of currency trading strategies into exchange rate return and interest rate components to check the driver(s) of cumulative wealth brought by these strategies. Doing so, we can confirm the similarity in the behavior of different strategies. If the cumulative wealth of the REER misalignment strategy is also positively driven by the yield component but negatively by the exchange rate return component, then REER misalignment strategy exhibits similar behavior to carry trades. If HML_{ERM} as a priced risk factor that explains the cross section of carry trade excess returns, forward premium puzzle may be understood by a probe into the mechanisms that the high interest-rate currencies tend to be overpriced (in terms of the deviations from the medium to long run equilibrium relationships among the real fundamentals) in good times and are positively exposed to crash (depreciation) risk in turmoil periods while the low interest-rate currencies that are likely to be undervalued in tranquil periods provide a hedge against the misalignment risk in bad times.

3. Crash Sensitivity

Ample literature has found the asymmetric dependence in asset prices (see Longin and Solnik, 2001; Ang and Chen, 2002; Poon, Rockinger, and Tawn, 2004; Hong, Tu, and Zhou, 2007), as the crash-averse investors evaluate the downside losses and upside gains distinctively, which is concordant with the "Prospect Theory" that investors are myopic loss-averse and evaluate their portfolios frequently (see Benartzi and Thaler, 1995; Barberis, Huang, and Santos, 2001). Although the evidence in the equity market has been extensively reported, only a little attention has been paid to currency market. We choose the copula approach to model the crash sensitivity because it is capable of capturing the nonlinear dependence structure of asset behavior in extreme circumstances, which is usually understated or unobservable using linear methods. It is superior than traditional methods, as it is an elegant and flexible bottom-up approach that allows us to combine well-specified marginal models with various possible dependence specifications (McNeil, Frey, and Embrechts, 2005). Patton (2004) reveals that investors without short-sale constraints can achieve significant economic and statistical gains while being informed of the high order moments (especially the skewness) and asymmetric dependence for decision-making in asset allocation by a time-varying copula. Utilizing a conditional copula, Patton (2006) attributes the asymmetry of the dependence between DEM and JPY to the asymmetric reactions of central banks to the directions of exchange rate movements. Dias and Embrechts (2010) find a remarkable time-varying dependence structure between EUR and JPY by a dynamic copula with Fisher transformation, particularly during the Subprime Mortgage Crisis. Christoffersen, Errunza, Jacobs, and Langlois (2012) propose a dynamic conditional copula model allowing for multivariate non-normality and distribution asymmetry to capture both short-run and long-run dependence in advanced economies and emerging markets. Christoffersen and Langlois (2013) investigate the joint dynamic of risk factors in the equity market for the sake of risk management and show that the linear model overestimate the diversification benefits in terms of large and positive extreme correlations.

Distinguishable from previous studies on this topic, we capture the crash sensitivity using the tail dependence between the individual currency and its "market portfolio" (see Lustig, Roussanov, and Verdelhan, 2011). All the coefficients of tail dependence are estimated by both parametric and semi-parametric copula models with rolling window to obtain monthly estimates of tail dependence for portfolio sorting purpose. To avoid possible model misspecification, we also employ nonparametric estimation as a robustness check, which does not involve any specification of copula functions, proposed by Frahm, Junker, and Schmidt (2005). The empirical results given by it are consistent with those from parametric and semiparametric methods in general. Currencies with high crash sensitivity should offer high risk premia to attract investors if they are crash-averse, while low crash sensitivity ones work as safe-haven currencies.

3.1. Copula

Copula is the function that connects multivariate distribution to their one-dimension margins (Sklar, 1959). Sklar's theorem states that if the margins are continuous, then there exists a unique copula function C merge n-dimension marginal Cumulative Distribution Functions (CDF) into a joint distribution F, which is a multivariate distribution with the univariate margins $F_1, ..., F_n$, then there exists a copula $C : [0,1]^n \to [0,1]$ that satisfies:

$$F(x_1, ..., x_n) = C\left(F_1(x_1), ..., F_n(x_n)\right), \ \forall \ x_n \in \mathbb{R}^n \tag{8}$$

where F represents a multivariate distribution function with margins $u_1 = F_1, ..., u_n = F_n$. If the margins are continuous, then there exists a unique multivariate copula function C defined as:

$$C(u_1, ..., u_n) = F\left(F_1^{-1}(u_1), ..., F_n^{-1}(u_n)\right) \tag{9}$$

where F_n^{-1} denotes the generalized inverse distribution function of the univariate distribution function F_n[6] and $x_n = F_n^{-1}(u_n), 0 \leq u_n \leq 1,$ for $i = 1, ..., n$. Conversely, let U to be a random vector with a distribution function C and set $X := \left[F_1^{-1}(U_1), ..., F_n^{-1}(U_n)\right]$, we can get:

$$\begin{aligned} \Pr\left(X_1 \leq x_1, ..., X_n \leq x_n\right) &= \Pr\left(F_1^{-1}(U_1) \leq x_1, ..., F_n^{-1}(U_n) \leq x_n\right) \\ &= \Pr\left(U_1 \leq F_1(x_1), ..., U_n \leq F_n(x_n)\right) \\ &= C\left(F_1(x_1), ..., F_n(x_n)\right) \end{aligned} \tag{10}$$

If the densities exist, then we can derive the representation of joint Probability Distribution Function (PDF) from the joint CDF:

$$f(x_1, ..., x_n) = c\left(F_1(x_1), ..., F_n(x_n)\right) \times \prod_{i=1}^{n} f_i(x_i) \tag{11}$$

where $c(u_1, ..., u_n) = \frac{\partial^n C(u_1, ..., u_n)}{\partial u_1 \cdot ... \cdot \partial u_n}$.

3.2. Tail Dependence

The coefficient of tail dependence measures the pairwise degree of dependence in the tail of a bivariate distribution for extreme events (see McNeil, Frey, and Embrechts, 2005; Frahm, Junker, and Schmidt, 2005; Joe, Li, and Nikoloulopoulos, 2010). Let X_1 and X_2 be random variables with continuous distribution functions F_1 and F_2, then the coefficients of Lower Tail Dependence (LTD) and Upper Tail Dependence (UTD) of X_1 and X_2 are given by:

[6] Here, $F^{-1}(u) = \inf\{x : F(x) \geq u\}$.

$$LTD: \; = \; LTD\,(X_1, X_2) = \lim_{q \to 0^+} \Pr\left(X_2 \leq F_2^{-1}(q) | X_1 \leq F_1^{-1}(q)\right) \quad (12)$$

$$UTD: \; = \; UTD\,(X_1, X_2) = \lim_{q \to 1^-} \Pr\left(X_2 \geq F_2^{-1}(q) | X_1 \geq F_1^{-1}(q)\right) \quad (13)$$

where q is the quantile. Using Equation (10) and condition probability function, the LTD coefficient can be computed as:

$$LTD = \lim_{q \to 0^+} \frac{\Pr\left(X_2 \leq F_2^{-1}(q), X_1 \leq F_1^{-1}(q)\right)}{X_1 \leq F_1^{-1}(q)} = \lim_{q \to 0^+} \frac{C(q, q)}{q} \quad (14)$$

Analogously, we have the formula for UTD coefficient as follows:

$$UTD = \lim_{q \to 1^-} \frac{\Pr\left(X_2 \geq F_2^{-1}(q), X_1 \geq F_1^{-1}(q)\right)}{X_1 \geq F_1^{-1}(q)} = \lim_{q \to 1^-} \frac{1 - 2q + C(q, q)}{1 - q} \quad (15)$$

The coefficients can be easily calculated when the copula has a closed-form expression. The C has lower tail dependence if $LTD \in (0, 1]$ and no lower tail dependence if $LTD = 0$. Similar conclusion holds for upper tail dependence. If the copulas are symmetric, then $LTD = UTD$, otherwise, $LTD \neq UTD$ (see Joe, 1997). To better assess the crash sensitivity, we measure the tail dependences at bottom and top 10% quantiles. Modelling the copula-based tail dependence requires us to specify the models for conditional marginal distributions first. Our univariate model used to estimate tail dependence combines the AR model for the conditional mean of daily returns, GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993) for the conditional variance and leverage effect, and a skewed-t distribution of Hansen (1994) for residuals.

[Insert Table A.3. about here]

The average lower and upper tail dependences of 34 currencies[7] over the sample period are provided in Table A.3. above. ARS, and two currencies of Asia countries, JPY and HKD are crash-insensitive currencies over our sample period in terms of both LTD and UTD, while EUR, Nordic currencies such as NOK, DKK, and SEK, and the currencies of Eastern Europe countries such as HUF, PLN, SKK, etc. are among the most crash-sensitive currencies. However, high crash-sensitivity currencies do not necessarily imply high excess returns, since we have financial derivatives, such as option, to hedge against the downside risk. But when these currencies are cheap to hedge, they become favorable to the crash-averse investors in good times, and make them willing to take up the risk positions which are compensated for the possible currency crashes in bad times. High crash-sensitivity currencies with high downside insurance costs are not appealing to the investors, while low crash-sensitivity currencies with low downside insurance costs do not carry risk premia to the investors. Low crash-sensitivity currencies with high downside insurance costs must offer risk premia to attract investors. So, double-sorting is more favorable to study the crash story of currency risk premia. Inspired by Bollerslev, Gibson, and Zhou (2011) who extract volatility risk premium as an investor risk aversion index and find that it is also related to a set of macro-finance state variables, we also set forth a measure of the downside risk of currency market that sums up the LTD at aggregate level as the indicator for global tail risk (GTD) to check if ΔGTD as a risk factor is priced in the cross section of currency excess returns. GDT suddenly increased dramatically in the September of 2008 (Lehman Brothers' bankruptcy and the outbreak of the Subprime Mortgage Crisis) and keep increasing during the Sovereign Debt Crisis in Europe, and up to the end of the sample period. Only two considerable drops happened in the March of 2009 and the February of 2012.

[7]Currency portfolios sorted by tail sensitivity are presented in Table B.1..

4. Downside Insurance Costs

Garleanu, Pedersen, and Poteshman (2009) put forward a theoretical foundation for the demand-pressure effect on option prices that the unhedgeable part of the variance increases the prices of the contract and this type of demand explains the skewness and expensiveness of the index options. As Brunnermeier, Nagel, and Pedersen (2009) point out that the investment currencies are subject to the crash risk, we apply their thoughts to the currency market to assess the risk premia associated with the unhedgeable volatility and skewness risk.

4.1. Moment Swaps

Moment swaps are a forward contract on the moments "realized" on the underlying asset over its life. The buyer of a moment swap written at time t with a maturity of T will receive the payoff per unit of notional amount $MP_{t,T}$ at the end of time $t+T$, which equals to the realized moment $RM_{t,T}$ subtracted by the moment swap rate $MS_{t,T}$:

$$MP_{t,T} = RM_{t,T} - MS_{t,T} \tag{16}$$

Both $RM_{t,T}$ and $MS_{t,T}$ are quoted in annualized terms but $RM_{t,T}$ is determined at the end of the contract $t+T$ while $MS_{t,T}$ is agreed at the start of the contract t. Given that $MP_{t,T}$ is expected to be zero under the risk-neutral measure, we have:

$$MS_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[RM_{t,T}] \tag{17}$$

where $\mathbb{E}_t^{\mathbb{Q}}[\,\cdot\,]$ is the expectation operator under risk-neutral measure $\mathbb{Q}$, and $RM_{t,T}$ is computed as the integrated moment, e.g. realized volatility $RV_{t,T} = \sqrt{\frac{1}{T}\int_t^{t+T}\sigma_s^2 \mathrm{d}s}$, wherein σ_s^2 denotes the stochastic volatility of the underlying.

4.2. Model-free and Realized Moments

The moment swaps can be synthesized using model-free approach pioneered by Britten-Jones and Neuberger (2000) that implied moments are derived from no-arbitrage condition without any specification of option pricing model. It is further refined, advanced and extensively studied by scholars including but not limited to Demeterfi, Derman, Kamal, and Zou (1999), Bakshi and Madan (2000), Bakshi, Kapadia, and Madan (2003), Bakshi and Kapadia (2003), Carr and Madan (2001), Jiang and Tian (2005), Neuberger (2012). They reveal that the moment swaps can be replicated by a strategy that combines a dynamically rebalanced portfolio of the underlying with a static portfolio of put and call options attached with appropriate weights as a function of the strikes and forward rates. The options contains an infinite range of all continuous strikes, and the puts and calls to hold are segmented by the strike at the forward rate at time t with maturity of T. And the model-free moments are valid even in presence of price jumps of the underlying. The valuations of the second (variance) and third (skewness) model-free moments for a currency pair[8] are given by:

$$\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}] = \frac{2B_{t,T}}{T}\left(\int_{F_{t,T}}^{\infty}\frac{1}{K^2}C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}}\frac{1}{K^2}P_{t,T}(K)\mathrm{d}K\right) \quad (18)$$

$$\mathbb{E}_t^{\mathbb{Q}}[RS_{t,T}] = \frac{6B_{t,T}}{T}\left(\int_{F_{t,T}}^{\infty}\frac{K - F_{t,+T}}{F_{t,T}K^2}C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}}\frac{F_{t,+T} - K}{F_{t,T}K^2}P_{t,T}(K)\mathrm{d}K\right) \quad (19)$$

where $B_{t,T} = \exp\left[-(r_{d,t} - r_{f,t})T\right]$, representing the present value of a zero-coupon bond with a risk-free rate as the interest differential between T-period domestic risk-free rate $r_{d,t}$ and foreign risk-free rate $r_{f,t}$. $P_{t,T}$, $C_{t,T}$

[8] Currencies are in indirect quotes as units of foreign currency per unit of domestic currency (USD).

is the put and call prices at time t with a strike price of K and a maturity of T, respectively. $F_{t,T}$ denotes the forward rate that matches the dates of the options. Della Corte, Ramadorai, and Sarno (2013) focus on the volatility swaps by taking the square root of $\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}]$, from which the convexity bias arises. This Jensen's inequality issue is shown empirically negligible using a second-order Taylor approximation and it explains why volatility swaps is preferably quoted by the practitioners in financial industry.

The next step is to recover the option prices by the currency option pricing model (Garman and Kohlhagen, 1983). In FX market, the OTC options are quoted in terms of at-the-money (ATM) implied volatilities (IV_{ATM}), (10-delta and 25-delta) out-of-the-money (OTM) option risk reversals ($RR_{10\Delta}$, $RR_{25\Delta}$) and butterflies ($BF_{10\Delta}$, $BF_{25\Delta}$). The other four implied volatilities at 10%, 25%, 75%, and 90% moneyness levels can be calculated as: $IV_{10\%M} = IV_{ATM} + BF_{10\Delta} - \frac{1}{2}RR_{10\Delta}$, $IV_{25\%M} = IV_{ATM} + BF_{25\Delta} - \frac{1}{2}RR_{25\Delta}$, $IV_{75\%M} = IV_{ATM} + BF_{25\Delta} + \frac{1}{2}RR_{25\Delta}$, and $IV_{90\%M} = IV_{ATM} + BF_{10\Delta} + \frac{1}{2}RR_{10\Delta}$, respectively. Thus, the corresponding strikes can be extracted from five plain vanilla options, then we follow the approach adopted by Jiang and Tian (2005) and Della Corte, Sarno, and Tsiakas (2011) that draws a cubic spline through these five data points. The advantage of this method is that it caters to the smooth volatility smile and therefore becomes a standard procedure in the literature. Beyond the maximum and minimum available strikes obtained from the European-type options, we assume the volatilities remain constant as other scholars do. Then we use adaptive Gauss-Kronrod quadrature approximation to solve the integral in Equation (18) and Equation (19). Although this introduces truncation and discretization errors, both of them are shown trivial in a similar method of trapezodial integration (Jiang and Tian, 2005).

4.3. Moment Risk Premia

The moment swaps are used to explore the risk premia associated with the moments (see Carr and Wu, 2009; Kozhan, Neuberger, and Schneider, 2013). We apply it to study the downside insurance costs of the currency positions, specifically, we check if the moment risk premia contain predictive information content about the future exchange rate returns using the ex-ante payoff of the moment swaps. Without the loss of generality, we define the moment risk premia as the differences between the physical and the risk-neutral expectations of the future realized moments:

$$MRP_{t,T} = \mathbb{E}_t^{\mathbb{P}}[RM_{t,T}] - \mathbb{E}_t^{\mathbb{Q}}[RM_{t,T}] \tag{20}$$

where $\mathbb{E}_t^{\mathbb{P}}[\,\cdot\,]$ is the conditional expectation operator under risk-neutral measure $\mathbb{P}$. We follow Bollerslev, Tauchen, and Zhou (2009) to adopt the lagged realized volatility, and continue to use our calculations of realized moments in Huang and MacDonald (2013). By doing this, we are able to observe ex-ante moment risk premia which does not involve any modeling assumption. Then the moment risk premia in Equation (20) can be rewritten as $MRP_{t,T} = RM_{t-T,T} - \mathbb{E}_t^{\mathbb{Q}}[RM_{t,T}]$. Note that we divide the skewness by the variance to the power of $\frac{3}{2}$ to get a normalized skewness coefficients. In comparison of the moment swap rates obtained from model-free approach with the implied moments derived by Breeden and Litzenberger (1978)[9], we can see that volatility risk premia are consistently understated by directly using ATM implied volatility, as it ignores the volatility smile. We also find that skew risk premia are often understated by using the information of 25-delta and 10-delta OTM options[10].

Inspired by the theory developed by Garleanu, Pedersen, and Poteshman (2009) and the empirical evidence provided to support their conjecture that

[9] For implied skewness: $\tilde{\varsigma}_{10\Delta} \approx 2.3409 \cdot RR_{10\Delta} \,/\, IV_{ATM}$, $\tilde{\varsigma}_{25\Delta} \approx 4.4478 \cdot RR_{25\Delta} \,/\, IV_{ATM}$; For implied kurtosis: $\tilde{\kappa}_{10\Delta} \approx 14.6130 \cdot BF_{10\Delta} \,/\, IV_{ATM}$, $\tilde{\kappa}_{25\Delta} \approx 52.7546 \cdot BF_{25\Delta} \,/\, IV_{ATM}$.

[10] See Figure B.1. and Figure B.2. in Appendix B.

end-user demand affects the option prices in the event of imperfect hedge, we can interpret a currency with high volatility risk premia ($VRP_{t,T}$) as the one "cheap to insure" (Della Corte, Ramadorai, and Sarno, 2013) given that its expected realized volatility is higher than the expected option-implied volatility, which is directly related to the option price used for downside protection. The low $VRP_{t,T}$ (high downside insurance costs) currencies should offer higher excess returns to attract investors. Notwithstanding, high downside-insurance-cost currencies again do not necessarily imply high excess returns unless they are simultaneously very sensitive to tail risk. So, we will show that double-sorting by these two dimensions may be more realistic.

Given that both realized and risk-neutral skewness move in the opposite direction in response to the exchange rate returns(Jurek, 2007), we group skew risk premia by the signs of corresponding skew. UIP predicts zero excess return if there is no risk premium and that USD tends to appreciate against foreign currencies when $r_{f,t} > r_{d,t}$, implying a significant negative skew - high probability of "$s_t < s_{t+1}$". In this case, a 1-month forward-looking implied (model-free) skew lower than the realized skew based on the 1-month backward-looking information available at time t means positive expected change in probability of USD appreciation (lower probability of deviation from UIP), and hence lower (crash) risk premium for a foreign currency against USD (see Graph 2 in Figure B.3. in Appendix B for illustration), and vice versa (Graph 4). In the case of positive skew implied by UIP when $r_{f,t} < r_{d,t}$, a lower forward-looking skew under risk-neutral (no-arbitrage) measure than the backward-looking realized skew means negative expected change in probability of USD depreciation "$s_t > s_{t+1}$" (lower probability of "$\beta > 0$ or $\beta = 1$ in Fama (1984) regression for UIP to hold"), and hence lower (crash) risk premium of a foreign currency against USD (Graph 3), and vice versa (Graph 1). The strategy of investing in low (negative) skew-risk-premium currencies funded by high (positive) skew-risk-premium currencies has a high correlation of 0.77 with currency carry trades, if it explains the cross-sectional excess returns of carry trades, high (low) interest-rate currencies tend to have negative (positive) skew risk premia, which means lower forward-looking probability for the UIP to hold. Again, we need to decompose the cumulative excess return (Della Corte, Ramadorai, and Sarno, 2013) to check if the skew risk premia strategy shares the common constituent drivers of cumulative wealth with carry trades.

[**Insert Table A.4. about here**]

The average volatility and skew risk premia of 27 currencies[11] over the sample period are provided in Table A.4. above. We can see that on average the VRP of AUD and NZD are positive, which means they are cheap to hedge against the downside risk. While the insurance costs for the currencies of Pan-American countries such as COP, CLP, MXN, and BRL are high in terms of negative VRP. The emerging-market currencies with rapid economic growth such as RUB, INR, ZAR, KRW, and TRY are also characterized by expensive insurance for downside risk. As for crash risk premium, BRL, TRY, and MXN are among the highest SRP currencies while HKD, and two safe-heaven currencies JPY and CHF are those with the lowest SRP.

5. Data and Methodology

Our financial data set, obtained from Bloomberg and Datastream, consists of spot rates and 1-month forward rates with bid, middle, and ask prices, 1-month interest rates, 5-year sovereign CDS spreads, at-the-money (ATM) option 1-month implied volatilities, 10-delta and 25-delta out-of-the-money (OTM) option 1-month risk reversals and butterflies of 34 currencies: EUR (EMU), GBP (United Kingdom), AUD (Australia), NZD (New Zealand), CHF (Switzerland), CAD (Canada), JPY (Japan), DKK (Denmark), SEK

[11]Currency portfolios sorted by moment risk premia are presented in Table B.2..

(Sweden), NOK (Norway), ILS (Israel), RUB (Russia), TRY (Turkey), HUF (Hungary), CZK (Czech Republic), SKK (Slovakia), PLN (Poland), RON (Romania), HKD (Hong Kong), SGD (Singapore), TWD (Taiwan), KR-W (South Korea), INR (India), THB (Thailand), MYR (Malaysia), PHP (Philippines), IDR (Indonesia), MXN (Mexico), BRL (Brazil), ZAR (South Africa), CLP (Chile), COP (Colombia), ARS (Argentina), PEN (Peru), all against USD (United States). We also acquire the macroeconomic data set from the Datastream's *Economic Intelligence Unit*, IMF's *International Financial Statistics* and *World Economic Outlook*, OECD's *Unit Labor Cost Indicators*, World Bank's *World Development Indicators*, the databases of the *National Bureau of Statistics*, and webpages of Chinn and Ito (2006)[12] and Lane and Milesi-Ferretti (2007)[13], for real effective exchange rates, real GDP per capita, terms of trade, imports and exports, CPI and PPI (for the test of Balassa-Samuelson effect), real interest rates, PPP conversion factor to market exchange rate ratios[14], government consumption as the percentage of GDP, NFA as the percentage of GDP, capital liberalization index, respectively. Please note that all variables used to estimate the BEER are in country-differential terms, and we drop the variable if its data is unavailable for a certain country. The data of four canonical risk factors in global stock market, the recently broached "Quality-Minus-Junk" and "Betting-Against-Beta" risk factors, hedge fund risk factors, and measures of government economic policy uncertainty in Europe and U.S. are available at the scholar websites established for Fama and French (1992, 1993) and Carhart (1997)[15],

[12]See the link `http://web.pdx.edu/~ito/Chinn-Ito_website.htm`.

[13]See the link `http://www.philiplane.org/EWN.html`.

[14]The ratios approximate the currency fair values. World Bank's database does not have the ratio for TWD and EUR, we use Deutsche Bank's Purchasing Power Parity EUR valuation against USD (available in monthly frequency) to do the calculations by taking the annual average of the data divided by the annual average of market exchange rates. Deutsche Bank does not have the data for TWD. We also exclude ARS since World Bank does not provide the data after 2006.

[15]See the link `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Asness, Frazzini, and Pedersen (2013) and Frazzini and Pedersen (2014)[16], Fung and Hsieh (2001)[17], and Baker, Bloom, and Davis (2012)[18], respectively. Our sample period is restricted by the availability of option historical data from the database terminals we can access[19]. To keep the consistency of time frame across assets, the sample period is optimally chosen from September 2005 to January 2013, which spans pre-crisis and post-crisis times.

5.1. Currency Trading Strategies

All currencies are sorted by forward premia, lag returns over the previous 1 month as formation period, PPP conversion factor to market exchange rate ratios, REER misalignment, volatility risk premia, skewness risk premia, tail dependences, from low to high, and allocated to five portfolios, e.g. Portfolio 1 (P_1) is the long position of currencies with lowest 20% sorting base while Portfolio 5 (P_5) contains the currencies with highest 20% sorting base. The portfolios are rebalanced at the end of each forward contract according to the updated sorting base[20]. The average monthly turnover ratio of five portfolios ranges from 19% to 28%, thereby the transaction costs should considerably affect the profitability of currency trading strategies. All currency portfolios are adjusted for transaction costs, which is quite high for some currencies (Burnside, Eichenbaum, and Rebelo, 2006). Given that CIP holds in our data at daily frequency (see also Akram, Rime, and Sarno, 2008), the log excess returns of a long position xr^L_{t+1} at time $t+1$ is computed as: $xr^L_{t+1} = r_{f,t} - r_{d,t} + s^B_t - s^A_{t+1} = f^B_t - s^A_{t+1}$, where f, s is the log forward rate, and spot rate, respectively; Superscript B, A denotes bid price, and ask price

[16]See the link http://www.econ.yale.edu/~af227/data_library.htm.

[17]See the link https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

[18]See the link http://www.policyuncertainty.com/index.html.

[19]Given that the option data of MYR, PHP, IDR, ILS, RON, ARS, and PEN either are not available or do not cover the sample period, we have 27 currencies remaining for the calculations of moment risk premia.

[20]The portfolios are rebalanced monthly except for REER misalignment and value ones that are done at the end of each year.

respectively. Similarly, for short position of P_1 (P_0)[21], the log excess returns xr^S_{t+1} at the time t+1: $xr^S_{t+1} = -f^A_t + s^B_{t+1}$. Currencies that largely deviate from CIP are removed from the sample for the corresponding periods[22]

[Insert Table A.5. about here]

The reported monthly excess returns and factor prices are annualized via multiplication by 12, standard deviation is multiplied by $\sqrt{12}$, skewness is divided by $\sqrt{12}$, and kurtosis is divided by 12. All return data are in percentages unless specified. As shown in Table A.5., currency carry trade and misalignment strategies generate comparable average excess returns (2.29% p.a. and 2.36% p.a. respectively) and Sharpe ratios (0.29 and 0.26 respectively). The Sharpe ratios are not as high as usual because our data span the recent financial crunch period. Trading on currency momentum[23] in a highly volatile period yields slightly negative average excess return (−0.75% p.a.). Investors are rewarded only 0.78% p.a. by trading on currency fair values[24] over the sample period. The performances of currency trading strategies based on crash sensitivity (holding high-CS currencies funded by low-CS ones) and downside protection cost (holding high-DI currencies funded by low-DI ones) are also poor due to the risk reversals. Trading on skew risk premia is remunerated with an average excess return of 1.53%. The highest average excess return among the eight currency trading strategies over the sample period, about 6.69% p.a. with a Sharpe ratio of 0.80, demonstrates the success of our double-sorting strategy[25] and lends supportive evidence

[21]Except for volatility risk premia portfolios that P_0 is the funding leg of P_5 because low (negative) VRP represents high downside protection costs.

[22]IDR from the end of December 2000 (September 2005 in our data) to the end of May 2007, THB from the end of October 2005 to March 2007, TWD from March 2009 to January 2013.

[23]Please refer to Table B.1. for the descriptive statistics of currency momentum portfolios.

[24]The strategy is investing the (undervalued) currencies with low PPP conversion factor to market exchange rate ratio funded by the high ones. Please also refer to Table B.1. for the descriptive statistics of currency value portfolios.

[25]See also in Figure A.5.

that both crash sensitivity and downside insurance cost are vital to understand the currency risk premia.

[Insert Figure A.2. about here]

Figure A.2. presents the decomposition of the cumulative excess returns to the eight currency trading strategies into exchange rate return and yield (interest rate differential) constituents (see also Della Corte, Ramadorai, and Sarno, 2013). We find the yield components contribute significantly to the cumulative wealth of the investors, e.g. currency carry trades, REER misalignments, fair values, and moment risk premia strategies, which all have a negative cumulative exchange rate return component. Especially, the strategy trading on skew risk premia mimics two pay-off components of carry trades, consistently upward trend in yield component and consistently downward trend in exchange rate component. The cumulative wealth of REER misalignment strategy is driven by both components before the crisis but almost solely by exchange rate return component after the crisis. The cumulative wealth of currency momentum strategy is nearly driven by the exchange rate predictability but not the yield component. As for the cumulative wealth of the currency value and volatility risk premia strategies, the gains in yield component are offset by the losses in exchange rate return component. The exchange rate return component has a major contribution to the crash sensitivity strategy before the crisis but its performance reverses after the crisis. Its yield component always exerts a negative impact on the cumulative wealth, which differentiates from other trading strategies. As for the risk reversal trade-off strategy, both yield and exchange rate return components positively contribute to the the cumulative wealth.

5.2. Monotonicity Tests and Double Sorting

We resort to the monotonicity (MR) test proposed by Patton and Timmermann (2010) to handle the question of whether there is an upward or downward trend in average excess returns across currency portfolios. Let $\mu_j = \mathbb{E}[xr_j]$. We follow their definition of $\Delta_j = \mu_j - \mu_{j-1}$ for $j = 2, ..., 5$ as the difference between average growth rates in the excess returns of two adjacent currency portfolios. The null hypothesis of a increasing pattern in excess returns of currency portfolios ($H_0 : \Delta = [\Delta_2, \Delta_3, \Delta_4, \Delta_5]^\top \leq 0$) against the alternative hypothesis ($H_1 : \Delta > 0$) can be tested by formulating the statistic $J_N = \max_{j=2,...,5} \widehat{\Delta}_j$, where $\widehat{\Delta}$ denotes the estimate of Δ with the sample size of N.

We use the stationary block bootstrap to compute the $p - values$ of J_N as suggested by Patton and Timmermann (2010). In addition, we also report the pairwise comparison tests (MR_P) of currency portfolios, and two less restrictive tests for general increasing (MR_U) and decreasing (MR_D) monotonicity patterns as follows respectively:

$$H_0 : \Delta = 0 \text{ vs. } H_1^+ : \sum_{j=2}^{5} |\Delta_j| 1\{\Delta_j > 0\} > 0; \;\; J_N^+ = \sum_{j=2}^{5} |\widehat{\Delta}_j| 1\{\widehat{\Delta}_j > 0\} \tag{21}$$

$$H_0 : \Delta = 0 \text{ vs. } H_1^- : \sum_{j=2}^{5} |\Delta_j| 1\{\Delta_j < 0\} > 0; \;\; J_N^- = \sum_{j=2}^{5} |\widehat{\Delta}_j| 1\{\widehat{\Delta}_j < 0\} \tag{22}$$

where $1\{\Delta_j > 0\}$ ($1\{\Delta_j < 0\}$) as an indicator function equals to unity if $\Delta_j > 0$ ($\Delta_j < 0$), and zero otherwise. That at lease some of the $\widehat{\Delta}$ are increasing (decreasing) is the sufficient condition for the alternative hypothesis H_1^+ (H_1^-) to hold. J_N^+ (J_N^-) is the "Up" ("Down") test statistic. Patton and Timmermann (2010) extend this methodology to test for monotonic patterns in parameters. Thus, we employ the MR test to examine the monotonicity in factor loadings for robustness check, under the null hypothesis $H_0 : \beta_1 \geq \beta_2 \geq \beta_3 \geq \beta_4 \geq \beta_5$ against the alternative hypothesis $H_1 : \beta_1 <$

$\beta_2 < \beta_3 < \beta_4 < \beta_5$. The coefficient vector $\hat{\beta}_j^{(b)}$ is obtained from bootstrap regressions to compute the statistic $J_{j,N} = \min_{j=2,\ldots,5} \left[(\hat{\beta}_j^{(b)} - \hat{\beta}_j) - (\hat{\beta}_{j-1}^{(b)} - \hat{\beta}_{j-1}) \right]$ for the test.

[Insert Table A.6. about here]

The top panel of Table A.6. indicates that only currency carry trade, misalignment, and value portfolios exhibit statistically significant monotonic patterns in excess returns. The bottom panel reveals the risk reversal of currency portfolios sorted by crash sensitivity (CS) and downside protection cost (DI) that in pre-crisis period, the crash-averse investors are in favor of high-CS and low-DI currencies but the situation switched in post-crisis period that low-CS and high-DI currencies become more appealing to the investors. The monotonicity in the excess returns of these portfolios in split sample period is confirmed by the MR tests respectively.

[Insert Figure A.3. about here]

Figure A.3. above presents the time-varying risk premia of the P_1 and P_5 currency portfolios sorted by crash sensitivity and downside insurance cost respectively. In pre-crisis period, both high-CS and low-DI portfolios outperformed their counterparts (low-CS and high-DI portfolios) but this pay-off pattern reverses in post-crisis period. This implies that crash-averse investors do attach a precautionary weight to the rare disastrous events such as currency crashes in the tranquil period, that's why they prefer high-CS and low-DI currencies over the counterparts. In the outbreak of the crisis, they starts to sell off the positions in these currencies and buy in safe assets such as low-CS currencies. Moreover, in the aftermath period, the high-DI currencies must offer a risk premia for the investors to hold. Given that majority of the high crash-sensitivity currencies have cheap downside protection costs, the performances of the corresponding portfolios are very similar. These empirical findings are concordant with Jurek's (2007) that the downside protection costs against the high crash risk implied in high interest-rate currencies are relatively low, and with also Huang and MacDonald's (2013) that higher interest-rate currencies are exposed to higher position-unwinding risk.

[**Insert Table A.8. about here**]

To investigate the risk reversal of these two types of currency portfolios, we doubly sort the currencies into 3×2 portfolios[26] by CS and DI respectively, as shown in Table A.8. above. An intriguing behavior of "Risk-on and Risk-off" across six portfolios is unveiled that, in the first four columns, we can see strict monotonicity in average excess returns in both dimensions. Low-CS and low-DI currencies have the worst performance of average excess return (-1.22% p.a.), low-CS but high-DI currencies offer a higher average excess return of 1.73% p.a. and the low-DI but medium-CS currencies give even higher average excess return (2.92% p.a.). Medium-CS and high-DI currencies have the best performance, 6.49% p.a., among all. The high-CS currencies become unappealing to the crash-averse investors in the aftermath of the crisis. And when the currencies with this feature are expensive to hedge, they become stale to the investors. That's why high-CS and high-DI currencies also generates negative average excess return, -0.57% p.a., which is yet slightly higher than their counterparts, because crash risk premia still play a role here. That high-CS but low-DI currencies yield a positive average excess return of 2.40% p.a. illuminates the importance of downside protection costs for the highly crash-sensitive currencies to the investors, particularly during the crisis period.

[26]Given that there are only 27 currencies' option data available, we cannot sort the currencies into 3×3 portfolios. Otherwise, sometimes a certain portfolio or more could be empty, and the empirical findings would be bias.

5.3. Asset Allocation and Risk Reversal Trade-off Strategy

Optimal portfolio as the combination of various currency trading strategies reflects a representative investor's choice on the asset allocation in high and low volatility regimes. We use monthly-rebalancing mean-variance optimization approach to get the optimal portfolio weights among the currency investment strategies with a closed form solution. Although Ang and Bekaert (2002) show that the effect of time-varying investment opportunity sets on portfolio optimization is not big, we do find considerably different asset allocation implications in pre-crisis and post-crisis periods. The investor maximizes the utility function given by:

$$\mathbb{E}[r_{o,t}] - \frac{\gamma}{2}\sigma^2_{r_{o,t}} = 0 \tag{23}$$

where $\mathbb{E}[xr_{o,t}]$ is the expected portfolio return of the combination of currency investment strategies, $\sigma^2_{r_{o,t}}$ denotes the volatility of the portfolio, and γ measures the risk aversion of the investor. The vector of optimal weights $\omega_k = \frac{1}{\gamma}\Sigma^{-1}_{k,k}\mathbb{E}[R_k]$, where $\mathbb{E}[R_k]$, $\Sigma_{k,k}$ is the expected return vector, and covariance matrix of currency investment strategies. We also look into the tangency portfolios, which are independent of risk-free rate and the coefficient of risk aversion.

[**Insert Figure A.4. about here**]

Figure A.4. illustrates the unconditional and time-varying efficient frontiers and tangency portfolios in optimal mean-variance allocations of several studied currency investment strategies. It is clear that optimal asset allocation by a representative investor according to the business cycles (such as pre-crisis and post-crisis periods) is of paramount importance to understand the currency risk premia. Table A.7. reports the portfolio weights of each currency investment strategies and the asset allocation results. In previous section, we show the risk reversal of two currency strategies trading on crash sensitivity and downside insurance cost after the outbreak of the financial crisis. Thus, the investor is better off by reallocating the portfolio holdings dramatically. We find that a crash-averse investor allocates a notable weight of 0.852 to high downside-insurance-cost currencies funded by the low counterparts in post-crisis period but a zero weight to the strategy in pre-crisis period. Similarly, he/she allocates a weight of 0.341 to high crash-sensitive currencies funded by low counterparts in pre-crisis period but a zero weight to the strategy in the post-crisis period. Due to the unstable performance of the momentum strategy in business cycles, the utility-maximizing investor does not allocate the wealth to the strategy. That the limits to arbitrage make this strategy unexploitable by the investors is emphasized by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). The weight to value strategy is very small in two split periods, but in the unconditional asset allocation, investor will assign a significant fraction of his/her wealth of 0.199 to the strategy. Carry trade strategy is revealed exposed to the global volatility (innovation) risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a). As the result, investor does not allocate the wealth to carry trade portfolio in the post-crisis period, which is characterized by "high volatility" regime. Currency misalignment strategy accounts for a large proportion of allocated wealth, 0.417, in pre-crisis period but its weight shrinks to 0.120 in post-crisis period, implying that overpriced (to the medium/long-run fundamental equilibrium values) currencies are subject to depreciation risk in period of financial turmoil. Currency carry trade and misalignment strategies have comparable weights in unconditional allocation. Investor also optimally allocates about 0.102 of the wealth to currency skew risk premia portfolio in pre-crisis period, which is close to the weight to carry trades. The Sharpe ratio of the optimal risky portfolios reaches 1.348 in tranquil period.

[**Insert Table A.7. about here**]

Figure A.5. presents a trading strategy[27] by investing in medium-CS and high-DI currencies funded by low-CS and medium-DI ones in 3×3 double sorting[28] in comparison with the Chicago Board Options Exchange's (CBOE) VIX index as the market risk sentiment that has a robust pay-off without any dramatic plummeting over the sample period, even in several times when the VIX suddenly hiked up[29].

[Insert Figure A.5. about here]

In the empirical test section, we will show which risk factor drives the payoff of this trading strategy. The tested risk factors include the changes in VIX (ΔVIX), the changes in T-Bill Eurodollar (TED) Spreads Index (ΔTED), the changes in Financial Stress Index (FSI) released by Federal Reserve Bank of St. Louis (ΔFSI), the changes in the measures of government economic policy uncertainty (Baker, Bloom, and Davis, 2012) in Europe (GPU_{EU}) and in U.S. (GPU_{US}), which are shown priced in the stock markets (see Brogaard and Detzel, 2012; Pastor and Veronesi, 2012, 2013, among others). excess returns of MSCI Emerging Market Index ($MSCI^{EM}$), canonical risk factors in currency, bond, and equity markets, "Quality-Minus-Junk" risk factor (QMJ) for stock markets (Asness, Frazzini, and Pedersen, 2013), "Betting-Against-Beta" risk factors (Frazzini and Pedersen, 2014) for foreign exchanges market (BAB_{FX}), equity market (BAB_{EM}), sovereign bond market (BAB_{BM}), and commodity market (BAB_{CM}), as well as hedge fund risk factors proposed by Fung and Hsieh (2001), which have been extensively

[27] Its descriptive statistics are indicated in Table A.5..

[28] We have checked the availability of featured currencies that are eligible to be allocated into these two baskets. There are only 1 out of 89 trading months in the investment leg and 3 out of 89 trading months in the funding leg that no trading action is taken. So these two portfolios are indeed actively managed.

[29] For example, the episodes such as BNP Paribas' withdrawal of three money market mutual funds in August 2007, disruption in USD money market in November 2007, Lehman Brothers bankruptcy in September 2008, Greek maturing sovereign debt rollover crisis in May 2010, U.S. government debt ceiling and deterioration of the crisis in Euro area in August 2011.

used by numerous recent studies (see Fung, Hsieh, Naik, and Ramadorai, 2008; Bollen and Whaley, 2009; Patton and Ramadorai, 2013; Ramadorai, 2013, among others). This set of monthly data includes excess returns on Standard & Poors (S&P) 500 Index (SNP), size spreads of Russell 2000 Index (SPD^{RS}) over S&P Index, changes in 10-year treasury constant maturity yields (TBY), changes in the credit spreads of Moody's BAA corporate bond yields over the T-Bill yields (SPD^{MB}), and excess returns on portfolios of lookback straddle options on bonds (TF^{B}), currencies (TF^{FX}), and commodities (TF^{CMD}) that replicate the performance of the trend-following strategies in respective asset classes.

5.4. Factor Models and Estimations

We introduce two types of factor models for the estimations: Linear Factor Model for the asset pricing tests (Cochrane, 2005; Burnside, 2011), and Generalized Dynamic Factor Model (Forni, Hallin, Lippi, and Reichlin, 2000, 2004, 2005; Doz, Giannone, and Reichlin, 2011, 2012) for testing the risk sources and return predictability of currency trading strategies.

5.4.1. Asset Pricing Tests

Here we briefly summarize the methodologies used for risk-based explanations of the currency excess returns. The benchmark asset pricing Euler equation with a SDF implies the excess returns must satisfy the no-arbitrage condition (Cochrane, 2005):

$$\mathbb{E}[m_t \cdot xr_{j,t}] = 0 \tag{24}$$

The SDF takes a linear form of $m_t = \xi \cdot \left[\, 1 - (f_t - \mu^*)^\top b \,\right]$, where ξ is a scalar, f_t is a $k \times 1$ vector of risk factors, $\mu^* = \mathbb{E}[f_t]$, and b is a conformable vector of factor loadings. Since ξ is not identified by its equation, we set it equal to 1, implying $\mathbb{E}[m_t] = 1$. Then the beta expression of expected excess returns across portfolios is written as:

$$\mathbb{E}[xr_{j,t}] = \underbrace{\text{cov}[xr_{j,t}, f_t]\,\Sigma_{f,f}^{-1}}_{\beta_j} \cdot \underbrace{\Sigma_{f,f}\,b}_{\lambda} \tag{25}$$

where $\Sigma_{f,f} = \mathbb{E}[(f_t - \mu^*)(f_t - \mu^*)^\top]$. β_j is a vector of risk quantities of n factors for portfolio j, and λ is a $k \times 1$ vector of risk prices associated with the tested factors. When factors are correlated, we should look into the null hypothesis test $b_j = 0$ rather than $\lambda_j = 0$, to determine whether or not to include factor j given other factors. If b_j is statistically significant (different from zero), factor j helps to price the tested assets. λ_j only asks whether factor j is priced, whether its factor-mimicking portfolio carries positive or negative risk premium (Cochrane, 2005). We reply on two procedures for the parameter estimates of the linear factor model: Generalized Method of Moments (Hansen, 1982), as known as "GMM", and Fama-MacBeth (FMB) two-step OLS approach (Fama and MacBeth, 1973)[30]. They are standard estimation procedures adopted by Lustig, Roussanov, and Verdelhan (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) that yields identical point estimates (see Burnside, 2011 for details). We report the $p - values$ of χ^2 statistics for the null hypothesis of zero pricing error based on both Shanken (1992) adjustment and Newey and West (1987) approach in FMB procedure, and the simulation-based $p - values$ for the test of whether the Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance ($HJ - dist$) is equal to zero[31] in the GMM procedure. Given that both the time span of our sample and the cross section of currency portfolios are limited, the R^2 and the Hansen-Jagannathan test are our principal concerns when interpreting the empirical findings, which are reported only if we can assuringly detect a

[30]Notably, we do not include a constant in the second step except for the tail sensitivity portfolios which are sorted according to the copula correlation with the currency "market portfolio". These portfolios have monotonic exposures to the global market, hence the dollar risk factor does not serve as a constant that allows for a common mispricing term.

[31]For more details, see Jagannathan and Wang (1996); Parker and Julliard (2005).

statistically significant λ.

5.4.2. Common Risk Factor of Currency Trading Strategies

To estimate the common risk sources and return predictability of the foreign exchanges (FX) trading strategies, we use Generalized Dynamic Factor Model (GDFM) (see Forni, Hallin, Lippi, and Reichlin, 2000, 2004, 2005; Doz, Giannone, and Reichlin, 2011, 2012) in a state space representation. This econometric methodology is typically useful for extracting the common latent component(s) of a large dimension of variables by compacting their information into a smaller dimension of information while minimizing the loss of information. We also apply GDFM to a pool of exchange rate series, as portfolio approach may lead to the loss of information. Ample studies exploit approximate factor models for dynamic panel data under similar assumptions (e.g. Stock and Watson, 2002a,b; Bai and Ng, 2002; Bai, 2003; Bai and Ng, 2006). Forni, Hallin, Lippi, and Reichlin (2005) find the superiority of their Generalized Principal Components Estimator (PCE) over other PCEs in terms of accuracy in the Monte Carlo experiments, especially when the dynamics in the common and idiosyncratic latent components are persistent[32]. Applications of GDFM to analyzing and forecasting the common fluctuations among a large set of macroeconomic fundamentals are popularized by the scholars (e.g. Kose, Otrok, and Whiteman, 2003; Stock and Watson, 2005; Giannone, Reichlin, and Small, 2008; Kose, Otrok, and Prasad, 2012). However, it is rare in the literature that applies GDFM to the financial markets.

We conduct a likelihood ratio to test the null hypothesis that the number of common components is zero, and reject it with a $p-value$ of 0.000. Then we employ information criteria developed by Hallin and Liška (2007)[33] and

[32]Boivin and Ng (2005) compare different PCEs, including various feasible Generalized PCEs but only find nuances in forecasting performances.

[33]Note that the information criteria proposed by Bai and Ng (2007) is for the Restricted

Ahn and Horenstein (2013)[34] to determine the number of dynamic and static factors respectively in GDFM. The results suggest two static and one dynamic factor that summarizes the common dynamics of the variables and explains over 50% variation in variables[35]. These factors are the representative "Coincident Indices" or "Reference Cycles" that measure the comovements of the exchange rate component of FX trading strategies, and of the global currencies (see Stock and Watson, 1989; Croux, Forni, and Reichlin, 2001). Let $Y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})^\top$, denoting a large dimension of variables. Y_t in a GDFM representation is given by:

$$Y_t = \Lambda\, F_t + u_t \tag{26}$$

$$\Theta(L)\, F_t = \upsilon_t \tag{27}$$

$$\Psi(L)\, u_t = \nu_t \tag{28}$$

where $F_t = [g_t^\top, g_{t-1}^\top, ..., g_{t-l}^\top]^\top$ is a $k \times 1$ vector of unobserved common "static" components with a corresponding $n \times k$ matrix of factor loadings Λ_i for $i = 1, 2, ..., l$ and a corresponding $k \times k$ matrix of autoregressive coefficients Θ_j for for $j = 1, 2, ..., p$, g_t is a $h \times 1$ vector of dynamic stationary factors such that $k = (1 + l)\, h$, and u_t is a $n \times 1$ matrix of idiosyncratic component with a corresponding $n \times n$ matrix of autoregressive coefficients Ψ. L in the parentheses is the lag polynomial operator, for example, $\Theta(L) = I - \Theta_1\, L - \Theta_2\, L^2 - \ ... \ - \Theta_p\, L^p$. g_t and u_t, u_t and υ_t are independent processes. All error terms follow the Gaussian $i.i.d.$ normal distribution and

Dynamic Factor Model.

[34]It is built on the methodology proposed by Bai and Ng (2002) by maximizing the adjoining eigenvalue ratio with respect to the number of factors.

[35]50.87% of total variation of the FX trading strategies, and 62.46% of total variation of the global currencies. Currencies for which the CIP unhold in certain periods are excluded. Currency, such as ARS, has a zero correlation with the market portfolio (global market) is also excluded.

cross-sectionally independent for any $t_1 \neq t_2$. Doz, Giannone, and Reichlin (2012) show that under the assumption of no cross-sectional correlation in the idiosyncratic component, Equation (26) can be estimated by (Quasi) Maximum Likelihood Estimator (MLE) using Expectation Maximization (EM) algorithm. Doz, Giannone, and Reichlin (2011) propose a two-step estimator that combines principal component approach with state space (Kalman filter) representation. These two methods are particularly useful for a large dimension of variables, such as global currencies. We adopt Forni, Hallin, Lippi, and Reichlin's (2005) one-sided generalized PCE for the FX trading strategies. The first common dynamic factors that explain over half of the total variations of the variables extracted by MLE and PCE methods are robust, as they have very high correlations of over 0.95.

6. Empirical Results

We first focus on currency carry trades. The top panel of Table A.9. below shows the asset pricing results with GDR and HML_{ERM}. The highest interest-rate currencies load positively on misalignment risk and the low interest-rate currencies offer a hedge against it. The risk exposures are monotonically increasing with the interest rate differentials. The cross-sectional R^2 is very high, about 0.973[36]. The coefficients of β, b and λ are all statistically significant, so misalignment risk helps to price currency carry portfolios and this factor is priced in the excess returns of these portfolios. The factor price of misalignment risk is 5.881% p.a., and the Mean Absolute Error (MAE) is only about 20 basis points (bps), which is very low. The $p - values$ of χ^2 tests from Shanken (1992) and Newey and West (1987) standard errors, and those of the $HJ - dist$ (Hansen and Jagannathan, 1997) all suggest that we accept the model.

[36] So do the time-series R^2s that are persistently over 0.90 across portfolios.

[Insert Table A.9. about here]

In the bottom panel of Table A.9., we substitute the slope factor with the skew risk premia factor and find that the factor price is also statistically significant (about 5.422% p.a.) and hence priced in the cross-sectional excess returns of currency carry trades. The risk exposures also exhibit monotonic pattern across portfolios. The model is also confirmed correct by χ^2 and $HJ - dist$ tests, with a MAE of about 23 bps. All these suggest that high interest-rate currencies are likely to be overpriced to their equilibrium values that keep their macroeconomic fundamentals in a sustainable path and high interest-rate currencies also tend to have higher crash risk premia. Skew risk premia contain valuable ex-ante information about the profitability of currency carry trades.

[Insert Table A.10. about here]

Table A.10. provides the robustness checks on the monotonicity in factor exposures to currency misalignment and crash risk, and on corresponding beta-sorted portfolios. We can see both sets of risk exposures pass strict and pairwise MR tests. And both types of portfolios sorted by the beta of each currency with respective risk factors exhibit a very close monotonic pattern in average excess returns and forward discounts. Although they mimic the monotonicity in average excess returns and forward discount of currency carry trades, their higher moments are not alike those of the currency carry portfolios. This means sorting currencies by beta with currency misalignment or crash risk is relevant to but not identical to currency carry trades, which needs more precise explanations. Global tail risk has statistically significant factor price but does not possess much cross-sectional pricing power on currency carry trades.

[Insert Table A.11. about here]

We then run a horse race of currency misalignment risk with Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) global FX volatility (innovation) risk (GVI). As shown in Table A.11., only a very little improvement on the cross-sectional R^2. We can still see monotonicity in risk exposures to HML_{ERM} but not to GVI, and statistically significant factor price of HML_{ERM} but not of GVI[37]. All the evidence testifies that currency misalignment risk dominates volatility risk in explaining the cross section of the excess returns of currency carry portfolios. In the horse race of currency crash risk with GVI, neither of these two factors dominates in the cross-sectional regressions. REER misalignment risk factor is the best proxy for currency risk premia in carry trades over the sample period in terms of cross-sectional R^2 and statistical significance of factor price(see Huang and MacDonald, 2013, for the horse races of other candidate risk factors). In the horse race of currency skew premium risk (HML_{SRP}) with GVI, the factor prices of both factors become statistically insignificant. And HML_{ERM} still outperforms HML_{SRP} in the cross-sectional test.

[Insert Table A.12. about here]

We then look into the currency momentum strategy. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) argue that it is the limits to arbitrage that prevent this type of trading profitability from being exploitable. We offer evidence analogous to that of Avramov, Chordia, Jostova, and Philipov (2007) in equity market that stock momentum is mainly found in high credit risk firms[38] which are subject to illiquidity risk. And the difficulty in selling short can hinder the arbitrage activity as well. The top panel of Table A.12. above reveals that sovereign credit risk (HML_{SC}) proposed by Huang and MacDonald (2013) drives currency momentum over our sample period

[37] In a two-factor linear model of $GDR + GVI$, the risk exposures to GVI exhibit a monotonic pattern and the factor price of GVI is statistically significant (-0.326% with a standard error of 0.250).

[38] For instance, those whose corporate bonds are rated at non-investable grade.

in which the investors have experienced Subprime Mortgage Crisis and Europe Sovereign Debt Crisis. We also find strictly monotonic risk exposures across currency momentum portfolios, winner currencies load negatively on HML_{SC} while loser currencies positively, implying that winner currencies perform well when sovereign credit risk is low and loser currencies provide a hedge against it when sovereign credit risk is high. This is concordant with poor performance of currency momentum strategy during the recent period of credit crunch. The factor price of HML_{SC} is negative, so sovereign credit risk offers a high premium about 13.496% p.a (with an acceptable statistical significance). to the currency momentum investors. This model has a R^2 of 0.651 with a MAE of about 42 bps, and is accepted by χ^2 and $HJ-dist$ tests for zero pricing errors. Sovereign credit risk is the only factor that yields statistical significant factor price and good cross-sectional pricing power among the canonical risk factors used in Huang and MacDonald (2013).

We also investigate the currency value strategy by testing the cross-sectional pricing power and statistical significance in factor price of each of these canonical risk factors, and find that only the sovereign credit risk, to some extent, may contribute to the value risk premia (see the bottom panel of Table A.12.). The significance of the factor price is statistically acceptable. The undervalued currencies in terms of PPP positively load on sovereign credit risk while the overvalued currencies provides a hedge against it, and the risk exposures to sovereign credit risk across portfolios exhibit a monotonic pattern. However, the exposure of the undervalued currency portfolio to dollar risk is just about half of those of other four currency value portfolios, which have roughly the same loadings on dollar risk. This makes it difficult for the two factor linear model to capture the cross section of the excess returns of currency value portfolios without a constant.

[Insert Table A.13. about here]

Now, we turn to moment risk premium strategies. The top panel of

Table A.13. indicates that the profit brought by a trading strategy which borrows low downside-insurance-cost (high volatility risk premium) currencies to invest in the currencies characterized by high position-protection cost (low volatility risk premium) can be understood from the angle of sovereign credit risk as well. The crash-averse investors are actually paying high insurance premia to protect their currency positions against sovereign credit risk implied in the currencies. The price for this factor to this trading strategy is 5.198% p.a. and statistically significant. The cross-sectional R^2 is 0.820 with a MAE of approximately 55 bps. Misalignment risk does not explain the volatility risk premium portfolios well but it does a pretty good job in explaining skew risk premium portfolios that REER misalignment is the key to justify the high crash risk premia in currencies. As shown in the bottom panel of Table A.13., we find monotonically increasing risk exposures and high R^2 of 0.974 with a MAE of only 14 bps. Crash-averse investors are rewarded by 4.584% p.a. excess returns per unit of overpricing risk quantity for their holdings of low skew (high crash) risk premium currencies. The results are compelling given both models are accepted correctly specified by χ^2 and $HJ-dist$ tests. In sum, higher sovereign default probability makes the downside risk of a currency more expensive to hedge and the REER misalignment exaggerates the skewness of a currency.

[Insert Table A.14. about here]

Finally, we investigate the currency crash sensitivity portfolios. Since sorting currencies by lower tail dependences is equivalent to sorting them by market beta, the dollar risk factor (GDR) does not serves as a constant in the cross-sectional regressions. The disappointing results in Table A.14. suggest that the excess returns generated by this trading strategy cannot be justified by any of the tested canonical risk factors[39], surprisingly including dollar risk. We further test if the position-unwinding likelihood indicator

[39]We only report two of them in Table A.14..

of currency carry trades (see Huang and MacDonald, 2013, for details) also works as a caveat of the market crash for other currency trading strategies. It turns out that the profitabilities of the investment strategies we study all rely on the forward bias of the currencies. On one hand, this result implies forward bias is the dominant risk in currency market because none of these strategies is traded on the interest rate differentials. On the other hand, it also indicates that forward premia (discounts) are, to some extend, related to macroeconomic fundamentals, comprehensively to the REER overvaluations (undervaluations).

[**Insert Table A.15. about here**]

We propose a double-sorting trading strategy accordingly that buys medium crash-sensitivity and high downside-insurance-cost currencies while sells low crash-sensitivity and medium downside-insurance-cost currencies. Choosing the medium level in one sorting dimension that is subject to risk reversals in both long and short positions while keeping another in top (for long position) and bottom (for short position) levels is actually a trade-off of time-varying risk premia in between two regimes. That's why its payoff is almost immunized from the reversals in risk premia in high volatility regime while still perform well in low volatility regime, as shown in Figure A.5. The cumulative excess return series of this trading strategy has a statistically significant drift term of 9.60% p.a. in the linearity fitting with time, representing very high expected excess returns regardless of the business cycle risk. Understand the risk nature of it is our next task.

[**Insert Figure A.6. about here**]

Table A.15. presents the time-series asset pricing test on the excess returns of our proposed trading strategy. We have five groups of risk factors: Common risk factors in currency market (Lustig, Roussanov, and Verdelhan, 2011) plus two additional risk factors that capture currency momentum

(Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b) and fair value in the Panel A; Common risk factors in stock market (Fama and French; 1992, 1993) plus winner-minus-loser (Carhart, 1997) and quality-minus-junk (Asness, Frazzini, and Pedersen, 2013) risk factors in Panel B; Hedge fund risk factors (Fung and Hsieh, 2001) in the Panel C; Betting-against-beta risk factors for foreign exchanges, equity, sovereign bond, and commodity markets (Frazzini and Pedersen, 2014) in Panel D; And other risk factors, including measures of government economic policy uncertainty (Baker, Bloom, and Davis, 2012), are grouped together in the Panel E. It is shown that the alpha estimates of our proposed strategy are all statistically significant and essentially unaffected by the inclusion of any of these risk factors. The estimated annualized alphas are virtually close to the average annual excess returns brought by this strategy, which means the anomaly is substantial. Although in terms of statistical significance, this anomaly is related to forward bias risk, commodity trend-following risk, risk associated with the betting against sovereign bond beta, emerging market risk, volatility risk. But only forward bias risk can explain the pay-off of this strategy at an acceptable $Adjusted - R^2$ level.

[**Insert Table A.16. about here**]

The correlation of the dynamic latent factors between the exchange rate return component of FX trading strategies and a large set of individual currencies is 0.83 (see Figure A.6). The common dynamic factor of FX trading strategies has a smaller variation than that of global currencies because the weighted averages of idiosyncratic components in portfolio returns converge to zero. The FX trading strategies have distinctive loadings on their common dynamic factor while most of the individual currencies share similar loadings on their common dynamic factor[40] (see Table A.16.). Currency

[40]All currencies except for JPY, which has a slightly negative loading, positively load on the common dynamic factor.

strategies trading on interest-rate differentials, misalignments, crash sensitivity, and skew risk premia positively load on the common dynamic factor while currency momentum, value, and downside protection cost strategies share similar negatively loadings. Our risk reversal trade-off strategy has the lowest loadings in absolute value on the common dynamic factor so that the influence of the risk reversal of the common risk source is minimum among the studied FX trading strategies.

[**Insert Table A.17. about here**]

Panel A of Table A.17. presents the tests of risk sources on the common dynamic factor of the FX trading strategies (DF_{PFL}). The changes in global sovereign CDS spreads ($\Delta SVRN$) as the proxy for sovereign credit risk alone captures about 59% of the variation of DF_{PFL} and is statistically significant at 1% level. The best-performance combination in a two-factor linear model - global skew (crash) risk (GSQ) and $\Delta SVRN$ together explain approximately 70% of the variation of DF_{PFL}. Panel B of Table A.17. reports the dynamic correlations (see Croux, Forni, and Reichlin, 2001) between DF_{PFL} and $\Delta SVRN$. Both of the dynamic and static correlations are quite high, especially the short-term correlation reaches 0.88. In sum, sovereign credit risk is the common risk source of the FX trading strategies.

[**Insert Figure A.7. about here**]

[**Insert Table A.18. about here**]

Figure A.7. and Table A.18. show the forecasting performance of the common exchange rate components of eight currency investment strategies from 1-month to 6-month ahead using GDFM. We find GDFM does a relatively good job in 1-month ahead forecasting but its performance is not stable over the time horizons; and on average the currency investment strategy trading on volatility risk premia has the best exchange rate predictability by

GDFM among others, which is concordant with the findings of Della Corte, Ramadorai, and Sarno (2013).

7. Conclusion

Our empirical findings vindicate that misalignment risk contributes to the currency carry trade premia. High interest-rate currencies positively load on misalignment risk while low interest-rate currencies provide a hedge against it. The mechanism is related to Gourinchas and Rey's (2007) analytical framework that highlights to the valuation channel of global imbalances. It is discussed in detail in Huang and MacDonald (2013). However, that external adjustment is just an ingredient of misalignment risk entails the theory to be extended, encompassing the internal adjustment of the economy as well. Investments in currencies that are overpriced to their fundamental equilibrium values, funded by undervalued currencies is remunerated with a pay-off that is similar to carry trades. Both of the currency carry and misalignment portfolios trade on the position-unwinding likelihood indicator (Huang and MacDonald, 2013) that explores the probability of the UIP to hold in the option pricing model, so do other currency investment strategies studied in this paper. Apart from the recent NBER recession period, the exchange rate return component positively contributes to the cumulative wealth to the strategy trading on REER misalignments, which is unlike currency carry trades. We also reveal that currency misalignments drive the crash (skew) risk premia but the reverse is not true. High (low) interest-rate currencies are likely to have low negative (high positive) skew risk premia in our definition, which contains predictive information about the expected changes in the likelihood for UIP to hold in the future (crash risk premia of the foreign currencies versus USD). The profitability of currency carry trades may not just rely on interest rate differentials, since skew risk premia also offer valuable ex-ante information about the future spot-rate movements. Moreover, the skew risk premia strategy mimics both yield and exchange rate return components of currency carry trades. In our analysis, forward premia appear to be the crash risk premia driven by the REER misalignments in comprehensive evaluation. Sovereign credit risk partially contributes toward the REER misalignment.

Furthermore, we show that both the cross sections of currency portfolios sorted by momentum and downside protection cost can be understood from the perspective of sovereign credit risk. Winner currencies performance well when sovereign default probability is low and loser currencies provide the hedge against this type of risk when sovereign default probability becomes high. Sovereign credit risk also seems to push up the insurance costs for crash-averse investors to protect the downside risk of their currency positions. Misalignment risk is also priced in the currency portfolios sorted by skew risk premia and explains over 97% of the cross-sectional excess returns. Currency crash sensitivity portfolios cannot be priced by the candidate risk factors we consider in our cross-sectional asset pricing tests. Moreover, we propose a double-sorting trading strategy that strikes a balance in time-varying risk premia between low and high volatility regimes and avoids risk reversals effectively. It generates a sizeable alpha that cannot be rationalized by any canonical risk factors in time-series regressions. The changes in global sovereign CDS spreads is the key contributor to the factor that captures the common dynamics of the several studied currency trading strategies. From asset allocation perspective, a crash-averse investor would optimally choose a relatively diversified portfolio in tranquil period by allocating about 40% of the wealth to currency misalignment strategy and about 35% to crash sensitivity strategy, with about 10% to carry trades and skew risk premia strategy respectively. While in turmoil period, the investor would reallocate his/her portfolio holdings dramatically to volatility risk premia strategy with a weight of about 85% of the wealth. This behavior pattern is related to the risk-bearing capacity of the financial intermediaries (Gabaix and Maggiori, 2014), such as the market risk sentiment and the funding liquidity constraint during the financial distress.

Our next step is to extend the sample period as we've got a data set with longer time span. A lot of future work can be done, e.g. building a macro-finance pricing model for exchange rates with the respect to misalignment risk, identifying which macroeconomic fundamental makes a currency crash sensitive and expensive to hedge, verifying the time variation of "limit to arbitrage" and the hedgers and speculators' motivations for portfolio selections of currencies under informational ambiguity and learning process, etc.

References

Ahn, S. and A. Horenstein (2013). Eigenvalue ratio test for the number of factors. *Econometrica 81*(3), 1203–1227.

Akram, Q., D. Rime, and L. Sarno (2008). Arbitrage in the foreign exchange market: Turning on the microscope. *Journal of International Economics 76*(2), 237–253.

Andrews, D. (1991). Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica 59*(3), 817–858.

Ang, A. and G. Bekaert (2002). International asset allocation with regime shifts. *Review of Financial Studies 15*(4), 1137–1187.

Ang, A. and J. Chen (2002). Asymmetric correlations of equity portfolios. *Journal of Financial Economics 63*(3), 443–494.

Asness, C., A. Frazzini, and L. H. Pedersen (2013). Quality minus junk. *Available at SSRN No.2312432*.

Asness, C., T. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. *The Journal of Finance 68*(3), 929–985.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov (2007). Momentum and credit rating. *The Journal of Finance 62*(5), 2503–2520.

Bacchetta, P. and E. van Wincoop (2006). Can information heterogeneity explain the exchange rate determination puzzle? *The American Economic Review 96*(3), 552–576.

Bacchetta, P. and E. van Wincoop (2009). On the unstable relationship between exchange rates and macroeconomic fundamentals. *NBER Working Paper No.15008*.

Bai, J. (2003). Inferential theory for factor models of large dimensions. *Econometrica 71*(1), 135–171.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*(1), 191–221.

Bai, J. and S. Ng (2006). Confidence intervals for diffusion index forecasts and inference for factor-augmented regressions. *Econometrica 74*(4), 1133–1150.

Bai, J. and S. Ng (2007). Determining the number of primitive shocks in factor models. *Journal of Business and Economic Statistics 25*(1), 52–60.

Baker, S., N. Bloom, and S. Davis (2012). Measuring economic policy uncertainty. *Available at SSRN No.2198490*.

Bakshi, G. and N. Kapadia (2003). Delta-hedged gains and the negative market volatility premium. *Review of Financial Studies 16*(2), 527–566.

Bakshi, G., N. Kapadia, and D. Madan (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies 16*(1), 101–143.

Bakshi, G. and D. Madan (2000). Spanning and derivative-security valuation. *Journal of Financial Economics 55*(2), 205–238.

Barberis, N., M. Huang, and T. Santos (2001). Prospect theory and asset prices. *The Quarterly Journal of Economics 116*(1), 1–53.

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

Benartzi, S. and R. Thaler (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics 110*(1), 73–92.

Boivin, J. and S. Ng (2005). Understanding and comparing factor-based forecasts. *NBER Working Paper No.11285*.

Bollen, N. and R. Whaley (2009). Hedge fund risk dynamics: Implications for performance appraisal. *The Journal of Finance 64*(2), 985–1035.

Bollerslev, T., M. Gibson, and H. Zhou (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics 160*(1), 235–245.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *Review of Financial Studies 22*(11), 4463–4492.

Bollerslev, T. and V. Todorov (2011). Tails, fears, and risk premia. *The Journal of Finance 66*(6), 2165–2211.

Breeden, D. and R. Litzenberger (1978). Prices of state-contingent claims implicit in option prices. *The Journal of Business 51*(4), 621–651.

Britten-Jones, M. and A. Neuberger (2000). Option prices, implied price processes, and stochastic volatility. *The Journal of Finance 55*(2), 839–866.

Brogaard, J. and A. Detzel (2012). The asset pricing implications of government economic policy uncertainty. *Available at SSRN No.2075375*.

Brunnermeier, M., S. Nagel, and L. H. Pedersen (2009). Carry trades and currency crashes. In *NBER Macroeconomics Annual*, Volume 23, pp. 313–347. University of Chicago Press.

Burnside, C. (2011). The cross-section of foreign currency risk premia and consumption growth risk: Comment. *The American Economic Review 101*(7), 3456–3476.

Burnside, C., M. Eichenbaum, and S. Rebelo (2006). The returns to currency speculation. *NBER Working Paper No.12489*.

Carhart, M. (1997). On persistence in mutual fund performance. *The Journal of Finance 52*(1), 57–82.

Carr, P. and D. Madan (2001). Towards a theory of volatility trading. In *Option Pricing, Interest Rates and Risk Management, Handbook in Mathematical Finance*, pp. 458–476. Eds. Jouini, E. and Cvitanic, J. and Musiela, M., Cambridge University Press.

Carr, P. and L. Wu (2009). Variance risk premiums. *Review of Financial Studies 22*(3), 1311–1341.

Chan, L., N. Jegadeesh, and J. Lakonishok (1996). Momentum strategies. *The Journal of Finance 51*(5), 1681–1713.

Chernov, M., J. Graveline, and I. Zviadadze (2012). Sources of risk in currency returns. *CEPR Discussion Papers No.8745*.

Chinn, M. and H. Ito (2006). What matters for financial development? Capital controls, institutions, and interactions. *Journal of Development Economics 81*(1), 163–192.

Chordia, T. and L. Shivakumar (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of Finance 57*(2), 985–1019.

Christoffersen, P., V. Errunza, K. Jacobs, and H. Langlois (2012). Is the potential for international diversification disappearing? a dynamic copula approach. *Review of Financial Studies 25*(12), 3711–3751.

Christoffersen, P. and H. Langlois (2013). The joint dynamics of equity market factors. *Forthcoming in Journal of Financial and Quantitative Analysis*.

Clark, P. and R. MacDonald (1998). Exchange rates and economic fundamentals: A methodological comparison of BEERs and FEERs. *IMF Working Paper No.98/67*.

Cline, W. (2008). Estimating consistent fundamental equilibrium exchange rates. *PIIE Working Paper Series No.08-6*.

Cochrane, J. (2005). *Asset Pricing (Revised Edition)*. Princeton, NJ: Princeton University Press.

Cooper, M., R. Gutierrez, and A. Hameed (2004). Market states and momentum. *The Journal of Finance 59*(3), 1345–1365.

Croux, C., . Forni, and L. Reichlin (2001). A measure of comovement for economic variables: Theory and empirics. *Review of Economics and Statistics 83*(2), 232–241.

Della Corte, P., T. Ramadorai, and L. Sarno (2013). Volatility risk premia and exchange rate predictability. *CEPR Discussion Papers No.9549*.

Della Corte, P., L. Sarno, and I. Tsiakas (2011). Spot and forward volatility in foreign exchange. *Journal of Financial Economics 100*(3), 496–513.

Demeterfi, K., E. Derman, M. Kamal, and J. Zou (1999). A guide to volatility and variance swaps. *The Journal of Derivatives 6*(4), 9–32.

Dias, A. and P. Embrechts (2010). Modeling exchange rate dependence dynamics at different time horizons. *Journal of International Money and Finance 29*(8), 1687–1705.

Doz, C., D. Giannone, and L. Reichlin (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics 164*(1), 188–205.

Doz, C., D. Giannone, and L. Reichlin (2012). A quasi–maximum likelihood approach for large, approximate dynamic factor models. *Review of Economics and Statistics 94*(4), 1014–1024.

Égert, B., L. Halpern, and R. MacDonald (2006). Equilibrium exchange rates in transition economies: Taking stock of the issues. *Journal of Economic Surveys 20*(2), 257–324.

Engel, C., N. Mark, and K. West (2007). Exchange rate models are not as bad as you think. In *NBER Macroeconomics Annual*, Volume 22, pp. 381–441. University of Chicago Press.

Engel, C. and K. West (2005). Exchange rates and fundamentals. *The Journal of Political Economy 113*(3), 485–517.

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

Fama, E. and K. French (1992). The cross-section of expected stock returns. *the Journal of Finance 47*(2), 427–465.

Fama, E. and K. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. and J. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy 81*(3), 607–636.

Farhi, E. and X. Gabaix (2008). Rare disasters and exchange rates. *NBER Working Paper No.13805*.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2000). The generalized dynamic factor model: Identification and estimation. *Review of Economics and Statistics 82*(4), 540–554.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2004). The generalized dynamic factor model: Consistency and rates. *Journal of Econometrics 119*(2), 231–255.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2005). The generalized dynamic factor model: One-sided estimation and forecasting. *Journal of the American Statistical Association 100*(471), 830–840.

Frahm, G., M. Junker, and R. Schmidt (2005). Estimating the tail-dependence coefficient: Properties and pitfalls. *Insurance: Mathematics and Economics 37*(1), 80–100.

Frankel, J. and A. Rose (1995). Empirical research on nominal exchange rates. In *Handbook of International Economics*, Volume 3, pp. 1689–1729. Eds. Grossman, G. and Rogoff, K., Elsevier.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Fung, W. and D. Hsieh (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies 14*(2), 313–341.

Fung, W., D. Hsieh, N. Naik, and T. Ramadorai (2008). Hedge funds: Performance, risk, and capital formation. *The Journal of Finance 63*(4), 1777–1803.

Gabaix, X. (2012). Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *The Quarterly Journal of Economics 127*(2), 645–700.

Gabaix, X. and M. Maggiori (2014). International liquidity and exchange rate dynamics. *NBER Working Paper No.19854*.

Garleanu, N., L. H. Pedersen, and A. Poteshman (2009). Demand-based option pricing. *Review of Financial Studies 22*(10), 4259–4299.

Garman, M. and S. Kohlhagen (1983). Foreign currency option values. *Journal of International Money and Finance 2*(3), 231–237.

Giannone, D., L. Reichlin, and D. Small (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics 55*(4), 665–676.

Glosten, L., R. Jagannathan, and D. Runkle (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance 48*(5), 1779–1801.

Gourinchas, P.-O. and H. Rey (2007). International financial adjustment. *The Journal of Political Economy 115*(4), 665–703.

Griffin, J., X. Ji, and J. S. Martin (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance 58*(6), 2515–2547.

Grinblatt, M. and B. Han (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics 78*(2), 311–339.

Hallin, M. and R. Liška (2007). Determining the number of factors in the general dynamic factor model. *Journal of the American Statistical Association 102*(478), 603–617.

Hansen, B. (1994). Autoregressive conditional density estimation. *International Economic Review 35*(3), 705–730.

Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica 50*(4), 1029–1054.

Hansen, L. and R. Jagannathan (1997). Assessing specification errors in stochastic discount factor models. *The Journal of Finance 52*(2), 557–590.

Hong, H., T. Lim, and J. Stein (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55*(1), 265–295.

Hong, Y., J. Tu, and G. Zhou (2007). Asymmetries in stock returns: Statistical tests and economic evaluation. *Review of Financial Studies 20*(5), 1547–1581.

Huang, H. and R. MacDonald (2013). Currency carry trades, position-unwinding risk, and sovereign credit premia. *Available at SSRN No.2287287*.

Hvidkjaer, S. (2006). A trade-based analysis of momentum. *Review of Financial Studies 19*(2), 457–491.

Jagannathan, R. and Z. Wang (1996). The conditional CAPM and the cross-section of expected returns. *The Journal of Finance 51*(1), 3–53.

Jiang, G. and Y. Tian (2005). The model-free implied volatility and its information content. *Review of Financial Studies 18*(4), 1305–1342.

Joe, H. (1997). *Multivariate Models and Dependence Concepts*. Monographs on Statistics and Applied Probability, Volume 73, London: Chapmann & Hall / CRC.

Joe, H., H. Li, and A. Nikoloulopoulos (2010). Tail dependence functions and vine copulas. *Journal of Multivariate Analysis 101*(1), 252–270.

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

Jurek, J. (2007). Crash-neutral currency carry trades. In *AFA 2010 Atlanta Meetings Paper*.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–291.

Kilian, L. and M. Taylor (2003). Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics 60*(1), 85–107.

Korajczyk, R. and R. Sadka (2004). Are momentum profits robust to trading costs? *The Journal of Finance 59*(3), 1039–1082.

Kose, A., C. Otrok, and E. Prasad (2012). Global business cycles: Convergence or decoupling? *International Economic Review 53*(2), 511–538.

Kose, A., C. Otrok, and C. Whiteman (2003). International business cycles: World, region, and country-specific factors. *The American Economic Review 93*(4), 1216–1239.

Kozhan, R., A. Neuberger, and P. Schneider (2013). The skew risk premium in the equity index market. *Forthcoming in Review of Financial Studies*.

Lane, P. and G. Milesi-Ferretti (2007). The external wealth of nations Mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of International Economics 73*(2), 223–250.

Lettau, M., M. Maggiori, and M. Weber (2013). Conditional risk premia in currency markets and other asset classes. *NBER Working Paper No.18844*.

Liu, L. X. and L. Zhang (2008). Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies 21*(6), 2417–2448.

Longin, F. and B. Solnik (2001). Extreme correlation of international equity markets. *The Journal of Finance 56*(2), 649–676.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common risk factors in currency markets. *Review of Financial Studies 24*(11), 3731–3777.

MacDonald, R. (2005). *Exchange Rate Economics: Theories and Evidence.* Routledge.

MacDonald, R. and P. Dias (2007). Behavioural equilibrium exchange rate estimates and implied exchange rate adjustments for ten countries. *Peterson Institute of International Economics Working Paper, February*.

MacDonald, R. and M. Taylor (1994). The monetary model of the exchange rate: Long-run relationships, short-run dynamics and how to beat a random walk. *Journal of International Money and Finance 13*(3), 276–290.

McNeil, A., R. Frey, and P. Embrechts (2005). *Quantitative Risk Management: Concepts, Techniques, and Tools*. Princeton, NJ: Princeton University Press.

Meese, R. and K. Rogoff (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics 14*(1), 3–24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a). Carry trades and global foreign exchange volatility. *The Journal of Finance 67*(2), 681–718.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012b). Currency momentum strategies. *Journal of Financial Economics 106*(3), 660–684.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2013). Currency risk premia and macro fundamentals. *Available at SSRN No.2282480*.

Moskowitz, T., Y. H. Ooi, and L. H. Pedersen (2012). Time series momentum. *Journal of Financial Economics 104*(2), 228–250.

Neuberger, A. (2012). Realized skewness. *Review of Financial Studies 25*(11), 3423–3455.

Newey, W. and K. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Parker, J. and C. Julliard (2005). Consumption risk and the cross-section of expected returns. *The Journal of Political Economy 113*(1), 185–222.

Pastor, L. and P. Veronesi (2012). Uncertainty about government policy and stock prices. *The Journal of Finance 67*(4), 1219–1264.

Pastor, L. and P. Veronesi (2013). Political uncertainty and risk premia. *Journal of Financial Economics 110*(3), 520–545.

Patton, A. (2004). On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics 2*(1), 130–168.

Patton, A. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review 47*(2), 527–556.

Patton, A. and T. Ramadorai (2013). On the high-frequency dynamics of hedge fund risk exposures. *The Journal of Finance 68*(2), 597–635.

Patton, A. and A. Timmermann (2010). Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts. *Journal of Financial Economics 98*(3), 605–625.

Poon, S.-H., M. Rockinger, and J. Tawn (2004). Extreme value dependence in financial markets: Diagnostics, models, and financial implications. *Review of Financial Studies 17*(2), 581–610.

Ramadorai, T. (2013). Capacity constraints, investor information, and hedge fund returns. *Journal of Financial Economics 107*(2), 401–416.

Rietz, T. (1988). The equity risk premium: A solution. *Journal of Monetary Economics 22*(1), 117–131.

Sarno, L. and E. Sojli (2009). The feeble link between exchange rates and fundamentals: Can we blame the discount factor? *Journal of Money, Credit and Banking 41*(2-3), 437–442.

Sarno, L. and G. Valente (2009). Exchange rates and fundamentals: Footloose or evolving relationship? *Journal of the European Economic Association 7*(4), 786–830.

Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies 5*(1), 1–55.

Shefrin, H. and M. Statman (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance 40*(3), 777–790.

Shleifer, A. and R. Vishny (1997). The limits of arbitrage. *The Journal of Finance 52*(1), 35–55.

Sklar, M. (1959). *Fonctions de Répartition à N Dimensions et leurs Marges.* Université Paris 8.

Stock, J. and M. Watson (1989). New indexes of coincident and leading economic indicators. In *NBER Macroeconomics Annual*, Volume 4, pp. 351–409. MIT Press.

Stock, J. and M. Watson (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association 97*(460), 1167–1179.

Stock, J. and M. Watson (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics 20*(2), 147–162.

Stock, J. and M. Watson (2005). Understanding changes in international business cycle dynamics. *Journal of the European Economic Association 3*(5), 968–1006.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization 1*(1), 39–60.

Verardo, M. (2009). Heterogeneous beliefs and momentum profits. *Journal of Financial and Quantitative Analysis 44*(4), 795.

Weitzman, M. (2007). Subjective expectations and asset-return puzzles. *The American Economic Review 97*(4), 1102–1130.

Williamson, J. (1983). *Estimating Equilibrium Exchange Rates*. Washington DC: Peterson Institute of Interntional Economics.

Appendix A.

Table A.1. Global Real Effective Exchange Rate Misalignments

Currency	Misalignment (%)	Currency	Misalignment (%)
JPY	9.1	EUR	4.1
KRW	15.8	GBP	5.0
HKD	23.0	AUD	-5.5
TWD	12.4	NZD	-9.6
SGD	22.4	CAD	0.5
MYR	23.1	CHF	7.6
THB	10.7	SEK	13.9
PHP	6.8	DKK	10.4
IDR	11.0	NOK	7.2
INR	5.6	ZAR	0.9
RUB	5.0	BRL	-0.1
PLN	2.3	CLP	1.8
RON	6.9	COP	0.1
HUF	1.8	ARS	4.1
CZK	3.5	PEN	3.2
SKK	2.8	MXN	1.3
TRY	-6.3	ILS	5.7

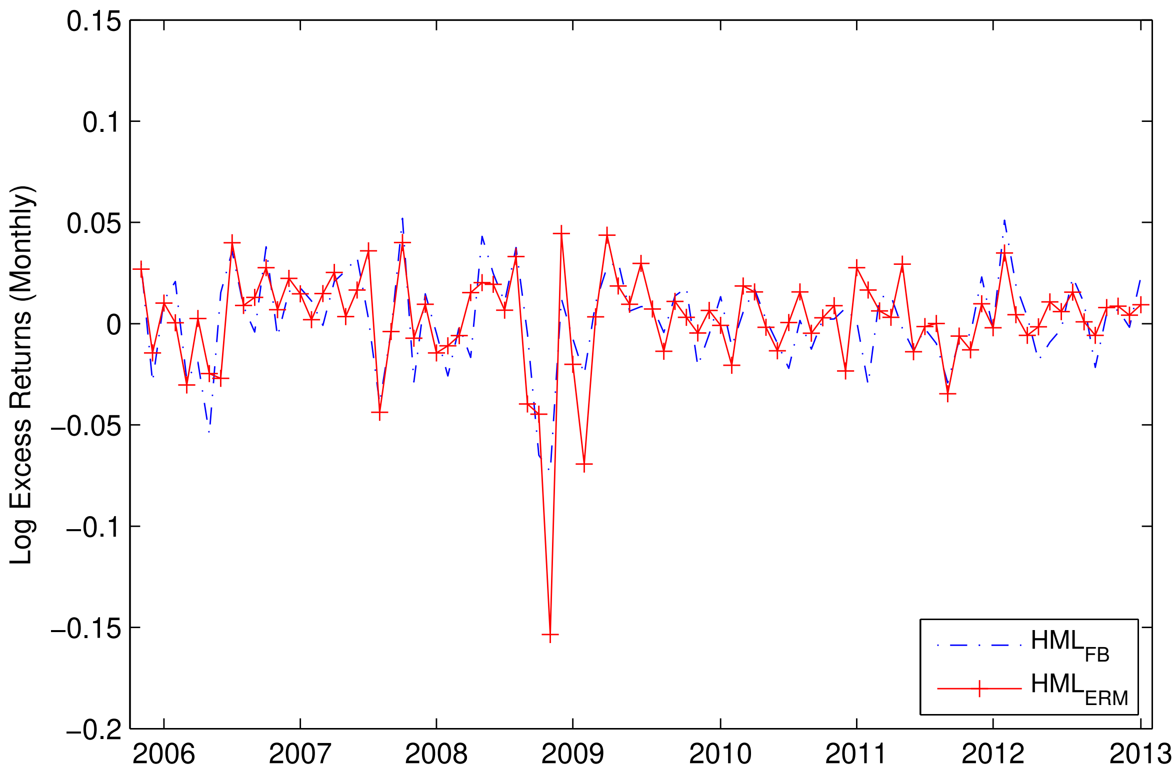
This table reports the average REER misalignments of 34 currencies. A positive (negative) value means that the currency needs to appreciate (depreciate) against USD to reach its equilibrium REER. The sample period is from 2005 to 2012.

Table A.2. Descriptive Statistics of Currency Portfolios (Carry & Misalignment)

All Countries with Bid-Ask Spreads					
Portfolios	$P_{1,CRT}$	$P_{2,CRT}$	$P_{3,CRT}$	$P_{4,CRT}$	$P_{5,CRT}$
Mean (%)	0.45	1.57	2.44	2.94	4.57
Median (%)	3.67	3.71	6.02	8.34	11.17
Std.Dev. (%)	7.41	8.56	9.31	10.61	10.71
Skewness	-0.16	-0.26	-0.56	-0.53	-0.51
Kurtosis	0.18	0.21	0.82	0.62	0.57
Sharpe Ratio	0.06	0.18	0.26	0.28	0.43
AC(1)	0.01	-0.09	0.05	0.15	0.14
Portfolios	$P_{1,FBM}$	$P_{2,FBM}$	$P_{3,FBM}$	$P_{4,FBM}$	$P_{5,FBM}$
Mean (%)	0.77	0.85	1.42	3.51	5.35
Median (%)	1.27	2.05	0.95	8.71	15.60
Std.Dev. (%)	6.08	8.44	10.05	9.65	12.00
Skewness	-0.01	-0.60	-0.25	-0.62	-0.67
Kurtosis	0.05	0.89	0.26	0.88	0.81
Sharpe Ratio	0.13	0.10	0.14	0.36	0.45
AC(1)	-0.01	0.04	0.14	0.04	0.06

This table reports descriptive statistics of the transaction-cost adjusted (bid-ask spreads) annualized excess returns in USD of currency carry (CRT) trade and misalignment (FBM) portfolios sorted by 1-month forward premium, and by REER misalignments, respectively. The 20% currencies with the lowest sort base are allocated to Portfolio P_1, and the next 20% to Portfolio P_2, and so on to Portfolio P_5 which contains the highest 20% sort base. The portfolios are rebalanced monthly according to the updated sort base. The sample period is from September 2005 to January 2013. The mean, median, standard deviation and higher moments are annualized (so is the Sharpe Ratio) and in percentage. Skewness and kurtosis are in excess terms. AC(1) is the first order autocorrelation coefficients of the monthly excess returns.

Figure A.1. Forward Bias Risk vs. REER Misalignment Risk



This figure shows exchange rate misalignment risk (HML_{ERM}) in comparison with Lustig, Roussanov, and Verdelhan's (2011) forward bias risk (HML_{FB}) from September 2005 to January 2013.

Table A.3. Global Currency Crash Sensitivity

Currency	LTD	UTD	Currency	LTD	UTD
JPY	0.048	0.010	EUR	0.626	0.599
KRW	0.115	0.202	GBP	0.349	0.281
HKD	0.027	0.080	AUD	0.455	0.412
TWD	0.141	0.183	NZD	0.428	0.346
SGD	0.457	0.513	CAD	0.368	0.329
MYR	0.162	0.230	CHF	0.332	0.248
THB	0.096	0.132	SEK	0.600	0.582
PHP	0.087	0.207	DKK	0.625	0.595
IDR	0.093	0.167	NOK	0.619	0.608
INR	0.148	0.238	ZAR	0.360	0.427
RUB	0.448	0.485	BRL	0.314	0.395
PLN	0.620	0.650	CLP	0.205	0.226
RON	0.557	0.582	COP	0.221	0.172
HUF	0.636	0.601	ARS	0.000	0.010
CZK	0.543	0.548	PEN	0.102	0.086
SKK	0.610	0.591	MXN	0.254	0.305
TRY	0.323	0.413	ILS	0.268	0.277

This table reports the average Lower Tail Dependences (LTD) at 10% quantile and Upper Tail Dependences (UTD) at 90% quantile of 34 currencies. The sample period is from September 2005 to January 2013.

Table A.4. Global Currency Downside Insurance Cost

Currency	VRP (%)	SRP	Currency	VRP (%)	SRP
JPY	-1.230	-0.515	EUR	-1.082	0.261
KRW	-2.396	0.802	GBP	-0.543	0.361
HKD	-0.553	-1.860	AUD	0.232	0.557
TWD	-2.036	0.129	NZD	0.073	0.586
SGD	-1.060	0.227	CAD	-0.407	0.269
MYR	N/A	N/A	CHF	-0.389	-0.031
THB	-2.142	0.273	SEK	-0.337	0.277
PHP	N/A	N/A	DKK	-1.204	0.245
IDR	N/A	N/A	NOK	-0.121	0.259
INR	-2.379	0.751	ZAR	-2.070	0.889
RUB	-2.406	0.801	BRL	-2.747	1.173
PLN	-1.473	0.656	CLP	-3.089	0.876
RON	N/A	N/A	COP	-4.005	0.751
HUF	-0.755	0.850	ARS	N/A	N/A
CZK	-0.953	0.374	PEN	N/A	N/A
SKK	-0.430	0.225	MXN	-2.899	1.036
TRY	-2.266	1.137	ILS	N/A	N/A

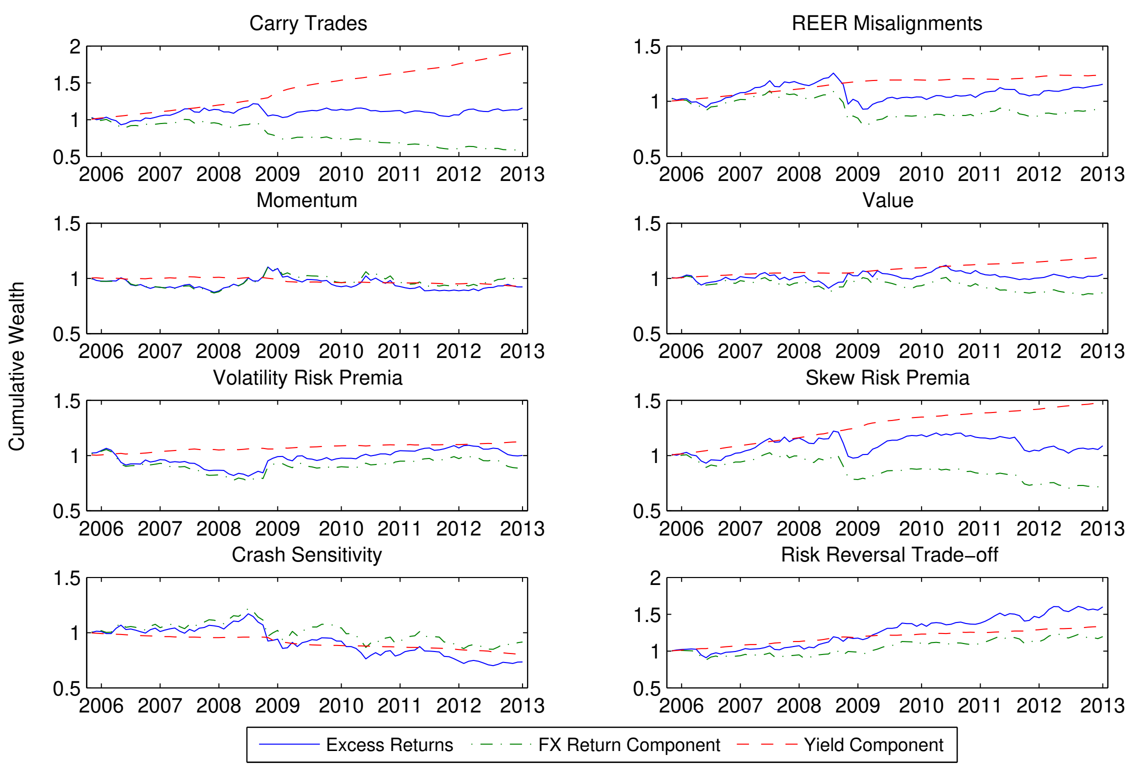
This table reports the average downside insurance costs measured by volatility and skew risk premia of 27 currencies using model-free approach. The sample period is from September 2005 to January 2013.

Table A.5. Descriptive Statistics of Currency Trading Strategies

	All Countries with Bid-Ask Spreads							
Portfolios	CRT	FBM	MMT	PPV	MCS	VRP	SRP	DS
Mean (%)	2.29	2.36	-0.75	0.78	-3.56	0.31	1.53	6.69
Median (%)	2.74	5.32	-0.71	0.63	-2.23	-0.88	5.83	7.23
Std.Dev. (%)	7.86	9.10	8.18	7.56	10.84	7.94	8.81	8.39
Skewness	-0.17	-0.75	0.11	0.12	-0.31	0.51	-0.36	-0.15
Kurtosis	0.11	1.12	0.19	0.14	0.25	0.88	0.33	0.08
Sharpe Ratio	0.29	0.26	-0.09	0.10	-0.33	0.04	0.17	0.80
AC(1)	0.14	0.04	-0.12	-0.10	-0.01	0.15	0.27	0.00

This table reports descriptive statistics of the transaction-cost adjusted (bid-ask spreads) annualized excess returns in USD of eight currency trading strategies: carry trades (CRT), REER misalignment (FBM), momentum (MMT), value (PPV), crash sensitivity (MCS), volatility risk premium (VRP), and skew risk premium (SRP). We invest in the top 20% currencies with the highest sort base funded by the bottom 20% currencies with lowest sort base. The last column contains the descriptive statistics of a double-sorting (DS) strategy that invests in medium-CS and high-DI currencies funded by low-CS and medium-DI ones. The portfolios are rebalanced monthly according to the updated sort base, if it is available. The sample period is from September 2005 to January 2013. The mean, median, standard deviation and higher moments are annualized and in percentage. Skewness and kurtosis are in excess terms. AC(1) are the first order autocorrelation coefficients of the monthly excess returns.

Figure A.2. Decomposition of Cumulative Wealth to Currency Trading Strategies



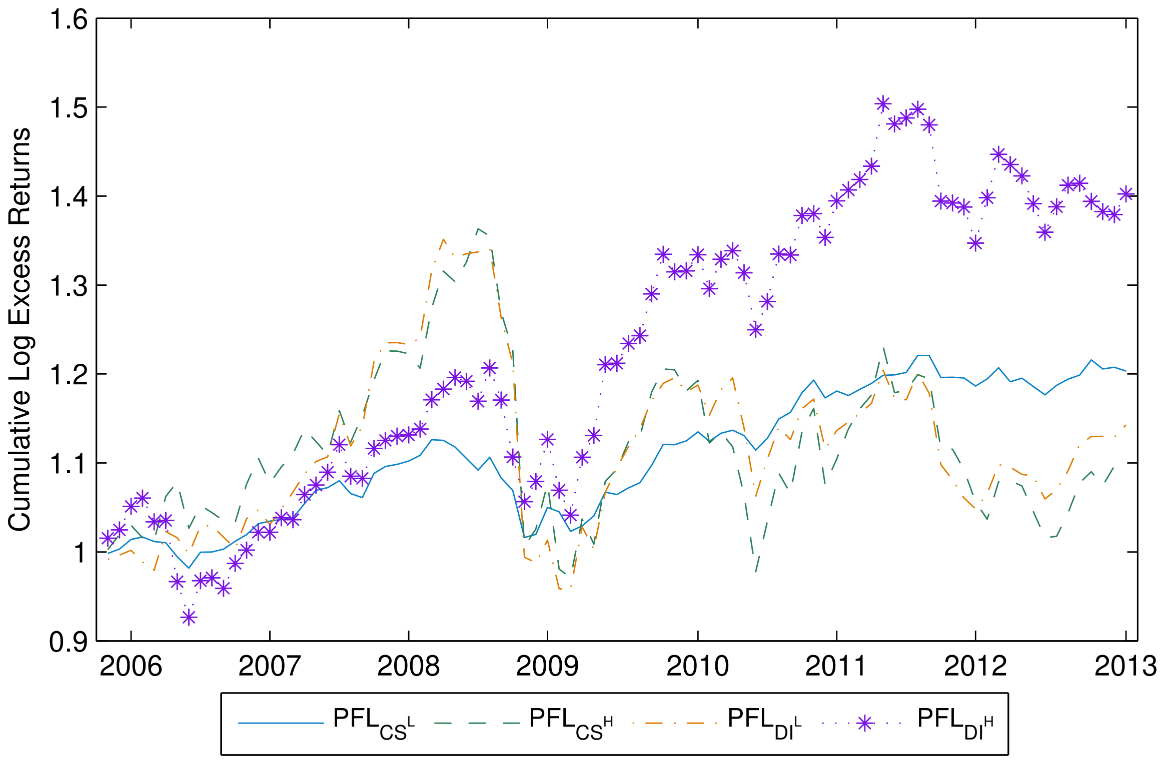
This figure shows the decompositions of the cumulative transaction-cost adjusted wealth (excess return) to the eight currency trading strategies into exchange rate (transaction-cost adjusted) return and yield (interest rate differential) components. The sample is from September 2005 to January 2013.

Table A.6. Monotonicity Tests for Excess Returns of Currency Portfolios

Whole Sample				
Portfolios	MR	MR_P	MR_U	MR_D
CRT	0.004	0.003	0.025	0.959
FBM	0.044	0.042	0.080	0.953
MMT	0.288	0.271	0.309	0.691
PPV	0.037	0.029	0.046	0.956
MCS	0.343	0.276	0.747	0.564
VRP	0.145	0.237	0.421	0.809
SRP	0.238	0.228	0.296	0.816
Pre-crisis				
Portfolios	MR	MR_P	MR_U	MR_D
MCS	0.544	0.389	0.040	0.593
VRP	0.977	0.935	0.621	0.093
Post-crisis				
Portfolios	MR	MR_P	MR_U	MR_D
MCS	0.746	0.833	0.952	0.051
VRP	0.184	0.161	0.067	0.865

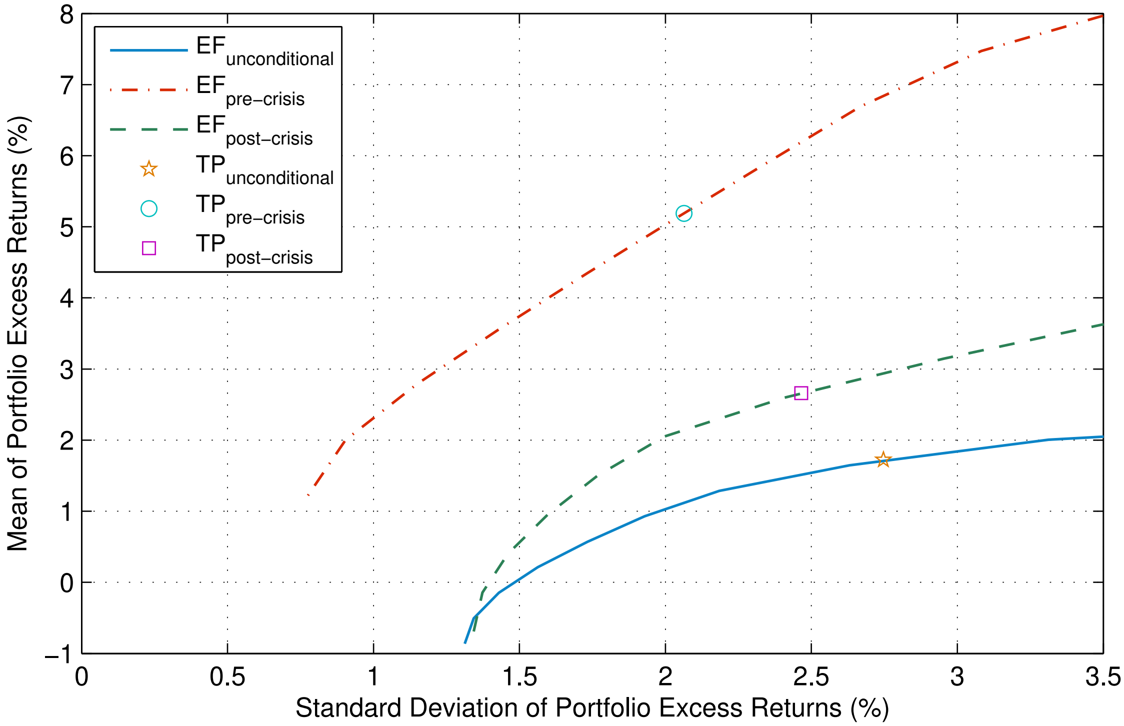
This table reports the p-values of the statistics from the monotonicity tests (Patton and Timmermann, 2010) for the excess returns of the five portfolios of each currency trading strategy: carry trades (CRT), REER misalignment (FBM), momentum (MMT), value (PPV) crash sensitivity (MCS), volatility risk premium (VRP), skew risk premium (SRP). The excess returns are transaction-cost adjusted (bid-ask spreads) and annualized in USD. MR, MR_P, and MR_U denotes the test of strictly monotonic increase across five portfolios, the test of strictly monotonic increase with pairwise comparisons, and the test of general increase pattern, respectively. MR_D represents the test of general decline pattern. The sample period is from September 2005 to January 2013. The profitability patterns of two strategies based on crash sensitivity and downside insurance cost notably reverse after the outbreak of the recent financial crisis, so we report further monotonicity tests that split the whole sample into pre-crisis and post crisis periods for these two strategies. Momentum strategy does not exhibit any strict or general monotonicity in profitability pattern across portfolios in all three sample categories.

Figure A.3. Time-varying Risk Premia of Crash Sensitivity & Downside Insurance Cost



This figure shows the regime-dependent behavior of currency risk premia, i.e. distinctive pre-crisis and post-crisis performances of the portfolios with the lowest crash sensitivity (PFL_{CS^L}) and highest crash sensitivity (PFL_{CS^H}), and the portfolios with lowest downside insurance cost (PFL_{DI^L}) and highest downside insurance cost (PFL_{DI^H}). The sample is from September 2005 to January 2013.

Figure A.4. Time-varying Efficient Frontiers & Tangency Portfolios



This figure shows the time-varying Efficient Frontiers (EF) and Tangency Portfolios (TP) in the whole sample (unconditional), pre-crisis, and post-crisis periods. The sample is from September 2005 to January 2013, and split by September 2008.

Table A.7. Optimal Risky Portfolios

	Portfolio Weights							Utility Maximization		
Portfolios	CRT	FBM	MMT	PPV	MCS	VRP	SRP	$\mathbb{E}[xr_{o,t}]$ (%)	$\sigma_{o,t}$ (%)	Sharpe Ratio
Unconditional	0.366	0.435	0	0.199	0	0	0	2.040	6.270	0.325
Pre-crisis	0.136	0.417	0	0.004	0.341	0	0.102	6.960	5.162	1.348
Post-crisis	0	0.120	0	0.028	0	0.852	0	3.480	6.305	0.552

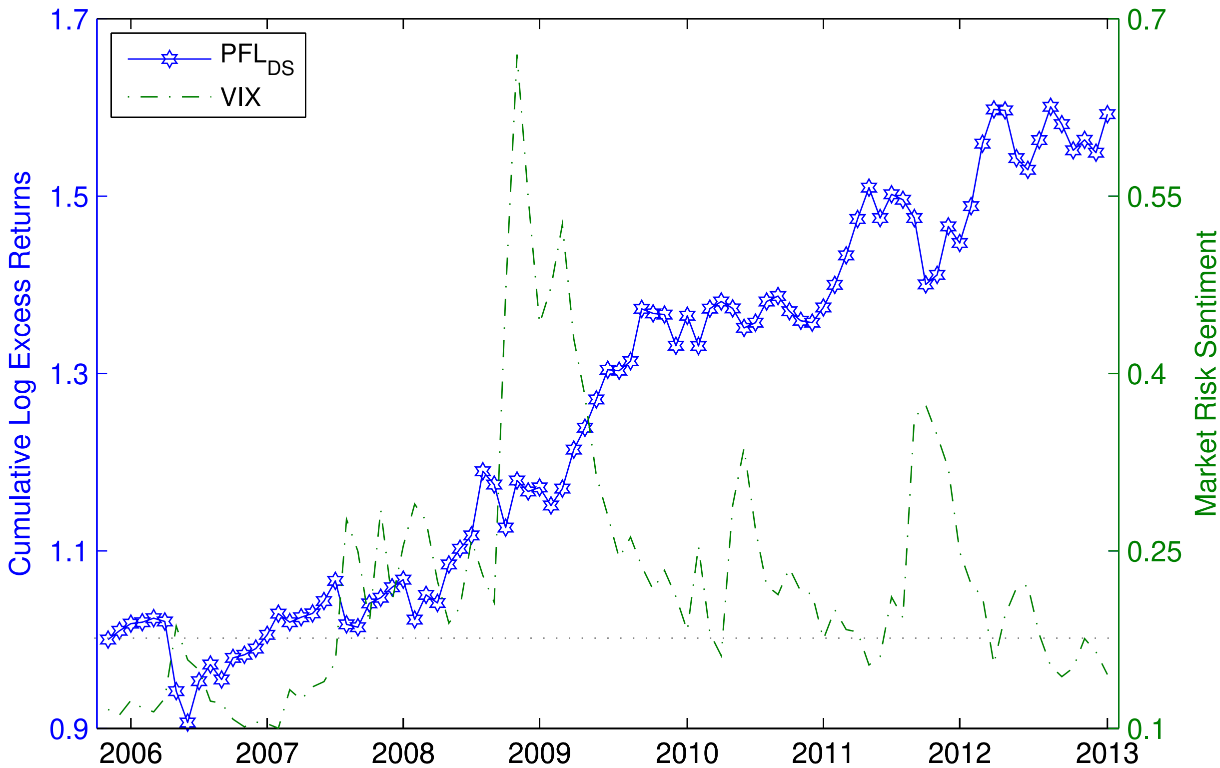
This table reports the optimal portfolio weights for several studied currency investment strategies in the whole sample (unconditional), pre-crisis, and post-crisis periods, as well as the corresponding excess returns ($\mathbb{E}[xr_{o,t}]$), volatilities ($\sigma_{o,t}$), and Sharpe ratios. The coefficient of risk aversion γ is set to 3. The sample is from September 2005 to January 2013, and split by September 2008.

Table A.8. Currency Portfolios Doubly Sorted by Crash Sensitivity & Downside Insurance Cost

All Countries without Transaction Costs						
CS	Bottom		Mezzanine		Top	
DI	Low	High	Low	High	Low	High
Mean (%)	-1.22	1.73	2.92	6.49	2.40	-0.57
Median (%)	3.65	2.73	4.14	11.43	7.17	4.81
Std.Dev. (%)	8.96	6.81	11.28	10.25	14.18	12.95
Skewness	-1.02	-0.08	-0.57	-0.21	-0.57	-0.39
Kurtosis	1.79	0.09	0.88	0.03	0.75	0.31
Sharpe Ratio	-0.14	0.25	0.26	0.63	0.17	-0.04
AC(1)	-0.08	0.12	0.19	0.03	0.04	0.01

This table reports descriptive statistics of the excess returns of currency portfolios sorted on both individual currencies' crash sensitivity (CS) measured by copula method and downside insurance cost (DI) implied in moment swaps, from September 2005 to January 2013. The portfolios are doubly sorted on bottom 30%, mezzanine 40%, and top 30% basis. All excess returns are monthly in USD with daily availability and adjusted for transaction costs (bid-ask spreads). The mean, median and standard deviation are annualized and in percentage. Skewness and kurtosis are in excess terms. The last row AC(1) shows the first order autocorrelation coefficients of the monthly excess returns.

Figure A.5. Global Crash Aversion



This figure shows the Chicago Board Options Exchange VIX index as the measure of market-wide risk sentiment and the cumulative excess returns of a trading strategy (PDL_{DS}) that holds high crash-sensitivity and high downside-insurance-cost currencies funded by the low counterparts via double-sorting approach. The sample is from September 2005 to January 2013.

Table A.9. Asset Pricing of Currency Carry Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{ERM}		b_{GDR}	b_{ERM}	λ_{GDR}	λ_{ERM}	R^2	$p-value$	MAE
$P_{1,CRT}$	1.013	-0.349							χ^2	
	(0.046)	(0.045)	FMB			2.380	5.881	0.973		0.208
$P_{2,CRT}$	1.060	-0.194				(3.197)	(4.207)		(0.976)	
	(0.052)	(0.059)				[3.174]	[4.238]		[0.976]	
$P_{3,CRT}$	1.007	0.033								
	(0.040)	(0.045)							$HJ-dist$	
$P_{4,CRT}$	1.090	0.117	GMM_1	-0.390	0.868	2.380	5.881	0.933	0.912	0.208
	(0.048)	(0.043)		(0.711)	(0.783)	(3.209)	(4.159)			
$P_{5,CRT}$	0.829	0.392	GMM_2	-0.368	0.879	2.653	6.138	0.932	0.900	0.259
	(0.047)	(0.050)		(0.691)	(0.759)	(3.268)	(4.129)			
	β_{GDR}	β_{SRP}		b_{GDR}	b_{SRP}	λ_{GDR}	λ_{SRP}	R^2	$p-value$	MAE
$P_{1,CRT}$	0.912	-0.288							χ^2	
	(0.047)	(0.048)	FMB			2.387	5.422	0.963		0.233
$P_{2,CRT}$	1.045	-0.234				(3.186)	(4.022)		(0.954)	
	(0.048)	(0.037)				[3.174]	[3.972]		[0.958]	
$P_{3,CRT}$	1.042	-0.017								
	(0.050)	(0.028)							$HJ-dist$	
$P_{4,CRT}$	1.104	0.131	GMM_1	-0.093	0.639	2.387	5.422	0.963	0.798	0.233
	(0.041)	(0.033)		(0.515)	(0.600)	(3.294)	(3.843)			
$P_{5,CRT}$	0.896	0.408	GMM_2	-0.047	0.638	2.792	5.642	0.875	0.707	0.398
	(0.052)	(0.050)		(0.508)	(0.603)	(3.289)	(3.892)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for comparison between two linear factor models (LFM) both based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor but differ in slope (country-specific) factor. The LFM in the top panel employs exchange rate misalignment risk (HML_{ERM}) and the LFM in the bottom panel adopts skew premium risk (HML_{SRP}). The test assets are the transaction-cost adjusted excess returns of five currency carry portfolios from September 2005 to January 2013. The coefficient estimates of Stochastic Discount Factor (SDF) parameters b and λ are obtained by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by fist-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Error (MAE) are also reported.

Table A.10. Robustness Check: Monotonicity Tests for Betas & Currency Portfolios Sorted by Betas

β_{ERM}							
Tests	Statistics	Portfolios	L	LM	M	UM	H
		Mean (%)	1.73	1.95	2.07	2.27	3.50
$\beta_5 - \beta_1$	0.74	Median (%)	4.33	4.39	2.01	5.91	5.85
$bootstrap - t$	5.64	Std.Dev. (%)	8.61	8.23	8.18	10.59	10.61
$p - value$	0.00	Skewness	-0.03	-0.37	-0.33	-0.61	-0.73
MR	0.00	Kurtosis	0.00	0.46	0.25	0.83	1.18
MR_P	0.00	Sharpe Ratio	0.20	0.24	0.25	0.21	0.33
		$f - s$ (%)	-0.42	1.15	2.28	2.70	5.12
β_{SRP}							
Tests	Statistics	Portfolios	L	LM	M	UM	H
		Mean (%)	1.75	1.93	2.17	2.44	3.58
$\beta_5 - \beta_1$	0.70	Median (%)	4.10	7.15	2.10	6.47	10.46
$bootstrap - t$	6.32	Std.Dev. (%)	10.41	13.20	5.95	10.42	11.81
$p - value$	0.00	Skewness	-0.14	-0.41	-0.46	-0.68	-0.59
MR	0.00	Kurtosis	0.07	0.38	0.61	1.11	0.74
MR_P	0.00	Sharpe Ratio	0.17	0.15	0.36	0.23	0.30
		$f - s$ (%)	-0.75	1.99	2.43	2.43	5.39

The left panel of this table reports the monotonicity tests (Patton and Timmermann, 2010) for the risk exposure to HML_{ERM} (REER misalignment factor), and to HML_{SRP} (skew risk premium factor), respectively. MR, and MR_P denotes the test of strictly monotonic increase across five portfolios, and the test of strictly monotonic increase with pairwise comparisons, respectively. The right panel of this table reports descriptive statistics of the excess returns of currency portfolios sorted on individual currencies' monthly rolling-window estimates of β_{ERM} and β_{SRP} respectively, from September 2005 to January 2013. The rolling window of 60 months is chosen to obtain stable estimations of β_{ERM} with very low volatility. Although the portfolios are rebalanced monthly, the rank of individual currencies' risk exposures is quite robust to the sorting (in terms of group label) over the entire sample period. The 20% currencies with the lowest β_{ERM} (β_{SRP}) are allocated to Portfolio 'L' (Low), and the next 20% to Portfolio 'LM' (Lower Medium), Portfolio 'M' (Medium), Portfolio 'UM' (Upper Medium) and so on to Portfolio 'H' (High) which contains the highest 20% β_{ERM} (β_{SRP}). All excess returns are monthly in USD with daily availability and adjusted for transaction costs (bid-ask spreads). The mean, median and standard deviation are annualized and in percentage. Skewness and kurtosis are in excess terms. The last row ($f - s$) shows the average annualized forward discounts of five portfolios in percentage.

Table A.11. Horse Race: $GDR + HML_{ERM} + GVI$

All Countries with Transaction Costs													
	Factor Exposures			Factor Prices									
	β_{GDR}	β_{ERM}	β_{GVI}		b_{GDR}	b_{ERM}	b_{GVI}	λ_{GDR}	λ_{ERM}	λ_{GVI}	R^2	$p-value$	MAE
C_1	1.04	-0.32	1.77									χ^2	
	(0.05)	(0.05)	(1.14)	FMB				2.39	4.73	-0.26	0.98		0.16
C_2	1.09	-0.16	1.95					(3.20)	(5.63)	(0.55)		(0.92)	
	(0.05)	(0.07)	(1.44)					[3.17]	[5.75]	[0.56]		[0.92]	
C_3	1.02	0.05	0.91										
	(0.04)	(0.05)	(1.34)									$HJ-dist$	
C_4	1.08	0.10	-0.77	GMM_1	-0.47	0.30	-19.21	2.39	4.73	-0.26	0.98	0.69	0.16
	(0.06)	(0.05)	(1.05)		(0.85)	(2.39)	(82.75)	(3.21)	(5.70)	(0.57)			
C_5	0.78	0.33	-3.87	GMM_2	-0.46	0.43	-16.52	2.75	5.44	-0.25	0.90	0.66	0.35
	(0.06)	(0.09)	(1.50)		(1.71)	(1.96)	(69.34)	(3.88)	(5.57)	(0.54)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for the linear factor model (LFM) based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor, exchange rate misalignment risk (HML_{ERM}) and global FX volatility (innovation) risk (GVI) both as slope (country-specific) factors. The test assets are the transaction-cost adjusted excess returns of five currency carry portfolios from September 2005 to January 2013. The coefficient estimates of Stochastic Discount Factor (SDF) parameters b and λ are obtained by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by fist-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Error (MAE) are also reported.

Table A.12. Asset Pricing of Currency Momentum & Value Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	MAE
$P_{1,MMT}$	1.128	0.090							χ^2	
	(0.085)	(0.071)	FMB			2.368	-13.496	0.651		0.421
$P_{2,MMT}$	1.188	0.058				(3.160)	(13.234)		(0.727)	
	(0.143)	(0.078)				[3.174]	[14.686]		[0.714]	
$P_{3,MMT}$	0.912	0.042								
	(0.036)	(0.072)							$HJ-dist$	
$P_{4,MMT}$	0.856	-0.060	GMM_1	0.122	-3.953	2.368	-13.496	0.651	0.381	0.421
	(0.055)	(0.038)		(0.483)	(4.047)	(3.415)	(12.844)			
$P_{5,MMT}$	0.885	-0.125	GMM_2	0.078	-4.253	2.074	-14.502	0.550	0.394	0.544
	(0.126)	(0.100)		(0.461)	(3.618)	(3.413)	(11.300)			
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	MAE
$P_{1,PPV}$	0.669	0.314							χ^2	
	(0.050)	(0.055)	FMB			2.211	2.100	-0.609		0.771
$P_{2,PPV}$	1.231	0.292				(3.198)	(2.492)		(0.486)	
	(0.066)	(0.059)				[3.176]	[2.545]		[0.452]	
$P_{3,PPV}$	1.065	0.044								
	(0.043)	(0.051)							$HJ-dist$	
$P_{4,PPV}$	1.047	-0.169	GMM_1	0.286	0.544	2.211	2.100	-0.609	0.096	0.771
	(0.041)	(0.051)		(0.405)	(0.614)	(3.180)	(2.526)			
$P_{5,PPV}$	1.123	-0.495	GMM_2	0.436	0.625	3.501	2.344	-3.953	0.015	1.471
	(0.039)	(0.034)		(0.423)	(0.615)	(3.199)	(2.518)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for comparison between two tested assets in a linear factor model (LFM) based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor and Huang and MacDonald's (2013) sovereign credit risk (HML_{SC}) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of five currency momentum portfolios (top panel), and five currency value portfolios (bottom panel) respectively, from September 2005 to January 2013. The coefficient estimates of Stochastic Discount Factor (SDF) parameters b and λ are obtained by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by fist-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ - dist$), and Mean Absolute Error (MAE) are also reported.

Table A.13. Asset Pricing of Currency Moment Risk Premia Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	MAE
$P_{1,VRP}$	0.892	0.508							χ^2	
	(0.155)	(0.108)	FMB			2.295	5.198	0.820		0.554
$P_{2,VRP}$	0.970	-0.004				(3.195)	(4.465)		(0.865)	
	(0.048)	(0.059)				[3.179]	[3.751]		[0.846]	
$P_{3,VRP}$	1.105	-0.102								
	(0.048)	(0.067)							$HJ-dist$	
$P_{4,VRP}$	1.231	-0.312	GMM_1	0.312	1.557	2.295	5.198	0.820	0.763	0.554
	(0.137)	(0.070)		(0.427)	(1.427)	(3.252)	(4.514)			
$P_{5,VRP}$	1.263	-0.188	GMM_2	0.271	1.579	1.3914	5.287	0.725	0.697	0.652
	(0.058)	(0.067)		(0.416)	(1.370)	(3.209)	(4.297)			
	β_{GDR}	β_{ERM}		b_{GDR}	b_{ERM}	λ_{GDR}	λ_{ERM}	R^2	$p-value$	MAE
$P_{1,SRP}$	1.007	0.299							χ^2	
	(0.111)	(0.103)	FMB			1.860	4.584	0.974		0.139
$P_{2,SRP}$	1.056	0.199				(3.354)	(5.941)		(0.996)	
	(0.062)	(0.056)				[3.178]	[4.845]		[0.992]	
$P_{3,SRP}$	1.193	0.073								
	(0.060)	(0.071)							$HJ-dist$	
$P_{4,SRP}$	1.275	-0.207	GMM_1	-0.303	0.676	1.860	4.584	0.974	0.894	0.139
	(0.062)	(0.061)		(0.838)	(0.950)	(3.218)	(4.807)			
$P_{5,SRP}$	0.930	-0.232	GMM_2	-0.311	0.674	1.775	4.510	0.965	0.894	0.163
	(0.051)	(0.072)		(0.774)	(0.856)	(3.223)	(4.412)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for comparison between two linear factor models (LFM) both based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor but differ in slope (country-specific) factor. The LFM in the top panel employs Huang and MacDonald's (2013) sovereign credit risk (HML_{SC}) and the LFM in the bottom panel adopts exchange rate misalignment risk (HML_{ERM}). The test assets are the transaction-cost adjusted excess returns of five currency volatility risk premium portfolios (top panel), and five currency skew risk premium portfolios (bottom panel) respectively, from September 2005 to January 2013. The coefficient estimates of Stochastic Discount Factor (SDF) parameters b and λ are obtained by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by fist-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Error (MAE) are also reported.

Table A.14. Asset Pricing of Currency Crash Sensitivity Portfolios

All Countries with Transaction Costs											
Factor Exposures			Factor Prices								
	β_{GDR}	β_{ERM}		b	b_{GDR}	b_{ERM}	λ_{GDR}	λ_{ERM}	R^2	$p-value$	MAE
$P_{1,MCS}$	0.42	-0.03								χ^2	
	(0.04)	(0.05)	FMB	2.25			0.11	1.58	0.52		2.25
$P_{2,MCS}$	0.81	-0.09		(1.73)			(3.63)	(4.58)		(0.64)	
	(0.06)	(0.05)		[1.72]			[3.61]	[4.50]		[0.14]	
$P_{3,MCS}$	0.87	0.45									
	(0.07)	(0.08)								$HJ-dist$	
$P_{4,MCS}$	1.26	-0.11	GMM_1	2.25	-0.23	0.32	0.11	1.58	0.52	0.07	2.25
	(0.06)	(0.07)		(1.74)	(0.86)	(0.92)	(3.65)	(4.57)			
$P_{5,MCS}$	1.60	-0.16	GMM_2	3.03	-0.45	0.50	-0.65	1.84	0.02	0.00	3.00
	(0.07)	(0.06)		(1.37)	(0.566)	(1.029)	(3.184)	(6.486)			
	β_{GDR}	β_{GVI}		b	b_{GDR}	b_{GVI}	λ_{GDR}	λ_{GVI}	R^2	$p-value$	MAE
$P_{1,MCS}$	0.39	-0.34								χ^2	
	(0.03)	(0.62)	FMB	2.10			0.26	-0.06	0.32		2.10
$P_{2,MCS}$	0.73	-0.49		(1.58)			(3.57)	(0.20)		(0.58)	
	(0.05)	(1.07)		[1.56]			[3.54]	[0.20]		[0.15]	
$P_{3,MCS}$	0.96	-9.50									
	(0.06)	(1.71)								$HJ-dist$	
$P_{4,MCS}$	1.30	4.80	GMM_1	2.10	-0.12	-5.60	0.26	-0.06	0.32	0.05	2.10
	(0.06)	(1.27)		(1.59)	(0.71)	(21.34)	(3.59)	(0.20)			
$P_{5,MCS}$	1.59	4.27	GMM_2	2.77	-0.12	-2.70	-0.39	-0.01	-0.00	0.00	2.76
	(0.05)	(1.15)		(1.37)	(0.566)	(1.029)	(3.184)	(6.486)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for comparison between two linear factor models (LFM) both based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor but differ in slope (country-specific) factor. The LFM in the top panel employs exchange rate misalignment risk (HML_{ERM}) and the LFM in the bottom panel adopts Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) global FX volatility (innovation) risk (GVI). The test assets are the transaction-cost adjusted excess returns of five currency tail dependence portfolios from September 2005 to January 2013. The coefficient estimates of Stochastic Discount Factor (SDF) parameters b and λ are obtained by Fama-MacBeth (FMB) with a constant in the second-stage regressions (Fama and MacBeth, 1973), and by fist-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Error (MAE) *excluding the constant* are also reported.

Table A.15. Risk Factors for the Trading Strategy Doubly Sorted by Currency Crash Sensitivity & Downside Insurance Cost)

Panel A: Currency Market Risk Factors								
α	β_{GDR}	β_{FB}	β_{MMT}	β_{PPV}				$Adjusted-R^2$
4.87*	0.31**	0.42**	0.08	0.24				0.30
(2.82)	(0.15)	(0.16)	(0.14)	(0.19)				
5.21*	0.13	0.51***						0.29
(3.02)	(0.22)	(0.13)						
Panel B: Stock Market Risk Factors								
α	β_{GMP}	β_{SMB}	β_{HML}	β_{UMD}	β_{QMJ}			$Adjusted-R^2$
9.36**	-0.09	-0.17	-0.08	-0.03	-0.39			-0.03
(3.79)	(0.09)	(0.18)	(0.23)	(0.13)	(0.26)			
Panel C: Hedge Fund Risk Factors								
α	β_{TBY}	$\beta_{SPD^{MB}}$	β_{SNP}	$\beta_{SPD^{RS}}$	β_{TFB}	$\beta_{TF^{FX}}$	$\beta_{TF^{CMD}}$	$Adjusted-R^2$
5.48*	-5.32	2.61	0.01	-0.02	-0.33	0.10	-0.40*	0.02
(3.31)	(17.01)	(18.65)	(0.07)	(0.03)	(0.20)	(0.15)	(0.23)	
Panel D: Betting-Against-Beta Risk Factors								
α	$\beta_{BAB_{FX}}$	$\beta_{BAB_{EM}}$	$\beta_{BAB_{BM}}$	$\beta_{BAB_{CM}}$				$Adjusted-R^2$
8.29**	-0.11	0.01	1.23**	-0.03				0.02
(3.61)	(0.20)	(0.15)	(0.51)	(0.07)				
Panel E: Other Risk Factors								
α	$\beta_{MSCI^{EM}}$	$\beta_{\Delta VIX}$	$\beta_{\Delta TED}$	$\beta_{\Delta FSI}$	$\beta_{\Delta GPU_{EU}}$	$\beta_{\Delta GPU_{US}}$		$Adjusted-R^2$
5.59**	0.09***	-0.15**	-0.66	0.00	-0.04	0.22		0.16
(2.68)	(0.02)	(0.06)	(0.50)	(0.00)	(0.20)	(0.15)		

This table reports the time-series asset pricing tests regressing the excess returns of a double-sorting trading strategy (that buys medium crash-sensitivity and high downside-insurance-cost currencies while sells low crash-sensitivity and medium downside-insurance-cost currencies) regressed on a series of risk factors. The excess returns are transaction-cost adjusted. We use the common risk factors in currency market (Lustig, Roussanov, and Verdelhan, 2011) plus two additional risk factors that captures currency momentum (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b) and fair value in Panel A, common risk factors in stock market (Fama and French; 1992, 1993) plus stock momentum risk factor (Carhart, 1997) in Panel B, hedge fund risk factors (Fung and Hsieh, 2001) in Panel C, quality-minus-junk (Asness, Frazzini, and Pedersen, 2013) and betting-against-beta risk factors (Frazzini and Pedersen, 2014) in Panel D, and other risk factors, including measures of government economic policy uncertainty in Europe and U.S. (Baker, Bloom, and Davis, 2012), are grouped together in Panel E. The sample period for each regression is normally from September 2005 to January 2013, but it also depends on the availability of the risk factors newly developed in the literature. Newey-West HAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) reported are in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates, respectively.

Figure A.6. Common Dynamic Factors in FX Trading Strategies & Global Currencies

This figure shows the common dynamic factors in the FX trading strategies (DF_{PFL}) and global currencies (DF_{FX}) estimated by Forni, Hallin, Lippi, and Reichlin's (2005) one-sided methodology and Doz, Giannone, and Reichlin's (2012) Quasi-MLE, respectively. The sample is from September 2005 to January 2013.

Table A.16. Factor Loadings of the Common Dynamic Factors

Portfolios	Factor Loadings	Currencies	Factor Loadings	Currencies	Factor Loadings
		JPY	-0.010	EUR	0.107
CRT	0.245	KRW	0.010	GBP	0.087
		HKD	0.025	AUD	0.106
FBM	0.321	TWD	N/A	NZD	0.097
		SGD	0.102	CAD	0.092
MMT	-0.146	MYR	0.092	CHF	0.084
		THB	N/A	SEK	0.103
PPV	-0.180	PHP	0.072	DKK	0.107
		IDR	N/A	NOK	0.096
MSC	0.267	INR	0.077	ZAR	0.087
		RUB	0.091	BRL	0.076
VRP	-0.157	PLN	0.110	CLP	0.083
		RON	0.104	COP	0.071
SRP	0.271	HUF	0.107	ARS	N/A
		CZK	0.100	PEN	0.052
DS	0.145	SKK	0.105	MXN	0.087
		TRY	0.084	ILS	0.068

This table reports the factor loadings of the common dynamic factor of FX trading strategies estimated by one-sided dynamic PCE (Forni, Hallin, Lippi, and Reichlin, 2005), and the factor loadings of the common dynamic factor of 30 individual currencies estimated by Quasi-MLE (Doz, Giannone, and Reichlin, 2012). The sample is from September 2005 to January 2013.

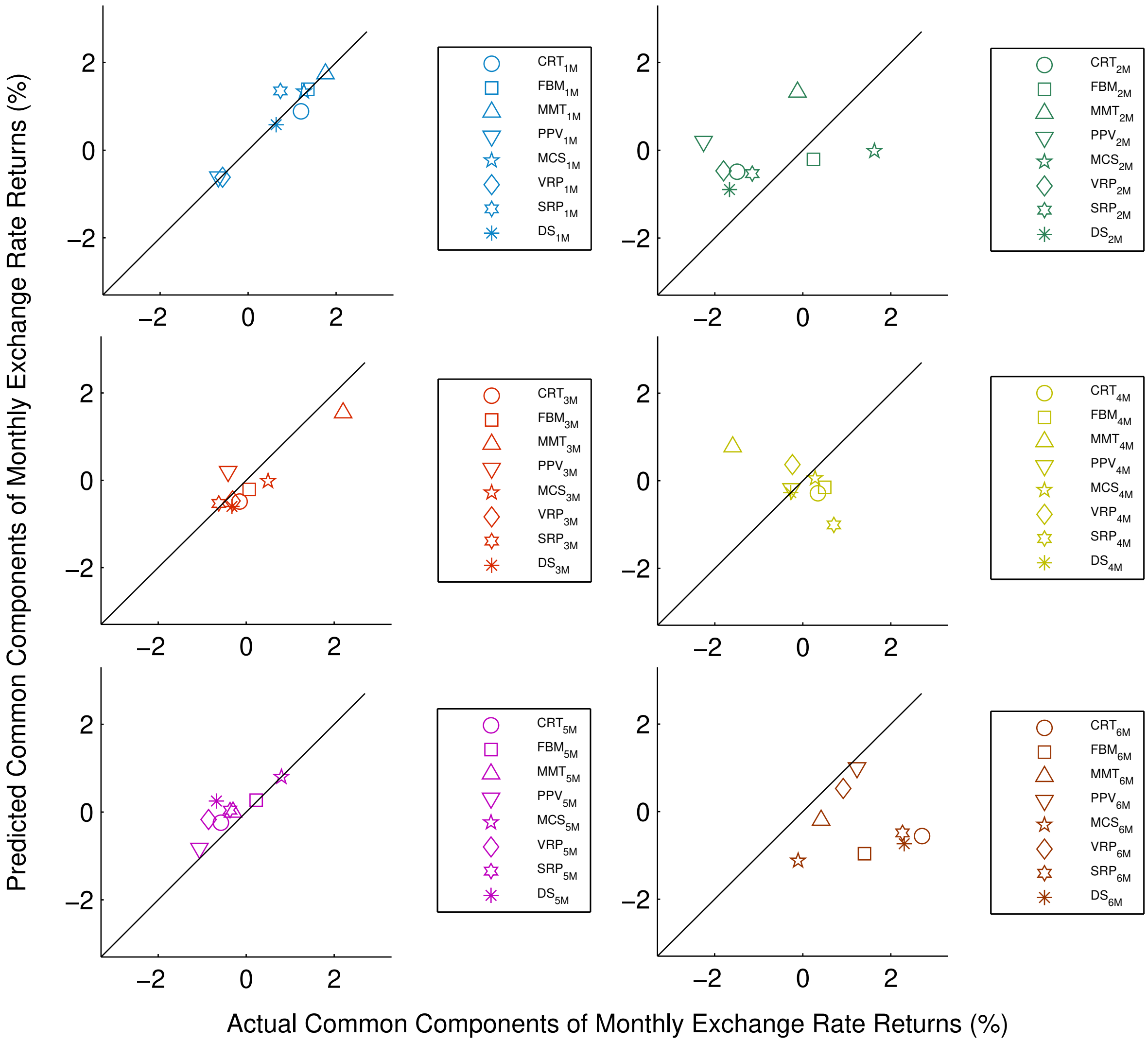
Table A.17. Common Risk Sources of FX Trading Strategies

Panel A: Exchange Rate Returns						
β_{GSQ}	β_{GVI}	$\beta_{\Delta VIX}$	$\beta_{\Delta TED}$	$\beta_{\Delta FSI}$	$\beta_{\Delta SVRN}$	$Adjusted-R^2$
0.39***						0.34
(0.07)						
	31.40***					0.43
	(11.07)					
		0.80***				0.44
		(0.14)				
			1.99			0.02
			(1.31)			
				0.04*		0.09
				(0.02)		
					0.14***	**0.59**
					(0.01)	
0.33***	24.99**					0.63
(0.03)	(9.89)					
0.28***		0.57***				0.62
(0.03)		(0.18)				
0.22***					0.10***	**0.70**
(0.04)					(0.02)	
	10.96**				0.11***	0.62
	(4.81)				(0.01)	
		0.34***			0.10***	0.64
		(0.09)			(0.01)	

Panel B: Dynamic Correlation between Common Dynamic Factor & Global Sovereign CDS Spreads ($\Delta SVRN$)			
Long Term	Medium Term	Short Term	Static Correlation
0.748	0.716	0.882	0.771

This table reports the time-series asset pricing tests for the common risk sources of the dynamic factor of the FX trading strategies. The exchange rate returns are transaction-cost adjusted. The sample period is from September 2005 to January 2013. Newey-West HAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) reported are in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates, respectively. See Huang and MacDonald (2013) for the categorization of level (global) and slope (country-specific) factors. The best-performance model in terms of $Adjust-R^2$ is highlighted. The dynamic correlations are estimated by Croux, Forni, and Reichlin's (2001) method for bivariate time series.

Figure A.7. Out-of-Sample Forecasts of the Common Components in Exchange Rate Returns of FX Trading Strategies



This figure presents forecasts of the common components in exchange rate returns of FX trading strategies from 1-month to 6-month ahead. The in-sample period is from September 2005 to July 2012, and out-of-sample from August 2012 to January 2013.

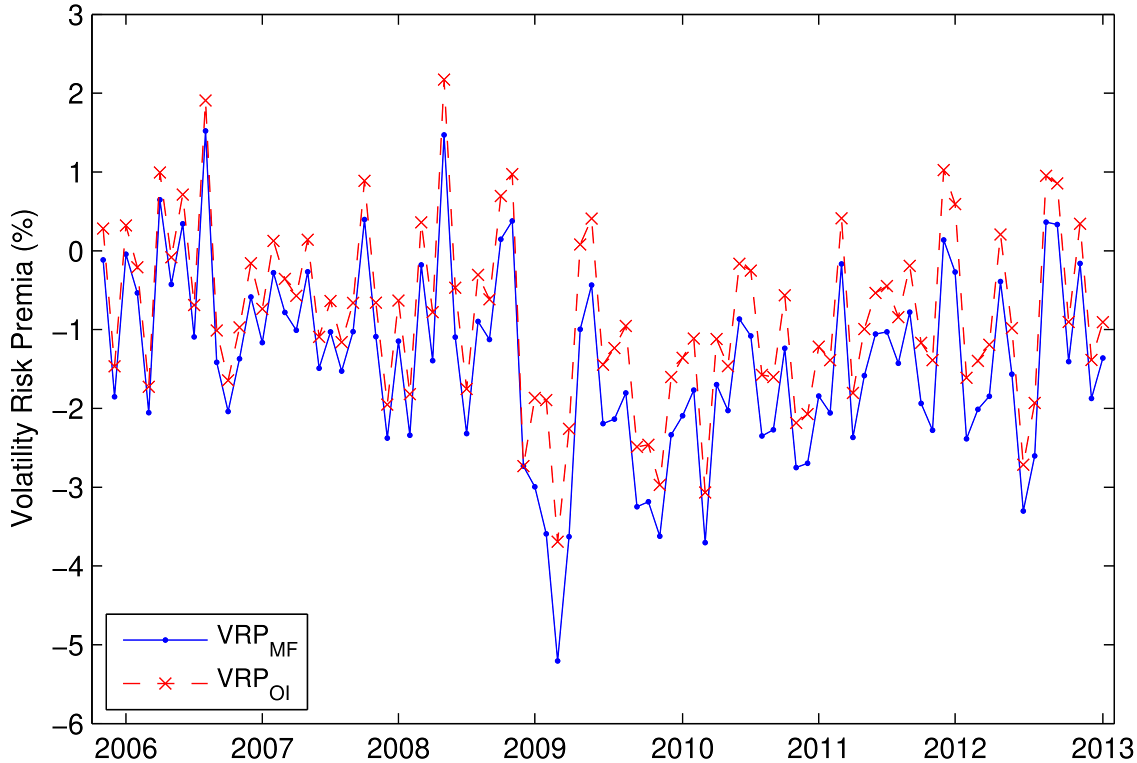
Table A.18. Forecasting Performance in Root Mean Square Error (RMSE)

Panel A: Time Horizons (%)							
1-Month	2-Month	3-Month	4-Month	5-Month	6-Month		
0.249	1.386	0.617	1.123	0.469	1.971		
Panel B: Cross Assets (%)							
CRT	FBM	MMT	PPV	MCS	VRP	SRP	DS
1.439	1.029	1.198	1.097	0.956	0.689	1.144	1.357

This table reports forecasting performance in percentage RMSE for both time horizons (from 1-month to 6-month ahead) and cross assets (eight studied currency investment strategies).

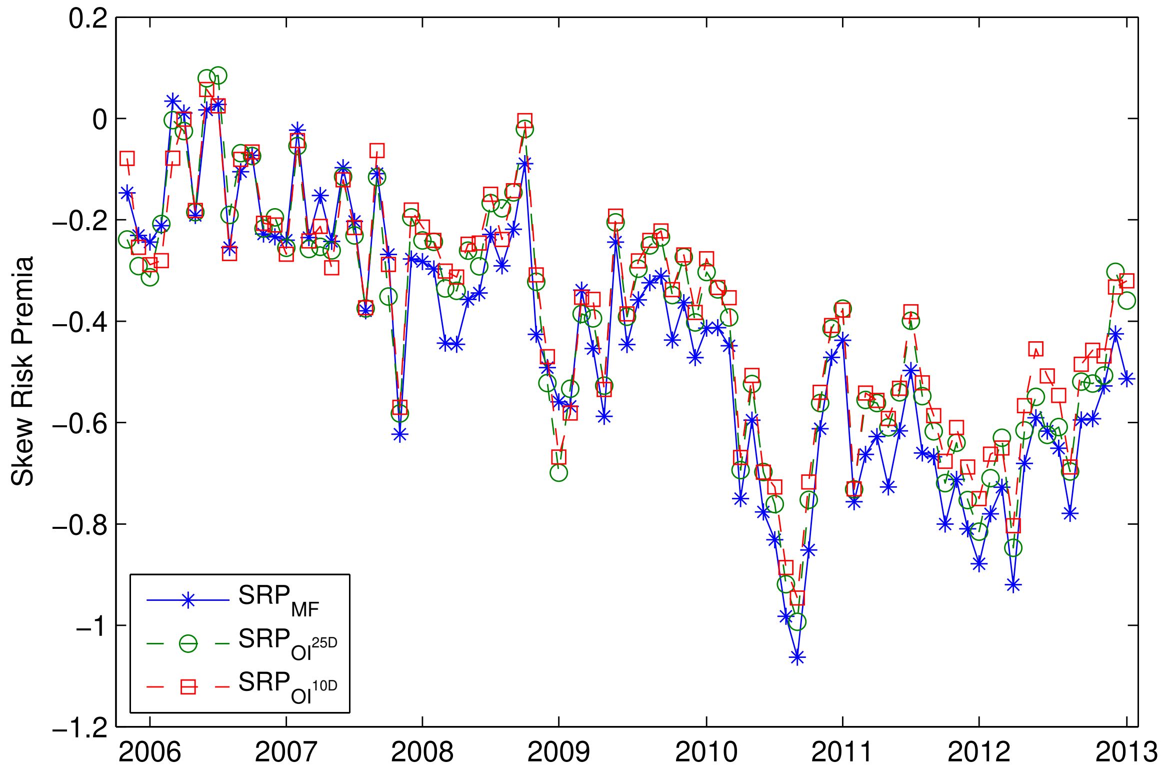
Appendix B.

Figure B.1. Volatility Risk Premia: Model-free vs. Option-implied Approaches (Aggregate Level)



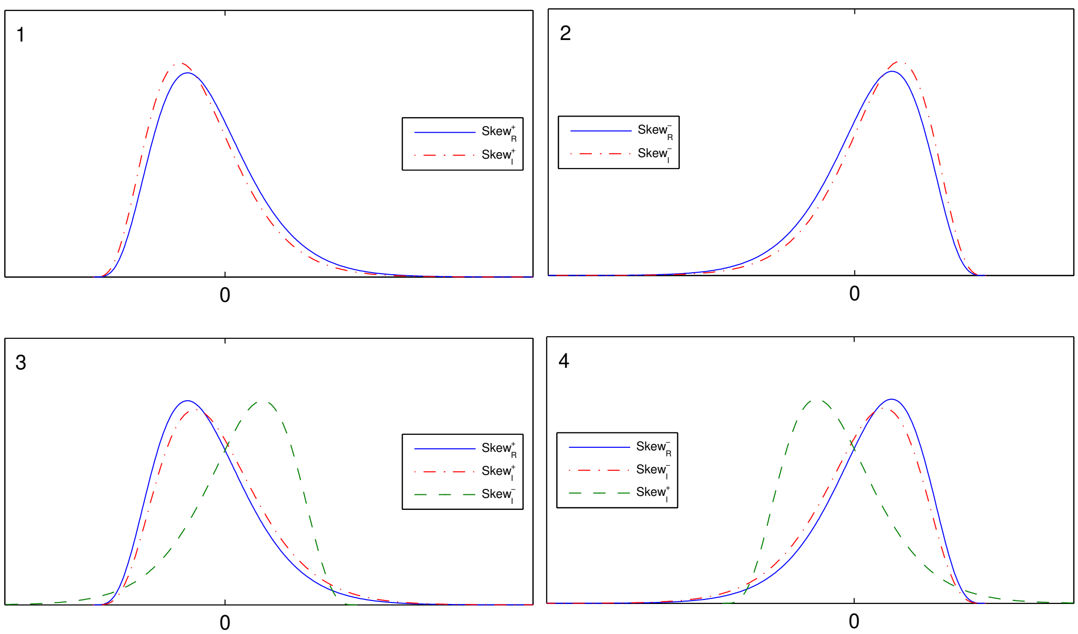
This figure shows the aggregate levels of annualized volatility risk premia across 27 currencies using model-free approach (VRP_{MF}) and option-implied ATM volatility(VRP_{OI}). The sample is from September 2005 to January 2013.

Figure B.2. Skew Risk Premia: Model-free vs. Option-implied Approaches (Aggregate Level)



This figure shows the aggregate levels of annualized skew risk premia across 27 currencies using model-free (SRP_{MF}) and option-implied (SRP_{OI}) approaches. The subscript $25D$, $10D$ denotes the computations from 25-delta, and 10-delta out-of-money options, respectively. The sample is from September 2005 to January 2013.

Figure B.3. Skew Risk Premia: Positive Skew & Negative Skew



This figure shows the how we treat positive skew and negative skew differently when measuring the crash risk premium. Note that the currency portfolios are in long positions (shorting USD to long foreign currencies). The superscript '+', '-' denotes positive, and negative skewness, respectively. The subscript I, R represents implied, and realized skewness, respectively. The graph at the upper-left corner (1): Positive skew risk premium, high crash risk of foreign currencies; The graph at the upper-right corner (2): Negative skew risk premium, low crash risk of foreign currencies; The graph at the lower-left corner (3): Positive skew risk premium, low crash risk of foreign currencies; The graph at the lower-right corner (4): Negative skew risk premium, high crash risk of foreign currencies.

Table B.1. Descriptive Statistics of Currency Portfolios (Momentum, Value & Crash Sensitivity)

All Countries with Bid-Ask Spreads					
Portfolios	$P_{1,MMT}$	$P_{2,MMT}$	$P_{3,MMT}$	$P_{4,MMT}$	$P_{5,MMT}$
Mean (%)	1.22	1.97	1.63	3.92	3.08
Median (%)	3.61	4.92	6.85	7.61	9.21
Std.Dev. (%)	10.63	11.10	8.41	7.91	8.89
Skewness	-0.50	-0.89	-0.43	-0.25	-0.27
Kurtosis	0.65	1.72	0.36	0.17	0.14
Sharpe Ratio	0.11	0.18	0.19	0.50	0.35
AC(1)	0.06	0.08	0.22	-0.02	-0.07
Portfolios	$P_{1,PPV}$	$P_{2,PPV}$	$P_{3,PPV}$	$P_{4,PPV}$	$P_{5,PPV}$
Mean (%)	3.83	2.34	1.90	2.24	1.78
Median (%)	6.60	7.73	7.01	5.24	1.87
Std.Dev. (%)	6.59	11.07	9.62	9.64	10.72
Skewness	-0.15	-0.63	-0.40	-0.53	-0.32
Kurtosis	0.05	0.79	0.32	0.78	0.38
Sharpe Ratio	0.58	0.21	0.20	0.23	0.17
AC(1)	0.19	0.10	0.11	0.01	-0.01
Portfolios	$P_{1,MCS}$	$P_{2,MCS}$	$P_{3,MCS}$	$P_{4,MCS}$	$P_{5,MCS}$
Mean (%)	2.58	1.62	3.03	2.47	2.18
Median (%)	3.93	3.28	9.99	7.69	3.02
Std.Dev. (%)	4.17	7.15	11.56	10.69	13.41
Skewness	-0.24	-0.30	-0.80	-0.30	-0.40
Kurtosis	0.25	0.32	1.25	0.28	0.38
Sharpe Ratio	0.62	0.23	0.26	0.23	0.16
AC(1)	0.13	0.16	0.12	0.02	-0.01

This table reports descriptive statistics of the transaction-cost adjusted (bid-ask spreads) annualized excess returns in USD of currency momentum (MMT), value (PPV) and crash sensitivity (MCS) portfolios sorted by 1-month lagged exchange rate return, and by tail dependence signed by the skewness, respectively. The 20% currencies with the lowest sort base are allocated to Portfolio P_1, and the next 20% to Portfolio P_2, and so on to Portfolio P_5 which contains the highest 20% sort base. The portfolios are rebalanced monthly according to the updated sort base. The sample period is from September 2005 to January 2013. The mean, median, standard deviation and higher moments are annualized (so is the Sharpe Ratio) and in percentage. Skewness and kurtosis are in excess terms. AC(1) is the first order autocorrelation coefficients of the monthly excess returns.

Table B.2. Descriptive Statistics of Currency Portfolios (Moment Risk Premia: Volatility & Skewness)

All Countries with Bid-Ask Spreads					
Portfolios	$P_{1,VRP}$	$P_{2,VRP}$	$P_{3,VRP}$	$P_{4,VRP}$	$P_{5,VRP}$
Mean (%)	4.99	1.60	1.15	1.64	2.49
Median (%)	9.22	9.07	10.17	11.63	11.60
Std.Dev. (%)	7.98	8.07	2.51	2.45	6.42
Skewness	-0.10	-0.38	-0.30	-0.89	-0.54
Kurtosis	0.02	0.29	0.37	1.55	0.76
Sharpe Ratio	0.54	0.18	0.11	0.14	0.22
AC(1)	0.10	0.04	0.02	0.08	0.13
Portfolios	$P_{1,SRP}$	$P_{2,SRP}$	$P_{3,SRP}$	$P_{4,SRP}$	$P_{5,SRP}$
Mean (%)	3.11	2.33	3.43	1.88	0.27
Median (%)	8.48	6.26	10.23	3.56	0.76
Std.Dev. (%)	11.80	11.41	10.98	10.05	6.70
Skewness	-0.56	-0.55	-0.45	-0.27	-0.19
Kurtosis	0.63	0.58	0.58	0.32	0.18
Sharpe Ratio	0.26	0.20	0.31	0.19	0.04
AC(1)	0.24	0.12	-0.05	0.03	-0.06

This table reports descriptive statistics of the transaction-cost adjusted (bid-ask spreads) annualized excess returns in USD of currency volatility (VRP) and skew (SRP) risk premium portfolios sorted by 1-month corresponding moment risk premium. The 20% currencies with the lowest sort base are allocated to Portfolio P_1, and the next 20% to Portfolio P_2, and so on to Portfolio P_5 which contains the highest 20% sort base. The portfolios are rebalanced monthly according to the updated sort base. Specifically, $P_{1,VRP}$ ($P_{5,VRP}$) is the portfolio with the highest (lowest) downside insurance cost, and $P_{1,SRP}$ ($P_{5,VRP}$) is the portfolio with the lowest (highest) crash risk premium. The sample period is from September 2005 to January 2013. The mean, median, standard deviation and higher moments are annualized (so is the Sharpe Ratio) and in percentage. Skewness and kurtosis are in excess terms. AC(1) is the first order autocorrelation coefficients of the monthly excess returns.