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Essays in International Finance

by

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Abstract

This Ph.D. thesis contains 3 essays in international finance with a focus on foreign exchange market from the perspectives of empirical asset pricing (Chapter 2 and Chapter 3), forecasting and market microstructure (Chapter 4).

In Chapter 2, we derive the measure of position-unwinding risk of currency carry trade portfolios from the currency option pricing model. The position-unwinding likelihood indicator is in nature driven by interest rate differential and currency volatility, and highly correlated with global currency skewness (crash) risk. We show that high interest-rate currencies are exposed to higher position-unwinding risk than low interest-rate currencies. We then provide a framework that decomposes carry trade payoffs into sovereign credit premium, interest rate differential, and expected exchange rate depreciation (overshooting) upon default components to analyze currency risk premia. We investigate the sovereign CDS spreads as the proxy for solvency of a state and find that high interest-rate currencies load up positively on sovereign default risk while low interest-rate currencies provide a hedge against it. Sovereign credit premia, as the dominant (country-specific) fundamental risk that drives market volatility (global contagion channel), together with position-unwinding likelihood indicator as the market risk sentiment, captures over 90% of cross-sectional variations of carry trade excess returns. In this context, the forward premium puzzle can be understood as a composite story of sovereign credit premia, global liquidity imbalances and reversal. We further reveal that sovereign default risk also explains large proportions of the cross sections of currency momentum (over 65%) and volatility risk premium (over 80%) portfolios.

In Chapter 3, we investigate 3 important properties of global currencies: misalignments measured by the deviations from equilibrium (real effective) exchange rates, crash

sensitivity captured by the copula tail dependence to the global market, and moment risk premia using a model-free method — volatility risk premia as the proxy for (relative) position insurance costs, and skew risk premia as the gauge for (carry trade) speculative inclinations. The overvalued (undervalued) currencies with respect to REER tend to be crash sensitive (insensitive) and relatively cheap (expensive) to hedge, and exhibit high (low) speculative risk premia. We further show that they have rich asset pricing and allocation implications. The profitability of currency carry trades can be understood as the compensation for misalignment and speculative risks, which explain over 96% of the cross-sectional excess returns and dominate other candidate factors, including sovereign credit and liquidity risks, and cover the information of volatility risk. Currency trading strategies exploiting these 3 properties provide striking crash-neutral and diversification benefits for portfolio optimization and risk management purposes. After examining the risk attributes and factor structure of 7 studied currency investment strategies and of over 30 individual currencies using generalized dynamic factor model, we identify an additional important factor which is related to hedging demand imbalances, also priced in the cross section of currency value portfolios (over 90% of the variations) and of global currencies (14% extra variations), but it is omitted in literature using standard portfolio approach.

In Chapter 4,we investigate the term structure of exchange rate predictability from 1-month to 12-month horizons by the decomposition of exchange rate returns into forward premia component and carry trade risk premia component, which is shown to be driven by common latent factors. We incorporate the term structure factors extracted from the cross section of carry components into the dynamics between the exchange rates and a large set of predictors in a time-varying parameter (TVP) VAR setting. We then employ dynamic (Bayesian) model averaging (DMA) method to handle model uncertainty and forecast the term structure of carry component. We utilize the time-variations in the DMA probability weighting of each factor-augmented empirical exchange rate model to measure regression-based (vis-à-vis survey-based) model disagreement, which has both contemporaneous and predictive relations with currency risk premia (and the term structure), volatility, and customer order flows. From the perspective of foreign exchange market microstructure, customer order flows

are also informative about the term structure of carry trade risk premia. We also apply the DMA probability weighting to examine the "scapegoat" drivers of customer order flows. Our findings reveal that heterogeneous agents learn to forecast exchange rates and switch trading rules over time, resulting in the dynamic country-specific and global exposures of exchange rates to short-run non-fundamental risk and long-run business cycle risk. We further comprehensively evaluate the statistical and economic significance of the predictive power of our model in a framework allowing for a full spectrum of currency investment management. Hedging pressure and liquidity are identified to contain predictive information that is common to a range of forecasting horizons. Policy-related predictors are important for short-run forecasts up to 3 months while crash risk indicators matter for long-run forecasts from 9 months to 12 months. Our term structure model is able to beat a driftless random walk in the forecasts up to 1-year horizon for the 7 most traded currencies, and generates substantial performance fees up to approximately 6.5% per annum.

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I am deeply obliged to my parents and elder sister Chujiao for their unconditional love, and for giving me maximum freedom and unwavering support to follow my own path — any success I have achieved as a Ph.D. student is instantly related to them. I also would like to thank my brilliant colleagues and friends, Shuo Cao, Ding Liu, Dr Qingyao Wu, and Yang Zhao for the constant discussion and help with their expertise.

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Dedication

To my parents, Meifeng Huang and Jinkui Huang.

Declaration

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

Chapter 2 and Chapter 3 are drawn from the collaborative work with my principal supervisor Professor Ronald MacDonald (Chapter 2 and Chapter 3). In both instances, the analyses and vast majority of the writing were undertaken by myself. Chapter 4 is my job market paper in which I am the sole author.

The papers written jointly with Professor Ronald MacDonald (currently under review for publications) are:

[1] Huang, H. and MacDonald, R. (2013) "Currency Carry Trades, Position-Unwinding Risk, and Sovereign Credit Premia" Working Paper, Available at SSRN No.2287287.

[2] Huang, H. and MacDonald, R. (2013) "Global Currency Misalignments, Crash Sensitivity, and Moment Risk Premia" Working Paper, Available at SSRN No.2393105.

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“*Life is like riding a bicycle. To keep your balance you must keep moving.*”

Albert Einstein

Chapter 1

Introduction

Currency is an important asset of a state, and the foreign exchange market is the most liquid financial market among all asset classes in the world according to the 2014 *Triennial Central Bank Survey* coordinated by the Bank for International Settlements. Managing currency risk is a crucial task of both central banks, commercial corporations and financial institutions who have large portfolio holdings of currencies either directly as reserves or investments of an asset class, or indirectly via local-currency-denominated assets. Thereby, understanding currency premia and forecasting exchange rates are core issues in international money and finance for purposes of exchange rate related policy formulation and implementation, as well as currency exposure hedging and investment management.

One of the most intriguing empirical findings associated with currency risk premia is that forward premium is a biased predictor of future exchange rate movements (Froot and Thaler, 1990; Engel, 1996). As a corollary, the empirical failure of the Uncovered Interest Rate Parity (UIP) implies the existence of positive excess returns of a naive currency carry strategy that invests in high-yield currencies funded by low-yield currencies. This strong relationship between currency risk premia and interest rate differentials is referred to as the "forward premium puzzle". Frankel and Froot (1989) offer the first test that tackles the assumptions made by this theory through the decomposition of the deviations from UIP into expectations errors and risk compensations. They show that neither of them is enough to rationalize the behavior of exchange rates. Perhaps some more pragmatic questions would be: What cause investors to systematically form biased expectations about the future exchange rate changes? And what exactly are the risk sources of the time-varying currency premia? Since the variations of conventional and theoretical factors are not compatible with those of the profitability of carry trades that exploit the violation of UIP (Burnside, 2011), this Ph.D. thesis provides a comprehensive review of the literature relevant to both questions in this chapter, and endeavors to provide some new insights with respect to the latter, for which we investigate the exchange rate dynamics that blends finance themes with macro-oriented issues, such as examining the properties of currency risk premia and carry trade position-unwinding risk, as well as linking the excess returns to sovereign default, equilibrium exchange rate misalignment, speculative and crash risks in the field of empirical asset pricing in Chapter 2 and Chapter 3 based on the joint affine term structure model of interest rates (Duffie and Kan, 1996; Duffie and Singleton, 1999; Cochrane and Piazzesi, 2009), exchange rates (Ahn, 2004; Bekaert, Wei, and Xing, 2007; Ang and Chen, 2010), and sovereign CDS spreads (Longstaff, Pan, Pedersen, and Singleton, 2011; Augustin, 2012), the theories of valuation channel (Gourinchas and Rey, 2007, 2013) and funding liquidity constraint (Gabaix and Maggiori, 2015) of global imbalances, and the story of speculative bubbles (Abreu and Brunnermeier, 2003; Brunnermeier, Nagel, and Pedersen, 2009; Plantin and Shin, 2011). Especially, we look into whether or not high (low) interest rate currencies tend to be overvalued (undervalued) with respect to real effective exchange rate (REER), crash sensitive (insensitive), relative cheap (expensive) to hedge, and exposed to high (low) speculative inclination of the market using a data-driven approach. And in the cross section of global currencies (rather than currency portfolios), we identify an additional factor that is related to Purchasing Power Parity (PPP) and hedging demand imbalances (volatility risk premia) besides the dollar risk and forward bias risk (Lustig, Roussanov, and Verdelhan, 2011).

Another heated and thematic debate in the foreign exchange market is the seemingly random walk nature of exchange rates, which is referred to as the "Meese-Rogoff puzzle", given that they are very difficult to forecast using theoretical predictors, such as economic fundamentals (Meese and Rogoff, 1983; Frankel and Rose, 1995). The

Efficient Market Hypothesis (EMH) states that bilateral exchange rates should be the best guess of the market about the relative fundamental value of two currencies based on all publicly available information at that time under the condition of either in absence of risk premia or if the time variation in the risk premia is small compared to that of the fundamental pricing kernel. Even under the EMH, bilateral exchange rates should correspond to their economic fundamentals, and should not fluctuate randomly around their past values. Evans and Lyons (2002, 2005b) shift the focus toward the private information originating from order flows, which offer better forecasts of exchange rates than economic fundamentals. The success of their method lies in the fact that order flows capture the surprise component (the expectations revision about both observable and unobservable exchange rate determinants) in the present value model of Engel and West (2005). In general, the answer to the question "Are exchange rates really predictable?" would be: "It depends" — on the choice of predictors, sample period, data transformation[1], forecasting horizon, model specification[2], and the evaluation method of forecasts. So, this Ph.D. thesis also provides an overall analysis of the existing literature in this chapter and accordingly we forecast exchange rate using a large set of predictors, including (i) macroeconomic fundamentals and yield curve factors, (ii) signals generated from technical analysis, (iii) option-implied information, (iv) crash sensitivity measured by copula tail dependence and hedging pressure via futures market, (v) financial indices of various asset classes, (vi) policy uncertainty indicator. Moreover, Lustig, Stathopoulos, and Verdelhan (2013) theoretically derive that the term structure of carry trade risk premia is downward sloping because investment currencies tend to have low local sovereign term premia relative to funding currencies. We then decompose exchange rate changes into forward premium component and carry trade risk premium component, which is the part that entails forecast. Hence, exchange rate returns over a range of forecasting horizons can be modelled as a function of common (term structure) factors. To summarize, we assess exchange rate predictability over a range of horizons using a term structure model of currency risk premia and from the perspective of market microstructure in Chapter 4,

[1] It includes de-trending, filtering, and adjustment for seasonality.

[2] In particular, structural models of exchange rate determination do not fit the data well, not to mention forecasting them. While reduced-form models are widely adopted in empirical studies.

which sheds some light on (i) the informational commonality and projection of exchange rate predictors over the term structure, (ii) how model uncertainty and disagreement across a large set of macroeconomic and financial predictors are related to currency risk premia, volatility, and market trading activities, (iii) the term structure of predictive information in customer order flows and their scapegoat drivers, and (iv) both the statistical and economic values of the term structure model.

Understanding the properties of currency risk premia and the position-unwinding risk of carry trades, as well as beating the driftless random walk in out-of-sample forecasts of exchange rates are of great practical values to policy-makers, hedgers, and speculators in the foreign exchange market, e.g. maintaining exchange rate stability for sustainable economic growth (Obstfeld and Rogoff, 1996; Levine, 1997; Aghion, Bacchetta, Ranciere, and Rogoff, 2009), currency overlay and absolute return products, and even factor investing (Ang, 2014) in which currencies are regarded as a special asset class. Typically, a small positive out-of-sample R^2 can still generate large economic benefits from dynamic asset allocation for investors (Campbell and Thompson, 2008). To provide further explanations of why these issues are important to address, a detailed literature review on both currency risk premia and exchange rate predictability is delegated to the following sections of this chapter. And the concluding chapter (Chapter 5) summarises the contributions of this Ph.D. thesis to the existing literature and how future work can be developed, as well as sketches out some policy implications.

1.1 The Forward Premium Puzzle and Currency Crashes

According to the Uncovered Interest Rate Parity (UIP) condition, if the investors with rational expectations are risk-neutral, the changes in the bilateral exchange rates will eliminate any profit arising from the appropriate interest differential. However, numerous empirical studies show that the appreciations of low interest-rate currencies do not compensate for the corresponding interest rate differentials. Instead, the high interest-rate currencies tend to appreciate rather than depreciate. Carry trade, as one of the most popular trading strategies in the foreign exchange (FX) market, exploits the profits from the violation of UIP by investing in high interest-rate currencies while financing in low interest-rate currencies. The excess returns of carry trades give rise to the so-called "forward premium puzzle" (Hansen and Hodrick, 1980; Fama, 1984): a projection of forward premium on interest differential produces a coefficient that is closer to minus one than plus one. Given the high liquidity in global FX market and the free mobility of international capital, it is difficult to justify the unreasonably long-existing profits of carry trade strategies[3]. Time-varying risk premia is a straightforward and theoretically convincing solution towards this puzzle in the economic sense that high interest-rate currencies deliver high returns merely as a compensation for high risk exposures during periods of turmoil (Fama, 1984; Engel, 1996; Christiansen, Ranaldo, and Söderlind, 2011). Verdelhan (2010) shows that agents with preference settings in Campbell and Cochrane (1999) can generate notable deviation from UIP due to the consumption habit. Infrequent currency portfolio decision (rational inattention) is another possible solution that also accounts for "delayed overshooting" (Bacchetta and Van Wincoop, 2010). Burnside, Eichenbaum, and Rebelo (2009) argue from the perspective of market microstructure that it is the adverse selection from which the forward premium puzzle arises. Burnside, Han, Hirshleifer, and Wang (2011), and Ilut (2012) further suggest behaviorial explanations of investors' overconfidence, and of slow reaction to news announcements induced by ambiguity aversion, respectively, for the existence of forward bias.

Carry trades as a profitable strategy in the FX market has experienced several periods[4] of "dramatic position-unwinding" in the past 30 years. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) find that standard business cycle risk factors are unable to account for these major shortfalls of carry trades. Using currency options to protect

[3]Although this type of trading strategies had suffered substantial losses since the outbreak of sub-prime mortgage crisis during 2007 (particularly after the bankruptcy of Lehman Brothers in the mid of September 2008, see Figure A.1. in Appendix .A), it recovered soon around the mid of 2009 and the losses are relatively small compared to its historical cumulative returns (Brunnermeier, Nagel, and Pedersen, 2009).

[4]They're around the second quarter of 1986 - the mid of 1986, the last quarter of 1987 - the first quarter of 1988, the mid of 1992 - the mid of 1993, the first quarter of 1995, the mid of 1997 - the mid of 1998, the mid of 2008 - the mid of 2009.

the downside risk, they construct hedged carry positions and show that the payoffs to such hedged strategies are very close to those of unhedged carry trades. This result may imply the mispricing of currency options (particularly those trading away from money) used for hedging the carry positions, as pointed out by Farhi and Gabaix (2008), that option might in principle does not cover the latent disaster risk. This is because if the crash risk of the underlying asset is ignored or underestimated, a currency option would be significantly undervalued, and in this situation the payoffs to the hedged carry trades could be different from those of the unhedged positions. This difference in between unhedged and hedged carry trade portfolios can be justified as the variance risk premium (Carr and Wu, 2009), the skewness risk premium (Kozhan, Neuberger, and Schneider, 2013), or even the kurtosis risk premium. Jurek (2007) shows that the excess returns of a crash-neutral currency carry position are statistically indistinguishable from zero. The crash risk premia contribute $30\% - 40\%$ to the total currency risk premia. In this sense, we put forward a measure of position-unwinding risk of currency carry trades from the option pricing model and argue that one possible way to understand the excess returns of the carry trades lies in the changes in the non-risk-neutral market sentiment of the probability that the positions might be unwound.

1.2 The Cross Section of Currency Carry Trade Portfolios

Bansal and Dahlquist (2000) are the first to examine the cross-sectional relations between currency risk premia and interest rate differentials. They show that UIP works better for currencies that experience higher inflation rates. In the more recent empirical literature, Lustig, Roussanov, and Verdelhan (2011) introduce a portfolio-sorting approach using forward discounts into the study of currency carry trades. Instead of analysing individual currencies, they focus on currency portfolios facilitating the elimination of a large amount of time-varying country idiosyncratic characteristics[5], in order to overcome the problem that these characteristics are potentially time-

[5] As highlight by Cochrane (2005), the prices of individual assets are highly volatile and thereby their expected returns, covariances and betas become difficult to measure accurately. a portfolio approach reduces the volatilities by diversification.

varying across countries, and to concentrate on their common characteristics. For those currencies that Covered Interest Rate Parity (CIP) holds, sorting by forward discounts is equivalent to sorting by interest rate differentials (see Akram, Rime, and Sarno, 2008). Lustig, Roussanov, and Verdelhan (2011) demonstrate that the first two principal components of the excess returns of the these portfolios account for most of the time series variations. The first principal component (PC_1) is essentially the average excess returns of all portfolios, which can be interpreted as the average excess returns of a zero-cost strategy that an investor borrows in USD for investing in the global money market outside U.S., so-called "dollar risk factor" (GDR). It is an intercept (level) factor because each portfolio shares roughly the same exposure to it. The second principal component, (PC_2), is a slope factor in the sense that the weight of each portfolio, from the one containing the highest interest-rate currencies to the one made up of low interest-rate currencies, decreases monotonically from positive to negative. It is also very similar to the excess returns of another zero-cost strategy with long positions in highest interest-rate currencies funded by short positions in lowest interest-rate currencies. Hence, we call it "forward bias risk factor", denoted by HML_{FB}.

The two common factors first documented in Lustig, Roussanov, and Verdelhan (2011) are the key ingredients for a risk-based explanation of currency carry trade excess returns. The risk factors identified by this data-driven approach are in fact in line with Arbitrage Pricing Theory by Ross (1976) while other standard risk factors, such as consumption growth (Lustig and Verdelhan, 2007) measured by durable Consumption-based CAPM (CCAPM) setting of Yogo (2006), Chicago Board Options Exchange's (CBOE) VIX index as the measure of volatility risk, T-Bill Eurodollar (TED) Spreads as the illiquidity risk indicator, Pástor and Stambaugh's (2003) liquidity measure, and Fama and French (1993) factors, do not covary enough with the currency excess returns to explain the profitability of carry trades (Burnside, 2011; Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011). Grounded on the theoretical foundations of Merton's (1973) Intertemporal CAPM (ICAPM)[6], Menkhoff, Sarno, Schmeling, and Schrimpf

[6]The ICAPM model assumes that investors are concerned about the state variables, which exert evolutionary influences on the investment opportunities set. Market-wide volatility (not the idiosyncratic volatility) is a good proxy for the investment sentiment of market states. As the result,

(2012a) propose the global volatility (innovation) risk (GVI) of FX market instead of HML_{FX} as the slope factor that, along with GDR as the level factor, also successfully explains the cross sectional excess returns of currency carry trades. They show that high interest-rate currencies deliver negative returns in the times of high unexpected volatility while low interest-rate currencies offer a hedge against the volatility risk by yielding positive returns. However, these studies haven't bridged the gap between currency risk premia and macroeconomic fundamentals.

1.3 Fundamental Risk and and Currency Premia

In this section, we provide the theoretical foundations that link the excess returns of currency carry trades to macroeconomic fundamental risk through two sources. One is a possible joint affine term structure model of interest rates and sovereign CDS spreads that market liquidity component and sovereign credit component are decomposed from the interest rates. We also count on the models of global imbalances that underscores the valuation channel of a nation's net foreign asset holdings towards exchange rate adjustments, and the liquidity provision role of financial intermediaries. All these provide a theoretically sound ground for this Ph.D. thesis to disentangle the mystery of currency risk premia from the aspects of sovereign credit, equilibrium exchange rate misalignment, speculative and crash risks.

1.3.1 Term Structure: Interest Rate and Sovereign CDS Spread

The arbitrage-free term structure models (AF-TSM) of interest rates are an affine dynamic function of a set of state vector with restrictive assumptions, allowing us to separate risk premia from risk-adjusted expectations about future short rates. The affine sovereign CDS model is useful for gauging the sovereign credit risk in currencies

a risk-averse agent wishes to hedge against unexpected changes (innovations) in market volatility, especially during the period of high unexpected volatility the hedging demand for assets that have negative exposures to systematic volatility risk drives up the prices of these assets. Campbell (1993), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008) have made remarkable extensive researches on the volatility risk of stock markets.

when jointly valuated with the interest rates. The TSMs of interest rates are well explored jointly with the UIP of currencies both theoretically and empirically but the TSMs of sovereign CDS are rarely linked to the study of forward premium anomaly.

Backus, Foresi, and Telmer (2001) translate Fama's (1984) condition for forward premium anomaly into restrictions on the pricing kernels, adapt those to the affine interest rate term structure models of Duffie and Kan (1996) class, and reveal that several alternative models (e.g. Cox, Ingersoll, and Ross, 1985) all have serious shortcomings in depicting the behavior of both exchange rates and interest rates in terms of the positive probability of negative interest rates or heterogeneous effects of factors on pricing kernels across different currencies. Bekaert, Wei, and Xing (2007) show that deviations from the Expectations Hypothesis of the Term Structure (EHTS) can only explain a minor fraction of the failure of UIP in the long run and imposing the EHTS does affect the currency risk premia.

Ahn (2004) studies the joint dynamics of interest rate term structures and exchange rates and shows that the currency risk premia are necessary to equalize the sovereign bond premia. Alvarez, Atkeson, and Kehoe (2009) point out that the risk premium of a currency pair is approximately equal to its interest rate differential. Clarida, Davis, and Pedersen (2009) show that the yield curve level factor is positively correlated with carry trade excess returns while the slope factor negatively, and the relationships are regime-irrelevant. The predictability of currency risk premia by the information extracted from the term structures of interest rates is consistent with the "no-arbitrage" condition (Diez, 2009). Ang and Chen (2010) find that yield curve predictors, e.g. term spreads and changes in interest rates, are capable of forecasting currency excess returns up to 12 months ahead. They also stress that any variable that impacts the price of sovereign bonds can potentially improve forecasting exchange rate movements. Chen and Tsang (2013) provide supportive evidence that the forward premium puzzle can be related to the inflation and business cycle risks via the yield curves. Nevertheless, Inci and Lu (2004) point out that currency risk premia are also attributable to other factors that does not lie in the yield curves.

The existing literature has established a strong relationship between the macroeconomy (such as monetary policy, real output growth, inflation, etc.) and the yield curve using either VAR with orthogonal factors (see Ang and Piazzesi, 2003) or dynamic factor approach with Kalman filter (see Diebold, Piazzesi, and Rudebusch, 2005; Diebold, Rudebusch, and Boragan Aruoba, 2006; Rudebusch and Wu, 2008; for latent factor analysis, specifically, level, slope, and curvature). Hördahl, Tristani, and Vestin (2006) build a joint econometric model of macroeconomic and term-structure dynamics with forward-looking setting that has comparable explanatory power for yield curves to those based on unobservable factors. Bikbov and Chernov (2010) show that macroeconomic variables explain 80% of the variation in short rates, 50% of the slope, and roughly 50% to 70% of the term premia. Pan and Singleton (2008) explore the nature of the default arrival and recovery/loss implicit in the affine term structure of sovereign CDS spreads and reveal a close linkage between the unpredictable component of the credit events and the measures of macroeconomic policy, global risk aversion, and financial market volatility. The comovement in global sovereign CDS spreads is a compensation (time-varying sovereign risk premium) for the common exposure to U.S. consumption growth and volatility risks (Augustin, 2012). All the evidence suggests the information about the sovereign credit risk as a leading indicator for macroeconomic conditions can be straightforwardly related to the changes of interest rates or term spreads, and thereby can be a possible solution to the forward premium puzzle. A joint valuation of the term structures of the interest rates, sovereign CDS spreads, and currency carry trades[7] is desirable in order to extract the implicit sovereign credit risk component from the yield curve for understanding the failure of UIP.

The reduced-form term structure model of sovereign bonds that are subject to default risk presented by Duffie and Singleton (1999) is an ideal analytical framework. Diebold, Li, and Yue (2008) further propose a global extension of Diebold and Li's (2006) dynamic version of Nelson and Siegel's (1987) TSM[8], allowing for both global and country-specific factors. Their model explains a large fraction of the yield curve dynamics and offers a guidance for the joint modeling in a global context. By

[7]See Lustig, Stathopoulos, and Verdelhan (2013), who provide the first study of the term premia of currency carry trades.

[8]Imposing Nelson and Siegel's (1987) structure on affine arbitrage-free TSMs can greatly facilitates the estimation and improve performance for forecasting (Christensen, Diebold, and Rudebusch, 2011).

decomposing the term structure of sovereign CDS spreads, Longstaff, Pan, Pedersen, and Singleton (2011) show that the default risk component is more associated with the global risk than with the country-specific risk. The shape of the term structure of sovereign CDS spreads is also informative about how global risk and country-specific risk are associated with sovereign credit risk (see Augustin and Tédongap, 2014, for details). Cochrane and Piazzesi (2009) build an affine TSM that incorporates bond risk premia by decomposing the yield curve. Furthermore, given that sovereign credit premia not only is the risk in medium and long run but also, more importantly, represent the short-run rollover risk of maturing debts and refinancing constraint by the pledgeable claims (Acharya, Gale, and Yorulmazer, 2011; He and Xiong, 2012), both the short-term interest rates and the term spreads thereby can be decomposed into the market liquidity premium component and sovereign credit premium component for linking the global liquidity imbalances (first component) and sovereign default risk (second component) to the excess returns of currency carry trades.

1.3.2 Global Imbalances: Valuation Channel and Funding Liquidity Constraint

Gourinchas and Rey (2007) show that the external imbalances of a country must contains information about future portfolio returns on net foreign assets and/or future path of current account surplus. A country currently running net external debt will inevitably experience a depreciation in its currency that is attributable to international financial adjustments through the balance sheet effect of the intertemporal budget constraint. Exchange rates not only adjust through the bilateral trade channel (Obstfeld and Rogoff, 1995) but also open a valuation channel on the external assets and liabilities that transfer wealth from creditor countries to debtor countries. They find that external imbalances predict the exchange rates at 1-quarter horizon ahead and beyond. Abhyankar, Gonzalez, and Klinkowska (2011) manage to price a large proportion of the variation in the cross-sectional excess returns (quarterly) of currency carry portfolios using conditioning information of a forward-looking net foreign assets via a standard C-CAPM. Therefore, global imbalances reflects the sovereign credit premia.

Moreover, some recent studies reveal that market attitude towards crash risk (e.g. Baek, Bandopadhyaya, and Du, 2005; Borri and Verdelhan, 2011), macroeconomic fundamentals such as the volatility of terms of trades (see Hilscher and Nosbusch, 2010), and financial fragility (e.g. Ang and Longstaff, 2013) are well embodied in sovereign credit premia in terms of statistical and economic significance. Durdu, Mendoza, and Terrones (2013) also show that the solvency of a state responds sufficiently to the external adjustments, suggesting that sovereign credit risk plays a pivotal role of "meta information[9]" about external imbalances. Caceres, Guzzo, and Segoviano Basurto (2010) further accentuate the proper management of the debt sustainability and sovereign balance sheets as the necessary conditions for preventing the sovereign default risk from feeding back into broader financial instability. Sovereign spreads thereby contain complex information for the valuation of currency risk premia in response to external adjustments of a nation. Caballero, Farhi, and Gourinchas (2008) propose another analytical framework of global imbalances that emphasizes the countries' ability to produce financial assets for global savers/insurers. Gabaix and Maggiori (2015) show that the currency of a debtor country must offer a risk premium for the financial intermediaries to absorb the exchange rate risk associated with the global imbalances arising from international capital flows, but it is exposed to the depreciation risk when their risk-bearing capacity declines, e.g. high market risk sentiment and funding liquidity constraint. Global imbalances serve as not only a influential determinant of equilibrium exchange rate (MacDonald, 2005), but also an important predictor of exchange rates (Jordà and Taylor, 2012). Thus, currency premia must imply the crash risk associated with global imbalances bear by the investors.

[9]It refers to the concept of the information on information in informatics.

1.4 The Meese-Rogoff Puzzle and Exchange Rate Forecasting

The history of exchange rate forecasting has witnessed a longstanding segregation between two schools of thoughts, chartists and fundamentalists. Proponents of chartism methods eschew macroeconomic fundamentals and focus on patterns, particularly using high frequency data, that are contained in the past history of exchange rates. Proponents of fundamental analysis evaluate the intrinsic value of exchange rates using macroeconomic fundamentals which are indicative of the overall competitiveness of a currency. However, the majority of empirical implementations of the macro-based models give severely inaccurate forecasts that are unable to explain a high percentage of variation in exchange rates (Frankel and Rose, 1995; Kilian, 1999; Berkowitz and Giorgianni, 2001; Faust, Rogers, and Wright, 2003; Cheung, Chinn, and Pascual, 2005).

1.4.1 Macro Fundamentals and Market Microstructure

Meese and Rogoff (1983) provide robust evidence over several decades that a structural macro-based model cannot outperform a naive random walk (RW). Furthermore, the macroeconomic fundamentals suggested by monetary models of exchange rate determination are not volatile enough to rationalize the volatility of exchange rates in post-Bretton Woods period (Flood and Rose, 1995). Bacchetta and Van Wincoop (2013) attribute uncertainty in expectations of the structural parameters for the unstable relationship between exchange rates and macroeconomic fundamentals. In a stylized rational expectations model, heterogeneous agents search and select a basket of indicators that are capable of (either coincidentally or occasionally) explaining observed exchange rate movements, and accordingly formulate trading strategies. The weights attached to these "scapegoat" variables change over time so that the behavior of exchange rates seems to be unrelated to certain macroeconomic fundamentals and the estimated parameters become instable (Rossi, 2005). This theory is empirically validated by Fratzscher, Rime, Sarno, and Zinna (2015). Engel and West (2005), Engel, Mark, and West (2007) offer an alternative explanation for the random walk nature of exchange rates that the macroeconomic fundamentals employed in macro-based model for exchange rate forecasting may follow I(1) processes but not necessarily random walks. As a result, when the Stochastic Discount Factor (SDF) in the present value relationship approaches unity, exchange rate series exhibit characteristics which are arbitrarily close to random walks. This assumption is further supported by the empirical findings of Sarno and Sojli (2009). The expectations of macroeconomic fundamentals are hence intuitively dominated by the innovation component.

To forecast the exchange rates more accurately, it is necessary to focus on the surprise component (the difference between the expectations and the realized values). Evans and Lyons (2002; 2005b) show that these surprises, by definition orthogonal to the public information, should exist in the order flow imbalances (the difference between buyer-initiated and seller-initiated orders), from which private information about the macroeconomic fundamentals is learned. They also find order flow has true ex-ante predictive power on exchange rates with an ever-higher empirical validation. Excess speculation and manipulation of institutional investors[10] (Cheung and Chinn, 2001) and order flow (Froot and Ramadorai, 2005; Bacchetta and Van Wincoop, 2010) are intimately associated with short-run exchange rate returns that portfolio balance effect plays a pivotal role in the contemporaneous correlation (Breedon and Vitale, 2010) while macroeconomic fundamentals that reflect the intrinsic values of exchange rates offer a better explanation for long-run returns. Moreover, "price cascade" catalyzed by stop-loss orders may contribute to the "exchange-rate disconnect puzzle" (Osler, 2005). Albuquerque, Bauer, and Schneider (2009) argue that return-chasing behavior of investors in global equity markets is not due to naive trend-following, but mostly due to private information. And the superior information acquired from the order flows of international equity markets forecasts currency returns as well[11] (Albuquerque, De Francisco, and Marques, 2008).

[10] Institutional investors, such as hedge funds, are the origins of superior information (Osler and Vandrovych, 2009).

[11] Dunne, Hau, and Moore (2010) further show that aggregate order flow in currency market can also explain equity returns better than macroeconomic fundamentals.

1.4.2 Announcement Effect and Order Flow

Currency market reactions to macro news are quick and widely observed in high frequency data, but they also dissipate rapidly as the post-announcement interval increases (Almeida, Goodhart, and Payne, 1998). Announcement surprises generate jumps in the conditional means of exchange rates, and bad news or negative shocks exerts greater impacts than their counterparts (Andersen, Bollerslev, Diebold, and Vega, 2003). Market volatility generally rises in the pre-announcement period, typically before the scheduled announcement (Bauwens, Ben Omrane, and Giot, 2005). The real-time adjustments of currencies are stronger when policy uncertainty[12] is high (Ehrmann and Fratzscher, 2005). As a result, the high frequency responses of exchange rates are also characterized by "overshooting" (Faust, Rogers, Wang, and Wright, 2007). Exchange rates do not absorb macro news instantaneously, rather they react directly and indirectly via customer order flows, from which private information stems (Evans and Lyons, 2005a, 2008; Love and Payne, 2008). Ample studies provide supportive evidence of the information effect of market microstructural trades (see Lyons, 1995; Payne, 2003; Bjønnes and Rime, 2005; Killeen, Lyons, and Moore, 2006, among others). News arrivals lead to the changes in trading activities of various types of end-users (e.g. hedge funds, mutual funds, and non-financial corporations[13]), which, in turn, induces price changes, and this influence can last for several days (Evans and Lyons, 2005a). Evans and Lyons (2008) further consider non-scheduled announcements and reveal that news arrivals transmit a large proportion of the effects on exchange rates through the volatility of order flow. The recent literature of the cross-section of customer order flows (Menkhoff, Sarno, Schmeling, and Schrimpf, 2013b) show that different groups of clients possess distinctive forecasting abilities and investment styles of exchange rates, and therefore differs in their risk exposures. Their empirical results suggest a significant economic value for the market participants to access customer order flows.

[12] Beber and Brandt (2006) find that the regularly schedule announcements reduce the uncertainty measured by option-implied volatility, and the changes in other higher-order moments depend on the nature of macro news.

[13] Bjønnes, Rime, and Solheim (2005) present evidence of the (overnight) liquidity provision role of non-financial customers, as their net positions are negative correlated with exchange rates. While financial customers' order flows are indicative of the directions of future exchange rate movements. Frömmel, Mende, and Menkhoff (2008) find similar results that commercial customers are less informed than financial ones.

Nevertheless, Sager and Taylor (2008) cast a doubt on the practical value of these commercially available data. Informational advantage is also found in the inter-dealer foreign exchange (FX) market that the price discovery of order flow is strengthen in the period of low market liquidity[14] (Berger, Chaboud, Chernenko, Howorka, and Wright, 2008), and that traders with active trading activities or market specialization, and those who engage in cross-rates (triangular) arbitrage, are best informed (Moore and Payne, 2011). Breedon, Rime, and Vitale (2010) find that carry-initiated order flow generates negative skew in currency returns.

1.4.3 Technical Analysis and Adaptive Learning

In the past decades scholars and practitioners have surmounted the skeptical nature of technical analysis[15] via exploring various market inefficiencies. Brock, Lakonishok, and LeBaron (1992) show that, overall in the stock market, buy signals generate higher returns and lower volatilities than sell signals, and the returns following sell signals are negative, which cannot be rationalized by existing equilibrium models. Sullivan, Timmermann, and White (1999) further reveal that the performances of a wide range of technical trading rules are robust to data-snooping biases. Lo, Mamaysky, and Wang (2000) propose a pattern-recognition approach using smoothing estimator and nonparametric kernel regression methods, and find that technical indicators do contain additional information about future movements of the stock market. Simple technical trading rules can also be employed to identify profit opportunities in the FX market, particularly are more profitable during the central bank intervention periods (see Frankel and Froot, 1990; Levich and Thomas, 1993; LeBaron, 1999). Taylor and Allen's (1992) survey indicates that the use of technical rules for high-frequency and short-term trading strategies increases with the frequency of trades and maybe self-fulfilling. Neely, Weller, and Dittmar (1997) utilize a genetic algorithm to learn technical trading rules,

[14] Volatility-volume relationship (Chan and Fong, 2000), persistent market volatility and information arrival rate (Berger, Chaboud, and Hjalmarsson, 2009) are attributable to the time-varying price impact of order flow imbalances, which is shown to be inversely proportional to the market depth (Cont, Kukanov, and Stoikov, 2013).

[15] Cyclical and range break trackers routinely use moving average (MA) and stochastic oscillators (SO), and optimize the windows and weights for these statistical indicators to make a trade-off between the timeliness of signals and the possibility of whipsaws.

which generate sizeable out-of-sample excess returns that cannot be justified by the exposures to systematic risk. Okunev and White (2003) construct zero investment-cost (long-short) momentum strategies using various optimization procedures to select an MA that produces persistently substantial risk-adjusted returns.

Technical analysis provides information about non-fundamental impacts on the short-run exchange rate fluctuations, and its trading rules yield higher profitability with more volatile currencies (Menkhoff and Taylor, 2007). The larger the share of chartist participation, the greater the noise-to-signal ratio, which becomes a major source of speculative profits of the chartism (De Grauwe and Grimaldi, 2006). Notwithstanding, it is agnostic about the process through which the information about the intrinsic values of exchange rates is incorporated into the new forecasts since, under the Efficient Market Hypothesis (EMH), all relevant information is assumed public and mapping into prices immediately. One of the principal assumptions of technical analysis is that the price equals to the sum of trend, cycle, and noise components, implying that the random walk natural of exchange rates may rule out any possibility for the chartists to beat the market. Yet, it conforms with the cognitive bias and the process of learning and adaption of Adaptive Market Hypothesis (AMH) proposed by Lo (2004) and further testified by Neely, Weller, and Ulrich (2009), and Ivanova, Neely, Rapach, and Weller (2014). Neely and Weller (2013) find supportive evidence that traders exploit and gradually eliminate market profit opportunities by learning from the market and competing with each other, and that sophisticated strategies survive and evolve over time. According to the market microstructure theory, we can instead concentrate on the process through which private information is dispersed and observed by market participants who set the trade prices and the expectations on macroeconomic fundamentals are revised and further incorporated into exchange rates. Osler (2003) find market microstructure evidence of the predictive success of technical analysis that take-profit order clusters predict mean reversions at support/resistance levels while stop-loss order clusters explains the accelerations of trends after the technical patterns cross such levels. In contrast to fundamentalists, chartists measure the relative values of exchange rates by statistically deriving the market beliefs about the fundamental equilibrium values of exchange rates from historical prices. Then the prevailing price will approach its true value via the observation of past moving average prices.

1.4.4 Heterogeneous Expectations, Combined Forecasts, and Forecasting Horizons

Currency misalignment from the fundamental equilibrium value is a dominant source of heterogeneity in exchange rate expectations Menkhoff, Rebitzky, and Schröder (2009) and of carry trade risk premia Huang and MacDonald (2013b), which, to some extent, reflect uncertainty that may be related to the limits to arbitrage (Shleifer and Vishny, 1997) wherein noise-trader risk (see De Long, Shleifer, Summers, and Waldmann, 1990a; Jeanne and Rose, 2002) weakens rational arbitrageurs' ability to correct mispricing in short run (De Long, Shleifer, Summers, and Waldmann, 1990b), and/or to the information dispersion about macroeconomic fundamentals (Bacchetta and Van Wincoop, 2006) . All these studies suggest that AMH is a plausible explanation for the fundamental disconnect and technical profitability puzzles. Dick and Menkhoff (2013) provide strong support for the chartist-fundamentalist framework proposed by De Grauwe and Grimaldi (2006) wherein agents switch forecasting rules based on Brock and Hommes (1997) mechanism. Chartists tend to follow trends and outperform fundamentalists at short horizons while fundamentalists are more concerned about (nonlinear) mean-reversion to Purchasing Power Parity (PPP) (see Taylor, Peel, and Sarno, 2001). As indicated by Neely, Rapach, Tu, and Zhou (2014), macroeconomic fundamentals and technical indicators provide complementary information about the stock market over business cycles. The equity risk premium is readily captured by technical indicators near the business-cycle peaks whereas it is better forecast by macroeconomic fundamentals near the cyclical troughs. The current state of the economy can be learnt by agents gradually, but customer order flows that mirror heterogeneous expectations of a broad set of macroeconomic fundamentals provide timely information (Rime, Sarno, and Sojli, 2010). A hybrid model of macroeconomic fundamental determination and a market microstructure approach, proposed by Evans (2010), Chinn and Moore (2011), exhibits greater in-sample stability and out-of-sample predictive power than the random walk, monetary models without order-flow augmentation and even with central bank reaction function. We show that a substantial proportion of currency risk premia is related to the combination of information from macroeconomic fundamentals, technical indicators, financial indices, policy uncertainty (Baker, Bloom, and Davis, 2012), to hedging pressure in futures market (Acharya, Lochstoer, and Ramadorai, 2013), crash sensitivity measured by copula methods and option-implied moment risk premia (see Huang and MacDonald, 2013b), in a dynamic (Bayesian) model averaging fashion.

Kilian and Taylor (2003) shows that exchange rate predictability is difficult to exploit in real time but increases with forecasting horizons (see also Mark, 1995; Mark and Sul, 2001; Groen, 2000, 2005; Rapach and Wohar, 2002, 2004, that suggest a long-run relationship between macroeconomic fundamentals and exchange rates). The relative weight attached to fundamental analysis, as opposed to technical analysis, also rises with forecasting horizon (Taylor and Allen, 1992; Menkhoff and Taylor, 2007). The studies of Colacito and Croce (2011) and Bansal and Shaliastovich (2013) establish a connection between exchange rate movements and the long-run risk (Bansal and Yaron, 2004; Bansal, Kiku, and Yaron, 2010). The predictability from short-term to medium-term and its origins remain unaddressed. Clarida and Taylor (1997), Clarida, Sarno, Taylor, and Valente (2003) demonstrate that an exchange rate forecasting model which exploits information embedded in the term structure of forward premia can outperform a random walk and other traditional models across a range of horizons. And it can also be utilized to produce profitable currency trading strategies in a realistic investment context (Sager and Taylor, 2014). Ahn (2004) theoretically derives the exchange rate risk premia as a function of the differentials of risk premia between bond factors of two countries. Ang and Chen (2010) emphasize that term spreads and changes in interest-rate levels contains additional information about future currency returns. Chen and Tsang (2013) extract yield curve factors from the relative term structure of interest rates to forecast exchange rates[16].

[16] Duffee (2011) points out that a substantial part of the bond risk premia, which have strong predictive power for future short-term rates and bond excess return, is hidden from the cross-section of bond yields and cannot be well explained by macroeconomic fundamentals.

Chapter 2

Currency Carry Trades, Position-Unwinding Risk, and Sovereign Credit Premia

2.1 Introduction

The Uncovered Interest Rate Parity (UIP) states that under the assumptions of rational expectations and risk neutrality, the change of future bilateral exchange rate must equal to the corresponding interest rate differential, or equivalently forward premium[1] — this guarantees no excess return of carry trade by taking a long position in the high-yield currency funded by the low-yield currency. However, ample literature finds contradicting behavior of exchange rates in reality (see Hansen and Hodrick, 1980; Fama, 1984; Engel, 1996, among others), which is namely "forward premium puzzle". The deviations from UIP generate sizeable excess returns over the past 30 years (Brunnermeier, Nagel, and Pedersen, 2009), and the higher inflation rates of the currencies, the higher profits of this trading strategy in practice (Bansal and Dahlquist, 2000).

Expectations errors and time-varying risk premia are natural solutions to this

[1] Akram, Rime, and Sarno (2008) provide compelling evidence that Covered Interest Rate Parity (CIP) holds in the data at different frequencies.

puzzle. Theoretical risk factors can barely explain the profitability of currency carry trade (Lustig and Verdelhan, 2007; Burnside, 2011). However, using a data-driven approach, Lustig, Roussanov, and Verdelhan (2011) reveal that two (global and country-specific) risk factors capture most of the variations in the cross section of currency carry trade portfolios. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) further find that global volatility risk is able to price a very large proportion of the cross-sectional variations with a statistically significant factor price. One contribution of our research to empirical asset pricing of currency carry trades is that we rationalize the carry trades' excess returns from the perspective of sovereign credit risk as the dominant macroeconomic fundamental (country-specific) risk, which is strongly supported by our empirical results. The investigation is founded on the theory of a country's external adjustment to the global imbalances through the valuation channel of exchange rates (Gourinchas and Rey, 2007). The heterogeneity in countries' ability to produce financial assets for global savers determines the dynamics of bilateral exchange rates in allocating portfolios between the imperfectly substitutable foreign and domestic assets (Caballero, Farhi, and Gourinchas, 2008). The currency of a debtor country must offer a risk premium for the financial intermediaries to absorb the exchange rate risk associated with the global imbalances arising from international capital flows (Gabaix and Maggiori, 2015), but it is exposed to large depreciation risk when their risk-bearing capacity declines, e.g. high market risk sentiment and funding liquidity constraint (Brunnermeier and Pedersen, 2009; Ferreira Filipe and Suominen, 2013). Moreover, global imbalances are the crucial macroeconomic determinant of sovereign credit risk. Hilscher and Nosbusch (2010) emphasize the volatility of terms of trade as the key component. Durdu, Mendoza, and Terrones (2013) show that a country with weak solvency needs to respond strongly to the Net Foreign Assets (NFA) to keep it on a sustainable path. In particular, Schularick and Taylor (2012) demonstrate that a credit boom is a powerful predictor of financial crises, only in which currency carry trades suffer substantial losses. However, global imbalances are weakly correlated with the financial distresses. We resort to sovereign credit risk because it embraces the information about both global imbalances and financial distress.

Our investigation is also rooted in the implicit sovereign component of the term structure models of interest rates and currency forward rates. The yield curve factors forecast future spot rate movements of the foreign exchange market from one month to two years ahead, which is robust to controlling for other predictors (Ang and Chen, 2010; Chen and Tsang, 2013). Clarida, Davis, and Pedersen's (2009) study indicates that yield curve factors are strongly correlated with carry trade excess returns. By decomposing the yield curve, Cochrane and Piazzesi (2009) incorporate bond risk premia in an affine term structure model. Longstaff, Pan, Pedersen, and Singleton (2011) decompose the term structure of sovereign CDS spreads (Pan and Singleton, 2008) and find a strong association between macroeconomic factors and the default risk component. In the multi-factor, two-country term structure and exchange rate model built by Ahn (2004), exchange rate risk premia are shown to be a function of the differentials in the sovereign bonds risk premia. In particular, both the short-term interest rates and the term spreads may be decomposed into a market liquidity risk component and a sovereign credit risk component that even short rates reflect the rollover risk of maturing debt and refinancing constraint of a country in short run (see Acharya, Gale, and Yorulmazer, 2011; He and Xiong, 2012 for the analyses of stock market). The currencies of debtor countries offer risk premia to compensate foreign creditors who are willing to finance the domestic defaultable borrowings, such as current account deficits. The business cycle theory of sovereign default proposed by Mendoza and Yue (2012) also implies that countercyclical sovereign credit risk may account for the currency risk premia. The advantages of tracking sovereign risk by a country's CDS spreads rather than its Net International Investment Position (NIIP) or sovereign bond yields are that (i) we cannot observe NFA in monthly frequency[2] but we can trade currencies on corresponding sovereign CDS spreads daily, and (ii) sovereign CDS contracts are less affected by funding liquidity and flight-to-safety issues.

Another contribution of our research is that we, motivated by the crash risk story about currency carry trades of Brunnermeier, Nagel, and Pedersen (2009), originally derive the position-unwinding likelihood indicator of carry trade portfolios from the extended version of classical option pricing model (Black and Scholes, 1973; Merton, 1974) for foreign exchanges by Garman and Kohlhagen (1983). That the crash (jump)

[2]Please refer tos Lane and Milesi-Ferretti (2007) for annual panel data.

risk is priced in currency excess returns is also stressed by other scholars' recent studies, such as Jurek (2007), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009), Chernov, Graveline, and Zviadadze (2012). But the option prices might in principle not cover latent disaster risk of exchange rates (Farhi and Gabaix, 2008). We thereby adjust the position-unwinding likelihood indicator for skewness and kurtosis by Gram-Charlier expansion for the standard normal distribution density function. The position-unwinding risk factor is highly correlated with the global (dollar) risk factor, which may be deemed as supportive evidence for Brunnermeier, Nagel, and Pedersen's (2009) liquidity spiral story. Carry trade excess returns portray the "self-fulfilling" behavior that investors boost the price (appreciation of a currency) in good times and realize their profits by unwinding carry positions in bad times, triggering further dips. Currency carry trades give rise to global liquidity transfer. The liquidity will keep injecting into the high interest-rate currencies and generate the negative skewness phenomenon against the low interest-rate currencies[3] (and that's why the position-unwinding likelihood indicator is closely associated with the global skewness factor we construct) as long as the position-unwinding likelihood does not exceed a critical value of sustainable "global liquidity imbalances", which is intimately related to the market sentiment and macroeconomic fundamentals, e.g. the mismatch between short-term and otherwise maturing external debts and the pledgeable value of external assets of a nation, and the funding liquidity constraints (Gabaix and Maggiori, 2015). As pointed out by Hellwig, Mukherji, and Tsyvinski (2006), the UIP may be attributable to the self-fulfilling expectations and multiple equilibria that traders have heterogeneous private information about the likelihood of a devaluation. When the imbalances in global liquidity is unsustainable, carry traders begin to unwind their positions as the bubble-correcting behavior of the market (Abreu and Brunnermeier, 2003), followed up by abrupt price reversal and liquidity withdrawal (Plantin and Shin, 2011). The liquidity eventually dries up, leading to the crash of high interest-rate currencies (dramatic depreciations relative to the low interest-rate currencies). Following the economic intuition of the position liquidation story of currency crashes, we further construct aggregate realized skewness and kurtosis factors as proxies for crash risk.

[3]See Plantin and Shin (2011). They build a strategic games framework to demonstrate the destabilizing effect of currency speculative positions.

The global skewness factor is also highly correlated with the global (dollar) risk factor. The position-unwinding risk of carry trades is highly correlated with the aggregate level of volatility and skewness risk in FX market. Thus, we suggest the position-unwinding likelihood indicator as the gauge of market risk appetite, and propose an alternative carry trade strategy that is immunized from crash risk by analyzing the threshold level[4].

Furthermore, we show that the two-factor model of sovereign credit risk and position-unwinding risk performs well and has a robust performance in terms of cross-sectional pricing power in our data. We also examine the robustness of our main findings in various specifications without altering their qualitative features: (i) We use an alternative measure of sovereign credit risk based on government bonds, which explains the excess returns of currency carry trades as well as the factor directly implied by the currencies and the AR(1) innovations in global sovereign CDS spreads. (ii) By double sorting of the currencies on both sovereign CDS spreads and equity premia, we show that equity risk premium is not priced in the cross-section of currency carry trade excess returns. (iii) We winsorize the series of the shocks to the aggregate level of sovereign CDS spreads at 95% and 90% levels, and confirm that this factor does not represent a peso problem as the factor price of the sovereign credit risk is still statistically significant. (iv) We show that sorting currencies on their betas with sovereign credit risk is quite similar but not identical to those sorted on forward discounts. Currency portfolios doubly sorted on betas with both sovereign credit risk and position-unwinding risk also exhibit monotonic patterns in returns along both dimensions and are more close to currency carry portfolios. (v) Given that the position-unwinding risk and AR(1) innovations in global CDS spreads are not return-based series, by building a factor-mimicking portfolio, we're able to confirm their validity and reliability as arbitrage-free traded factors. (vi) We verify that position-unwinding likelihood indicator is a good proxy for global crash risk by introducing two additional (moment) factors, global skewness and kurtosis risk. Moreover, we show that it is trivial to adjust the standard normal probability distribution for skewness and kurtosis in the option pricing model to compute the position-unwinding likelihood indicator of

[4] We employ a Smooth Transition Model (STR) to identify this threshold level captured by the position-unwinding likelihood indicator. This will be discussed in detail later in the supplementary appendix of this chapter.

carry trade positions. (vii) We compare the cross-sectional asset pricing power of our slope factor with volatility and liquidity factors and show that the sovereign credit risk dominates liquidity risk but not volatility risk. (viii) We investigate the behavior of currency momentum[5] and volatility risk premium strategies that is shown subject to sovereign credit risk as well. (ix) We use both linear and nonlinear Granger causality tests to analyze the dynamics among risk factors, and identify not only the sovereign credit risk as an impulsive factor that drives other country-specific factors, such as volatility and liquidity risk, but also the spillover channel of the contagious country-specific risk to the global economy.

The rest of this chapter is organized as follows: Section 2.2 introduces the measure of position-unwinding risk of carry trades by currency option pricing model. Section 2.3 describes the theoretical foundations for sovereign credit premia based on existing theories. Section 2.4 provides the information about the data set used in this chapter, and the approaches for portfolio and risk factor construction. In Section 2.5, we introduce the linear factor model and the estimation methodologies. In Section 2.6, we show the empirical results, compare the asset pricing performance of our benchmark model with others, and discuss the implications for forward premium puzzle. Section 2.7 presents several additional robustness checks for our findings. Conclusions are drawn in Section 2.8. The supplementary empirical results are delegated to Appendix .A including the contagion among risk factors using both linear and nonlinear Granger causality tests, and we also put forward a threshold carry trade strategy that is immunized from crash risk according to the position-unwinding likelihood indicator in this part.

2.2 Position-unwinding Likelihood Indicator

We build the position-unwinding likelihood indicator in a similar way to Vassalou and Xing's (2004) for evaluating the default risk premia in equity returns. We use the

[5]Analogous 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.

canonical option pricing formula (Black and Scholes, 1973) as they do. The difference is that their strike prices are the book value of firm's liabilities, as in Merton (1974), while we set the strike prices to be the forward rate so that both of the CIP and UIP are embodied in the option pricing model. We also compute the currency option prices based on Garman and Kohlhagen's (1983) version for currency option valuation for hedging the carry trade positions. The higher moments, such as skewness and kurtosis are ignored in these option pricing models. However, for the currency carry trades, Brunnermeier, Nagel, and Pedersen (2009) show a negative cross-sectional correlation between interest rate differentials and empirical skewness, also the implied (risk neutral) skewness of the out-of-money option "risk reversals". The tail risk is of paramount importance for illuminating currency crash premia (Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan, 2009) and the jump risk account for 25% of the total currency risk, and as high as 40% during the turmoil periods (Chernov, Graveline, and Zviadadze, 2012). They also show that the probability of the depreciation jump of a currency is positively associated with the increase in its interest rate. Moreover, if agents are averse to kurtosis, which measures the dispersion of the extreme observations from the mean, this is consistent with Dittmar's (2002) nonlinear pricing kernel framework. Hence, we adjust the option pricing model by introducing the third and fourth moments as the higher order terms expansion. Under the condition that CIP holds, we have:

$$1 + r_t = (1 + r_t^*)\,\frac{S_t}{F_t} \tag{2.1}$$

where S_t is the spot rates, and F_t is the forward rate with the same maturity of T as r_t, and r_t^*, which denotes domestic (U.S.) risk-free interest rate, and foreign risk-free interest rate, respectively. Therefore, $\ln F_t - \ln S_t \simeq r_t^* - r_t$. When $r_t^* > r_t$, implying $F_t > S_t$, a U.S. investor takes a carry position to short USD for long foreign currencies which is equivalent to betting on $S_{t+T} < F_t$. This means that the future sport rate of the USD will not appreciate as much as the CIP predicts or even will depreciate because of the failure of UIP, which claims that $S_{t+T} = \mathbb{E}_t[S_{t+T}|S_t] = F_t$. If the U.S. investor does not enter a forward contract for the carry position he has already taken, the amount of the assets in USD on his wealth balance sheet will be $(1 + r_t^*)\,S_t/S_{t+T}$ while $1 + r_t$

is the amount of USD-denominated liabilities that he has to pay back at $t+T$. Thus, if it turns out that $S_{t+T} \geq F_t$ at time $t+T$, the U.S. investor will go bankrupt and have to liquidate his carry position. Then, the position-unwinding probability of a currency pair i at t is the probability that the S_{t+T} will be greater than the F_t (see Appendix .A for the details of geometric Brownian motion (GBM) and Currency Option Pricing Model).

$$\psi_{t+T} = \Pr\left(S_{t+T} \geq F_t \mid S_t\right) = \Pr\left(\ln S_{t+T} \geq \ln F_t \mid \ln S_t\right) \tag{2.2}$$

We can rewrite the position-unwinding risk for a long position of carry trades by plugging Equation (2) in Appendix .A into Equation (2.2):

$$\psi_{t+T} = \Pr\left(\ln S_t - \ln F_t + \left(\mu - \frac{\sigma^2}{2}\right) T + \sigma\sqrt{T}\,\varepsilon_{t+T} \geq 0\right) \tag{2.3}$$

Equation (2.3) can be rearranged as below:

$$\psi_{t+T} = \Pr\left(-\frac{\ln(S_t/F_t) + \left(\mu - \frac{1}{2}\sigma^2\right) T}{\sigma\sqrt{T}} \leq \varepsilon_{t+T}\right) \tag{2.4}$$

Similarly, the formula for a short position is given by:

$$\psi_{t+T} = \Pr\left(-\frac{\ln(S_t/F_t) + \left(\mu - \frac{1}{2}\sigma^2\right) T}{\sigma\sqrt{T}} \geq \varepsilon_{t+T}\right) \tag{2.5}$$

We define the distance to "bankruptcy" (DB) for a FX trader, then the position-unwinding risk for a single currency pair is computed as follows:

$$DB_{t+T} = -\frac{\ln(S_t/F_t) + \left(\mu - \frac{1}{2}\sigma^2\right) T}{\sigma\sqrt{T}} \tag{2.6}$$

$$\psi_{t+T} = \begin{cases} 1 - \Pr\left(DB_{t+T}\right) & \text{if the currency is in long position;} \\ \Pr\left(DB_{t+T}\right) & \text{if the currency is in short position.} \end{cases} \tag{2.7}$$

where $\Pr\left(DB_{t+T}\right) = \mathbb{N}(DB_{t+T})$, which is the cumulative density function of standard normal distribution. DB_{t+T} tells us by how many standard deviations the log of the ratio of S_t/F_t needs to deviate from its mean in order for the "bankruptcy" to occur. Notice that value of the currency option does not depend on μ but DB_{t+T} does. This is because DB_{t+T} is determined by the future spot rates given in Equation (6) in Appendix .A. At time $t+T$, we use the conditional mean μ_{t+T} and conditional volatility σ_{t+T} over a period of T from time t for the estimations of μ, and σ, respectively. As implied in Equation (2.6) of the Black-Scholes-Merton universe, the cross-sectional variation of currency risk premia is naturally driven by interest rate differential and currency volatility, and this explains empirical asset pricing results of Lustig, Roussanov, and Verdelhan (2011); Menkhoff, Sarno, Schmeling, and Schrimpf (2012a).

So far, we use the theoretical distribution implied by standard option pricing models, which is standard normal distribution. However, $\mathbb{N}(\cdot)$ does not represent the true probability distribution of the currency returns because the tail risk of the currencies (skewness and kurtosis) is considerably significant. Noting that the first four moments of the underlying asset's distribution should capture most of the information for option valuation (Jarrow and Rudd, 1982), we adjust the standard normal distribution using Gram-Charlier expansion using Hermite Polynomials (Stuart and Ord, 2009) series (see Appendix .A for the details). As the historical observations of the position-unwinding behavior of carry trades is a collapse across these currency portfolios, we then compute the aggregate level of the position-unwinding risk for the whole FX market as:

$$PUW_{t+T} = \frac{1}{K_{t+T}} \sum_{i=1}^{K_{t+T}} \psi_{i,t+T} \tag{2.8}$$

where K_{t+T} is the number of the currencies available at time $t+T$. Strictly speaking, PUW_{t+T} is not a "bankruptcy" probability faced by the FX traders because it does not correspond to the true probability of unwound positions in large observations across business cycles. Therefore, we call PUW_{t+T} the "position-unwinding likelihood indicator", which corresponds to the excess returns of currency carry trades over the period of T from time t. Reassuringly, we will show that it is a good proxy for currency crash risk in Section 2.5, confirmed by the global skewness (GSQ) factor. It is also robust to the unadjusted PUW since the adjustment for both skewness and kurtosis is very trivial compared with the magnitude of probability distribution.

2.3 Mechanism of Sovereign Credit Premia

Existing literature suggests a plausible linkage between currency premia and sovereign credit risk, for which we develop a theoretical framework in this section. By introducing the time-varying sovereign default probability π_t and recovery rate δ[6] into carry trade, we can rewrite the carry trade payoffs that invests in foreign risky sovereign debt and currency funded by domestic safe currency (USD), and link $\mathbb{E}_t^{\mathbb{D}}[xr_{t+1}]$ with sovereign default to $\mathbb{E}_t[xr_{t+1}]$ with only exchange rate risk as in Coudert and Mignon (2013):

$$\mathbb{E}_t^{\mathbb{D}}[1+xr_{t+1}] = \underbrace{\mathbb{E}_t[1+xr_{t+1}][1-\pi_t(1-\delta)]}_{(1-\pi_t)\mathbb{E}_t[1+xr_{t+1}]+\pi_t\delta\,\mathbb{E}_t[1+xr_{t+1}]} + (1-\delta)\,\mathrm{cov}_t[\Delta s_{t+1}, I_{t+1}] \tag{2.9}$$

where $\mathbb{E}_t[\pi_{t+1}] = \pi_t$, I_{t+1} equals to 1 if sovereign default occurs in $t+1$ and 0 otherwise, and $\mathrm{cov}_t[\Delta s_{t+1}, I_{t+1}] = \pi_t \left\{\mathbb{E}_t[\Delta s_{t+1}|I_{t+1}=1] - \mathbb{E}_t[\Delta s_{t+1}]\right\}$. The first term of Equation (2.9) is the expected excess returns without the response of exchange rate to default event, and the second term captures the expected currency devaluation upon default. Under the assumption of rational expectations and risk neutrality of investors, $\mathbb{E}_t^{\mathbb{D}}[1+xr_{t+1}] = 1$ (no excess return), and Equation (2.9) can be rearranged to give:

$$\mathbb{E}_t^{\mathbb{Q}}[1+xr_{t+1}] = 1 + \frac{\pi_t^{\mathbb{Q}}(1-\delta)(1-\eta_t)}{1-\pi_t^{\mathbb{Q}}(1-\delta)} \tag{2.10}$$

where $\eta_t = \mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}|I_{t+1}=1] - \mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}]$, $\mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}] = f_t - s_t$. Equation (2.10) reveals that even under risk-neutral measure $\mathbb{Q}$, currency premia still exists. It is a positive function of sovereign default probability and a negative function of expected currency depreciation given default. Under the assumption of constant probability of default (PD) over the term structure of sovereign CDS spreads y_t[7], we use a common approximation of the risk-neutral PD, $\pi_t^{\mathbb{Q}} = y_t/(1-\delta)$. So the currency premia can be directly measured by y_t. Equation (2.10) can also be simplified as:

[6] For simplicity, we assume that U.S. (domestic) interest rate r_t is risk-free, $0 < \delta < 1$ and it is generally assumed to be at 40%.

[7] Given that the contracts of other maturities are not liquid, we cannot collect enough observations and thereby assume a flat term structure of sovereign CDS spreads.

$$\mathbb{E}_t^{\mathbb{Q}}[1+xr_{t+1}] = 1 + \underbrace{y_t \left\{\mathbb{E}_t[\Lambda_{t+1}/\Lambda_{t+1}^*] - \mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}|I_{t+1}=1]\right\}}_{\mathbb{E}_t^{\mathbb{Q}}[xr_{t+1}]} \tag{2.11}$$

where Λ_t/Λ_t^* is the ratio of domestic to foreign stochastic discount factor (SDF)[8]. Equation (2.11) further implies that position-unwinding risk ψ_t is positively correlated with sovereign credit risk and negatively with expected currency depreciation upon default, as $\Lambda_t/\Lambda_t^* \simeq r_t^* - r_t = f_t - s_t$ in logarithm and the forward premium term also shows up in Equation (2.6). The first term in Equation (2.11) indicates that interest rate differential drives the exchange rate to deviate from UIP through sovereign default channel. The second term captures the overshooting behavior of exchange rates in the case of currency crashes, and partially offsets the currency risk premia, which, thereby, depends on $\text{cov}_t[\Lambda_{t+1}/\Lambda_{t+1}^*, \Delta s_{t+1}|I_{t+1} = 1]$. To better interpret the asset pricing implications of sovereign credit premia, we need to differentiate two states of nature that currency carry trades earn sizeable excess returns in the state of no financial distress but suffer huge losses in financial distress.

$$\mathbb{E}_t^{\mathbb{Q}}\left[1+xr_{t+1}\middle|\frac{\Lambda_{t+1}}{\Lambda_{t+1}^*}<c\right] = 1+y_t\left\{\mathbb{E}_t\left[\frac{\Lambda_{t+1}}{\Lambda_{t+1}^*}\middle|\frac{\Lambda_{t+1}}{\Lambda_{t+1}^*}<c\right] - \mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}|I_{t+1}=1]\right\} \tag{2.12}$$

We define this stress scenario as $\Lambda_{t+1}/\Lambda_{t+1}^* < c$, or correspondingly $\Lambda_{t+1}^* > c^*$, a certain threshold that the foreign country is under financial distress to default on its risky sovereign bond and the carry trade positions are under unwinding pressure. Note that we standard framework of asset pricing model (Cochrane, 2005) implies that the PD under physical measure $\mathbb{P}$ is given by:

$$\begin{aligned} \pi_t^{\mathbb{P}} &= \frac{\pi_t^{\mathbb{Q}}}{(1+r_t^*)\mathbb{E}_t[\Lambda_{t+1}^*|\Lambda_{t+1}^*>c^*]} \\ &= \frac{\pi_t^{\mathbb{Q}}}{(1+r_t^*)\left\{\mathbb{E}_t[\Lambda_t^*]+\sqrt{\text{var}_t[\Lambda_t^*]}\cdot\vartheta(\alpha_t)\right\}} \end{aligned} \tag{2.13}$$

[8]The SDF as the growth rate of pricing kernel is unique if the market is complete.

where $\vartheta(\alpha_t) = \varphi(\alpha_t)/[1 - \Phi(\alpha_t)]$ is the inverse Mills ratio[9], and $\alpha_t = (c^* - \mathbb{E}_t[\Lambda_t^*])/\sqrt{\text{var}_t[\Lambda_t^*]}$. Since $\mathbb{E}_t[\Lambda_{t+1}^*|\Lambda_{t+1}^* > c^*]$ is not directly observable, we need to estimate it using an endogenous threshold approach (see also Espinoza and Segoviano, 2011). They show that one can obtain a coherent measure of PD from the historical data if c^* is chosen such that the definition of the stress scenario is in line with the finally estimated PD, and prove that the analytical solution is unique[10]. The assumption of risk-free domestic (U.S.) sovereign bond implies that Λ_t and Λ_t^* are independent. Then, Equation (2.12) can be modified as:

$$\mathbb{E}_t^{\mathbb{Q}}\left[xr_{t+1}\middle|\frac{\Lambda_{t+1}}{\Lambda_{t+1}^*} < c\right] \approx y_t \left\{(r_t^* - r_t) - \mathbb{E}_t^{\mathbb{Q}}[\Delta s_{t+1}|I_{t+1} = 1] + \left(\pi_t^{\mathbb{P}} - \pi_t^{\mathbb{Q}}\middle|\frac{\Lambda_{t+1}}{\Lambda_{t+1}^*} < c\right)\right\} \tag{2.14}$$

This framework allows us to decompose the payoffs of currency carry trades in financial turbulence and estimate the effects separately. The last term $\pi_t^{\mathbb{P}} - \pi_t^{\mathbb{Q}}$ in the bracket of Equation (2.14) measures the sovereign credit premia — the key to understand why UIP holds during the financial distress — it is largely negative since the insurance cost inevitably increases as a result of a higher compensation for risk required by the investors[11]. This framework is also concordant with currency denomination story of sovereign debts — an important issue to understand currency premia from the aspect of sovereign credit risk.

A country with high sovereign default risk displays a high propensity to issue debts denominated in foreign (less risky) currencies to make its debts more appealing to investors, and offers a high interest rate to attract foreign savings for funding its external deficit. Typically, when a country's external debts are denominated in foreign currencies, any initial depreciation of domestic currency as a consequence of e.g. a permanent negative demand shock will impose a destabilizing effect on the its net foreign asset positions via valuation channel, i.e. an increased burden of external obligations. The exchange rate will be forced to depreciate even greater or overshoot

[9] $\varphi(\alpha_t)$ is the standard normal probability distribution function, and $\Phi(\alpha_t)$ is the corresponding cumulative distribution function.

[10] We set $c^* = \mathbb{E}[\Lambda_t^*] + \Phi^{-1}(1 - \pi_t^{\mathbb{P}}) \cdot \sqrt{\text{var}[\Lambda_t^*]}$, and solve the nonlinear Equation (2.13) for $\pi_t^{\mathbb{P}}$.

[11] See Espinoza and Segoviano (2011) for the analysis of the U.S. banking sector.

its long run equilibrium value to restore the external balance via the trade channel. The capital flight triggered by the weakened external imbalance will further result in a speculative attack and a crash on the debtor's currency. Given that the external liabilities of a creditor country are primarily denominated in domestic (safe) currency, even if it encounters with a negative global demand shock, any initial depreciation of the creditor's currency will bring a stabilizing effect via both valuation and trade channel. So during an economic recession (high volatility regime) the low sovereign default risk and low interest-rate currencies tend to appreciate against the high sovereign default risk currencies which offer high interest-rates for servicing its external liabilities. In contrast, during the expansion phase of the business cycle (low volatility regime), optimistic prospects in the future economy makes investors less risk-averse and more willing to take upon large positions of risky assets of the debtor country, including the high yield and high default risk sovereign debts. Appreciation pressures on the debtor's risky currency made by this behavior alleviates its debt burden but deteriorates the trade balance, which, in turn, increases sovereign credit risk. The relief in debt burden and the global demand of risky assets drive the debtor country to finance it external deficit via the issuances of more sovereign debts, rather than to depreciate its currency (destabilization). The liquidity keeps injecting into the debtor country to support its debt financing, creating the "global liquidity imbalances" among the economies. However, when the liquidity dries up due to the funding liquidity constraint of financial intermediaries associated with international capital flows (Gabaix and Maggiori, 2015), and the pledgeable claims of debtor countries may not meet the short-run rollover needs of the maturing debts, then the liquidity will be withdrawn and the capital flow will reverse. The liquidity spiral brings about the crash of the debtor's currency. As for the creditor country, the heavier burden of the sovereign debts it is servicing brought by the depreciation pressure on its currency can be compensated by the amelioration of the trade balance and the decline in sovereign credit risk (stabilization). The retreat of liquidity back to the creditor country will give rise to the appreciation of its currency. This is implied by the Gamma model of (Gabaix and Maggiori, 2015), and also concordant with Clarida, Davis, and Pedersen's (2009) findings that UIP holds when volatility is in the top quartile (the periods of financial distress) and that yield curve premia comove with the currency risk premia. Following this economic logic, we expect a strong relationship between the currency risk premia and the sovereign credit risk.

2.4 Data, Portfolio Sorting and Risk Factors

Our 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 35 currencies: EUR (EMU), GBP (United Kingdom), AUD (Australia), NZD (New Zealand), CHF (Switzerland), CAD (Canada), JPY (Japan), DKK (Denmark), SEK (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), KRW (South Korea), CNY (China), 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); and corresponding countries' equity indices (MSCI) and government bond total return indices (Bank of American Merrill Lynch and J.P. Morgan TRI)[12] in USD.

Our sample period is restricted by the availability of sovereign CDS historical data, which only dates back to 2001 and begins with a limited coverage of countries. The unragged data for our sample countries starts from 2004, according to the database of Markit[13] and CMA Datavision[14]. To ensure consistency of time frame across assets, the sample period is chosen from September 2005 to January 2013 in a daily frequency. Furthermore, there is no existing sovereign CDS for EMU as the whole, thus

[12] There are 26 countries' data available: EMU, Great Britain, Australia, New Zealand, Canada, Switzerland, Norway, Sweden, Denmark, Russia, Turkey, Hungary, Czech Republic, Poland, Japan, South Korea, Hong Kong, Taiwan, Singapore, China, India, Malaysia, Thailand, Indonesia, South Africa, and Mexico. China and India are only available from July 2007.

[13] Markit is also a leading global financial information services provider of independent data, valuation and trading process across all asset classes, also with a specialization in CDS data.

[14] CMA Datavision is the world's leading source of independent accurate OTC market pricing data and technology provider, typically specializing in the sovereign CDS pricing.

we calculate its proxy spread as the external-debt weighted sovereign CDS spreads of EMU's 13 main member countries, Germany, France, Italy, Spain, Netherland, Belgium, Austria, Greece, Portugal, Ireland, Slovenia, and Luxembourg, which account for over 99% of the EMU's GDP on average in our sample period.

2.4.1 Portfolio Sorting

All currencies are sorted by forward premia from low to high, and allocated to five portfolios, e.g. Portfolio 1 (C_0) consists of the short position of currencies with the lowest 20% interest-rate differentials (lowest forward premia) while Portfolio 5 (C_5) is the long position of currencies with highest 20% interest-rate differentials (highest forward premia). The portfolios are rebalanced at the end of each forward contract according to the updated forward rate. The average monthly turnover ratio of five portfolios is about 25%, thereby the transaction costs should be considered for evaluating the profitability of carry trades. The log excess returns of a long position xr^L_{t+1} at time t+1 is computed as:

$$xr^L_{t+1} = r^*_t - r_t + s^B_t - s^A_{t+1} = f^B_t - s^A_{t+1} \tag{2.15}$$

where f, s is the log forward rate, and spot rate, respectively; Superscript B, A denotes bid price, and ask price respectively. Similarly, for a short position the log excess returns xr^S_{t+1} at the time t+1:

$$xr^S_{t+1} = -f^A_t + s^B_{t+1} \tag{2.16}$$

Currencies that largely deviate from CIP are removed from the sample for the corresponding periods[15]: 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. And due to the managed floating exchange

[15]ZAR from the end of July 1985 to the end of August 1985, MYR from the end of August 1998 to the end of June 2005, TRY from the end of October 2000 to the end of November 2001, UAE (United Arab Emirates) from the end of June 2006 to the end of November 2006. These currencies or periods are not included in our data.

rate regime of CNY, we also exclude it for the whole sample periods. Table 2.1 below shows the descriptive statistics of currency carry portfolios.

Table 2.1 Descriptive Statistics of Currency Carry Portfolios

All Countries with Bid-Ask Spreads								
Portfolios	C_0	C_1	C_2	C_3	C_4	C_5	Avg.	H/L
Mean (%)	-2.28	0.45	1.57	2.44	2.94	4.57	2.39	2.29
Median (%)	-6.35	3.67	3.71	6.02	8.34	11.17	5.33	2.74
Std.Dev. (%)	7.40	7.41	8.56	9.31	10.61	10.71	8.69	7.86
Skewness	0.14	-0.16	-0.26	-0.56	-0.53	-0.51	-0.49	-0.17
Kurtosis	0.17	0.18	0.21	0.82	0.62	0.57	0.60	0.11
Sharpe Ratio	-0.31	0.06	0.18	0.26	0.28	0.43	0.28	0.29
AC(1)	0.01	0.01	-0.09	0.05	0.15	0.14	0.07	0.14

This table reports descriptive statistics of the excess returns in USD of currency carry portfolios sorted on 1-month forward premia. The 20% currencies with the lowest forward premia are allocated to Portfolio C_1, and the next 20% to Portfolio C_2, and so on to Portfolio C_5 which contains the highest 20% forward premia. Portfolio C_0 is Portfolio C_1 in short position and others are in long positions. The portfolios are rebalanced at the end of each former forward-rate agreement according to the updated contract. 'Avg.', and 'H/L' denotes the average excess returns of five portfolios in long positions, and difference in the excess returns between Portfolio C_5 and Portfolio C_0 respectively. All excess returns are monthly and adjusted for transaction costs (bid-ask spreads) with the sample period from September 2005 to January 2013 with daily availability. 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 coefficient of the monthly excess returns in monthly frequency.

C_1 is C_0 is long position. The statistics of portfolio mean, median, and standard deviation in excess returns all exhibit monotonically increasing patterns. We also see a monotonically decreasing skewness from C_1 to C_5, except that the skewness of C_4 is a little bit higher than that of C_5, probably due to the time span limitation. We will show in the empirical tests section that the position-unwinding risk matches with the skewness of excess returns of each carry trade portfolios. The unconditional average excess returns is 2.39% per annum from holding the equally-weighted foreign-currency portfolio, reflecting the low but positive risk premium demanded by the U.S. investors in holding foreign currencies. There is a sizeable spread of 2.29% per annum between C_5 and C_0 over the sample period when currency carry trades have suffered a huge loss in the September of 2008. The currency carry portfolios are adjusted for transaction costs, which is quite high for some currencies (Burnside, Eichenbaum, and Rebelo, 2006). Monthly excess returns and factor prices are annualized via multiplication by 12, the 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. The Sharpe ratios are not as high as usual because our data span the recent financial crunch period (See Figure A.1 in Appendix .A.) for the cumulative excess returns of five currency carry portfolios (long positions) in the sample period. The cumulative excess returns of carry trades plummeted during the 2008 crisis but the positions recovered soon after a few months, especially for the high interest-rate currencies.

2.4.2 Risk Factors

We also follow Lustig, Roussanov, and Verdelhan (2011) to construct the dollar risk factor (GDR) and forward bias risk factor (HML_{FB}):

$$GDR = \frac{1}{5}\sum_{j=1}^{5} PFL_{FB,j} \tag{2.17}$$

$$HML_{FB} = PFL_{FB,5} - PFL_{FB,1} \tag{2.18}$$

GDR has a correlation of 0.99 with PC_1 and is almost uncorrelated with PC_2 in our data. HML_{FB} is 0.90 correlated with PC_2, however, remains a considerable correlation of 0.39 with PC_1. Therefore, strictly speaking, it is not a pure slope factor[16]. However, its correlated part may offer valuable information about the contagious country-specific risk that may spill over and contaminate the global economy. In addition, we demonstrate the construction of other risk factors used in this chapter, including the factors of sovereign credit risk, equity premium risk, currency crash risk, volatility risk, and liquidity risk.

Sovereign Credit

Foreign investors require compensation for a sudden devaluation of the local currency when a default on government bonds occurs. If sovereign credit risk explains the cross-section of the excess return of currency carry trades, then high sovereign CDS-spread

[16]See Table A.3. in Appendix .A for principal component analysis of currency carry portfolios, and Table A.4. in Appendix .A for the correlations between risk factors and principal components.

currencies are expected to be associated with high interest rates and tend to appreciate against low sovereign CDS-spread currencies that are expected to be accompanied with low interest rates. The countries with weak solvency conditions have higher propensity to issue sovereign debts denominated in foreign (safe) currencies. Currencies of debtor-countries offer risk premia to compensate foreign creditors who are willing to finance the domestic defaultable borrowings. We evaluate sovereign default risk by the payoff of a strategy that invests in the highest $\frac{1}{3}$ sovereign default risk currencies funded by the lowest $\frac{1}{3}$ sovereign default risk currencies as the size (market capitalization) factor in Fama and French (1993).

Sovereign credit risk (HML_{SC}) has a correlation of 0.71 with PC_2, and is almost orthogonal to PC_1 (with a correlation of -0.08) and it can therefore be regarded with more accuracy as a slop factor. Since it is positively correlated with the slope factor, the factor price of sovereign credit risk is expected to be positive. Ideally, high interest-rate currencies should be positively exposed to sovereign credit risk while low interest-rate currencies with negative exposures provide a hedge to it (see principal component analysis of currency carry portfolios in Table A.3. in Appendix .A). We also directly employ the AR(1) innovations in global (equally-weighted) sovereign CDS spreads (GSI) as the slope factor to price the cross section of currency carry trades.

Equity Premium

Foreign investors require a compensation for the risk to hold the local-currency denominated stock shares in a distressed market, which is usually accompanied with low interest rate policy. Since there is a high possibility of persistent recession trap, the risk of capital flight will lay considerable downside pressure upon the local currency. To check if any compensation for this type of risk is implied in currency excess return as well, it is necessary to examine the average excess return differences among the portfolios that are doubly sorted on both sovereign CDS spreads and equity premia over the U.S. market[17]. Constrained by the availability of the currencies, we sort the

[17] De Santis and Gerard (1998) employ a conditional ICAPM with a parsimonious multivariate GARCH process to unveil the currency risk implied in total equity premia. One can follow their approach to ask the reverse question simply by conditioning the currency premia on the equity risk. This would be our next task to decompose currency risk premia.

currencies into 3×3 portfolios. Each dimension is partitioned into three portfolios, containing the currencies with the sort base in ascending order, denoted by "L" for low level, "M" for medium level, and "H" for high level of either sovereign CDS spreads or equity premia. This approach matches the currency sorting on sovereign default risk above.

Figure A.2. shows a very intriguing pattern that the equity premium risk (HML_{EP}) seems to be priced in currency excess returns. A U.S. investor is compensated in terms of the appreciation of the local currency, not only for holding equities in a distressed market but also for investing in a boom equity market, which might be rationalized as a compensation for the crash risk of bubbles in an overheated economy. As a result, we do not see any favourable monotonic pattern of excess returns in the equity premia dimension. Clearly, on the other dimension, we observe a monotonic increase in excess returns of the currency portfolios sorted by sovereign CDS spreads in ascending order.

Position-unwinding Risk and Currency Crashes

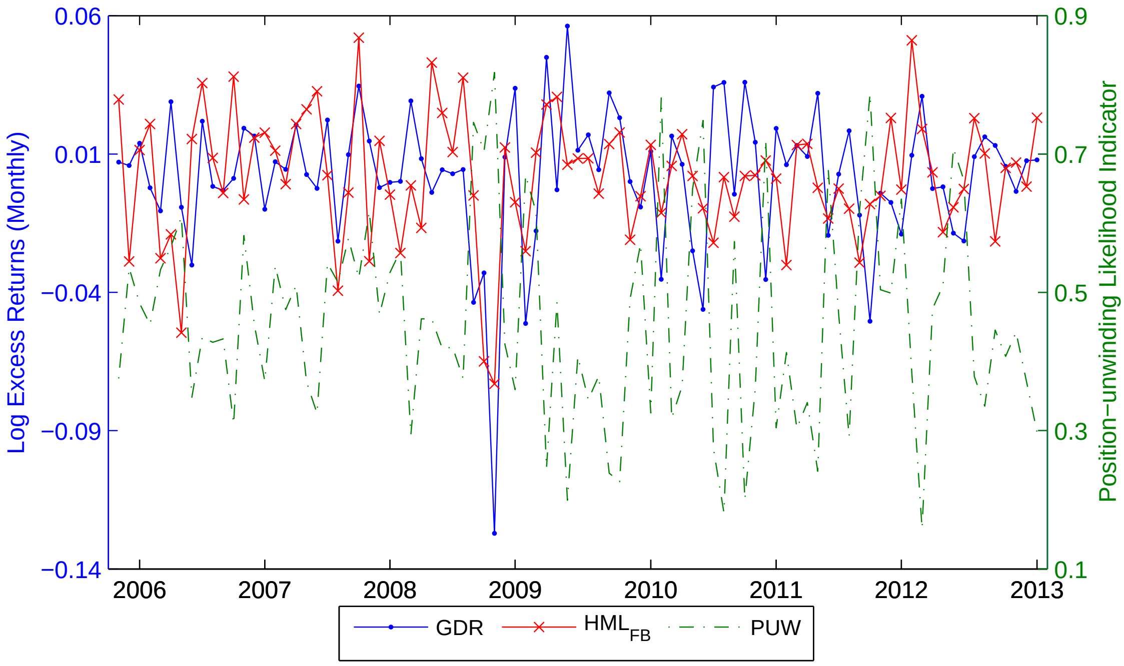
In the research of Andersen, Bollerslev, Diebold, and Labys (2001) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), volatility risk is measured with "realized" feature that assumes a zero unconditional mean of daily returns. This assumption embeds the martingale properties in daily return series. We follow this method to construct two factors that is meant to measure the crash risk in the FX market. We use the standard formulae for moment computations[18] over the period of T (time-to-maturity of the forward contract) for the daily returns $\Delta s_{i,\tau}$ of individual currency i at time $t{+}T$ as the proxies for the realized moments: realized volatility ($\hat{\sigma}_{t+T}$), realized (excess) skewness ($\hat{\varsigma}_{t+T}$), and realized (excess) kurtosis ($\hat{\kappa}_{t+T}$). We substitute the annualized values[19] $\hat{\sigma}_{i,t+T} \cdot \sqrt{T_\tau}$ and $\hat{\mu}_{i,t+T} \cdot T_\tau$ in to Equation (2.6) for the calculation of distance to "bankruptcy", which is then the input of Equation (2.7). By combining it with the adjusted values of $\hat{\varsigma}_{i,t+T} \,/\, \sqrt{T_\tau}$ and $\hat{\kappa}_{i,t+T} \,/\, T_\tau$ as the inputs[20] of

[18] $\hat{\sigma}_{i,t+T} = \sqrt{\frac{1}{T_\tau} \sum_{\tau=t}^{T_\tau} \Delta s_{i,\tau}^2}$, $\hat{\varsigma}_{i,t+T} = \frac{1}{T_\tau} \frac{\sum_{\tau=t}^{T_\tau} \Delta s_{i,\tau}^3}{\sigma_{i,t}^3}$, $\hat{\kappa}_{i,t+T} = \frac{1}{T_\tau} \frac{\sum_{\tau=t}^{T_\tau} \Delta s_{i,\tau}^4 - 3}{\sigma_{i,t}^4}$.

[19] N_τ is the number of trading days in a year and then $T = \frac{1}{12}$ in Equation (2.6).

[20] Time-aggregation scaling adjustments are necessary to match the statistical moment estimates with the option pricing model over the forward contract maturity T, based on the assumption of *i.i.d.* returns.

Figure 2.1 Position-Unwinding Risk (Skewness-&-Kurtosis Adjusted)

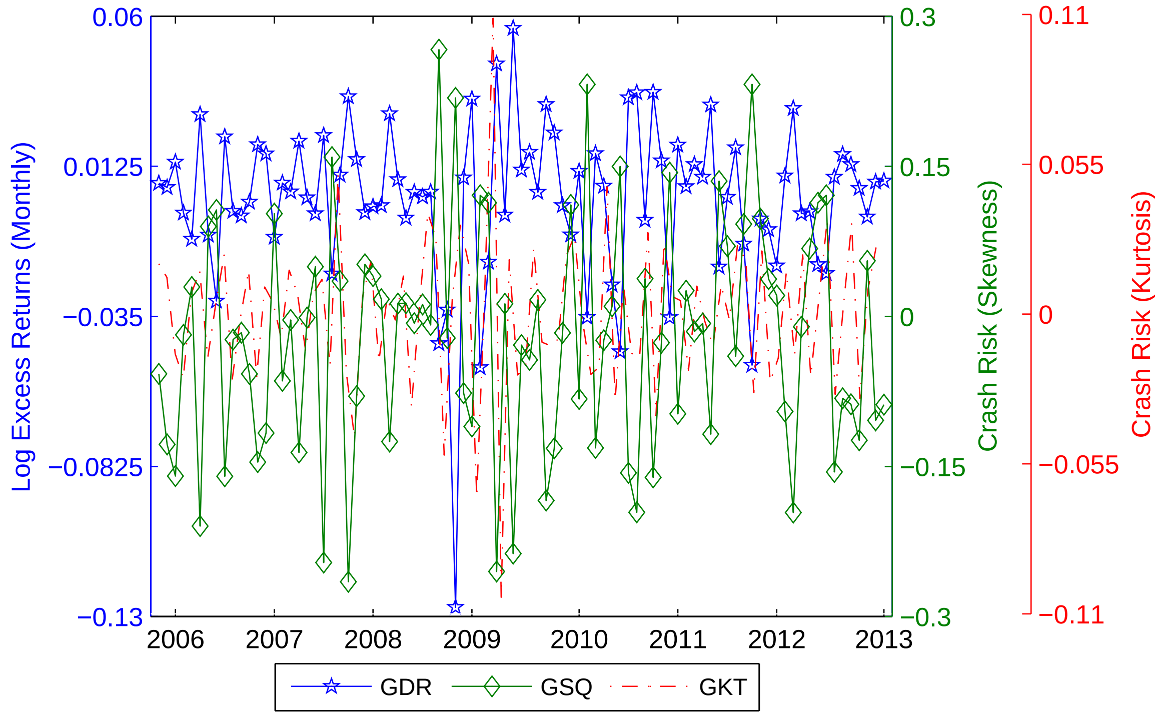


This figure shows skewness-and-kurtosis adjusted position-unwinding likelihood indicator (PUW) of the currency carry trades in comparison with Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) and forward bias risk (HML_{FB}) from September 2005 to January 2013.

Equation (10), we get the position-unwinding likelihood indicator $\hat{\psi}_{i,t+T}$ for individual currency. Finally, we can compute the aggregate level of position-unwinding risk PUW by Equation (2.8). As shown in Figure 2.1., position-unwinding likelihood indicator is closely associated with dollar risk (with a high negative correlation of −0.92) and with forward bias risk (with a correlation of −0.42). Therefore, we expect negative exposures of currency carry portfolios to PUW and a negative factor price. Currencies with higher position-unwinding likelihood will increase the risk premia of the portfolio into which it is allocated.

There is a large literature that stresses the role of skewness in asset pricing exercise. Kraus and Litzenberger (1976) show that investors are in favour of positive return skewness under most preferences. As a result, it is rational to require more compensation for assets with negative return skewness. Grounded in Merton's (1973) ICAPM where skewness is also viewed as state variable that characterize investment opportunities, Conrad, Dittmar, and Ghysels (2013), and Chang, Christoffersen, and Jacobs (2013) find strong evidence in the cross-sectional pricing power of skewness on excess returns in stock market. Now we apply their thoughts to the FX market.

Figure 2.2 Dollar Risk vs. Crash Risk



This figure shows global skewness risk (GSQ) and global kurtosis risk (GKT) both as the proxy for currency crash risk in the graph for easier comparison with Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) from September 2005 to January 2013.

As emphasized by Harvey and Siddique (2000), the skewness of the returns distribution is also important for asset pricing, typically the crash risk for currency carry trades (Jurek, 2007; Brunnermeier, Nagel, and Pedersen, 2009; Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan, 2009; Chernov, Graveline, and Zviadadze, 2012), we also construct two other moment factors to measure currency crash risk (besides the position-unwinding likelihood indicator) simply taking the average of individual currency's skewness and the changes in kurtosis at aggregate level as in Equation (2.8).

$$GSQ_{t+T} = \frac{1}{K_{t+T}} \sum_{i=1}^{K_{t+T}} \left(\frac{\hat{\varsigma}_{i,t+T}}{\sqrt{T_\tau}} \right) \tag{2.19}$$

$$GKT_{t+T} = \frac{1}{K_{t+T}} \sum_{i=1}^{K_{t+T}} \left(\frac{\Delta \hat{\kappa}_{i,t+T}}{T_\tau} \right) \tag{2.20}$$

where T_τ is the number of trading days available over the period of T from t. The skewness does not need to be signed by the interest rate differentials or equivalently by the forward premium, because skewness is already associated with the interest rate differential (Brunnermeier, Nagel, and Pedersen, 2009). If crash risk explains carry trade excess returns, the portfolios are expected to have negative exposures to the global skewness factor and the factor price should be negative. The global kurtosis factor is constructed to match the concept of crash risk. Positive excess kurtosis is also called a Leptokurtic distribution (characterized by high peak and fat tail relative to standard normal distribution) in which volatility is driven by a few extreme events, and vice versa for Platykurtosis (negative excess kurtosis). Figure 2.2. above shows the comovement of global skewness and kurtosis risk with dollar risk. PUW has a high positive correlation with GSQ of 0.85. Since GSQ directly measures the tail risk associated with the underlying position, PUW possesses the consistent economic intuition of crash risk. Because the position-unwinding risk is closely associated with the skewness of the portfolio excess returns which is already shown highly related to the interest rate differentials (see Brunnermeier, Nagel, and Pedersen, 2009), it is straightforward to expect the portfolio with higher interest-rate currencies to have higher exposure to PUW. GKT is regarded as the volatility of volatility, and hence the complementary measure to volatility risk.

Volatility and Liquidity

We employ Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) innovation of using an AR(1) process (GVI) in the global FX volatility (GVL) as the proxy for volatility risk in FX market, and compare it with the simple changes in Chicago Board Options Exchange's (CBOE) VIX index (ΔVIX) that is adopted e.g. by Ang, Hodrick, Xing, and Zhang (2006).

$$GVL_{t+T} = \frac{1}{T} \sum_{\tau \in T} \left(\frac{1}{K_\tau} \sum_{i \in K_\tau} |\Delta s_{i,\tau}| \right) \tag{2.21}$$

where K_τ denotes the number of currencies available on day τ. We then exploit a market microstructure approach that measures illiquidity risk in FX market as the global relative FX bid-ask spreads (GLR) (see also Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a), and compare it with the changes in T-Bill Eurodollar (TED) Spreads Index (ΔTED)[21] as used by, for example, Brunnermeier, Nagel, and Pedersen (2009).

$$GLR_{t+T} = \frac{1}{T}\sum_{\tau \in T}\left[\frac{1}{K_\tau}\sum_{i \in K_\tau}\left(\frac{S^A_{i,\tau} - S^B_{i,\tau}}{S^M_{i,\tau}}\right)\right] \tag{2.22}$$

where a superscript, M, denotes the mid price of spot rates. This measure is grounded in Glosten and Milgrom's (1985) theory which is the first to investigate the adverse selection behavior in market transactions. They show that informational asymmetry leads to positive bid-ask spreads. Amihud and Mendelson (1986) further set forth a model that predicts the market observed expected returns as an increasing and concave function of the bid-ask spreads, wherein expected holding periods play a vital role. Amihud (2002) show that expected excess returns in equity markets represents an illiquidity premium[22].

2.5 Linear Factor Model and Methodologies

In this section, we introduce the linear factor model for time-series and cross-sectional analyses of the tested assets, and the econometric methodology to estimate the model.

2.5.1 Linear Factor Model

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

[21] Originally, it is a 3-month index. Thus, it has to be divided by $\frac{1}{3}$ to match the monthly excess returns.

[22] The difference is that he measures illiquidity as the average daily ratio of absolute return to dollar volume across stocks. But this measurement is not exploitable for the foreign exchange market since it is a highly liquid market with massive daily trading volume. Instead, we adopt relative bid-ask spread approach.

$$\mathbb{E}_t[m_{t+1} \cdot xr_{j,t+1}] = 0 \tag{2.23}$$

where $\mathbb{E}_t[\,\cdot\,]$ is the expectation operator with the information available at time t. The unconditional moment restrictions is given by applying the law of iterated expectations to Equation (3.25):

$$\mathbb{E}[m_t \cdot xr_{j,t}] = 0 \tag{2.24}$$

The SDF takes a linear form of:

$$m_t = \xi \cdot \left[\, 1 - (xf_t - \rho)^\top b \,\right] \tag{2.25}$$

where ξ is a scalar, xf_t is a $k \times 1$ vector of risk factors, $\rho = \mathbb{E}[xf_t]$, and b is a conformable vector of factor loadings. Since ξ is not identified by Equation (2.25), we set it equal to 1, implying $\mathbb{E}[m_t] = 1$. Rearranging Equation (3.26) with Equation (2.25) gives:

$$\mathbb{E}[xr_t] = \mathrm{cov}[xr_t \cdot {xf_t}^\top] \cdot b \tag{2.26}$$

or

$$\mathbb{E}[xr_{j,t}] = \underbrace{\mathrm{cov}[xr_{j,t}, xf_t]\, \Sigma^{-1}_{xf,xf}}_{\beta_j} \cdot \underbrace{\Sigma_{xf,xf}\, b}_{\lambda} \tag{2.27}$$

where $\Sigma_{xf,xf} = \mathbb{E}[(xf_t - \rho)(xf_t - \rho)^\top]$. Equation (2.27) is the beta representation of the asset pricing model. β_j is the vector of exposures of portfolio j to k risk factors, it varies with the portfolios. λ is a $k \times 1$ vector of factor prices associated with the tested risk factors, and all portfolios confront the same factor prices. The beta representation of the expected excess returns by our two-factor linear model can be written as:

$$\mathbb{E}[xr_{j,t}] = \beta_{j,PUW} \cdot \lambda_{PUW} + \beta_{j,SC} \cdot \lambda_{SC} \tag{2.28}$$

where the subscripts denote the corresponding risk factors. The higher position-unwinding risk (PUW), the higher expected excess returns of the currency carry trades. Thereby, we expect negative betas (β_{PUW}) and negative factor price (λ_{PUW}) across all portfolios. The exposures to the sovereign credit risk (HML_{SC}) vary across the portfolios. Its factor price (λ_{SC}) should be positive, high expected excess-return portfolios should have a positive beta (β_{SC}) while low expected excess-return portfolios with a negative beta provide a hedge against sovereign credit risk.

2.5.2 Estimations

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).

Generalized Method of Moments

In the first procedure, we estimate the parameters of the SDF — b and ρ using the GMM and the moment restrictions in Equation (2.26) which can be rewritten as:

$$\mathbb{E}\{xr_t \cdot [\,1 - (xf_t - \rho)^\top\, b\,]\} = 0 \tag{2.29}$$

The GMM estimators of ρ is set equal to a vector of the sample mean of risk factors, $\overline{xf}$. While b is given by:

$$\hat{b} = \left(\hat{\Sigma}_{xr,xf}^\top\, W_N\, \hat{\Sigma}_{xr,xf}\right)^{-1} \hat{\Sigma}_{xr,xf}^\top\, W_N\, \overline{xr} \tag{2.30}$$

where $\hat{\Sigma}_{xr,xf}$ is the sample covariance matrix of xr_t and xf_t, W_N is a weighting matrix, $\overline{xr}$ is the sample mean of excess returns. Then the estimates of factor prices $\hat{\lambda} = \hat{\Sigma}_{xf,xf}\,\hat{b}$, where $\hat{\Sigma}_{xf,xf}$ is the sample covariance matrix of xf_t. Following Burnside (2011), we include an additional set of corresponding moment restrictions on the factor mean vector and factor covariance matrix:

$$g(\phi_t, \theta) = \begin{bmatrix} xr_t \cdot [\, 1 - (xf_t - \rho)^\top b \,] \\ xf_t - \rho \\ (xf_t - \rho)(xf_t - \rho)^\top - \Sigma_{xf,xf} \end{bmatrix} = 0 \tag{2.31}$$

where θ is a parameter vector containing $(b, \rho, \Sigma_{xf,xf})$, ϕ_t represents the data (xr_t, xf_t). By exploiting the moment restrictions $\mathbb{E}[g(\phi_t, \theta)] = 0$ defined by Equation (2.31), the estimation uncertainty[23] is thus incorporated in the standard errors of λ, and this method of point estimates is identical to that of Fama-MacBeth two-pass OLS approach (see Burnside, 2011). The standard errors are computed based on Newey and West's (1987) VARHAC procedure with the data-driven approach of Andrews's (1991) optimal number of lags selection in a Bartlett kernel. In the first stage of GMM estimator, $W_N = I_n$; In the subsequent stages of GMM estimator, W_N is chosen optimally. The empirical results for the first stage GMM and the iterate-to-convergence GMM are reported.

Fama-MacBeth Approach

Additionally, we report the empirical results from the second procedure, FMB estimates. The first step is a time-series regression of each portfolio's excess returns on proposed risk factors to obtain corresponding risk exposures:

$$xr_{j,t} = \alpha_j + \beta_{j,PUW}\, PUW_t + \beta_{j,SC}\, HML_{SC\,t} + u_{j,t} \tag{2.32}$$

where $u_{j,t}$ is $i.i.d.$ $(0, \sigma^2_{j,\varepsilon})$. The second step is a cross-sectional regression of each portfolio's average excess returns on the estimated betas from the first step to acquire the risk prices:

$$\overline{xr}_j = \hat{\beta}_{j,PUW} \cdot \hat{\lambda}_{PUW} + \hat{\beta}_{j,SC} \cdot \hat{\lambda}_{SC} \tag{2.33}$$

Since PUW has a correlation of -0.24 with the slope factor, it may have a cross-sectional relation with the currency carry portfolios with statistically significant factor

[23]It is due to the fact that factor mean vector and covariance matrix have to be estimated.

price[24]. It also seems to serve as a constant that allows for a common mispricing term as it is highly correlated (-0.75) with the level factor[25]. Therefore, we do not include a constant in the second step of FMB. The estimates of the risk prices from FMB is numerically identical to those from GMM. The standard errors adjusted for measurement errors by Shanken's (1992) approach are also reported besides Newey and West (1987) HAC standard errors with automatic lag length selection (Andrews, 1991).

The predicted expected excess returns by the model is thereby $\hat{\Sigma}_{xr,xf}\,\hat{b}$, and the pricing errors are the model residuals $\hat{u} = \overline{xr} - \hat{\Sigma}_{xr,xf}\,\hat{b}$. Then a statistic for over-identifying restrictions, $N\,\hat{u}^{\top}\,V_N^{-1}\,\hat{u}$, can be constructed to test the null hypothesis that all pricing errors across portfolios are jointly zero, where N is the sample size, V_N is a consistent estimate of asymptotic covariance matrix of $\sqrt{N}\,\hat{u}$ and its inverse form is generalized. The test statistic is asymptotic distributed as χ^2 with $n-k$ degrees of freedom. We report its $p-values$ based on both Shanken (1992) adjustment and Newey and West (1987) approach for 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[26] for the GMM procedure. The cross-sectional R^2 and Mean Absolute Pricing Errors (MAPE) are also reported. 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).

[24] We find the position-unwinding likelihood indicator alone captures over about 55% of the cross-sectional variation of currency carry trade portfolios with statistically significant factor price.

[25] See also Burnside (2011); Lustig, Roussanov, and Verdelhan (2011) on the issue of whether or not to include a constant.

[26] Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance gives a least-square distance between the tested pricing kernel and the closest pricing kernel among a set of pricing kernels that price the tested assets correctly. It is calculated by a weighted sum of random variables that follow a χ^2 distribution. For more details, see Jagannathan and Wang (1996); Parker and Julliard (2005).

2.6 Empirical Results

In this section, we show and discuss the empirical results from the asset pricing tests. The factor prices are all annualized. By using a different slope factor rather than the forward bias risk constructed directly from the currency carry portfolios with a persistent monotonic excess returns pattern, we no longer need to restrict the intercept betas that $\beta_{g,1} = \beta_{g,5}$, and the slope betas that $\beta_{c,5} - \beta_{c,1} = 1$. As a result, we are able to observe better estimates on global risk exposures of the lowest and highest interest-rate currencies portfolios. The following paragraphs will reveal that the higher interest-rate currencies are exposed to higher systematic risk, which is not detectable when imposed with above two restrictions.

2.6.1 Sovereign Default as the Dominant Fundamental Risk

The top panel of Table 2.2 shows the asset pricing results with GDR and HML_{SC}. The high interest-rate currencies are positively exposed to sovereign credit 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 0.933[27]. The coefficients of β, b and λ are all statistically significant. The statistically significant price of sovereign credit risk is 3.287% per annum, and the Mean Absolute Pricing Error (MAPE) is about 30 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 to accept the model. By using alternative slope factor to relax the constraints on βs of the lowest and highest interest-rate currencies portfolios, we are able to detect increasing exposures to global risk. Since interest rate differentials covary with the skewness of portfolio excess returns, global risk essentially represent a crash risk, which can be confirmed by our other two risk factors PUW and GSQ.

Table 2.3 above shows the the asset pricing results with GDR and HML_{PC}, which is the principal component of HML_{SC} and HML_{FB}. So HML_{PC} can be deemed

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

Table 2.2 Asset Pricing of Currency Carry Portfolios: HML_{SC} vs. HML_{GB}

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	$MAPE$
C_1	0.726	-0.324							χ^2	
	(0.050)	(0.051)	FMB			2.395	3.287	0.933		0.302
C_2	0.900	-0.187				(2.196)	(1.413)		(0.893)	
	(0.073)	(0.063)				[2.174]	[1.270]		[0.901]	
C_3	1.022	-0.153								
	(0.039)	(0.031)							$HJ-dist$	
C_4	1.192	0.189	GMM_1	0.327	0.833	2.395	3.287	0.933	0.819	0.302
	(0.041)	(0.053)		(0.200)	(0.385)	(1.787)	(1.568)			
C_5	1.160	0.474	GMM_2	0.311	0.695	2.340	2.717	0.915		0.359
	(0.076)	(0.054)		(0.206)	(0.258)	(1.811)	(1.055)			
	β_{GDR}	β_{GB}		b_{GDR}	b_{GB}	λ_{GDR}	λ_{GB}	R^2	$p-value$	$MAPE$
C_1	0.997	-0.186							χ^2	
	(0.059)	(0.030)	FMB			2.386	9.544	0.952		0.268
C_2	1.110	-0.147				(2.196)	(3.829)		(0.940)	
	(0.054)	(0.026)				[2.174]	[3.507]		[0.940]	
C_3	1.057	-0.019								
	(0.048)	(0.028)							$HJ-dist$	
C_4	1.047	0.098	GMM_1	-0.279	0.408	2.386	9.544	0.952	0.849	0.268
	(0.047)	(0.023)		(0.384)	(0.227)	(1.633)	(3.750)			
C_5	0.788	0.253	GMM_2	-0.224	0.388	2.633	9.563	0.920		0.288
	(0.038)	(0.024)		(0.425)	(0.208)	(2.159)	(3.345)			

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 sovereign credit risk (HML_{SC}) implied in currencies and the LFM in the bottom panel adopts alternative measure of sovereign credit risk via government bonds total return indices (HML_{GB}). 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 Pricing Error ($MAPE$) are also reported.

Table 2.3 Asset Pricing of Currency Carry Portfolios: $GDR + HML_{PC}$

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{PC}		b_{GDR}	b_{PC}	λ_{GDR}	λ_{PC}	R^2	$p-value$	$MAPE$
C_1	0.872	-0.283							χ^2	
	(0.038)	(0.024)	FMB			2.388	5.695	0.968		0.193
C_2	0.942	-0.122				(2.191)	(2.545)		(0.960)	
	(0.065)	(0.029)				[2.174]	[2.476]		[0.963]	
C_3	1.048	-0.069								
	(0.045)	(0.019)							$HJ-dist$	
C_4	1.154	0.104	GMM_1	0.182	0.364	2.388	5.695	0.968	0.895	0.193
	(0.038)	(0.024)		(0.202)	(0.179)	(1.728)	(2.607)			
C_5	1.049	0.335	GMM_2	0.181	0.355	2.351	5.549	0.967		0.210
	(0.039)	(0.022)		(0.213)	(0.152)	(1.852)	(2.303)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a linear factor model (LFM) based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor, the first principal component (HML_{PC}) of sovereign credit risk (HML_{SC}) and Lustig, Roussanov, and Verdelhan's (2011) forward bias risk (HML_{FB}) as the slope (country-specific) factor. 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 Pricing Error ($MAPE$) are also reported.

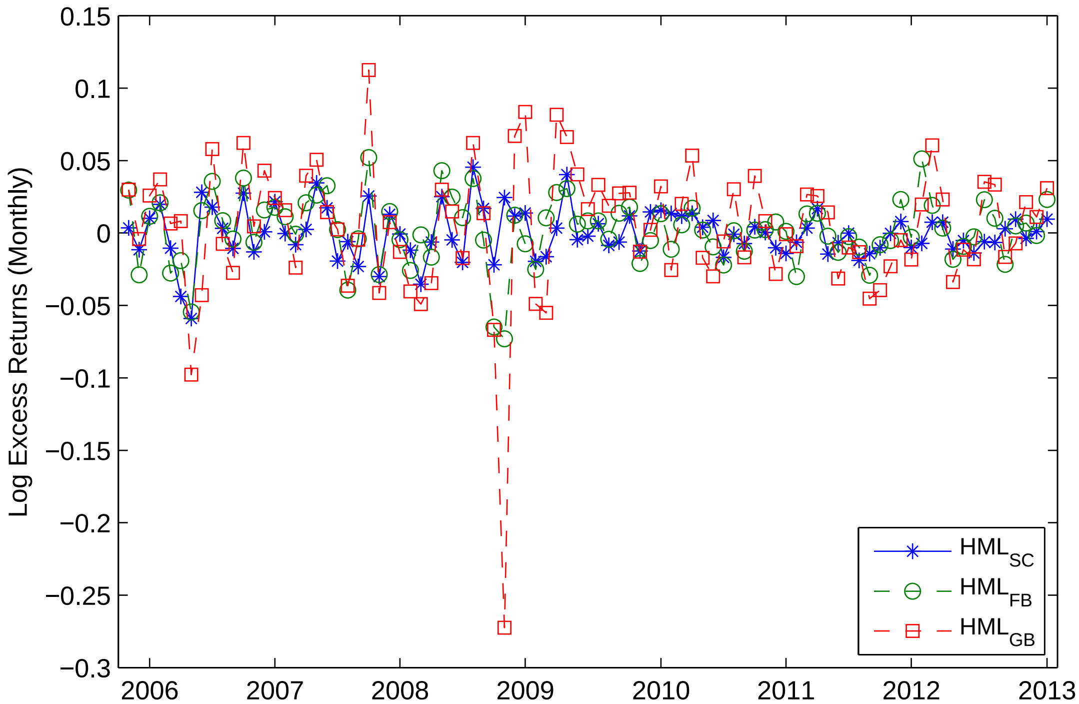
as the sovereign credit risk implied in the forward bias risk. The empirical results are very similar to those obtained from using the direct sovereign credit risk measure, with a little higher factor price of 5.695% per annum and an even higher R^2 of 0.968. This might mean that there is informational "noise" captured by HML_{SC} that is not valuable for explaining currency carry trade excess returns. However, we will verify that this noisy component is not useless in the next test. The model is also confirmed correct by χ^2 and $HJ - dist$ tests, with a MAPE of about 19 bps.

Both orthogonal components (to HML_{PC}) of forward bias and sovereign credit risk factors, $HML_{FB_\perp}$ and $HML_{SC_\perp}$, do not capture additional cross-sectional variations of currency carry trades. These findings confirm that sovereign credit risk is a good substitutive slope factor. In fact it is even better than the forward bias risk because it not only relaxes the estimation restrictions, but also offers a traceable source of risk against which we are able to hedge.

2.6.2 Alternative Measures of Sovereign Credit Risk

We also resort to government bonds for an alternative measure of sovereign credit risk by sorting government bond total return indices into five portfolios based on their respect redemption yields. By doing this, we not only form the government bond portfolios for robustness test later, but also evaluate the sovereign credit risk from the excess returns of a total-return-index investment strategy that holds long positions in the highest 20% sovereign default risk government bonds funded by the lowest 20% sovereign default risk government bonds[28] (HML_{GB}).

Figure 2.3 Forward Bias Risk vs. Sovereign Credit Risk



This figure shows sovereign credit risk (HML_{SC} implied by currencies, and HML_{GB} implied by government bonds) in comparison with Lustig, Roussanov, and Verdelhan's (2011) forward bias risk (HML_{FB}) from September 2005 to January 2013.

In Figure 2.3. as shown below, we can see the inextricably tied-up fluctuations of the three factors, HML_{FB}, HML_{SC}, and HML_{GB}, implying that forward premia, to some degree, represent the sovereign credit risk, which could be the dominant source of country-specific fundamental risk priced in cross section of currency carry trade excess

[28]Please refer to Table A.1. for descriptive statistics of government bond portfolios.

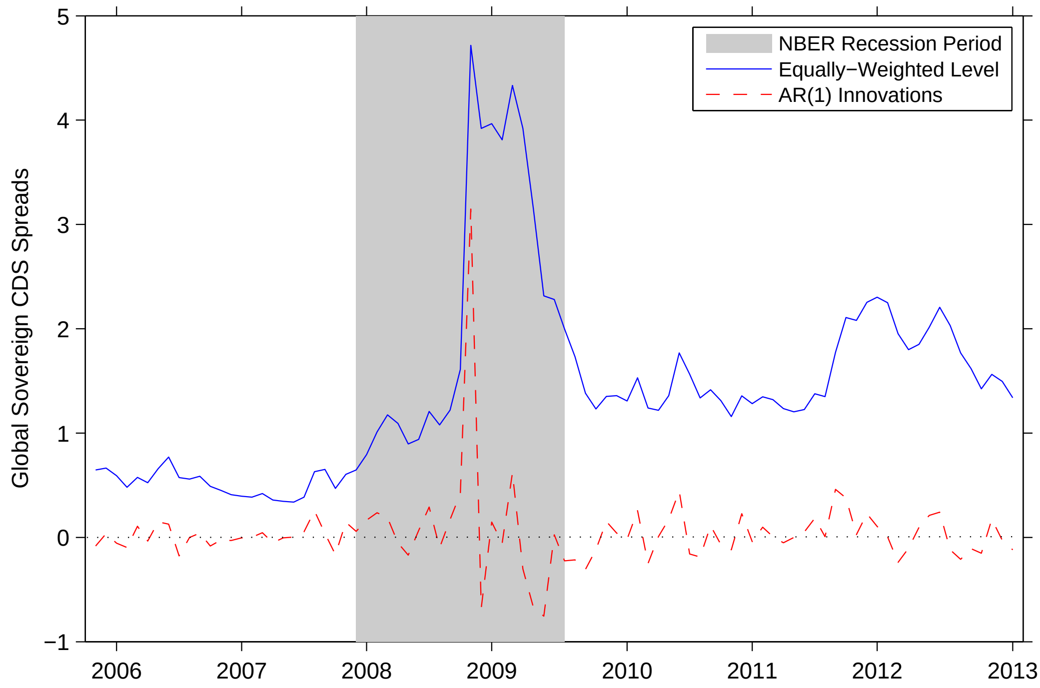
returns[29]. The correlation between HML_{SC} and HML_{GB} is 0.96, which mutually manifests that our measures are valid for evaluating sovereign credit risk and the short-term exchange rates move in the directions to compensate for sovereign credit risk. This means that when holding high default risk sovereign debts denominated in local currencies, the investors still confront a high probability of large currency devaluations that may not yet be compensated enough by the bond yields. However, it seems that in the short run the demand for the government bond holders to hedge currency devaluation risk would be small because, according to our empirical results, the currencies of high sovereign default risk tend to appreciate in short run.

The bottom panel of Table 2.2 shows the asset pricing results with GDR and HML_{GB}. Again, we can see monotonic exposures of the currency carry portfolios to HML_{GB}. Our alternative measure of sovereign credit risk from government bonds total return indices has slightly higher cross-sectional pricing power (an R^2 of 0.952). Again, the coefficients of β, b and λ are all statistically significant. The price for sovereign credit risk implied in government bond is much higher, 9.544% per annum, owing to greater variation in the factor as the compensation for liquidity risk; and the Mean Absolute Pricing Error (MAPE) is still low, about 27 bps. The $p-values$ of χ^2 tests and the $HJ-dist$ all suggest to accept the model. These results add additional credibility on the measure of sovereign credit risk and its cross-sectional pricing power. The success of the pricing power of sovereign credit premia measured by government bonds is consistent with the findings by Ludvigson and Ng (2009) that investors must be compensated for the countercyclical sovereign credit premia, which is strongly associated with macroeconomic activity. In this economic sense, our findings to some extent testify that the disconnect puzzle of currency risk premia may not exist.

Figure 2.4. shows the aggregate level of sovereign CDS spreads across over 30 countries and its innovations of AR(1) process. There are pronounced upswings at the outbreaks of the Subprime Mortgage Crisis and Sovereign Debt Crisis in Europe, during which currency carry trade position began to unwind. Table 2.4 further confirms that the global sovereign credit risk proxy GSI is able to price about 0.786 of the cross-

[29] In time-series analysis, both HML_{SC} and HML_{GB} cannot outperform HML_{FB} in pricing the currency carry portfolios since the forward bias risk is directly constructed from the portfolios themselves. And these portfolios already shows a persistently monotonic pattern in excess returns.

Figure 2.4 Global Sovereign CDS Spreads: Aggregate Level & Shocks



This figure shows global sovereign CDS spreads at aggregate level of the whole sample countries with equal weights (GSR), and the innovations of its AR(1) process without a constant (GSI) from September 2005 to January 2013.

sectional variation of the currency carry trade portfolios with statistically significant factor price (-0.943 per annum) while passing the pricing-error and $HJ - dist$ tests.

Since our two-factor models with alternative measures of sovereign default risk explain a large proportion of the cross-sectional variance of currency carry trade excess returns, it is reasonable to believe that one solution towards forward premium puzzle is sovereign credit premia, even in short run. Because sovereign credit premia not only reflect a country's medium to long run risk, but also indicate the short-run rollover risk of maturing sovereign debt, which would particularly be exacerbated during the market liquidity deterioration (Acharya, Gale, and Yorulmazer, 2011; He and Xiong, 2012).

Table 2.4 Asset Pricing of Currency Carry Portfolios: $GDR + GSI$

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{GSI}		b_{GDR}	b_{GSI}	λ_{GDR}	λ_{GSI}	R^2	$p-value$	$MAPE$
C_1	0.875	0.925							χ^2	
	(0.047)	(0.261)	FMB			2.420	-0.943	0.786		0.616
C_2	1.145	1.994				(2.209)	(0.444)		(0.758)	
	(0.056)	(0.365)				[2.174]	[0.446]		[0.766]	
C_3	0.978	-0.472								
	(0.047)	(0.288)							$HJ-dist$	
C_4	1.077	-0.874	GMM_1	-0.463	-6.320	2.420	-0.943	0.786	0.576	0.616
	(0.051)	(0.325)		(0.440)	(3.067)	(1.601)	(0.425)			
C_5	0.944	-1.573	GMM_2	-0.109	-3.481	2.643	-0.672	0.692		0.655
	(0.051)	(0.375)		(0.136)	(1.357)	(1.846)	(0.286)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a linear factor model (LFM) based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor, the innovations of the AR(1) process of the global (weighted-average) sovereign CDS spreads (GSI) as the slope (country-specific) factor. 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 Pricing Error ($MAPE$) are also reported.

2.6.3 Forward Position-unwinding Premia

To show that the position-unwinding likelihood indicator is a good measure of global (crash) risk, we run time-series and cross-sectional regressions of currency carry portfolios on PUW and HML_{SC} as our benchmark model. As shown in Table 2.5 below, the lower (negative) skewness (crash risk) of the excess return distribution (see Table 2.1), the higher position-unwinding risk of the corresponding carry trade position, in terms of lower negative factor exposures. Brunnermeier, Nagel, and Pedersen (2009) find a strong correlation between the interest rate differential and the crash risk measured by skewness of individual currency, which is further conformed by the carry trade portfolios conducted in asset pricing literature, such as Lustig, Roussanov, and Verdelhan (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). Our data also exhibits very similar but not exact results, possibly owing to the fact that the time span of our data is not long enough. Nevertheless, we may still reach a quite robust conclusion that the higher interest-rate currencies are exposed to higher position-unwinding risk when allocated into the carry trade portfolios, as the correlation between interest rate differentials and the skewness of the excess returns' distribution is well established. We will show that this conclusion is also robust to using the global skewness factor (GSQ) as the proxy for crash risk (in the horse race section), and the PUW_{UA} that is unadjusted for skewness and kurtosis.

Table 2.5 Asset Pricing of Currency Carry Portfolios: PUW + HML_{SC}

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{PUW}	β_{SC}		b_{PUW}	b_{SC}	λ_{PUW}	λ_{SC}	R^2	$p-value$	$MAPE$
C_1	-0.091	-0.591							χ^2	
	(0.012)	(0.114)	FMB			-27.269	3.334	0.912		0.325
C_2	-0.125	-0.538				(12.671)	(1.049)		(0.866)	
	(0.013)	(0.085)				[12.874]	[1.080]		[0.875]	
C_3	-0.139	-0.548								
	(0.019)	(0.117)							$HJ-dist$	
C_4	-0.167	-0.279	GMM_1	-0.069	0.677	-27.269	3.334	0.912	0.764	0.325
	(0.021)	(0.133)		(0.033)	(0.385)	(13.393)	(1.674)			
C_5	-0.148	0.042	GMM_2	-0.058	0.559	-22.849	2.762	0.812		0.429
	(0.023)	(0.135)		(0.029)	(0.227)	(10.969)	(1.050)			
	$\beta_{PUW_{UA}}$	β_{SC}		$b_{PUW_{UA}}$	b_{SC}	$\lambda_{PUW_{UA}}$	λ_{SC}	R^2	$p-value$	$MAPE$
C_1	-0.090	-0.591							χ^2	
	(0.012)	(0.114)	FMB			-27.420	3.331	0.913		0.325
C_2	-0.124	-0.538				(12.802)	(1.049)		(0.866)	
	(0.013)	(0.085)				[12.005]	[1.080]		[0.875]	
C_3	-0.138	-0.548								
	(0.019)	(0.117)							$HJ-dist$	
C_4	-0.166	-0.279	GMM_1	-0.068	0.676	-27.420	3.331	0.913	0.764	0.325
	(0.021)	(0.133)		(0.033)	(0.386)	(13.910)	(1.588)			
C_5	-0.148	0.042	GMM_2	-0.057	0.559	-22.975	2.760	0.812		0.429
	(0.023)	(0.135)		(0.028)	(0.228)	(11.063)	(1.050)			

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 sovereign credit risk (HML_{SC}) as the slope (country-specific) factor but differ in intercept (global) factor. The LFM in the top panel employs skewness-and-kurtosis adjusted position-unwinding risk (PUW) and the LFM in the bottom panel adopts unadjusted position-unwinding risk (PUW_{UA}). 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 Pricing Error ($MAPE$) are also reported.

In both cases, the coefficients of β, b and λ are all statistically significant. The prices for position-unwinding risk are consistently negative as expected, -27.269% per annum for PUW and -27.420% per annum for PUW_{UA}, respectively. The R^2s are 0.912 and the MAEs are also approximately the same, about 32 bps. The $p-values$ of χ^2 tests and the $HJ-dist$ all suggest acceptance of the model. These empirical results add additional credibility to the measure of position-unwinding risk and its cross-sectional pricing power.

$$\begin{aligned} PUW_t = \underset{(0.014)}{0.451} + \underset{(0.005)}{0.017} \cdot GSI_t \qquad R^2 : 28\% \end{aligned} \tag{2.34}$$

We test whether or not sovereign default risk drives the position-unwinding risk of currency carry trade as implied by our framework in Section 2.3. We find that GSI explains the largest proportion of PUW among all candidate risk factors (see Equation (2.34)) and the parameter is statistically significant.

2.6.4 Factor-mimicking Portfolios

To better scrutinize the factor price of the global sovereign credit risk (innovations) and position-unwinding risk in a natural way, it is necessary to convert it into a return series by following Breeden, Gibbons, and Litzenberger (1989), Ang, Hodrick, Xing, and Zhang (2006) to build a factor-mimicking portfolio of position-unwinding likelihood indicator. If this factor is a traded asset, its risk price should equal to the mean return of the traded portfolio for satisfying the no-arbitrage condition.

We regress the risk factor xf_t (GSI and PUW respectively) on the vector of excess returns of five carry trade portfolios xr_t to obtain the factor-mimicking portfolio $xr_{FMP,t}$:

$$xf_t = \alpha + \beta' \, xr_t + \upsilon_t \tag{2.35}$$

Table 2.6 Asset Pricing of Currency Carry Portfolios: GSI_{FMP} & PUW_{FMP}

All Countries with Transaction Costs										
	Factor Exposures			Factor Prices						
	β_{GDR}	$\beta_{GSI_{FMP}}$		b_{GDR}	$b_{GSI_{FMP}}$	λ_{GDR}	$\lambda_{GSI_{FMP}}$	R^2	$p-value$	$MAPE$
C_1	1.073	2.829							χ^2	
	(0.082)	(0.580)	FMB			2.416	-0.504	0.821		0.558
C_2	1.583	5.856				(2.182)	(0.224)		(0.806)	
	(0.029)	(0.183)				[2.174]	[0.222]		[0.784]	
C_3	0.924	-0.946								
	(0.087)	(0.538)							$HJ-dist$	
C_4	0.895	-2.474	GMM_1	-0.520	-6.907	2.416	-0.504	0.821	0.764	0.558
	(0.076)	(0.531)		(0.605)	(4.594)	(1.711)	(0.212)			
C_5	0.524	-5.265	GMM_2	-0.188	-4.150	2.572	-0.431	0.748		0.565
	(0.070)	(0.574)		(0.580)	(3.964)	(1.845)	(0.188)			
	$\beta_{PUW_{FMP}}$	β_{SC}		$b_{PUW_{FMP}}$	b_{SC}	$\lambda_{PUW_{FMP}}$	λ_{SC}	R^2	$p-value$	$MAPE$
C_1	-0.123	-0.504							χ^2	
	(0.010)	(0.082)	FMB			-16.361	2.996	0.913		0.325
C_2	-0.175	-0.423				(7.542)	(0.987)		(0.868)	
	(0.016)	(0.073)				[8.162]	[1.061]		[0.874]	
C_3	-0.197	-0.419								
	(0.011)	(0.064)							$HJ-dist$	
C_4	-0.245	-0.130	GMM_1	-0.068	0.676	-16.361	2.996	0.913	0.787	0.325
	(0.005)	(0.039)		(0.032)	(0.338)	(8.484)	(1.416)			
C_5	-0.224	0.171	GMM_2	-0.057	0.555	-13.530	2.463	0.796		0.444
	(0.015)	(0.090)		(0.028)	(0.235)	(7.393)	(1.008)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for examining the arbitrage-free attribute of non-return risk factors, innovations in global sovereign CDS spreads (GSI) and position-unwinding likelihood indicator (PUW). The LFM in the top panel $GDR + GSI$ and the LFM in the bottom panel $PUW + HML_{SC}$. 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 Pricing Error ($MAPE$) are also reported.

where $\upsilon_{j,t}$ is $i.i.d.$ $(0, \sigma^2_{j,\upsilon})$. Then the factor-mimicking portfolio $xr_{FMP,t} = \hat{\beta}' \, xr_t$ is given by:

$$
\begin{aligned}
xr^{FMP}_{GSI,t} &= -0.02 \cdot xr_{1,t} + 0.10 \cdot xr_{2,t} - 0.06 \cdot xr_{3,t} - 0.06 \cdot xr_{4,t} - 0.05 \cdot xr_{5,t} \\
xr^{FMP}_{PUW,t} &= 2.22 \cdot xr_{1,t} - 1.33 \cdot xr_{2,t} - 0.29 \cdot xr_{3,t} - 3.75 \cdot xr_{4,t} - 0.30 \cdot xr_{5,t}
\end{aligned}
$$

As expected, the factor-mimicking portfolio of innovations in global sovereign credit risk (GSI_{FMP}) is -0.62 correlated with forward bias factor, that of position-unwinding risk (PUW_{FMP}) is -0.93 correlated with dollar risk factor. It is natural to expect this high correlation since they play a role of slope, and level factor, respectively. The estimated annualized factor price of the global sovereign CDS spreads (innovations) $\lambda^{FMP}_{GSI} = -0.504\%$ per annum, which is very close to the average annual excess return of the factor-mimicking portfolio $\overline{xr}^{FMP}_{GSI} = -0.512\%$ per annum. That of position-unwinding risk $\lambda^{FMP}_{PUW} = -16.361\%$ per annum, and there is a monthly nuance to $\overline{xr}^{FMP}_{PUW} = -16.162\%$ per annum. These results confirm that the risk price of our factors, GSI and PUW, are arbitrage-free and has economically meaningful implications for dynamic hedging against currency sovereign credit and crash risk, especially we will show that by analyzing the threshold level of PUW we're able to predict the position-unwinding behavior of the market before any finance turmoil occurs.

2.6.5 Horse Races

We run two horse races of the sovereign credit risk, one with volatility risk measures, i.e. global FX volatility (innovation) risk factor (GVI) by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), and simple changes in Chicago Board Options Exchange's (CBOE) VIX index (ΔVIX); another one with illiquidity risk measures, i.e. global FX bid-ask spreads (GLR), and changes in T-Bill Eurodollar (TED) Spreads Index (ΔTED). Our empirical results corroborate Bandi, Moise, and Russell's (2008) evidence that stock market volatility drives out liquidity in cross-sectional asset pricing exercises, FX market shares this similarity.

Table 2.7 Asset Pricing of Currency Carry Portfolios: $GDR + HML_{SC} + \Delta VIX$

All Countries with Transaction Costs													
	Factor Exposures				Factor Prices								
	β_{GDR}	β_{SC}	$\beta_{\Delta VIX}$		b_{GDR}	b_{SC}	$b_{\Delta VIX}$	λ_{GDR}	λ_{SC}	$\lambda_{\Delta VIX}$	R^2	$p-value$	$MAPE$
C_1	0.77	-0.29	0.03									χ^2	
	(0.05)	(0.05)	(0.02)	FMB				2.39	2.46	-11.88	0.95		0.30
C_2	1.00	-0.11	0.07					(1.60)	(1.12)	(12.36)		(0.78)	
	(0.07)	(0.07)	(0.02)					[1.59]	[1.10]	[12.24]		[0.80]	
C_3	1.00	-0.17	-0.02										
	(0.04)	(0.05)	(0.02)									$HJ-dist$	
C_4	1.18	0.18	-0.01	GMM_1	0.03	0.41	-0.20	2.39	2.46	-11.88	0.95	0.593	0.30
	(0.05)	(0.05)	(0.01)		(0.82)	(0.89)	(0.50)	(1.68)	(1.13)	(12.41)			
C_5	1.06	0.39	-0.08	GMM_2	-0.01	0.28	-0.23	2.44	2.03	-12.29	0.94		0.30
	(0.06)	(0.06)	(0.03)		(0.85)	(0.98)	(0.53)	(1.65)	(1.11)	(12.95)			

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, sovereign credit risk (HML_{SC}) and s simple changes in Chicago Board Options Exchanges (CBOE) VIX index (ΔVIX) 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 Pricing Error ($MAPE$) are also reported.

Table 2.8 Asset Pricing of Currency Carry Portfolios: $GDR + HML_{SC} + GVI$

	All Countries with Transaction Costs												
	Factor Exposures				Factor Prices								
	β_{GDR}	β_{SC}	β_{GVI}		b_{GDR}	b_{SC}	b_{GVI}	λ_{GDR}	λ_{SC}	λ_{GVI}	R^2	$p-value$	$MAPE$
C_1	0.82	-0.29	3.29									χ^2	
	(0.04)	(0.05)	(0.91)	FMB				2.39	0.36	-0.38	0.98		0.16
C_2	0.97	-0.16	2.65					(1.60)	(1.17)	(0.44)		(0.94)	
	(0.06)	(0.07)	(1.57)					[1.57]	[1.16]	[0.40]		[0.93]	
C_3	1.02	-0.15	-0.23										
	(0.04)	(0.03)	(1.13)									$HJ-dist$	
C_4	1.17	0.18	-0.87	GMM_1	-0.71	-0.23	-36.34	2.39	0.36	-0.38	0.98	0.46	0.16
	(0.05)	(0.05)	(1.08)		(1.58)	(1.41)	(53.26)	(1.63)	(1.25)	(0.41)			
C_5	1.03	0.43	-4.84	GMM_2	-0.87	-0.44	-45.88	3.34	-0.17	-0.48	0.47		0.95
	(0.05)	(0.05)	(1.11)		(1.57)	(1.48)	(55.05)	(2.28)	(1.38)	(0.44)			

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, sovereign credit risk (HML_{SC}) 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 Pricing Error ($MAPE$) are also reported.

Table 2.9 Asset Pricing of Currency Carry Portfolios: $GDR + GSI + GVI$

	All Countries with Transaction Costs												
	Factor Exposures				Factor Prices								
	β_{GDR}	β_{GSI}	β_{GVI}		b_{GDR}	b_{GSI}	b_{GVI}	λ_{GDR}	λ_{GSI}	λ_{GVI}	R^2	$p-value$	$MAPE$
C_1	0.89	0.32	4.06									χ^2	
	(0.06)	(0.38)	(1.36)	FMB				2.39	-0.61	-0.35	0.99		0.11
C_2	1.14	2.01	-0.14					(2.20)	(0.30)	(0.18)		(0.94)	
	(0.06)	(0.47)	(1.26)					[2.17]	[0.29]	[0.16]		[0.93]	
C_3	0.99	-0.74	1.76										
	(0.05)	(0.40)	(1.24)									$HJ-dist$	
C_4	1.07	-0.84	-0.22	GMM_1	-0.43	2.18	-35.97	2.39	-0.61	-0.32	0.99	0.51	0.11
	(0.05)	(0.40)	(1.23)		(0.47)	(3.18)	(12.33)	(1.69)	(0.33)	(0.12)			
C_5	0.89	-0.75	-5.46	GMM_2	-0.49	2.39	-38.34	2.16	-0.60	-0.36	0.96		0.23
	(0.06)	(0.82)	(2.01)		(0.59)	(2.85)	(14.73)	(1.88)	(0.26)	(0.13)			

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, innovations in global sovereign CDS spreads (GSI) 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 Pricing Error ($MAPE$) are also reported.

Table 2.10 Asset Pricing of Currency Carry Portfolios: $GDR + HML_{SC} + GLR$

All Countries with Transaction Costs													
	Factor Exposures				Factor Prices								
	β_{GDR}	β_{SC}	β_{GLR}		b_{GDR}	b_{SC}	b_{GLR}	λ_{GDR}	λ_{SC}	λ_{GLR}	R^2	$p-value$	$MAPE$
C_1	0.74	-0.33	10.14									χ^2	
	(0.05)	(0.05)	(7.08)	FMB				2.41	3.47	0.02	0.94		0.26
C_2	0.90	-0.19	1.89					(2.20)	(1.27)	(0.07)		(0.80)	
	(0.07)	(0.06)	(10.48)					[2.17]	[1.18]	[0.07]		[0.78]	
C_3	1.02	-0.15	-1.83										
	(0.04)	(0.03)	(11.25)									$HJ-dist$	
C_4	1.18	0.19	-13.79	GMM_1	0.41	0.87	87.39	2.41	3.47	0.02	0.94	0.69	0.26
	(0.04)	(0.05)	(7.25)		(0.33)	(0.32)	(293.65)	(1.77)	(1.16)	(0.06)			
C_5	1.16	0.47	3.59	GMM_2	0.41	0.73	88.82	2.51	2.89	0.02	0.93		0.34
	(0.08)	(0.05)	(8.30)		(0.30)	(0.22)	(288.46)	(1.85)	(0.84)	(0.06)			

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, sovereign credit risk (HML_{SC}) and global FX liquidity risk (GLR) measured by the aggregate level of relative bid-ask spreads, 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 Pricing Error ($MAPE$) are also reported.

Table 2.11 Asset Pricing of Currency Carry Portfolios: $GDR + HML_{SC} + \Delta TED$

All Countries with Transaction Costs													
	Factor Exposures			Factor Prices									
	β_{GDR}	β_{SC}	$\beta_{\Delta TED}$		b_{GDR}	b_{SC}	$b_{\Delta TED}$	λ_{GDR}	λ_{SC}	$\lambda_{\Delta TED}$	R^2	$p-value$	$MAPE$
C_1	0.73	-0.33	-0.03									χ^2	
	(0.05)	(0.05)	(0.23)	FMB				2.40	3.23	-0.33	0.93		0.30
C_2	0.90	-0.18	0.13					(2.19)	(1.65)	(3.34)		(0.74)	
	(0.08)	(0.07)	(0.14)					[2.17]	[1.54]	[3.30]		[0.75]	
C_3	1.03	-0.14	0.21										
	(0.04)	(0.02)	(0.18)									$HJ-dist$	
C_4	1.19	0.19	0.08	GMM_1	0.32	0.80	-0.46	2.40	3.23	-0.33	0.93	0.38	0.30
	(0.04)	(0.05)	(0.17)		(0.35)	(1.26)	(11.44)	(1.78)	(1.19)	(2.91)			
C_5	1.15	0.46	-0.38	GMM_2	0.32	0.73	0.40	2.34	2.78	-0.08	0.92		0.36
	(0.07)	(0.05)	(0.30)		(0.35)	(1.22)	(11.74)	(1.82)	(1.17)	(3.01)			

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, sovereign credit risk (HML_{SC}) and changes in T-Bill Eurodollar (TED) Spreads Index (ΔTED) 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 Pricing Error ($MAPE$) are also reported.

In the horse races, ΔVIX cannot dominate HML_{SC} and the cross-sectional pricing power does not improve much (see Table 2.7). As shown in Table 2.8, when racing with GVI, the estimates of b and λ with respect to HML_{SC} become statistically insignificant in pricing the cross section of currency excess returns, although both factor exposures exhibit monotonic and statistically significant patterns in time-series regressions. This is caused by multicollinearity problem that GVI dominates HML_{SC} in cross-sectional regression. The rationale behind this suggests that there must be some other ingredients containing valuable information about the cross section of currency excess returns that drives the cross-sectional volatility in the FX market, but sovereign credit risk already constitutes a major part of the innovations in global FX volatility because HML_{SC} and HML_{GB} as the proxy for sovereign default risk both possess very close cross-sectional pricing power to GVI. When comparing GVI with the direct measure of sovereign credit risk using the innovations in global sovereign CDS spreads GSI, we find neither of them can dominate in both cross-sectional and time-series dimensions, and both factor prices are statistically significant (see Table 2.9). Thereby, we take a further step to employ both linear and nonlinear Granger causality tests to show that sovereign default risk leads to innovations in global FX volatility.

GLR performs badly in terms of statistically insignificant parameter estimates when racing with HML_{SC} (see Table 2.10). While Table 2.11 shows that HML_{SC} also dominates ΔTED in both time-series and cross-sectional regressions. Unlike HML_{SC}, ΔTED loses its monotonic risk exposure pattern and its estimates of b and λ become very statistically insignificant. Again, this is not surprising because ΔTED is also an indicator of credit risk in the general economy while HML_{SC} is constructed directly from the currency excess returns, admittedly, it should be more specialized in gauging (sovereign) credit risk in currency market. Given the fact that credit risk and liquidity risk are always the twins that interact dynamically in the global economy, credit risk is usually the trigger of liquidity risk, and liquidity risk sequentially amplifies credit risk. So we should expect that HML_{SC} overwhelms ΔTED in terms of cross-sectional pricing information.

To summarize, global FX volatility risk cannot dominate sovereign default risk in pricing the cross section of currency carry portfolios. Sovereign default risk is the dominant country-specific fundamental risk in terms of persistent monotonic time-series factor exposures and very high cross-sectional pricing power. Follow the economic intuition, sovereign credit conditions should be the driver of volatility and illquidity risk in FX market and the reverse may not necessarily be true. These will be testified by both linear and nonlinear Granger causality later in this chapter.

2.7 Robustness

We stick to conditional risk premia, since it is more reasonable to look at the empirical results obtained from managed investments that in reality FX traders open, close, or adjust their positions based on daily updated information. Given the sample period is not long enough, splitting sample by time and/or category (advanced economies and emerging market) is not ideal because these will introduce measurement errors in betas in terms of smaller variations in their estimated values, which will in turn make the market prices appear higher and less accurately estimated than on full sample. However, our reported results are still robust to peso problem, state-dependent factor exposures, beta-sorted portfolios and nonlinearity checks besides alternative measures of sovereign credit risk and crash risk, and unadjusted position-unwinding likelihood indicator, and factor-mimicking portfolios. By removing the illiquid currencies from the portfolios, we also confirm that our asset pricing results remain qualitatively very similar. These results are not presented in this chapter, again we will be glad to provide on request.

2.7.1 Peso Problem

Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) argue that the key characteristics of a peso state is a high value of SDF, not large losses in carry trades. To show that the sovereign credit risk does not represent a "peso problem" because sovereign default is a rare event and the factor price for GSI is very small, we winsorize the sample outliers of the GSI at the 95% and 90% levels, respectively, to cut off the spikes.

As shown in Table 2.14, we still obtain very robust empirical results with R^2s of from

Table 2.12 Asset Pricing of Currency Carry Portfolios: Peso Problem

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	$\beta_{GSI_{W95}}$		b_{GDR}	$b_{GSI_{W95}}$	λ_{GDR}	$\lambda_{GSI_{W95}}$	R^2	$p-value$	$MAPE$
C_1	0.838	1.879							χ^2	
	(0.067)	(0.764)	FMB			2.408	-0.486	0.850		0.319
C_2	1.061	3.145				(2.186)	(0.192)		(0.831)	
	(0.098)	(0.780)				[2.174]	[0.187]		[0.799]	
C_3	1.059	0.556								
	(0.052)	(0.527)							$HJ-dist$	
C_4	1.084	-2.003	GMM_1	-0.390	-14.088	2.408	-0.486	0.850	0.788	0.504
	(0.055)	(0.520)		(0.401)	(6.691)	(1.731)	(1.23)			
C_5	0.959	-3.578	GMM_2	-0.097	-8.164	2.557	-0.336	0.892		0.377
	(0.075)	(0.931)		(0.317)	(4.375)	(1.744)	(1.24)			
	β_{GDR}	$\beta_{GSI_{W90}}$		b_{GDR}	$b_{GSI_{W90}}$	λ_{GDR}	$\lambda_{GSI_{W90}}$	R^2	$p-value$	$MAPE$
C_1	0.826	2.181							χ^2	
	(0.067)	(0.898)	FMB			2.404	-0.443	0.862		0.494
C_2	1.016	2.918				(2.186)	(0.172)		(0.839)	
	(0.100)	(1.020)				[2.174]	[0.161]		[0.810]	
C_3	1.067	0.984								
	(0.049)	(0.619)							$HJ-dist$	
C_4	1.100	-2.239	GMM_1	-0.376	-18.392	2.404	-0.443	0.862	0.788	0.494
	(0.052)	(0.738)		(0.378)	(7.964)	(1.826)	(0.156)			
C_5	0.991	-3.844	GMM_2	-0.098	-10.888	2.536	-0.301	0.783		0.513
	(0.076)	(1.074)		(0.278)	(5.138)	(1.780)	(0.114)			

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 position-unwinding risk (PUW) as the intercept (global) factor but differ in slope (country-specific) factor. The LFM in the top panel employs sovereign credit risk winsorized at 95% level ($HML_{SC_{W95}}$) and the LFM in the bottom panel adopts sovereign credit risk winsorized at 90% level ($HML_{SC_{W90}}$). 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 Pricing Error ($MAPE$) are also reported.

0.850 to 0.862. The quantitative changes are the estimates of risk exposures and factor prices of GSI, and the price of the factor estimated with it. Due to the winsorization, the variance of GSI becomes smaller, hence λ_{GSI} would naturally become smaller as well. The factor prices and loadings (b_{GSI}) remain statistically significant, -0.486% per annum when 5% of the extreme observations are excluded; -0.443% per annum when 10% of the extreme observations are excluded. So, the qualitative attributes of the sovereign credit risk story about the UIP puzzle do not change.

2.7.2 Beta-sorted Portfolios

Table 2.13 Currency Portfolios Sorted on Betas with HML_{SC}

All Countries without Transaction Costs							
Portfolios	L	LM	M	UM	H	Avg.	H/L
Mean (%)	1.71	2.15	2.26	3.24	4.07	2.69	2.36
Median (%)	2.91	4.73	4.53	4.91	7.48	5.38	3.51
Std.Dev. (%)	9.33	10.57	7.27	5.20	10.64	8.60	9.42
Skewness	-0.07	-0.26	-0.34	-0.25	-0.41	-0.27	-0.22
Kurtosis	0.03	0.26	0.35	0.15	0.49	0.26	0.60
Sharpe Ratio	0.18	0.20	0.31	0.62	0.38	0.34	0.25
$f-s$ (%)	-0.77	0.69	1.49	4.30	5.05	2.15	5.82

This table reports descriptive statistics of the excess returns of currency portfolios sorted on individual currencies' average β_{SC}, which are the risk exposures to HML_{SC} (sovereign credit factor), from September 2005 to January 2013. The rolling window of 60 months is chosen to obtain stable estimations of β_{SC} with very low volatility. The rank of individual currencies' risk exposures is relatively persistent to the sorting over the sample period, hence the portfolios do not need to be rebalanced during the whole sample period. The 20% currencies with the lowest β_{SC} 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_{SC}. 'Avg.', and 'H/L' denotes the average excess returns of five portfolios, and difference in the excess returns between Portfolio 'H' and the Portfolio 'L' respectively. All excess returns are monthly in USD with daily availability and adjusted for transaction costs (bid-ask spreads). The mean, median, standard deviation and higher moments 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.

We adopt 60-month rolling window for the estimation of betas which is commonly used for the studies in the field of stock markets because it always generates relatively stable parameter estimates. We do not need to dynamically rebalance our portfolios over the sample period as the rank of the factor exposures across currencies is quite stable in our data. Instead, we sort the currencies into portfolios according to their

Table 2.14 Currency Portfolios Doubly Sorted on Betas with HML_{SC} & PUW

All Countries without Transaction Costs											
β_{SC}	Bottom			Mezzanine			Top				
β_{PUW}	Low	Medium	High	Low	Medium	High	Low	Medium	High	Avg.	H/L
Mean (%)	0.99	1.42	2.18	1.81	2.57	3.68	2.91	2.79	5.13	2.61	4.14
Median (%)	2.69	3.31	6.74	2.21	4.76	6.97	4.90	7.17	8.18	5.21	6.45
Std.Dev. (%)	6.53	10.85	13.05	3.17	9.09	13.86	5.49	11.35	11.85	9.47	10.83
Skewness	-0.03	-0.05	-0.23	-0.13	-0.41	-0.27	-0.20	-0.32	-0.44	-0.23	-0.37
Kurtosis	0.07	0.10	0.18	0.12	0.50	0.25	0.09	0.29	0.57	0.24	0.39
Sharpe Ratio	0.15	0.13	0.17	0.57	0.28	0.27	0.53	0.25	0.43	0.31	0.38
$f - s$ (%)	-0.61	-0.22	0.46	2.32	2.39	3.96	2.06	3.95	5.95	2.24	6.57

This table reports descriptive statistics of the excess returns of currency portfolios sorted on both individual currencies' average β_{SC} and average β_{PUW}, which are the risk exposures to HML_{SC} (sovereign credit factor) and to PUW (position-unwinding likelihood indicator) respectively, from September 2005 to January 2013. The rolling window of 60 months is chosen to obtain stable estimations of β_{SC} and β_{PUW} with very low volatility. The rank of individual currencies' risk exposures is relatively persistent to the sorting over the sample period, hence the portfolios do not need to be rebalanced during the whole sample period. The portfolios are doubly sorted on bottom 30%, mezzanine 40%, and top 30% basis. 'Avg.' denotes the average excess returns of nine portfolios, and 'H/L' is difference in the excess returns between the portfolio that consists of the top 30% currencies in both β_{SC} and β_{PUW} and the portfolio that consists of the bottom 30% currencies in both β_{SC} and β_{PUW}. All excess returns are monthly in USD with daily availability and adjusted for transaction costs (bid-ask spreads). The mean, median, standard deviation and higher moments 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.

average betas. Table 2.13, Table 2.14 shows the descriptive statistics of the currency portfolios sorted on betas with HML_{SC}, and doubly sorted on betas with both HML_{SC} and PUW, respectively.

CHF and JPY are the currencies with the lowest and the third lowest exposure to sovereign credit risk, their average β_{SC} over the sample period are -0.794 and -0.658 respectively. These results are coherent with the findings by Ranaldo and Söderlind (2010) that CHF and JPY are characterized as safe-haven currencies because they have negative exposures to risky assets and appreciates when market risk increase. Intriguingly, JPY is also the currency with the lowest position-unwinding risk, it has a unique positive average β_{PUW} of 0.014, while all other currencies all have average negative β_{PUW}s. This implies a weak hedge position of JPY for global currencies against position-unwinding risk. CHF's average β_{PUW} is -0.145, a medium position-unwinding risk exposure among the currencies in the sample.

The countries with the highest exposures to HML_{SC} are "BRIC[30]", "MIST", and "CIVETS[31]" coined by Jim O'Neil in Goldman Sachs' "Global Economic Paper" series in order to differentiate them from a variety of emerging markets. The corresponding average β_{SC}s of these currencies are shown in the parentheses in descending order: COP (1.107), TRY (1.102), ZAR (0.931), MXN (0.801), INR (0.559), BRL (0.489), KRW (0.471), IDR (0.452). The next group contains the currencies of the countries from "EAGLEs'[32] Nest" members, e.g. PHP, PEN, MYR, ARS. Nordic currencies, such as SEK, NOK, and DKK, feature safe assets with respect to low negative β_{SC}. All these countries do not have a common level of exposures to the PUW. AUD and NZD, among the most popular carry trade currencies, are in the group of high position-unwinding risk. HKD with an average $\beta_{PUW} = -0.003$ seems to be isolated from the position-unwinding risk, as it is known pegged to USD, which provides additional supportive evidence that our position-unwinding likelihood indicator essentially substantiates the (global) dollar risk as a systematic risk.

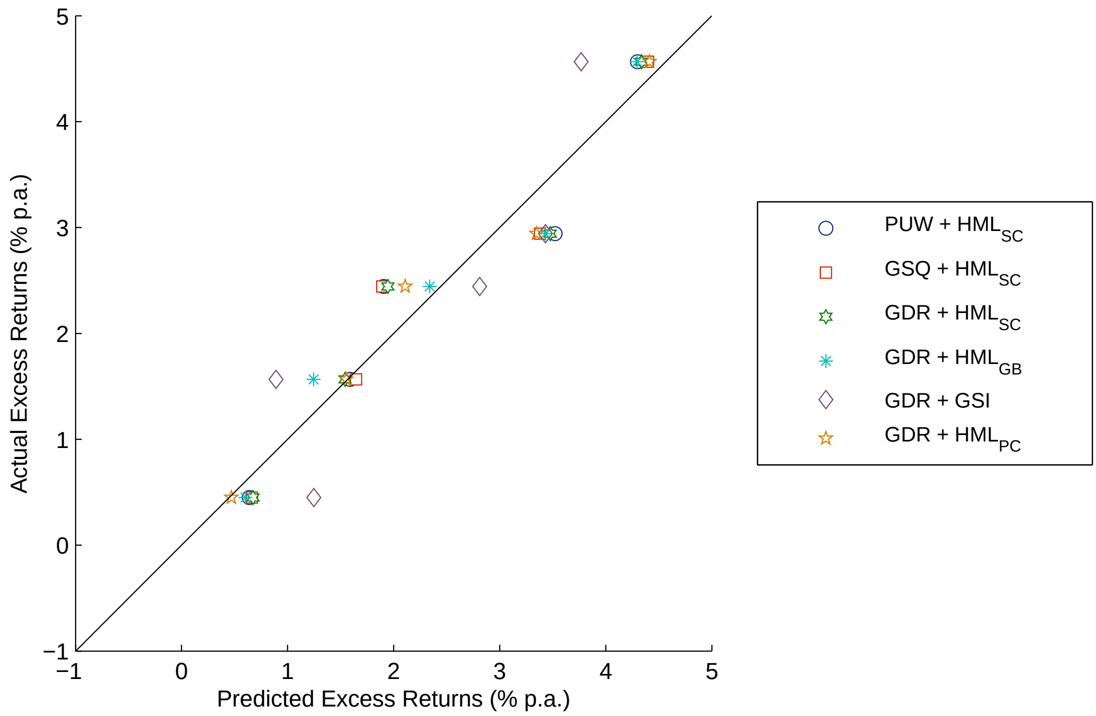
[30] Except for China which is excluded in our currency portfolio, and Russia which ranks medium in the exposure to sovereign credit risk.

[31] Except for Vietman and Egypt which are not included in our sample.

[32] EAGLEs is a grouping acronym created by BBVA Research in late 2010, standing for Emerging and Growth-leading Economies, whose expected contribution to the world economic growth in the next 10 years is greater than the average of the G6 advanced economies (G7 excluding U.S.).

Furthermore, the excess returns and forward discounts "$f - s$" increase monotonically with both β_{SC} and β_{PUW} dimensions across portfolios, which confirms that our beta-sorted portfolios reproduces the cross section of currency carry portfolios' excess returns. However, the skewness of our beta-sorted portfolios exhibit very similar, but not exactly the same, pattern of those sorted on forward discounts. Moreover, unlike the volatility of the currency carry portfolios, the portfolios sorted solely on β_{SC} does not show a monotonic pattern. These suggest that sorting currencies on β_{SC} alone is closely related to, but not utterly identical to the currency carry portfolios. Sorting currencies on both β_{SC} and β_{PUW} is much more close to the currency carry portfolios in terms of volatility and skewness patterns, because the position-unwinding risk drives volatility innovations in FX market. This reasonably suggests that forward bias risk reflects not only sovereign credit premia but also forward crash premia, as it is correlated with both level factor and slope factor[33].

Figure 2.5 Cross Sectional Goodness of Fit: Currency Carry Portfolios



This figure shows the cross-sectional predictive power of position-unwinding risk and sovereign credit risk on five currency carry portfolios. The excess returns are in percentage per annum.

[33]Figure 2.5. shows the cross-sectional fitness of five currency carry portfolios of six different models.

2.7.3 Currency Momentum and Volatility Risk Premium Portfolios

Besides global government bond market, we further look into global equity market. The equity momentum factor (see Jegadeesh and Titman, 1993, 2001) is given by the differences in the excess returns between the top 20% winner portfolio and the bottom 20% loser portfolio[34] (HML_{EM}). It would be interesting to check if equity momentum risk is also priced in currency carry portfolios as well. However, we cannot find any supportive evidence.

We further investigate another popular currency trading strategy - momentum - to check if its profitability is related to relevant explanations for the equity market version, e.g. 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); heterogeneous beliefs (Verardo, 2009); "Prospect Theory" and "Mental Accounting" (Grinblatt and Han, 2005). The existing literature generally concentrates on the time series of currency momentum. In contrast, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) focus instead on the cross section dimension and assert that it is the "Limits to Arbitrage" (Shleifer and Vishny, 1997) preventing this trading strategy from being easily exploitable in the currency market. 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[35] which are subject to illiquidity risk, and the difficulty in selling short can hinder the arbitrage activity as well. 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 top panel of Table 2.15 below reveals that sovereign credit risk (HML_{SC}) drives currency momentum over our sample period in which the investors have experienced Subprime Mortgage Crisis

[34] Please refer to Table A.2. for descriptive statistics of equity momentum portfolios.

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

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 default probability is low and loser currencies provide the hedge against this type of risk when sovereign default probability rises. 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% per annum (with an acceptable statistical significance) to the currency momentum investors. This model has a R^2 of 0.651 with a MAPE 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 this chapter and Huang and MacDonald (2013b).

We also investigate the currency volatility risk premium 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 contributes to the volatility risk premia. The bottom panel of Table 2.15 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 an insurance premia to protect their currency positions against sovereign credit risk implied in the currencies (see Huang and MacDonald, 2013b, for the interpretation of volatility risk premia). Higher sovereign default probability makes the downside risk of a currency more expensive to hedge. The price for this factor to this trading strategy is 5.198% per annum and statistically significant. The cross-sectional R^2 is 0.820 with a MAPE of approximately 55 bps. The χ^2 and $HJ - dist$ tests all indicate that the model is correctly specified.

Table 2.15 Asset Pricing of Currency Momentum & Volatility Risk Premium Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	$MAPE$
$P_{1,MMT}$	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				(2.160)	(5.234)		(0.727)	
	(0.143)	(0.078)				[2.174]	[5.686]		[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)		(0.161)	(1.681)	(1.390)	(5.709)			
$P_{5,MMT}$	0.885	-0.125	GMM_2	0.078	-4.253	2.074	-14.502	0.550		0.544
	(0.126)	(0.100)		(0.183)	(1.705)	(1.632)	(5.794)			
	β_{GDR}	β_{SC}		b_{GDR}	b_{SC}	λ_{GDR}	λ_{SC}	R^2	$p-value$	$MAPE$
$P_{1,VRP}$	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				(2.195)	(2.465)		(0.865)	
	(0.048)	(0.059)				[2.179]	[2.571]		[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)		(0.212)	(0.675)	(1.810)	(2.267)			
$P_{5,VRP}$	1.263	-0.188	GMM_2	0.271	1.579	1.3914	5.287	0.725		0.652
	(0.058)	(0.067)		(0.234)	(0.700)	(1.979)	(2.342)			

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 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 volatility risk premium portfolios (bottom panel) respectively (see Huang and MacDonald, 2013b), 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 Pricing Error ($MAPE$) are also reported.

2.8 Conclusion

In this chapter we argue that what we label sovereign credit condition is the dominant fundamental risk that drives the cross-sectional excess returns of currency carry trades. This conclusion is based on the striking and robust time-series and cross-sectional evidence presented here. The cross-sectional pricing power of sovereign credit does not reflect a "Peso problem" and it impulsively drives other country-specific risk, such as volatility and liquidity risk in both linear and nonlinear Granger causality tests. High interest-rate currencies load up positively on sovereign default risk while the low interest-rate currencies provide a hedge against it, which is consistent with the external valuation adjustment story of Gourinchas and Rey (2007). A country with high sovereign default risk displays a high propensity to issue debts denominated by foreign (safe) currencies to make them more appealing to investors, and inclines to offer a high interest rate to attract foreign savings for funding its external deficit. The destabilizing effect on the debtor's currency drives the currency risk premia. This is robust to alternative measure of sovereign default risk directly by government bonds. Currency risk premia does not disconnect from fundamentals given that sovereign bond risk premia contains substantial information about the macroeconomy (Ludvigson and Ng, 2009). The sovereign credit premia not only reflects a country's medium to long run fundamental risk, but also response to short-run rollover risk of maturing debt and liquidity constraint of a state. Interest rates imply a market liquidity premium component and a sovereign credit premium component, which should be taken into account for measuring the "effective" forward premia. Furthermore, we show that both the cross sections of currency portfolios sorted by momentum and position insurance costs can be understood from the perspective of sovereign credit risk as well. 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.

We also explain a "self-fulfilling" nature of currency carry trades according to the analysis of position-unwinding risk. In the Black-Scholes-Merton universe, the cross-sectional variation of currency risk premia is naturally driven by interest rate differential and currency volatility, and the construction of position-unwinding likelihood indicator implies empirical asset pricing results of Lustig, Roussanov, and Verdelhan (2011); Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). Its factor-mimicking portfolio confirms that position-unwinding risk is an arbitrage-free traded asset. It is fed by the forward bias risk in both linear and nonlinear Granger causality tests, in which complicated global contagion channels are highlighted. The position-unwinding likelihood indicator is also consistent with the liquidity spiral story of Brunnermeier, Nagel, and Pedersen (2009) as it measures the currency crash risk in terms of high correlation with the global skewness factor. We show high interest-rate currencies are exposed to higher position-unwinding (crash) risk than low interest-rate currencies, owing to the global liquidity transfer brought by carry trades themselves. Once the risk-bearing capacity (e.g. funding liquidity constraint) of the financial intermediaries is unable to sustain the "global liquidity imbalance", the global liquidity reversal/withdrawal triggers currency crashes (Gabaix and Maggiori, 2015). Accordingly, we propose a threshold carry trade strategy that is immunized from currency crash risk and earns a much higher annualized excess return than the plain vanilla one. Our threshold carry trades is a risk-managed strategy, and increases the Sharpe ratio substantially (approximately twice as big as its original version). It works because of the crash timing capacity of the position-unwinding likelihood indicator. However, this presents a new challenge to theories that attempt to explain currency carry trade excess returns.

Chapter 3

Global Currency Misalignments, Crash Sensitivity, and Moment Risk Premia

3.1 Introduction

Meese and Rogoff (1983) highlight that it is difficult to find a theoretically-grounded factor that can beat a 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. The recent exchange rate literature emphasizes that the apparent disconnection of exchange rates from macro fundamentals 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 (2013) 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 (2013a) apply the decomposition of the covariance between the excess returns of an asset and corresponding pricing kernel, originally broached by Hassan (2013), to building macro-based currency portfolios, and find that economic fundamentals have substantial predictive power on exchange rates in the cross-sectional dimension. Currency risk premia are the compensations for dynamic business cycle risk.

Huang and MacDonald (2013a) show that the excess returns of currency carry trades can be understood using sovereign credit premia and their results are robust to alternative measures of innovations in global sovereign CDS spreads and sovereign default risk implied in government bonds. However, this is not the full story. Because the 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 currency risk premia, because other factors such as productivity shocks, changes in the terms of trade, etc. are also of paramount importance for exchange rate determination and risk premia (MacDonald, 2005). The deviation from the equilibrium exchange rates determined by the macroeconomic fundamentals is an important predictor of exchange rates but has been omitted in the recent influential studies (Jordà and Taylor, 2012). Therefore, it is not unreasonable to conjecture that currency risk premia originate from such misalignments, as equilibrium exchange rates are the composite indicators of the competitiveness of the states and exchange rate misalignments reflect the sustainability of the economic growth. We find currency misalignment risk explains over 97% of the cross-sectional excess returns of carry trades. 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[1] (see Engel, Mark, and West, 2007, for specification) individually. Engel (2011) modifies Clarida, Galí, and Gertler's (2002) model to allow for currency misalignment and emphasize an optimal monetary policy trade-off should be made not only between Taylor rule fundamentals (inflation and output gap) but also involve the exchange rate misalignment. We contribute to this literature by showing that exchange rate misalignment is the composite fundamental source of currency risk premia and explains well both time series and cross section of the profitability of

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

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 exposure). Given a certain macroeconomic fundamental and policy environment, global currency misalignments is unsustainable beyond a threshold level, identifying the misalignment bound is conducive to timing the risk reversals in the rare but extreme events of currency crashes.

Recently, the concept of 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; Gourio, Siemer, and Verdelhan, 2013) and this suggests that the 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 crash risk. Given 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 an 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.

In this chapter we employ copula methods to capture crash sensitivity in terms of tail dependence and use model-free approach to measure the moment risk premia (volatility risk premia as the proxy for downside insurance costs), as we are considering that crash risk cannot solely explain 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.

We find that skew risk premia as the proxy for crash risk premia associated with speculative activities explain 96% of the cross section of currency carry trade excess returns as well as the misalignment risk. Skew risk premia measure the expected changes in probability for the Uncovered Interest Rate Parity (UIP) to hold so that they contain ex-ante information about future carry trade gains (losses) that lead to an increase (decrease) in speculative positions. Exchange rate misalignment is driven by skew/speculative risk premia but the reverse is not true. 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 in both dimensions — 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 a large set of risk factors[2]. Unlike currency carry trades, the profit of risk reversal trade-off strategy is not simply driven by interest rate differentials but

[2]It includes, for instance, canonical currency and stock market 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).

also exchange rate returns. So, it works a currency selection procedure that picks high interest-rate (low) currencies which are going to appreciate (depreciate) out of a basket of currencies.

From the asset allocation perspective, a crash-averse investor would optimally allocate over 40% of the wealth to the currency-misalignment portfolio over the sample period, about 40% to the crash-sensitive portfolio and about 10% to skew risk premium strategy in the tranquil period and be better-off by dramatically reallocating his/her portfolio holdings to downside-insurance-cost strategy with a weight of over 60% during the financial turmoil. This behavior is related to the risk-bearing capacity of the financial intermediaries (Gabaix and Maggiori, 2015) during the financial distress, for instance, market risk sentiment and funding liquidity constraint. Trading strategies that exploit REER misalignment, crash sensitivity, and moment risk premia these three properties of currencies also provide remarkable diversification benefits for risk management purpose in terms of considerable reductions in conditional value-at-risk (expected shortfall) of the efficient frontiers.

We further extract the coincidence indices of over 30 individual currencies and 7 currency investment strategies studied in our paper by Forni, Hallin, Lippi, and Reichlin's (2005) one-sided method for the estimates of Generalized Dynamic Factor Model (GDFM) to examine their risk attributes and factor structure in FX market, and find that sovereign default risk measured by the innovations in global sovereign CDS spreads is the key driver to three factors that capture the common dynamics[3] in FX market. We identify an additional[4] important factor that accounts for extra 14% of the cross-sectional variation in global currencies. However, it is omitted in the literature using the standard portfolio approach. It is not only related to the payoff of currency volatility risk premium (as the proxy for position insurance cost) strategy but also priced in the cross section of currency value portfolios (explaining over 90% of the variations). But a large proportion of its risk sources is still a mystery. According to the properties of the factors extracted by GDFM, we can also categorize the FX

[3]They explain over 90% of the total variations in the variables.

[4]The first two factors are essentially the global dollar risk (GDR) and country-specific forward bias (HML_{FB}) risk of Lustig, Roussanov, and Verdelhan (2011) respectively.

trading strategies into three groups[5], which exhibit great economic values for hedging purposes.

To the best of our knowledge, this is the first empirical asset pricing work that studies global currency misalignments, crash sensitivity captured by the copula method, skew risk premia measured by a model-free approach, also the risk attributes and factor structure of the cross section of individual currencies. The rest of this chapter is organized as follows: Section 3.2 introduces the ideas and two standard approaches (FEER and BEER) for computing exchange rate misalignments. Section 3.3 describes the copula methods and measure of crash sensitivity by tail dependence. Section 3.4 shows the evaluation of downside insurance costs via moment risk premia, and compare the model-free (swap) method with option-implied method. Section 3.5 contains the information about the data set used in this chapter, construction of currency trading strategies by portfolio approach, preliminary analyses of (i) optimal asset allocations in currency investment, (ii) monotonicity tests for portfolio excess returns and risk exposures, and (iii) the risk reversal trade-off in business cycles. In Section 3.6, we demonstrate the standard empirical asset pricing procedures and generalized dynamic factor model estimates, and discuss our empirical results. The conclusion is drawn in Section 3.7. Appendix .B contains the supplementary materials.

3.2 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)

[5] Currency carry trade, misalignment, and skew risk premium strategies in the first group, while the strategies trading on currency values, crash sensitivities, and position insurance costs in the second group; Currency momentum is solo in the third group.

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.

3.2.1 Equilibrium Exchange Rate Determinations

Williamson (1983) first proposes the idea of a FEER in which 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 the 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 exchange rates are volatile and unpredictable (see Frankel and Rose, 1995; Kilian and Taylor, 2003) and the relationship between exchange rates and macroeconomic fundamentals seems to evolve over time (Sarno and Valente, 2009).

Clark and MacDonald (1998) propose the BEER as an alternative way to assess equilibrium 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:

$$\mathbb{E}_t[REER_{t+T}] = REER_t + (\mathbb{E}_t[\tilde{r}_t] - \mathbb{E}_t[\tilde{r}^*_t]) + \lambda_t \tag{3.1}$$

where $\mathbb{E}_t[\,\cdot\,]$ is the expectation operator. $\tilde{r}_t$, $\tilde{r}^*_t$ 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 (3.1) can rearranged as:

$$REER_t = \mathbb{E}_t[Z^L_{t+T}] - (\mathbb{E}_t[\tilde{r}_t] - \mathbb{E}_t[\tilde{r}^*_t]) - \lambda_t \tag{3.2}$$

Given that λ_t is time-varying, Equation (3.2) can be simplified by the imposition of rational expectations:

$$REER_t = Z^L_t - (\tilde{r}_t - \tilde{r}^*_t) \tag{3.3}$$

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.

$$REER_t = REER_t\left(Z^L_t, Z^M_t, Z^S_t\right) \tag{3.4}$$

Égert, Halpern, and MacDonald (2006), MacDonald and Dias (2007) identify a standard set of variables for the estimation of equilibrium exchange rates, including real interest rates, real GDP per capita[6], terms of trade, Net Foreign Asset (NFA) as the pecentage of GDP[7], export plus import as the percentage of GDP as the proxy for economic openness[8], government expenditures as the pecentage of GDP as the proxy for risk premium.

3.2.2 Reduced-Form Estimations

To estimate the relationships between the REER and relevant variables in Equation (3.4) is tantamount to estimate a reduced-form model:

[6] It measures the total factor productivity, while CPI-to-PPI ratio is the proxy for Balassa-Samuelson effect.

[7] We adopt trade balances instead (see Lane and Milesi-Ferretti, 2007), as the coefficient estimates on the NFA are often inaccurate.

[8] We also take the financial openness into account (see Chinn and Ito, 2006).

Table 3.1 Global Real Effective Exchange Rate Misalignments, Crash Sensitivity, and Moment Risk Premia

FX	ERM (%)	LTD	UTD	VRP (%)	SRP	FX	ERM (%)	LTD	UTD	VRP (%)	SRP
JPY	9.12	0.05	0.01	-1.26	0.49	EUR	4.11	0.63	0.60	-1.10	-0.29
KRW	15.83	0.12	0.20	-2.41	-0.80	GBP	5.07	0.35	0.28	-0.53	-0.38
HKD	23.01	0.03	0.08	-0.55	1.84	AUD	-5.55	0.46	0.41	0.10	-0.56
TWD	12.48	0.14	0.18	-2.05	-0.18	NZD	-9.60	0.43	0.35	-0.08	-0.58
SGD	22.42	0.46	0.51	-1.07	-0.26	CAD	0.58	0.37	0.33	-0.45	-0.31
MYR	23.17	0.16	0.23	N/A	N/A	CHF	7.61	0.33	0.25	-0.45	-0.01
THB	10.74	0.10	0.13	-2.20	-0.35	SEK	13.92	0.60	0.58	-0.38	-0.31
PHP	6.86	0.09	0.21	N/A	N/A	DKK	10.50	0.63	0.60	-1.21	-0.27
IDR	11.05	0.09	0.17	N/A	N/A	NOK	7.23	0.62	0.61	-0.17	-0.29
INR	5.65	0.15	0.24	-2.34	-0.70	ZAR	0.97	0.36	0.43	-2.02	-0.87
RUB	5.02	0.45	0.49	-2.42	-0.81	BRL	-0.12	0.31	0.40	-2.80	-1.19
PLN	2.37	0.62	0.65	-1.50	-0.66	CLP	1.84	0.21	0.23	-2.89	- 0.93
RON	6.90	0.56	0.58	N/A	N/A	COP	0.13	0.22	0.17	-4.08	-0.81
HUF	1.87	0.64	0.60	-0.86	-0.87	ARS	4.11	0.00	0.01	N/A	N/A
CZK	3.52	0.54	0.55	-1.02	-0.43	PEN	3.28	0.10	0.09	N/A	N/A
SKK	2.84	0.61	0.59	-0.45	-0.27	MXN	1.36	0.25	0.31	-2.93	-1.03
TRY	-6.31	0.32	0.41	-2.28	-1.13	ILS	5.75	0.27	0.28	N/A	N/A

This table reports the average REER misalignments (ERM), average Lower Tail Dependences (LTD) at 10% quantile and average Upper Tail Dependences (UTD) at 90% quantile of 34 currencies, as well as average downside insurance costs measured by volatility (VRP) and skew (SRP) risk premia of 27 currencies using model-free approach. A positive (negative) value means that the currency needs to appreciate (depreciate) against USD to reach its equilibrium REER. The sample period is from September 2005 to January 2013.

$$REER_t = \beta_L Z_t^L + \beta_M Z_t^M + \beta_S Z_t^S + \varepsilon_t \tag{3.5}$$

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 (3.5) from the observed REER. Then the current misalignment (CM_t) of REER can be computed as:

$$CM_t = REER_t - \beta_L Z_t^L - \beta_M Z_t^M = \beta_S Z_t^S + \varepsilon_t \tag{3.6}$$

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

$$\begin{aligned} TM_t &= REER_t - \beta_L \bar{Z}_t^L - \beta_M \bar{Z}_t^M \\ &= CM_t + [\beta_L(Z_t^L - \bar{Z}_t^L) + \beta_M(Z_t^M - \bar{Z}_t^M)] \end{aligned} \tag{3.7}$$

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-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.

We calculate the current and total misalignments of 34 global currencies in our sample individually using the ragged quarterly and annual data from 1984 to 2012, and standard econometric procedures for vector cointegration and error correction models, such as unit-root test, optimal lag selection according to information criteria, Johansen (1995) rank tests (both trace and maximum eigenvalue), and stability tests (Hansen, 1992; Quintos, 1998) for cointegration relations. 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 the REER introduced in the estimations,

Table 3.2 Descriptive Statistics of Currency Portfolios (Carry & Misalignment)

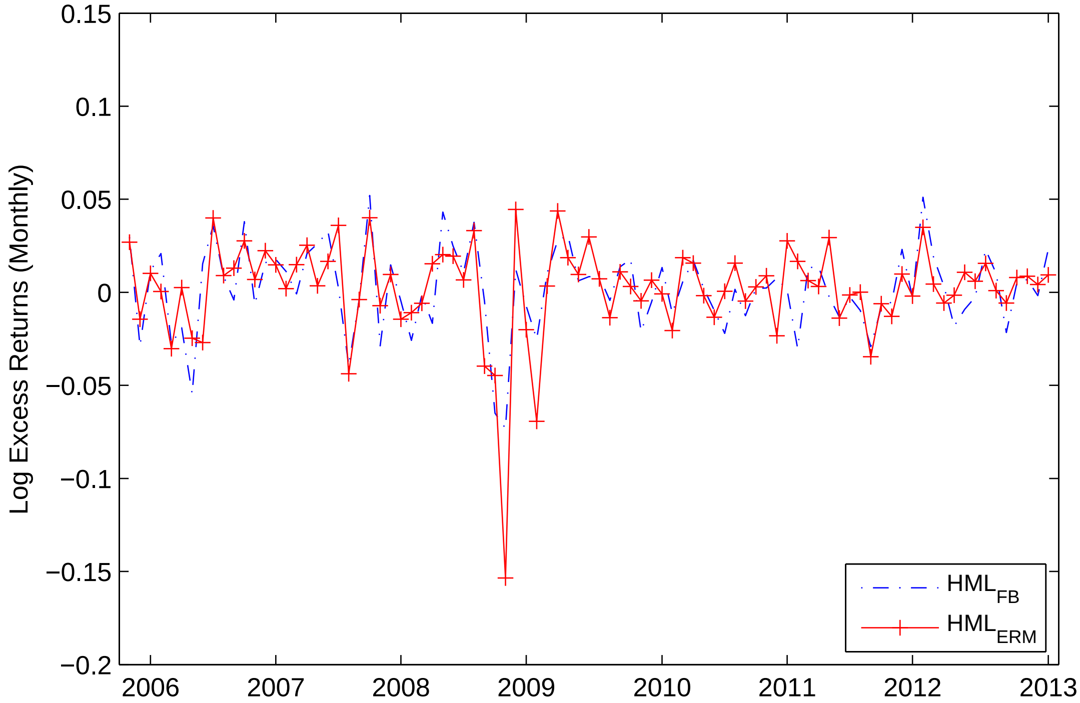
All Countries with Bid-Ask Spreads					
Portfolios	$P_{1,CRT}$	$P_{2,CRT}$	$P_{3,CRT}$	$P_{4,CRT}$	$P_{5,CRT}$
Mean (%)	0.45	1.57	2.44	2.94	4.57
Median (%)	3.67	3.71	6.02	8.34	11.17
Std.Dev. (%)	7.41	8.56	9.31	10.61	10.71
Skewness	-0.16	-0.26	-0.56	-0.53	-0.51
Kurtosis	0.18	0.21	0.82	0.62	0.57
Sharpe 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.

they inevitably exist. However, we harness the REER misalignments 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 3.1 above indicates the average REER misalignments of 34 global currencies over the sample period using both approaches. Overall, the majority of currencies are underpriced against USD except for AUD, NZD, and TRY that are significantly overvalued. This is consistent with the fact that investment in the global money market outside U.S. funded by USD yields an excess return about 2.39% in our the sample period.

We sort the currencies into five portfolios based on their interest rate differentials (forward discounts), and estimated average REER misalignments of FEER and BEER

Figure 3.1 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.

approaches, respectively. Table 3.2 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.

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 3.1. 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 decomposing 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 the REER misalignment strategy exhibits similar behavior to carry trades. If HML_{ERM} as a priced risk factor explains the cross section of carry trade excess returns, the forward premium puzzle may be understood by an investigation of the mechanisms that cause high interest-rate currencies to be overpriced (in terms of the deviations from the medium to long run equilibrium relationships among the real fundamentals) in good times and to be 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.

3.3 Crash Sensitivity

In this section, we briefly explain why we choose copula methods to measure the crash sensitivity (at a certain quantile) of a currency in terms of joint distribution with the global market and show how they can capture the asymmetries in upper and lower tail dependence. Preliminary analysis of individual currency's tail sensitivity is provided.

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). Li and Yang's (2013) theoretical model shows that the diminishing sensitivity[9] can be attributed to both disposition and momentum effects. 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

[9]It refers to the asymmetric value function of investors in the gain domain (concave) and loss domain (convex).

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 dynamics 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 semiparametric 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 are consistent with those from parametric and semiparametric methods in general.

3.3.1 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 merging 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:

$$F(x_1, ..., x_n) = C\left(F_1(x_1), ..., F_n(x_n)\right),\ \forall\ x_n \in \mathbb{R}^n \tag{3.8}$$

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:

$$C(u_1, ..., u_n) = F\left(F_1^{-1}(u_1), ..., F_n^{-1}(u_n)\right) \tag{3.9}$$

where F_n^{-1} denotes the generalized inverse distribution function of the univariate distribution function F_n, $F^{-1}(u) = \inf\{x : F(x) \geq u\}$, 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 get:

$$\begin{aligned}
\Pr\left(X_1 \leq x_1, ..., X_n \leq x_n\right) &= \Pr\left(F_1^{-1}(U_1) \leq x_1, ..., F_n^{-1}(U_n) \leq x_n\right) \\
&= \Pr\left(U_1 \leq F_1(x_1), ..., U_n \leq F_n(x_n)\right) \\
&= C\left(F_1(x_1), ..., F_n(x_n)\right)
\end{aligned} \tag{3.10}$$

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

$$f(x_1, ..., x_n) = c\left(F_1(x_1), ..., F_n(x_n)\right) \times \prod_{i=1}^{n} f_i(x_i) \tag{3.11}$$

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

3.3.2 Tail Dependence

The coefficient of tail dependence measures the pairwise degree of dependence in the tail of a bivariate or multivariate 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:

$$
\begin{aligned}
LTD: &= LTD\,(X_1, X_2) = \lim_{q \to 0^+} \Pr\left(X_2 \le F_2^{-1}(q) | X_1 \le F_1^{-1}(q)\right) &(3.12)\\
UTD: &= UTD\,(X_1, X_2) = \lim_{q \to 1^-} \Pr\left(X_2 > F_2^{-1}(q) | X_1 > F_1^{-1}(q)\right) &(3.13)
\end{aligned}
$$

where q is the quantile. Using Equation (3.10) and condition probability function, the LTD coefficient can be computed as:

$$
LTD = \lim_{q \to 0^+} \frac{\Pr\left(X_2 \le F_2^{-1}(q), X_1 \le F_1^{-1}(q)\right)}{\Pr\left(X_1 \le F_1^{-1}(q)\right)} = \lim_{q \to 0^+} \frac{C(q,q)}{q} \tag{3.14}
$$

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

$$
UTD = \lim_{q \to 1^-} \frac{\Pr\left(X_2 > F_2^{-1}(q), X_1 > F_1^{-1}(q)\right)}{\Pr\left(X_1 > F_1^{-1}(q)\right)} = \lim_{q \to 1^-} \frac{1 - 2q + C(q,q)}{1-q} \tag{3.15}
$$

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. 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.

The average lower and upper tail dependences of 34 currencies[10] over the sample period are provided in Table 3.1 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 extreme downside risk of currency market by the AR(2) innovations to the equally-weighted averaging of lower tail dependence (GTD). We check if the shock series as an indicator for global tail risk (GTI) is priced and captures additional information in the time series and cross section of currency carry trade excess returns[11].

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

[11] GTD suddenly increased dramatically in September 2008 (Lehman Brothers' bankruptcy and the outbreak of the Subprime Mortgage Crisis), and keep increasing during the Sovereign Debt Crisis in Europe (See Figure B.1. in Appendix .B.)

3.4 Downside Insurance Costs and Speculative Positions

In this section, we briefly explain why moment risk premium can be the proxy for downside insurance cost for crash-averse investors, and show how they can be derived from the option prices by the model-free approach. A detailed discussion of the linkage between skew risk premium and UIP, as well as some findings with regard to individual currency's moment risk premia are also given here.

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.

3.4.1 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 $MS_{t,T}$:

$$MP_{t,T} = RM_{t,T} - MS_{t,T} \tag{3.16}$$

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:

$$MS_{t,T} = \mathbb{E}_t^{\mathbb{Q}}[RM_{t,T}] \tag{3.17}$$

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.

3.4.2 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 valuation of the second (variance), third (skewness), and fourth (kurtosis) model-free moments for a currency pair[12] is respectively given by:

$$\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}] = \frac{2B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{1}{K^2} C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}} \frac{1}{K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{3.18}$$

$$\mathbb{E}_t^{\mathbb{Q}}[RS_{t,T}] = \frac{6B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{K - F_{t,T}}{F_{t,T}K^2} C_{t,T}(K)\mathrm{d}K - \int_0^{F_{t,T}} \frac{F_{t,T} - K}{F_{t,T}K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{3.19}$$

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

$$\mathbb{E}_t^{\mathbb{Q}}[RK_{t,T}] = \frac{12B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{(K-F_{t,T})^2}{F_{t,T}^2 K^2} C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}} \frac{(K-F_{t,T})^2}{F_{t,T}^2 K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{3.20}$$

where $B_{t,T} = \exp\left[-(r_t - r_t^*)T\right]$, 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_t and foreign risk-free rate r_t^*. $P_{t,T}$, $C_{t,T}$ 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 (3.18) and Equation (3.19). Although this introduces truncation and discretization errors, both of them are shown trivial in a similar method of trapezodial integration (Jiang and Tian, 2005). We focus on volatility and skew risk premia in this chapter.

3.4.3 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:

$$MRP_{t,T} = \mathbb{E}_t^{\mathbb{P}}[RM_{t,T}] - \mathbb{E}_t^{\mathbb{Q}}[RM_{t,T}] \tag{3.21}$$

where $\mathbb{E}_t^{\mathbb{P}}[\,\cdot\,]$ is the conditional expectation operator under physical measure $\mathbb{P}$. We follow Bollerslev, Tauchen, and Zhou (2009) to adopt the lagged realized volatility, and use the calculations of realized moments as in Huang and MacDonald (2013a). 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 (3.21) 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)[13], 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[14].

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

[13]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: $\tilde{\kappa}_{10\Delta} \approx 14.6130 \cdot BF_{10\Delta} \,/\, IV_{ATM}$, $\tilde{\kappa}_{25\Delta} \approx 52.7546 \cdot BF_{25\Delta} \,/\, IV_{ATM}$.

[14]See Figure B.2. and Figure B.3. in Appendix .B.

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.

Both realized and risk-neutral skewness move in the opposite direction in response to the exchange rate returns (Jurek, 2007). The risk-neutral skew is negatively correlated with interest rate differentials and predicts lower future realized skew (Brunnermeier, Nagel, and Pedersen, 2009). UIP states that USD tends to appreciate against foreign currencies when $r_t^* > r_t$, implying a significant negative skew of exchange rate returns. 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, and vice versa. In the case of positive skew implied by UIP when $r_t^* < r_t$, 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 (lower probability of UIP to hold), and hence lower (crash) risk premium of a foreign currency against USD, and vice versa. Thus, skew risk premia provide ex-ante information about future carry trade gains (losses) that lead to an increase (decrease) in speculative positions. The strategy of investing in low (negative) speculative-risk-premium currencies funded by high (positive) speculative-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. Again, we need to decompose the cumulative excess return (Della Corte, Ramadorai, and Sarno, 2013) to check if the skew risk premium strategy shares the common constituent drivers of cumulative wealth with carry trades.

The average volatility and skew risk premia of 27 currencies[15] over the sample period

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

are provided in Table 3.1. We can see that on average the VRP of the investment currency AUD is positive, implying that it is 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 skew risk premia, BRL, TRY, and MXN are among the lowest SRP (highest crash risk) currencies while HKD, and two safe-haven currencies CHF and JPY (also a funding currency) are those with the highest SRP.

3.5 Data and Preliminary Analyses

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 (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), KRW (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)[16] and Lane and Milesi-Ferretti (2007)[17], for real effective exchange rates, real GDP per capita,

[16]See the link `http://web.pdx.edu/~ito/Chinn-Ito_website.htm`.
[17]See the link `http://www.philiplane.org/EWN.html`.

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[18], government consumption as the percentage of GDP, NFA as the percentage of GDP, capital liberalization index, respectively. Please note that 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)[19], Asness, Frazzini, and Pedersen (2013) and Frazzini and Pedersen (2014)[20], Fung and Hsieh (2001)[21], and Baker, Bloom, and Davis (2012)[22], respectively. Our sample period is restricted by the availability of option historical data from the database terminals we can access[23]. 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.

3.5.1 Currency Investment Strategies and Asset Allocations

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

[18]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. Neither does Deutsche Bank have the data for TWD. We also exclude ARS since World Bank does not provide the data after 2006.

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

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

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

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

[23]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.

Table 3.3 Descriptive Statistics & Correlation Matrix of FX Trading Strategies

	All Countries with Bid-Ask Spreads							
TS	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
CRT	1.00							
FBM	**0.72**	1.00						
MMT	-0.21	-0.22	1.00					
PPV	0.13	-0.35	0.03	1.00				
MCS	0.15	**0.57**	-0.08	**-0.81**	1.00			
VRP	0.09	-0.29	0.08	**0.62**	**-0.57**	1.00		
SRP	**0.77**	**0.68**	-0.31	0.02	0.28	-0.08	1.00	
DS	**0.54**	0.31	-0.07	0.09	0.20	0.34	**0.53**	1.00

This table reports descriptive statistics of the transaction-cost adjusted (bid-ask spreads) annualized excess returns in USD of 8 FX 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.

forward contract according to the updated sorting base[24]. 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: $xr^L_{t+1} = r^*_t - r_t + s^B_t - s^A_{t+1} = f^B_t - s^A_{t+1}$, where f, s is the log forward rate, and spot rate, respectively; Superscript B, A denotes bid price, and ask price respectively. Similarly, for short position of P_1 (P_0)[25], the log

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

[25]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.

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[26]

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 3.3, 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 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[27] 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 8 currency investment 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[28] and lends supportive evidence that both crash sensitivity and downside insurance cost are vital to understand the currency risk premia.

Figure 3.2. presents the decomposition of the cumulative excess returns to the 8 currency investment 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 payoff components of

[26] 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.

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

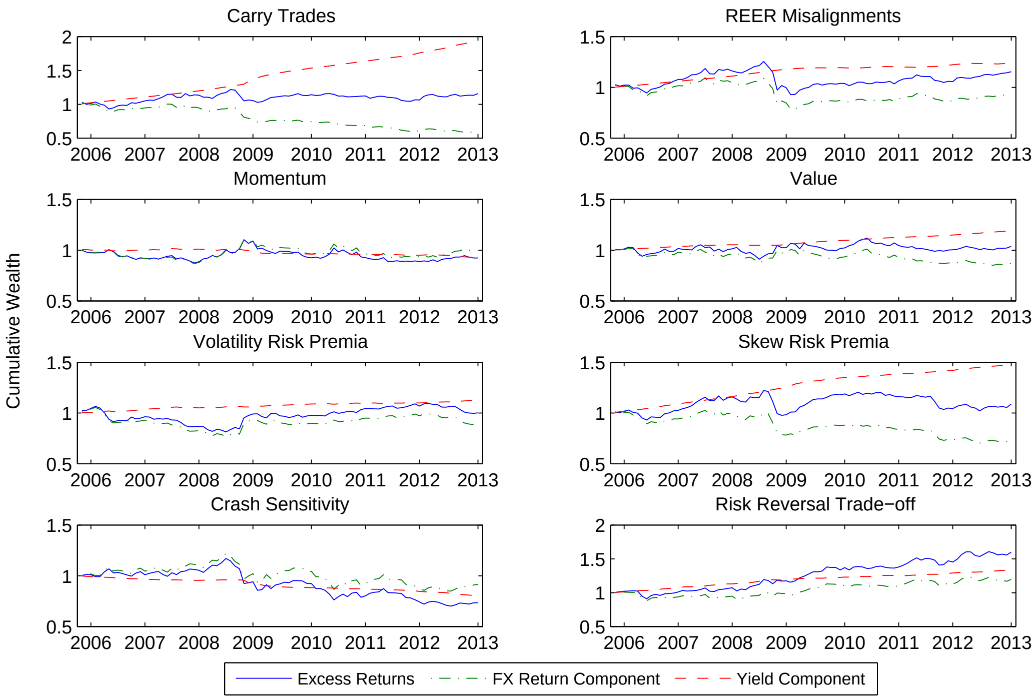
[28] See also in Figure 3.6.

Table 3.4 Systematic Risks of FX Trading Strategies

	All Countries with Bid-Ask Spreads							
TS	CRT	FBM	MMT	PPV	MCS	VRP	SRP	DS
GSI	-2.92***	-4.82***	2.92***	1.82**	-4.20***	2.33*	-3.87***	-0.40
	(0.38)	(0.42)	(0.30)	(0.71)	(0.46)	(1.22)	(0.43)	(1.27)
$Adj-R^2$	0.25	0.53	0.23	0.10	0.28	0.15	0.38	**-0.01**
GVI	-12.64***	-16.99***	11.00***	6.34**	-14.06***	8.01*	-14.80***	-3.69
	(1.79)	(3.45)	(2.06)	(3.13)	(3.37)	(4.61)	(2.28)	(4.56)
$Adj-R^2$	0.32	0.44	0.22	**0.08**	0.21	0.12	0.35	**0.01**
GSQ	-0.07***	-0.12***	0.03	0.08***	-0.19***	0.04	-0.10***	-0.09***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
$Adj-R^2$	0.12	0.29	**0.01**	0.15	0.49	**0.04**	0.19	0.18
PUW	-0.07***	-0.09***	0.02	0.04*	-0.12***	0.01	-0.04***	-0.07***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Adj-R^2$	0.22	0.25	**0.01**	**0.05**	0.35	**-0.00**	0.24	0.20

This table reports the time-series asset pricing tests that investigate the systematic risks of the FX trading strategies. We select four typical foreign exchange market-based non-return factors. GSI, PUW, GVI, and GSQ denotes the factor proxy for global sovereign risk, carry trade position-unwinding risk, global volatility risk and crash risk, respectively (see Huang and MacDonald, 2013a, for details). GVI represents the global volatility risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a) 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. The risk factor that is statistically insignificant or has a weak explanatory power in variation (in terms of $Adj-R^2$ less than 10%) is highlighted.

Figure 3.2 Decomposition of Cumulative Wealth to FX Trading Strategies



This figure shows the decompositions of the cumulative transaction-cost adjusted wealth (excess return) to the 8 FX trading strategies into exchange rate (transaction-cost adjusted) return and yield (interest rate differential) components. The sample period is from September 2005 to January 2013.

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, not the yield component. As for the cumulative wealth of the currency value and volatility risk premium 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 is nearly unrelated to crash sensitivity before the crisis but exerts a negative impact on the cumulative wealth after the crisis owing to the fact that currencies of the countries involved in the crisis are highly crash sensitive and the central banks adopt loose credit and easy monetary policies such as low interest rates. This differentiates it 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.

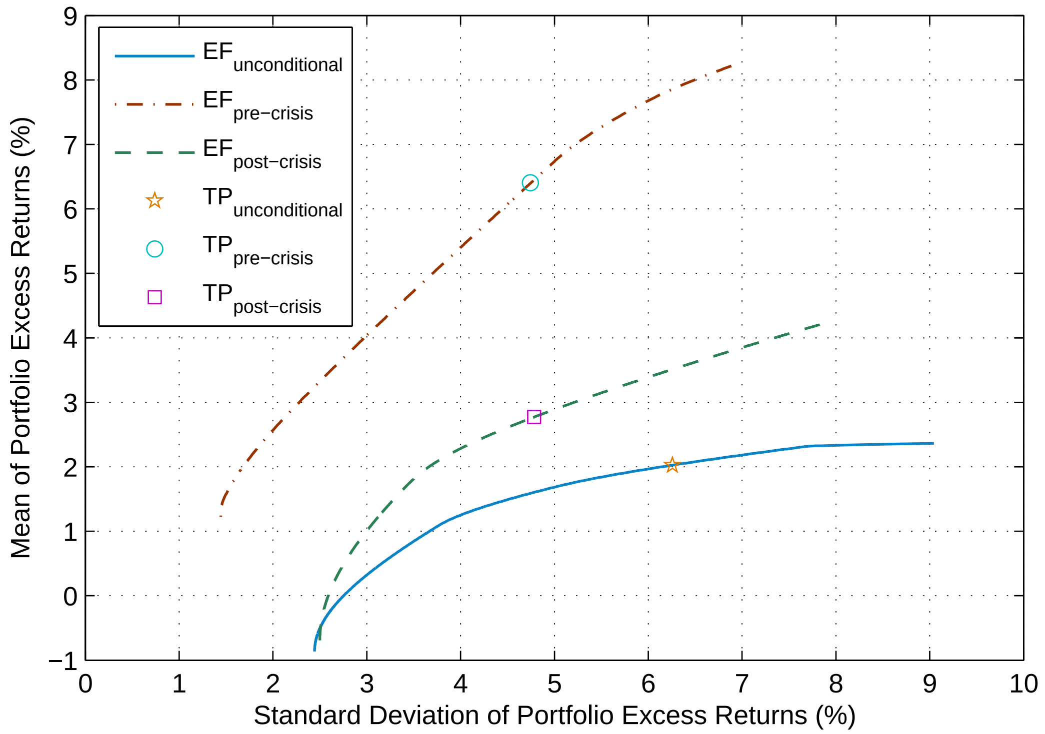
Table 3.4 presents the systematic risks of 8 currency investment strategies. We select four typical FX market-based non-return factors. Currency carry, misalignment, and skew risk premium portfolios all trade on the position-unwinding likelihood indicator (PUW) that explores the probability of the UIP to hold using the option pricing model, and global crash (skewness) risk (GSQ) as in (Huang and MacDonald, 2013a). This conforms with the results of empirical asset pricing exercises in the next section. We also find that both currency momentum and downside-insurance-cost strategies are not related to PUW, nor GSQ. Coherently, crash-sensitivity strategy has the largest proportion of variation among others explained by PUW and GSQ. Both global sovereign (GSI) risk (see Huang and MacDonald, 2013a, for details) and volatility (GVI) risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a) factors cannot explain our risk reversal trade-off strategy (see the following sub-section). GSI has comparable statistical significance to GVI but stronger pricing power on explaining the variation of the currency investment strategies except for carry trade.

To emphasize the importance of REER misalignment, crash sensitivity, and moment risk premia in understanding the currency risk premia, we look into the economic significance of the corresponding currency investment strategies via mean-variance/CVaR asset allocations. Optimal risky portfolio with regime shifts as the combination of various asset classes or trading strategies reflects a representative investor's choice on the asset allocation in high and low volatility regimes. Ang and Bekaert (2002) show that the time-varying investment opportunity set does not impair diversification benefits, and we find considerably distinctive asset allocation implications in pre-crisis and post-crisis periods in the foreign exchange market. We use the mean-variance optimization approach to get the optimal risky portfolio weights among the monthly-rebalancing currency investment strategies with a closed form solution. The agent maximizes the utility function given by:

$$\max_{\omega} \left\{ \mathbb{E}[\mu_{p,t+1}] - \frac{\gamma}{2}\sigma^2_{p,t+1} \right\} \tag{3.22}$$

where $\mathbb{E}[\mu_{p,t+1}]$ is the expected portfolio excess return of the combination of currency investment strategies, $\sigma_{p,t+1}$ denotes the volatility of the portfolio, and γ measures the risk aversion of the investor. The vector of optimal weights $\omega = \frac{1}{\gamma}\Sigma_{xr,xr}^{-1}\mathbb{E}[xr]$, where $\mathbb{E}[xr]$, $\Sigma_{xr,xr}$ is the expected excess return vector, and covariance matrix of currency investment strategies. We focus on the tangency portfolios, which are independent of risk-free rate and the coefficient of risk aversion. The vector of tangency weights $\bar{\omega} = \frac{\Sigma_{xr,xr}^{-1}\mathbb{E}[xr]}{\iota^{\top}\Sigma_{xr,xr}^{-1}\mathbb{E}[xr]}$.

Figure 3.3 Time-Varying Efficient Frontiers & Tangency Portfolios



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

Figure 3.3. illustrates the unconditional and time-varying efficient frontiers and tangency portfolios in optimal mean-variance allocations (no short selling[29]) 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 3.5 reports the portfolio weights of each currency investment strategies and the

[29]We adopt the long-only approach because in practice benchmark restrictions, implementation costs, and factor decay/illiquidity issues often offset the value added by the short leg.

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 62.7% to high downside-insurance-cost currencies funded by the low counterparts in post-crisis period but a zero weight to this strategy in pre-crisis period. Similarly, he/she allocates a weight of 40.0% 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 and trivial diversification benefit of the momentum strategy in business cycles, the utility-maximizing investor does not allocate the wealth to the strategy. The limits to arbitrage make this strategy unexploitable to the investors as emphasized by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). The weight to value strategy is very small in pre-crisis period, but in the unconditional and post-crisis asset allocation, investor will assign a significant fraction of his/her wealth of 19.9% and 17.8% to the strategy, respectively. Carry trade strategy is revealed exposed to the global volatility (innovation) risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a) and offers no diversification benefit in post-crisis period. As the result, investor does not allocate the wealth to carry trade portfolio in the post-crisis period. Currency misalignment strategy accounts for a large proportion of allocated wealth, 43.5%, in whole sample period and its weights are still substantial in two split periods (27.0% and 21.5%, respectively), implying that overpriced (to the medium/long-run fundamental equilibrium values) currencies subject to depreciation risk in period of financial turmoil offer significant diversification benefits. Currency carry trade and misalignment strategies have comparable weights in unconditional allocation. Investor also optimally allocates about 11.6% of the wealth to currency skew risk premium portfolio in pre-crisis period, which is close to the weight to carry trades. The Sharpe ratio of the optimal risky portfolios reaches 1.351 in tranquil period.

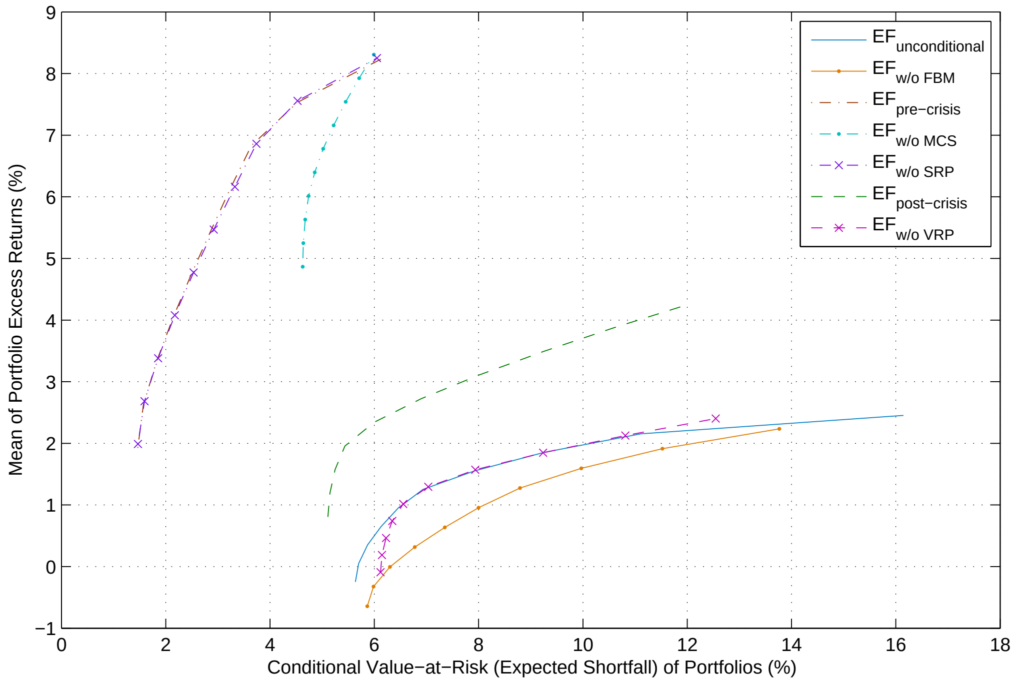
We further evaluate the economic significance in terms of downside risk. Figure 3.4. indicates the efficient frontier in optimal mean-CVaR (conditional value-at-risk) allocations (also no short sale) with and without the access to currency misalignment, crash sensitivity, volatility risk premium, and skew risk premium investment strategies.

Table 3.5 Optimal Risky Portfolios

	Portfolio Weights							Investment Performance		
TS	*CRT*	*FBM*	*MMT*	*PPV*	*MCS*	*VRP*	*SRP*	$\mathbb{E}[\mu_p]$ (%)	σ_p (%)	Sharpe Ratio
Unconditional	0.366	0.435	—	0.199	—	—	—	2.022	6.258	0.323
Pre-crisis	0.182	0.270	—	0.032	0.400	—	0.116	6.406	4.743	1.351
Post-crisis	—	0.215	—	0.178	—	0.627	—	2.772	4.784	0.579

This table reports the optimal portfolio weights for 7 simple currency investment strategies in the whole sample (unconditional), pre-crisis, and post-crisis periods, as well as the corresponding excess returns ($\mathbb{E}[\mu_p]$), volatilities (σ_p), and Sharpe ratios. The coefficient of risk aversion γ is set to 3. The sample period is from September 2005 to January 2013, and split by September 2008.

Figure 3.4 Mean-CVaR Portfolio Optimization



This figure shows the time-varying Efficient Frontiers (EF) under mean-CVaR (conditional value-at-risk / expected shortfall) portfolio optimization scheme in the whole sample (unconditional), pre-crisis, and post-crisis periods, with and without (w/o) the accessibility to REER misalignment (FBM), crash sensitivity (MCS), volatility risk premium (VRP), and skew risk premium (SRP) currency investment strategies. The sample period is from September 2005 to January 2013, and split by September 2008.

CVaR is also called expected shortfall and defined as $ES_\alpha = -\frac{1}{\alpha}\int_{-\infty}^{-VaR_\alpha} xf(x)\ \mathrm{d}x$. We set $\alpha = 5\%$ and find impressive diversification benefit of volatility risk premia in post-crisis period, as it reduces the 1-month $ES_{5\%}$ by at least about 1% p.a.. The diversification benefit of currency misalignment strategy is an up to approximately 2% p.a. reduction in 1-month $ES_{5\%}$ below a certain threshold (around 12.2% CVaR) in the whole sample period. In pre-crisis period, we can benefit from diversification in terms of a reduction in 1-month $ES_{5\%}$ by up to 2% p.a. via the investments in crash sensitivity strategy, but the diversification benefit is trivial when we trade currencies on skew (crash) risk premia.

All these asset allocation results suggest that currency misalignment, crash sensitivity, and moment risk premia are of great economic values to investors in FX market. They exhibit desirable properties that cannot be well replicated using information from other currency investment strategies. The currencies that are overvalued (undervalued) with respect to REER tend to be crash sensitive (insensitive), and have relatively low (high) downside insurance costs but high (low) speculative risk premia. The safe-haven currency JPY is typically the latter.

3.5.2 Monotonicity Tests and Risk Reversal Trade-off

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 $J_N = \max\limits_{j=2,...,5} \widehat{\Delta}_j$, 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:

$$H_0 : \Delta = 0 \text{ vs. } H_1^+ : \sum_{j=2}^{5} |\Delta_j| 1\{\Delta_j > 0\} > 0; \quad J_N^+ = \sum_{j=2}^{5} |\widehat{\Delta}_j| 1\{\widehat{\Delta}_j > 0\} \tag{3.23}$$

$$H_0 : \Delta = 0 \text{ vs. } H_1^- : \sum_{j=2}^{5} |\Delta_j| 1\{\Delta_j < 0\} > 0; \quad J_N^- = \sum_{j=2}^{5} |\widehat{\Delta}_j| 1\{\widehat{\Delta}_j < 0\} \tag{3.24}$$

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 a sufficient condition for the alternative hypothesis H_1^+ (H_1^-) to hold. J_N^+ (J_N^-) is the "Up" ("Down") test statistic. This methodology is extended in Patton and Timmermann (2010) 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.

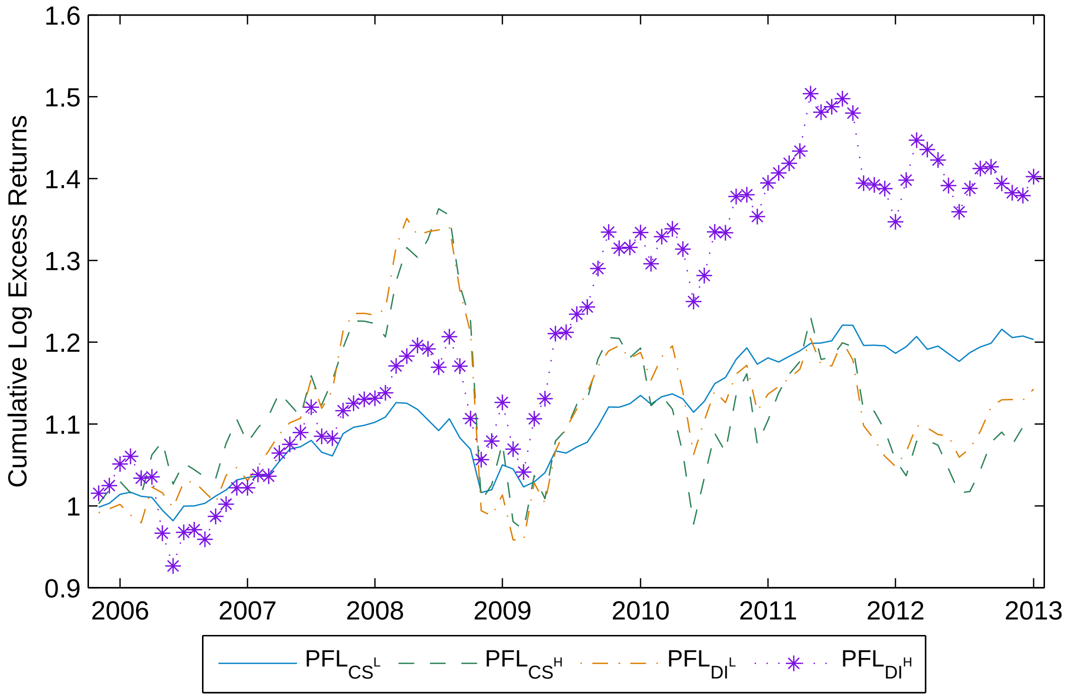
Table 3.6 Monotonicity Tests for Excess Returns of Currency Portfolios

Whole Sample				
TS	MR	MR_P	MR_U	MR_D
CRT	**0.004**	**0.003**	0.125	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**	0.546	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	0.507	0.816
Pre-crisis				
TS	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				
TS	MR	MR_P	MR_U	MR_D
MCS	0.746	0.833	0.952	0.159
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.

The top panel of Table 3.6 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 reversed 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.

Figure 3.5 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 period is from September 2005 to January 2013.

Figure 3.5. below 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 payoff 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 (2013a) that higher interest-rate currencies are exposed to higher position-unwinding risk.

Table 3.7 Global Crash Aversion

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

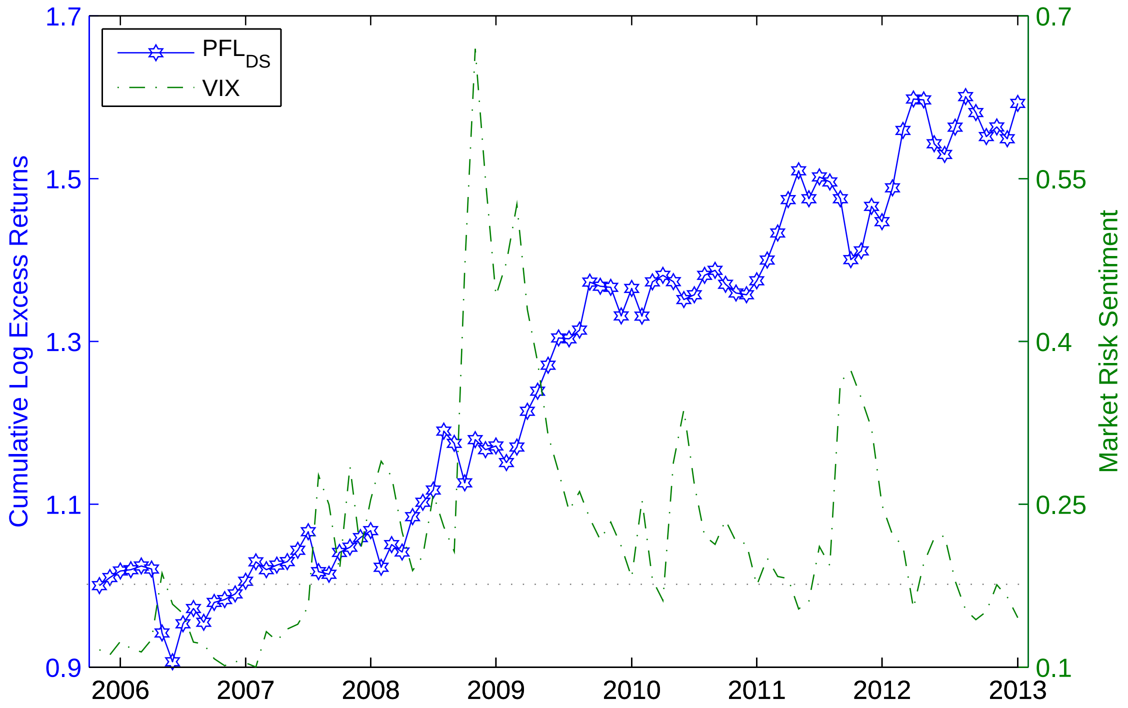
This table reports descriptive statistics of the excess returns of currency portfolios sorted on both individual currencies' crash sensitivity (CS) measured by copula method and downside insurance cost (DI) implied in variance swaps, from September 2005 to January 2013. The portfolios are doubly sorted on bottom 30%, mezzanine 40%, and top 30% basis for the downside insurance cost dimension, and on low 50% and high 50% basis for the crash sensitivity dimension. 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.

To investigate the risk reversal of these two types of currency portfolios, we doubly sort the currencies into 3×2 portfolios[30] by CS and DI respectively, as shown in Table 3.7 below. 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

[30]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.

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.

Figure 3.6 Risk Reversal Trade-off



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 (PFL_{DS}) that holds high crash-sensitivity and high downside-insurance-cost currencies funded by the low counterparts via double-sorting approach. The sample period is from September 2005 to January 2013.

Figure 3.6. presents a trading strategy[31] by investing in medium-CS and high-DI currencies funded by low-CS and medium-DI ones in 3×3 double sorting[32] in

[31] Its descriptive statistics are indicated in Table 3.3.

[32] 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.

comparison with the Chicago Board Options Exchange's (CBOE) VIX index as the market risk sentiment that has a robust payoff without any dramatic plummeting over the sample period, even in several times when the VIX suddenly hiked up[33]. 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. 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.

Yet, we need to understand the risk nature of this trading strategy. The tested risk factors that drive the payoff 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; Pástor 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 the foreign exchange 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 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

[33]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.

Table 3.8 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}				$Adj-R^2$
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}			$Adj-R^2$
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}	$\beta_{TF^{FX}}$	$\beta_{TF^{CMD}}$	$Adj-R^2$
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	$\beta_{BAB_{FX}}$	$\beta_{BAB_{EM}}$	$\beta_{BAB_{BM}}$	$\beta_{BAB_{CM}}$				$Adj-R^2$
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	$\beta_{MSCI^{EM}}$	$\beta_{\Delta VIX}$	$\beta_{\Delta TED}$	$\beta_{\Delta FSI}$	$\beta_{\Delta GPU_{EU}}$	$\beta_{\Delta GPU_{US}}$		$Adj-R^2$
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 is 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.

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.

Table 3.8 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 risk factors in Panel B; Hedge fund risk factors in the Panel C; Betting-against-beta risk factors for foreign exchanges, equity, sovereign bond, and commodity markets in Panel D; Other risk factors, including measures of government economic policy uncertainty, 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 payoff of this strategy at an acceptable $Adjusted-R^2$ level. As shown in Figure 3.2. that the risk reversal trade-off strategy is actually a currency selection procedure that filters high (low) interest-rate currencies which are about to appreciate (depreciate).

3.6 Methodologies and Empirical Results

3.6.1 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.

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):

$$\mathbb{E}[m_t \cdot xr_{j,t}] = 0 \tag{3.25}$$

The SDF takes a linear form of $m_t = \xi \cdot \left[1 - (xf_t - \rho)^\top b\right]$, where ξ is a scalar, xf_t is a $k \times 1$ vector of risk factors, $\rho = \mathbb{E}[xf_t]$, 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:

$$\mathbb{E}[xr_{j,t}] = \underbrace{\mathrm{cov}[xr_{j,t}, xf_t]\, \Sigma_{xf,xf}^{-1}}_{\beta_j} \cdot \underbrace{\Sigma_{xf,xf}\, b}_{\lambda} \tag{3.26}$$

where $\Sigma_{xf,xf} = \mathbb{E}[(xf_t - \rho)(xf_t - \rho)^\top]$. β_j is a vector of risk quantities of k 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)[34]. 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[35] 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 statistically significant λ.

Risk Attributes and Factor Structure in FX Market

To estimate the risk attributes and factor structure of the foreign exchange (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

[34]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.

[35]Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance gives a least-square distance between the tested pricing kernel and the closest pricing kernel among a set of pricing kernels that price the tested assets correctly. It is calculated by a weighted sum of random variables that follow a χ^2 distribution. For more details, see Jagannathan and Wang (1996); Parker and Julliard (2005).

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[36]. 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)[37] and Ahn and Horenstein (2013)[38] to determine the number of dynamic and static factors in GDFM. The results suggest three factors that summarize the common dynamics of the variables and explain over 90% of the variations in these variables[39]. These factors are the representative "Coincident Indices" or "Reference Cycles" that measure the comovements of the pay-offs 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:

$$Y_t = \Lambda\, G_t + u_t \tag{3.27}$$

$$\Theta(L)\, G_t = v_t \tag{3.28}$$

$$\Psi(L)\, u_t = \nu_t \tag{3.29}$$

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

[37]Note that the information criteria proposed by Bai and Ng (2007) is for the Restricted Dynamic Factor Model.

[38]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.

[39]These dynamic factors that the corresponding eigen values are greater than one explain 53.25%, 26.52%, and 10.38% of the total variation of 7 simple FX trading strategies, and 62.30%, 11.52%, and 6.99% of the total variation of 30 individual currencies. Currencies for which the CIP unholds in certain periods are excluded. Currency, such as ARS, which has a zero correlation with the market portfolio (global market) is also excluded.

where $G_t = [g_t^\top, g_{t-1}^\top, ..., g_{t-l}^\top]^\top$ is a $k \times 1$ vector of common latent 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 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 v_t are independent processes. All error terms follow the Gaussian *i.i.d.* normal distribution and 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 (3.27) can be estimated by (Quasi) Maximum Likelihood Estimator (MLE) using Expectation Maximization (EM) algorithm[40]. Doz, Giannone, and Reichlin (2011) also 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. The dynamic factors are robust to different extraction methods.

3.6.2 Discussions

We first focus on currency carry trades. The top panel of Table 3.9 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[41]. 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 Pricing Error (MAPE) 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

[40] It is shown to be implementable with large number of variables, also robust to both non-Gaussianity and weak cross-sectional correlations among the idiosyncratic components (Doz, Giannone, and Reichlin, 2012).

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

Table 3.9 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	$p-value$	$MAPE$
$P_{1,CRT}$	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				(2.197)	(2.207)		(0.976)	
	(0.052)	(0.059)				[2.174]	[2.238]		[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	0.973	0.912	0.208
	(0.048)	(0.043)		(0.368)	(0.348)	(1.665)	(2.411)			
$P_{5,CRT}$	0.829	0.392	GMM_2	-0.368	0.879	2.653	6.138	0.932		0.259
	(0.047)	(0.050)		(0.468)	(0.399)	(3.406)	(2.292)			
	β_{GDR}	β_{SRP}		b_{GDR}	b_{SRP}	λ_{GDR}	λ_{SRP}	R^2	$p-value$	$MAPE$
$P_{1,CRT}$	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				(2.186)	(2.022)		(0.954)	
	(0.048)	(0.037)				[2.174]	[1.972]		[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)		(0.094)	(0.325)	(1.718)	(2.081)			
$P_{5,CRT}$	0.896	0.408	GMM_2	-0.047	0.638	2.792	5.642	0.875		0.398
	(0.052)	(0.050)		(0.041)	(0.348)	(1.985)	(2.127)			

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 Pricing Error ($MAPE$) are also reported.

Table 3.10 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.

model. The forward premia (discounts) are related to macroeconomic fundamentals in a comprehensive evaluation by the REER misalignment.

In the bottom panel of Table 3.9, we substitute the slope factor with the skew risk premium 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 MAPE 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.

Table 3.10 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 skew (crash) risk premia is relevant to but not identical to currency carry trades, which needs more precise explanations. The global tail risk (GTI) factor does not possess much time-series and cross-sectional pricing power on currency carry trades.

We then run a horse race of currency misalignment risk with Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) global FX volatility risk (GVI). As shown in Table 3.11, 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[42], but both b and λ become statistically insignificant from zero. Although currency misalignment risk cannot dominate volatility risk in explaining the cross section of the excess returns of currency carry portfolios, it links carry trade risk premia to a single composite macroeconomic fundamental indicator. When competing with Huang and MacDonald's (2013a) global sovereign default risk GSI — AR(1) innovations in aggregate-level sovereign CDS spreads, the factor loading and price of HML_{ERM} are still statistically significant while those of GSI are not (see Table 3.12). In the horse race of currency skew premium risk (HML_{SRP}) with GVI and GSI, it dominates GSI in terms of statistically insignificant in b and λ while neither GVI or HML_{SRP} dominates

[42]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 -0.323% and statistically significant.

Table 3.11 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	$p-value$	$MAPE$
$P_{1,CRT}$	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
$P_{2,CRT}$	1.09	-0.16	1.95					(2.20)	(4.63)	(0.25)		(0.92)	
	(0.05)	(0.07)	(1.44)					[2.17]	[4.75]	[0.26]		[0.92]	
$P_{3,CRT}$	1.02	0.05	0.91										
	(0.04)	(0.05)	(1.34)									$HJ-dist$	
$P_{4,CRT}$	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)		(0.30)	(0.85)	(48.27)	(1.61)	(4.92)	(0.29)			
$P_{5,CRT}$	0.78	0.33	-3.87	GMM_2	-0.46	0.43	-16.52	2.75	5.44	-0.25	0.90		0.35
	(0.06)	(0.09)	(1.50)		(0.36)	(0.81)	(47.28)	(2.00)	(5.06)	(0.30)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a 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 Menkhoff, Sarno, Schmeling, and Schrimpf's (2012a) 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 Pricing Error ($MAPE$) are also reported.

Table 3.12 Horse Race: $GDR + HML_{ERM} + GSI$

All Countries with Transaction Costs													
Factor Exposures				Factor Prices									
	β_{GDR}	β_{ERM}	β_{GSI}		b_{GDR}	b_{ERM}	b_{GSI}	λ_{GDR}	λ_{ERM}	λ_{GSI}	R^2	$p-value$	$MAPE$
$P_{1,CRT}$	1.07	-0.36	-0.10									χ^2	
	(0.05)	(0.05)	(0.30)	FMB				2.38	6.17	-0.40	0.98		0.17
$P_{2,CRT}$	1.18	-0.08	1.76					(2.20)	(2.36)	(0.25)		(0.92)	
	(0.06)	(0.06)	(0.46)					[2.17]	[2.37]	[0.23]		[0.92]	
$P_{3,CRT}$	0.98	0.00	-0.46										
	(0.05)	(0.04)	(0.32)									$HJ-dist$	
$P_{4,CRT}$	1.05	0.07	-0.66	GMM_1	-0.32	1.05	1.82	2.38	6.17	-0.40	0.98	0.93	0.17
	(0.06)	(0.05)	(0.39)		(0.55)	(0.49)	(0.32)	(1.54)	(2.60)	(0.27)			
$P_{5,CRT}$	0.79	0.36	-0.54	GMM_2	-0.28	1.03	1.93	2.42	6.08	-0.39	0.98		0.18
	(0.06)	(0.06)	(0.68)		(0.67)	(0.54)	(2.86)	(1.68)	(2.89)	(0.25)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a 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 Huang and MacDonald's (2013a) global sovereign default (innovations in aggregate-level CDS spreads) risk (GSI) 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 Pricing Error ($MAPE$) are also reported.

in the cross-sectional regression[43]. HML_{ERM} outperforms HML_{SRP} in the cross-sectional test[44]. These results suggest that high interest-rate currencies share common characteristics in (overvalued) REER misalignment and (negative/high) skew/crash risk premium.

Table 3.13 further shows that currency misalignment portfolios are also subject to speculative (crash) risk (a R^2 of 0.695), but to a lesser degree than carry trade portfolios. Overvalued currencies positively load on skew risk premium factor while the undervalued ones provide a hedge against this type of risk. The factor price is statistically significant, about 8.560% p.a. and the model passes all zero pricing-error tests. However, the reverse is not true that the cross section of skew risk premium portfolios cannot be explained by currency misalignment risk.

The correlations of the dynamic latent factors between FX trading strategies and a large set of individual currencies are 0.83, 0.73, and 0.41, respectively (see Figure 3.7). The coincidence indices of FX trading strategies have smaller variations than those of global currencies because the weighted averages of idiosyncratic components of individual currencies in portfolios converge to zero. DF^1_{FX} represents the systematic risk of the global foreign exchange market because most of the individual currencies share similar loadings on it[45] while DF^2_{FX} and DF^3_{FX} are hedgeable risks as some currencies load oppositely to the others (see Table 3.14). Safe haven currencies such as JPY, CHF, and HKD are particularly useful for hedging against the risks embedded in DF^2_{FX} and DF^3_{FX}.

Table 3.15 presents the risk attributes and factor structure of the payoffs to the simple FX trading strategies studied in this chapter. Panel A of Table 3.15 indicates that the payoffs to the strategies trading on interest-rate differentials, currency misalignments, and skew (speculative) risk premia explain a large proportion of the variations in DF^1_{TS}, and DF^2_{TS} is closely associated with currency values, crash sensitivities, and position insurance cost premia[46] while DF^3_{TS} is uniquely identified

[43] The results are not reported but can be provided upon request.

[44] See Huang and MacDonald (2013a) for the horse races of other candidate risk factors.

[45] All currencies except for JPY, which has a slightly negative loading, positively load on DF^1_{FX}.

[46] The correlations between PPV and MCS, PPV and VRP, and VRP and MCS are -0.81, 0.62, and -0.57, respectively (see Table 3.3).

Table 3.13 Asset Pricing of Currency Misalignment Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	β_{GDR}	β_{SRP}		b_{GDR}	b_{SRP}	λ_{GDR}	λ_{SRP}	R^2	$p-value$	$MAPE$
$P_{1,FBM}$	0.691	-0.213							χ^2	
	(0.071)	(0.049)				2.319	8.560	0.695		0.959
$P_{2,FBM}$	0.935	-0.016				(2.183)	(4.126)		(0.207)	
	(0.050)	(0.055)				[2.174]	[4.139]		[0.204]	
$P_{3,FBM}$	1.087	-0.006								
	(0.095)	(0.068)							$HJ-dist$	
$P_{4,FBM}$	1.026	0.065	GMM_1	-0.380	1.136	2.319	8.560	0.695	0.310	0.959
	(0.045)	(0.039)		(0.431)	(0.506)	(1.773)	(4.329)			
$P_{5,FBM}$	1.207	0.202	GMM_2	-0.331	1.580	4.993	12.898	-1.878		2.703
	(0.084)	(0.060)		(0.335)	(0.886)	(2.118)	(5.264)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a linear factor model (LFM) based on Lustig, Roussanov, and Verdelhan's (2011) dollar risk (GDR) as the intercept (global) factor but differ in slope (country-specific) factor, and skew premium risk (HML_{SRP}) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of five currency misalignment 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 Pricing Error ($MAPE$) are also reported.

as the currency momentum payoff (see also the factor loadings on the coincidence indices of the FX trading strategies in Table 3.14). Panel B of Table 3.15 reports that DF^1_{TS} is highly related to volatility, sovereign credit, and global crash (skewness) risks. The latter two also, to some extent, respectively explains DF^2_{TS}, and DF^3_{TS}. It is noteworthy that government economic policy uncertainty in Europe drives DF^1_{TS} and DF^2_{TS} as well.

Table 3.16 below shows the risk attributes and factor structure of the payoffs to trading global currencies. DF^1_{FX} is identified as the "market portfolio" — the weighted average of the excess returns to an investment strategy in global currencies funded by USD (GDR). It is also highly related to currency misalignment, value, and crash sensitivity premia[47], and significantly exposed to global crash (skewness) risk and the

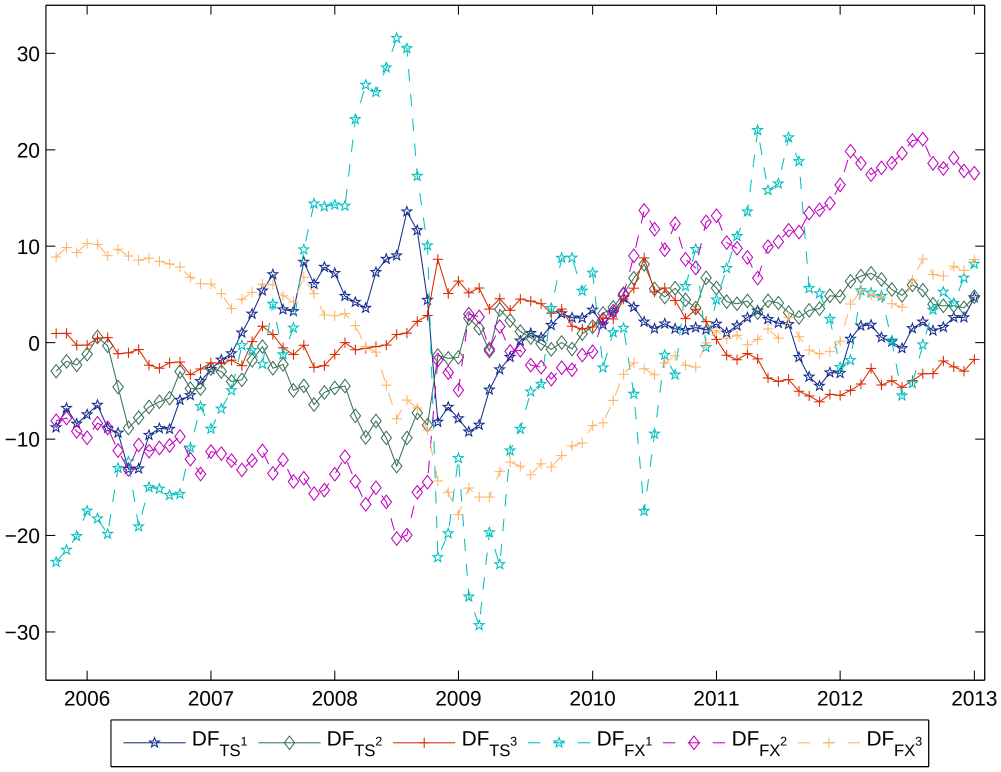
[47] The payoff is highly (0.86) correlated with GDR.

Table 3.14 Factor Loadings on Coincidence Indices: FX Trading Strategies & Global Currencies

TS	DF^1_{TS}	DF^2_{TS}	DF^3_{TS}	FX	DF^1_{FX}	DF^2_{FX}	DF^3_{FX}	FX	DF^1_{FX}	DF^2_{FX}	DF^3_{FX}
				JPY	-0.001	0.141	0.173	EUR	0.076	0.055	-0.002
				KRW	0.066	-0.078	0.056	GBP	0.060	0.014	-0.104
CRT	0.138	-0.102	0.065	HKD	0.020	0.046	0.028	AUD	0.070	-0.077	-0.063
				TWD	N/A	N/A	N/A	NZD	0.063	-0.071	-0.023
FBM	0.159	0.010	0.049	SGD	0.069	-0.011	0.141	CAD	0.060	-0.078	-0.096
				MYR	0.061	-0.042	0.172	CHF	0.061	0.091	0.116
MMT	-0.071	0.033	0.254	THB	N/A	N/A	N/A	SEK	0.071	-0.002	-0.036
				PHP	0.044	-0.108	0.178	DKK	0.075	0.055	-0.004
PPV	-0.059	-0.190	0.006	IDR	N/A	N/A	N/A	NOK	0.066	-0.009	-0.069
				INR	0.048	-0.099	0.151	ZAR	0.055	-0.113	-0.058
MCS	0.105	0.151	0.021	RUB	0.064	-0.017	0.035	BRL	0.047	-0.125	0.036
				PLN	0.075	-0.006	-0.019	CLP	0.053	-0.094	-0.011
VRP	-0.057	-0.154	0.027	RON	0.072	0.026	-0.015	COP	0.043	-0.109	0.072
				HUF	0.074	0.023	-0.015	ARS	N/A	N/A	N/A
SRP	0.147	-0.071	0.020	CZK	0.071	0.068	-0.020	PEN	0.031	-0.077	-0.002
				SKK	0.074	0.053	-0.025	MXN	0.053	-0.140	-0.048
				TRY	0.051	-0.123	-0.013	ILS	0.045	-0.012	-0.017

This table reports the factor loadings on the coincidence indices (that explain over 90% cross-sectional variations) of the excess returns to 7 simple FX trading strategies (ΔDF_{TS}) and 30 individual currencies (DF_{FX}), both estimated by one-side generalized PCE (Forni, Hallin, Lippi, and Reichlin, 2005). The sample period is from September 2005 to January 2013.

Figure 3.7 Coincident Indices (Cumulative Wealth) of FX Trading Strategies & Global Currencies



This figure shows the factor loadings on three coincidence indices that explain over 90% cross-sectional variations) of the cumulative wealth (excess returns) to 7 simple currency trading strategies (DF_{TS}), and to 30 individual currencies (DF_{FX}), respectively, both estimated by one-side generalized PCE (Forni, Hallin, Lippi, and Reichlin, 2005). The sample period is from September 2005 to January 2013.

global component of sovereign credit risk. DF^2_{FX} reflects the currency carry trades and skew (speculative) risk premia and has notable exposures to the country-specific component of sovereign credit and broad market volatility risks. DF^3_{FX} embodies the risk associated with position insurance costs of currencies and, to some extent, the sovereign default risk as well. However, a very large proportion of risk sources remains mysterious, and it plays an important role in the factor investing structure of global foreign exchange market.

Given the risk attributes and factor structure of the individual currencies, it is not surprising that DF^2_{FX} explains the very large proportions of the cross sections of currency carry trade (over 90%) and skew risk premium (about 70%) portfolios, while it is noteworthy that DF^3_{FX} cannot be well explained by any known risk factors in FX

Table 3.15 Risk Attributes & Factor Structure of the Payoffs to FX Trading Strategies

Panel A: Factor Exposures								
TS	CRT	FBM	MMT	PPV	MCS	VRP	SRP	GDR
ΔDF^1_{TS}	5.06***	4.98***	-2.51	-2.30	2.78***	-1.99	4.72***	4.48***
	(0.94)	(0.42)	(1.52)	(1.48)	(0.89)	(1.76)	(0.76)	(0.85)
$Adj-R^2$	**0.64**	**0.83**	0.17	0.12	0.37	0.10	**0.70**	**0.61**
ΔDF^2_{TS}	-2.46***	0.26	0.76	-4.77***	2.62***	-3.48***	-1.52*	1.83***
	(0.83)	(0.65)	(0.80)	(0.37)	(0.31)	(0.65)	(0.86)	(0.30)
$Adj-R^2$	0.23	0.00	0.02	**0.80**	**0.50**	**0.47**	0.11	0.16
ΔDF^3_{TS}	0.88	0.55	3.35***	0.07	0.19	0.31	0.23	0.07
	(0.60)	(0.80)	(0.36)	(0.71)	(0.58)	(0.43)	(0.47)	(0.62)
$Adj-R^2$	0.05	0.03	**0.81**	0.00	0.00	0.01	0.00	0.00
Panel B: Risk Sources								
RF	ΔVIX	ΔTED	GSI	GVI	GSQ	PUW	ΔGPU_{EU}	ΔGPU_{US}
ΔDF^1_{TS}	-1.69***	-4.67*	-28.34***	-66.45***	-0.72***	-0.06	-3.01	-2.18
	(0.33)	(2.74)	(1.73)	(22.96)	(0.14)	(0.05)	(2.07)	(1.80)
$Adj-R^2$	**0.48**	0.02	**0.62**	**0.37**	**0.35**	0.04	0.09	0.08
ΔDF^2_{TS}	0.22	3.87	-3.02	-2.91	-0.25***	-0.01	-1.88**	-0.44
	(0.25)	(2.44)	(3.84)	(12.49)	(0.09)	(0.03)	(0.85)	(0.76)
$Adj-R^2$	0.01	0.02	0.01	0.00	**0.07**	0.00	**0.05**	0.01
ΔDF^3_{TS}	0.07	-0.34	4.60***	10.19	-0.06	-0.01	0.03	0.54
	(0.20)	(1.24)	(1.45)	(8.08)	(0.08)	(0.02)	(0.88)	(0.47)
$Adj-R^2$	0.00	0.00	**0.04**	0.02	0.01	0.01	0.00	0.01

This table reports the time-series asset pricing tests for the risk attributes and factor structure of the coincidence indices (that explain over 90% cross-sectional variations) of the excess returns to 7 simple FX trading strategies (ΔDF_{TS}) estimated by one-side generalized PCE (Forni, Hallin, Lippi, and Reichlin, 2005). 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.

market (only a modest correlation with the payoffs to currency value strategy), but is able to price the cross section of currency value portfolios with a high R^2 of 0.913, monotonic risk exposures, and a statistically significant factor price of 2.715% p.a.[48] (see Table 3.17) — even the high-minus-low factor of currency value portfolios itself cannot achieve. The model also passes all zero pricing-error tests and has a very small MAPE of 16 bps. It also explains extra 14% of the cross-sectional variation of global

[48]Since the original dynamic factors are not identified, we scale them to match the return-based series using factor loadings.

Table 3.16 Risk Attributes & Factor Structure of the Payoffs to Global Currencies

Panel A: Factor Exposures								
TS	CRT	FBM	MMT	PPV	MCS	VRP	SRP	GDR
ΔDF^1_{FX}	4.37*	8.06***	-2.51	-9.65***	9.28***	-6.58***	5.55***	12.32***
	(2.20)	(0.84)	(3.24)	(1.82)	(0.54)	(2.04)	(1.91)	(0.29)
$Adj-R^2$	0.10	**0.45**	0.04	**0.44**	**0.85**	0.23	0.20	**0.96**
ΔDF^2_{FX}	-3.09***	-1.63***	1.57**	-1.96*	0.84	-0.84	-2.59***	-0.56
	(0.31)	(0.45)	(0.67)	(1.00)	(0.74)	(1.25)	(0.21)	(0.71)
$Adj-R^2$	**0.51**	0.19	0.14	0.19	0.07	0.04	**0.45**	0.02
ΔDF^3_{FX}	-0.41	-0.76*	0.25	1.01**	-0.47	1.12***	-0.17	0.03
	(0.41)	(0.39)	(0.49)	(0.41)	(0.35)	(0.31)	(0.41)	(0.63)
$Adj-R^2$	0.02	0.10	0.01	0.12	0.05	**0.16**	0.00	0.00
Panel B: Risk Sources								
RF	ΔVIX	ΔTED	GSI	GVI	GSQ	PUW	ΔGPU_{EU}	ΔGPU_{US}
ΔDF^1_{FX}	-2.65***	-5.31	-52.54***	-110.96***	-2.14***	-0.15*	-8.31**	-4.49
	(0.65)	(3.71)	(5.01)	(38.50)	(0.23)	(0.08)	(3.84)	(3.39)
$Adj-R^2$	0.24	0.01	**0.44**	0.21	**0.65**	0.05	0.14	0.07
ΔDF^2_{FX}	0.73***	2.48	11.55***	24.20**	0.10	0.01	-0.09	0.91
	(0.19)	(2.70)	(1.72)	(11.03)	(0.09)	(0.03)	(1.10)	(0.67)
$Adj-R^2$	**0.19**	0.01	**0.22**	0.11	0.01	0.00	0.00	0.03
ΔDF^3_{FX}	0.08	-2.21*	4.45*	7.02	-0.08	-0.01	0.08	0.46
	(0.14)	(1.14)	(2.63)	(9.85)	(0.07)	(0.02)	(0.84)	(0.66)
$Adj-R^2$	0.01	0.02	**0.08**	0.02	0.02	0.00	0.00	0.02

This table reports the time-series asset pricing tests for the risk attributes and factor structure of the coincidence indices (that explain over 90% cross-sectional variations) of the excess returns to 30 individual currencies (ΔDF_{FX}) estimated by one-side generalized PCE (Forni, Hallin, Lippi, and Reichlin, 2005). 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.

currencies with a statistically significant factor price of 9.749% p.a.[49], which is a high risk compensation. So, DF^3_{FX} is an additional important risk factor omitted in the literature using the standard portfolio approach.

[49] The standard deviation of the estimated $\lambda_{DF^3_{FX}}$ is 4.555% using both FMB and fist-stage GMM_1 methods.

Table 3.17 Asset Pricing of Currency Value Portfolios

All Countries with Transaction Costs										
Factor Exposures			Factor Prices							
	$\beta_{DF^1_{FX}}$	$\beta_{DF^3_{FX}}$		$b_{DF^1_{FX}}$	$b_{DF^3_{FX}}$	$\lambda_{DF^1_{FX}}$	$\lambda_{DF^3_{FX}}$	R^2	$p-value$	$MAPE$
$P_{1,PPV}$	0.486	0.948							χ^2	
	(0.038)	(0.178)				2.542	2.715	0.913		0.164
$P_{2,PPV}$	0.921	0.016				(2.050)	(1.493)		(0.983)	
	(0.07)	(0.29)				[2.057]	[1.559]		[0.986]	
$P_{3,PPV}$	0.837	-0.006								
	(0.025)	(0.181)							$HJ-dist$	
$P_{4,PPV}$	0.828	-0.101	GMM_1	0.195	4.598	2.542	2.715	0.913	0.689	0.164
	(0.051)	(0.202)		(0.160)	(2.279)	(2.154)	(1.601)			
$P_{5,PPV}$	0.942	-0.174	GMM_2	0.214	4.495	2.824	2.653	0.815		0.279
	(0.027)	(0.122)		(0.205)	(2.580)	(2.801)	(1.520)			

This table reports time-series factor exposures (β), and cross-sectional factor loadings (b) and factor prices (λ) for a linear factor model (LFM) based on the first dynamic factor (ΔDF^1_{FX}) as the intercept (global) factor, and the third dynamic factor (ΔDF^3_{FX}) as the slope (country-specific) factor. They are extracted from 30 individual currencies by one-side generalized PCE (Forni, Hallin, Lippi, and Reichlin, 2005). The test assets are the transaction-cost adjusted excess returns of five currency misalignment 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 Pricing Error ($MAPE$) are also reported.

3.7 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. Investments in currencies that are overpriced to their fundamental equilibrium values, funded by undervalued currencies is remunerated with a payoff that is similar to carry trades. 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 carry trade excess returns are driven by currency crash (skew) risk premia. High (low) interest-rate currencies are likely to have low negative (high positive) skew risk premia, which measure the expected changes in the likelihood for UIP to hold (crash risk premia of the foreign currencies versus USD). The profitability of currency carry trades may not be just driven by interest rate differentials, as skew risk premia contain valuable ex-ante information about the future carry trade gains (losses) that lead to an increase (decrease) in speculative positions. Moreover, the skew risk premium strategy mimics both yield and exchange rate return components of currency carry trades. Both REER misalignment and skew (speculative) risk premia explain over 96% of the cross-sectional excess returns 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. Skew premium risk is also priced in the currency portfolios sorted by REER misalignment and explains about 70% of the cross-sectional excess returns, but the reverse is not true. Currency value, crash sensitivity and skew risk premium portfolios cannot be priced by any candidate risk factor we consider in our cross-sectional asset pricing tests, while sovereign default risk is priced in the cross sections of currency momentum and volatility risk premium portfolios (see Huang and MacDonald, 2013a).

To examine the crash story of currency risk premia, we employ the copula method to capture the tail sensitivity of currencies to the global market, and compute the moment risk premia using a model-free approach with volatility risk premia as the proxy for downside insurance costs. We find notable risk reversals in currency premia in pre-crisis and post-crisis periods with respect to both dimensions, and intriguing patterns in the average excess returns of currency portfolios doubly sorted by these two dimensions. We then propose a novel trading strategy that makes a 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, higher than other 7 simple currency investment strategies over the sample period) and an alpha that cannot be explained by canonical risk factors, or by hedge fund and betting-against-beta risk factors, government policy uncertainty, and other financial indices. Unlike other currency investment strategies, its cumulative wealth is driven by both exchange rate and yield components. So, it is actually a currency filtering procedure that selects high (low) interest-rate currencies that are going to appreciate (depreciate).

From the asset allocation perspective, a crash-averse investor would optimally choose a relatively diversified portfolio by allocating over 40% of the wealth to currency misalignment strategy over the sample period, about 40% to crash sensitivity strategy and about 10% to skew risk premium strategy in the tranquil period. While during the financial turmoil, the investor would be better-off by reallocating his/her portfolio holdings dramatically to currency volatility risk premium strategy with a weight of over 60% of the wealth. This behavioral pattern is related to the risk-bearing capacity of the financial intermediaries (Gabaix and Maggiori, 2015), such as market risk sentiment and funding liquidity constraint during the financial distress. Trading strategies that exploit the properties such as currency misalignment, crash sensitivity, and moment risk premia also offer remarkable diversification benefits for risk management purpose in terms of considerable reductions in conditional value-at-risk (expected shortfall) of the efficient frontiers.

We also utilize the generalized dynamic factor model to identify an additional important factor (besides Lustig, Roussanov, and Verdelhan's (2011) global dollar risk and forward bias risk return-based factors) that accounts for extra 14% of the cross-sectional variation in the whole FX market. It is related to the payoff of the currency strategy trading on volatility risk premia (as the proxy for position insurance costs) and priced in the cross section of currency value portfolios (explaining over 90% of the variations). However, it is omitted in the literature using the standard portfolio approach. The risk attributes and factor structure of the investments in currencies and relevant strategies are studied. Sovereign credit risk is the key driver to the factors that capture the common dynamics of the global currencies and also the simple FX trading strategies studied in this chapter. Beyond the systematic (dollar) risk, there are two types of diversifiable risks implied in these investment strategies — one is intimately associated with currency interest rate differentials, REER misalignments, and skew (speculative) risk premia while the another with highly correlated with currency values, crash sensitivities, and volatility risk premia.

Chapter 4

The Term Structure of Exchange Rate Predictability: Commonality, Scapegoat, and Disagreement

4.1 Introduction

Numerous empirical studies suggest that exchange rates are notoriously difficult to forecast (Frankel and Rose, 1995; Kilian, 1999; Berkowitz and Giorgianni, 2001; Faust, Rogers, and Wright, 2003; Cheung, Chinn, and Pascual, 2005). In particular, it is evidenced by Meese and Rogoff (1983) that the macro-based structural models can hardly beat a naive random walk (RW). The macroeconomic fundamentals used by monetary models are not volatile enough to explain the fluctuations in exchange rates (Flood and Rose, 1995). Scholars attribute the feeble relationship between exchange rates and the corresponding determinants to either the I(1) property of macroeconomic fundamental and the near unity Stochastic Discount Factor (SDF) (Engel and West, 2005; Engel, Mark, and West, 2007; Sarno and Sojli, 2009), or the time-varying "scapegoat" effect of exchange rate predictors (Rossi, 2005; Bacchetta and Van Wincoop, 2013; Fratzscher, Rime, Sarno, and Zinna, 2015). Evans and Lyons (2002, 2005b) propose that instead of using the publicly available information, we should focus on the private and superior information implied in the market microstructure to forecast exchange rates. Especially in the short run, exchange rates are largely influenced by the speculation, manipulation, and portfolio-balancing operation of institutional investors (Cheung and Chinn, 2001; Froot and Ramadorai, 2005; Bacchetta and Van Wincoop, 2010; Breedon and Vitale, 2010). Exchange rates absorb macro news gradually through the arrivals of customer order flows (Evans and Lyons, 2005a, 2008; Love and Payne, 2008), which are thereby informative about future exchange rate movements (Lyons, 1995; Payne, 2003; Bjønnes and Rime, 2005; Killeen, Lyons, and Moore, 2006). Furthermore, the "price cascade" of stop-loss orders may lead to the "exchange-rate disconnect puzzle" (Osler, 2005). A model that blends macroeconomic fundamentals with market microstructure information can outperform the random walk (Evans, 2010; Chinn and Moore, 2011).

Some other scholars argue that technical indicators also contain valuable predictive information about exchange rates (Frankel and Froot, 1990; Levich and Thomas, 1993; LeBaron, 1999; Okunev and White, 2003). The profitability of technical trading rules may be self-fulfilling (Taylor and Allen, 1992) and cannot be justified by the exposure to systematic risk (Neely, Weller, and Dittmar, 1997). It takes the advantage of greater noise-to-signal ratio when the participation rate of the chartists (De Grauwe and Grimaldi, 2006), or the market volatility (Menkhoff and Taylor, 2007) becomes higher. Neely, Weller, and Ulrich (2009); Ivanova, Neely, Rapach, and Weller (2014) show supportive evidence for the adaptive learning (see Lo, 2004, for details) feature of technical patterns. As a result, Dick and Menkhoff (2013); Neely, Rapach, Tu, and Zhou (2014) claim that technical indicators should be utilized as a complementary information set (typically for short-run forecasting) with fundamentalism, which provides a long-run angle, such as Purchasing Power Parity (PPP) (Taylor, Peel, and Sarno, 2001), for exchange rate predictions. Moreover, the use of technical analysis is also related to the informativeness of order clusters (Osler, 2003), which reflect timely heterogeneous beliefs about the macroeconomy (Rime, Sarno, and Sojli, 2010).

Exchange rate predictability increases with forecasting horizons (Mark, 1995; Mark and Sul, 2001; Kilian and Taylor, 2003; Groen, 2000, 2005; Rapach and Wohar, 2002, 2004), so does the relative weight attached to fundamental analysis, as opposed to technical analysis (Taylor and Allen, 1992; Menkhoff and Taylor, 2007). One main contribution of our research is that we are the first to investigate the term structure of exchange rate predictability by decomposing exchange rate returns into carry trade risk premia and forward premia components. Lustig, Stathopoulos, and Verdelhan (2013) theoretically derive that the term structure of carry trade risk premia is downward sloping because investment currencies tend to have low local sovereign term premia relative to funding currencies. We focus on the term structure of carry component, from which the predictability origins. In other words, exchange rates over a range of horizons are driven by common latent factors. We extract term structure factors from the cross section of carry components, and incorporating these factors into the dynamics between carry trade excess returns and exchange rate predictors in a time-varying parameter (TVP) VAR setting. This framework allows us to not only investigate the projection of predictive information over the forecasting horizons (commonality) but also track how the carry trade term structure reacts to a large set of scapegoat variables. We then employ dynamic (Bayesian) model averaging (DMA) method to handle model uncertainty and forecast the term structure of carry component. Our term structure model beats random walk in the forecasts up to 12-month horizon in terms of both statistical (R^2_{OOS} up to 20%, $\Delta RMSE$ up to 4.5%, and rejection of equal predictability at 1-month forecasting horizon at up to 5% significance level in the Diebold-Mariano-West test) and economic (performance fees up to approximately 6.5% per annum for a full spectrum of currency investment management) significance for 7 most traded currencies. Hedging pressure and liquidity are identified to contain predictive information that is common to a range of forecasting horizons. Policy-related predictors are important for short-run forecasts up to 3 months while crash risk indicators matter for long-run forecasts from 9 months to 12 months. Other substantial contributions of our research include: (i) from the perspective of foreign exchange market microstructure, we examine whether or not customer order flows are informative about the term structure of currency carry trade risk premia; (ii) we introduce probability weighting into the identification of "scapegoat" drivers of customer order flows; and (iii) we apply these weights of probabilities to capture model disagreement and analyze how this regression-based (vis-à-vis survey-based (see Carlin, Longstaff, and Matoba, 2014)) model uncertainty measure is dynamically related to currency risk premia, volatility, and customer order flows, for which Andrei, Carlin, and Hasler (2014) recently propose a relevant theoretical model.

The rest of this chapter is organized as follows: In Section 4.2, we provide theoretical foundations for analyzing the term structure of exchange rate predictability wherein agents with heterogenous beliefs learn and switch empirical models or "scapegoat" variables. Section 4.3 contains information about the data sets used in this chapter, and describes the empirical methodologies, i.e. dynamic Nelson-Siegel model, time-varying parameter estimations, dynamic (Bayesian) model averaging and disagreement. Section 4.4 introduces both economic and statistical evaluations of the our model. Section 4.5 presents detailed discussions on the results, respectively. We draw a conclusion in Section 4.6. Appendix .C is a complementary appendix.

4.2 Theoretical Foundations

In this section, we provide an overview of the theories of exchange rate determination, from macro-based models to market microstructure, to support our analysis of the term structure of exchange rate predictability.

4.2.1 Present Value Model of Exchange Rate Predictability

The present value model (PVM) of Engel and West (2005) that nests many predictive regressions, exchange rate is described as:

$$s_t = (1-\eta)\sum_{\tau=0}^{\infty}\eta^{\tau}\mathbb{E}_t[z_{t+\tau}] \tag{4.1}$$

where s_t is the log of nominal spot exchange rate defined as the foreign price of domestic currency, z_t denotes observed and unobserved exchange rate determinants. We iterate forward to get:

$$s_t = \mathbb{E}_t[z_t] + \frac{\eta}{1-\eta}\mathbb{E}_t[\Delta s_{t+1}] \tag{4.2}$$

which can be rearranged to give:

$$\Delta s_{t+1} = \frac{1-\eta}{\eta}(s_t - \mathbb{E}_t[z_t]) + \varepsilon_{t+1} \tag{4.3}$$

where $\varepsilon_{t+1} \equiv (1-\eta)\sum_{\tau=0}^{\infty}\eta^{\tau}(\mathbb{E}_{t+1} - \mathbb{E}_t)[z_{t+1+\tau}]$. Even though z_t are identified as I(1) processes, rather than random walks, it is still difficult to forecast Δs_{t+1} if η is close to unity. There is very little predictability unless Δz_t exhibit strong autocorrelations (see Evans and Lyons, 2005b, for details).

4.2.2 Macro Scope: Models of Exchange Rate Determination

In a standard macro-based model of exchange rate, we have a system of four equations as follows.

Covered Interest Rate Parity (CIP):

$$f_t^{(\tau)} - s_t = r_t^{(\tau),*} - r_t^{(\tau)} \tag{4.4}$$

Uncovered Interest Rate Parity (UIP):

$$\mathbb{E}_t[s_{t+\tau}] = f_t^{(\tau)} \tag{4.5}$$

Purchasing Power Parity (PPP):

$$p_t^* = s_t + p_t \tag{4.6}$$

Monetary Fundamentals[1] (MOF):

$$\begin{aligned} m_t^* - p_t^* &= y_t^* - \phi\, r_t^{(\tau),*} \\ m_t - p_t &= y_t - \phi\, r_t^{(\tau)} \end{aligned} \tag{4.7}$$

[1] Mark (1995), Mark and Sul (2001) impose additional restriction that the coefficient of output level equals to unity. The horizon τ depends on the data frequency.

In the case that interest rates are set according to a Taylor Rule (TRI):

$$
\begin{aligned}
r_t^{(\tau),*} &= \theta_0 + \theta_1 \pi_t^{(\tau),*} + \theta_2 \tilde{y}_t^{(\tau),*} \\
r_t^{(\tau)} &= \theta_0 + \theta_1 \pi_t^{(\tau)} + \theta_2 \tilde{y}_t^{(\tau)}
\end{aligned} \tag{4.8}
$$

where $f_t^{(\tau)}$, and $r_t^{(\tau)}$ is the log of forward rate, and domestic nominal risk-free interest rate (zero-coupon bond yield), respectively, both with a maturity of τ; p_t, m_t, y_t, $\tilde{y}_t^{(\tau)}$, and $\pi_t^{(\tau)}$, denotes domestic price level, money supply, national income, τ-period output gap, and τ-period inflation rate, respectively, all in logarithm forms except for the inflation rate. Those with asterisk notations are foreign variables, i.e. $r_t^{(\tau),*}$, p_t^*, m_t^*, y_t^*, $\tilde{y}_t^{(\tau),*}$, $\pi_t^{(\tau),*}$. ϕ, θ_1, $\theta_2 > 0$; θ_0 contains information about the target inflation rate and the real equilibrium interest rate[2]. $\tau = 1$ for monthly observations.

To allow for deviations from UIP based on rational expectations and risk neutrality, we introduce ξ_t as an expectation error and/or risk premium into Equation (4.5). We substitute Equations (4.4), (4.6) (4.7) into Equation (4.5) to yield the reduced form:

$$
s_t = \frac{1}{1+\phi}\left[(m_t^* - m_t) - (y_t^* - y_t) - \phi\, \xi_t\right] + \frac{\phi}{1+\phi}\mathbb{E}_t[\Delta s_{t+1}] \tag{4.9}
$$

Similarly, by introducing real exchange rate targeting $\theta_3[s_t - (p_t^* - p_t)]$ and/or interest rate smoothing $\theta_4[r_{t-1}^{(1),*} - r_{t-1}^{(1)}]$ into Equation (4.8) to formulate an augmented (relative) Taylor rule, we get:

$$
\begin{aligned}
s_t = &-\frac{1}{1+\theta_3}\left\{\theta_1[\pi_t^{(1),*} - \pi_t^{(1)}] + \theta_2[\tilde{y}_t^{(1),*} - \tilde{y}_t^{(1)}] + \theta_3(p_t^* - p_t)\right\} \\
&-\frac{1}{1+\theta_3}\left\{\theta_4[r_{t-1}^{(1),*} - r_{t-1}^{(1)}] + \xi_t\right\} + \frac{1}{1+\theta_3}\mathbb{E}_t[\Delta s_{t+1}]
\end{aligned} \tag{4.10}
$$

Ample empirical evidence finds a weak relationship between nominal exchange rate and macroeconomic fundamentals. Bacchetta and Van Wincoop (2004) broach

[2]See Taylor (1993). There is no difference between the actual and the target interest rates as long as the target is retained (Molodtsova and Papell, 2009).

a "scapegoat" model with noisy rational expectations to explain the phenomenon of exchange rate fluctuations. In their model, market participants with heterogeneous information on the source of exchange rate predictability attribute exchange rate movements to variables, which are typically taken as "scapegoats", especially when there is an unobservable variable affects the exchange rate. As a result, the weights attached to these variables change over time, and their reduced form relationship with the exchange rate is driven by the time-varying expectations on the structure parameters (Bacchetta and Van Wincoop, 2013).

4.2.3 Micro Scope: Uncertainty Aversion, Bayesian Learning, and Hybrid Models

In the forecasting of exchange rates, investors are confronted with parameter and model uncertainty. Kozhan and Salmon (2009) find notable uncertainty aversion in FX market, typically of chartists. Evans, Honkapohja, Sargent, and Williams (2012) propose an analytical framework that agents equipped with Bayesian techniques utilize multiple models and a weighted average of forecasts to deal with uncertainty issues and to form their expectations about the future asset prices. De Grauwe and Grimaldi (2006) develop a model of the exchange rate in which agents switch FX trading rules based on the ex-post evaluations of the profitability of each forecasting model, which gives rise to the fundamental disconnect puzzle. This coincides with the "scapegoat" theory. Hence, from the perspective of market microstructure, we employ the Dynamic (Bayesian) Model Averaging (DMA) method of Koop and Korobilis (2012) to investigate the implied probability weighting of each empirical model or "scapegoat" variable in customer order flows. Chakraborty and Evans (2008) demonstrate that perpetual (discount least-squares) learning (Evans and Honkapohja, 2001) can explain a typical exchange rate behavior — forward premium puzzle (see also Mark, 2009). Spronk, Verschoor, and Zwinkels (2013) reveal that the interactions between carry traders and chartists also lead to the violation of UIP, and this impact is strengthened when chartists extrapolate trends from carry trade activities. Statistical learning of the chartists also replicates volatility clustering in the FX market (De Grauwe and

Markiewicz, 2013). All these imply that it is important to consider technical signals in exchange rate predictions.

The probability of informed trading is a determinant of equilibrium asset returns (Easley, Hvidkjaer, and O'Hara, 2002). Carlson and Osler (2000) suggest a connection between speculative activity and exchange rate volatility without relying on information asymmetry that high (low) level of informed rational speculation magnifies (stabilizes) the effects of interest rate shocks. Pasquariello and Vega (2007) develop a speculative trading model with two types of market frictions, information heterogeneity and imperfect competition among informed traders. They show that the information effect of order flow becomes stronger when market signals are noisy and belief dispersions are high. Using a large set of survey data of market participants, MacDonald and Marsh (1996) identify the idiosyncratic interpretations of relevant information as a major cause of heterogeneous beliefs that determine trading volume, and Beber, Breedon, and Buraschi (2010) reveal that heterogeneous beliefs affect currency option prices, the shape of implied volatility smile, volatility risk premia as the proxy for investors' hedging demand (see Garleanu, Pedersen, and Poteshman, 2009), and the position-unwinding risk (see Huang and MacDonald, 2013a) of currency carry trade. Following this economic intuition, we resort to currency option-implied information, hedging pressure in futures market, and crash sensitivity to the global market for exchange rate predictability as well.

To summarize, the recent literature generally holds the point of view that agents with heterogeneous beliefs learn the probability weighting of each predictor or forecasting model, and relevant information is partially impounded into prices via the switching process of FX trading rules.

4.3 Data and Methodology

Our financial data set is obtained from Datastream and Bloomberg, including spot rates, forward rates and risk-free interest rates[3] of weekly (1-week, 2-week, and 3-week),

[3]The zero-coupon bond yields are bootstrapped from short-term money market rates and medium- to long-term swap rates, which are best parsimonious proxy for risk-free interest rates (Feldhütter and

monthly (from 1-month to 11 month consecutively), and annually (1-year) maturities, 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 for EUR (EMU), GBP (United Kingdom), AUD (Australia), NZD (New Zealand), CHF (Switzerland), CAD (Canada), and JPY (Japan)[4]. All Option data are used to construct volatility risk premia (see Della Corte, Ramadorai, and Sarno, 2013), skew and kurtosis risk premia (see Huang and MacDonald, 2013b), which contain ex-ante information about future exchange rate movements and tail risk premium and are denoted by VRP, SRP, and KRP, respectively. Motivated by the fact that most of the high-yield currencies are commodity currencies, we choose the Raw Industrial Sub-index of the CRB Spot Commodity Index (see also Bakshi and Panayotov, 2013), denoted by CRB. We also adopt CBOE's VIX index, and T-Bill Eurodollar Spread TED Index as the proxies for global volatility, and liquidity risk, respectively. A currency's crash sensitivity is measured by its lower tail dependence on the whole FX market using copula approach as in Huang and MacDonald (2013b). we acquire data on the positions of currency futures traders (both commercial and non-commercial) from the Commitment of Traders (COT) published by the Commodity Futures Trading Commission (CFTC)[5].

Our macroeconomic data set is collected from several sources. To measure money supply, we use non-seasonally adjusted M1[6] from IMF's *International Financial Statistics* (*IFS*) and *Ecowin*'s national central bank database. The money supply is deseasonalized by implementing the procedure of Gómez and Maravall (2000). We use seasonally adjusted Industrial Production Index (IPI) also from *IFS* as the proxy for real output[7]. The price level is captured by Consumption Price Index (CPI) from OECD's *Main Economic Indicators* (*MEI*)[8]. The output gap is defined as the

Lando, 2008).

[4]All currencies are against USD except for EUR, GBP, AUD, and NZD that are expressed as the domestic (U.S.) price of foreign currencies.

[5]The report only covers the G10 currencies in our sample. The predictive value of the information content of net hedging positions about future risk premia is inconclusive (see De Roon, Nijman, and Veld, 2000; Gorton, Hayashi, and Rouwenhorst, 2013, for example).

[6]Except for the U.K. that adopts M0 instead due to the unavailability of M1.

[7]Since the IPI data of Australia, New Zealand, Switzerland, Hong Kong, Singapore, and South Africa are only available at quarterly frequency, we obtain additional observations via monthly linear interpolation.

[8]We also implement monthly linear interpolation for the CPI data of Australia and New Zealand that are published at quarterly frequency. The inflation rate is computed as the annual log-difference

deviations from a Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997). We update the HP trend at time t only using the information up to $t-1$ to mimic the real-time data (see Orphanides, 2001; Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2008, for details). All macroeconomic data except for interest rates are converted by taking logarithms and then multiplying by 100. We further employ Economic Policy Uncertainty Indices (EPU) available from Federal Reserve Bank of St. Louis[9] to investigate the aggregate impact of disagreement among economic forecasters and media coverage of policy-related uncertainty on future exchange rate movements. In addition, we employ a unique market microstructure data set that consists of daily customer order flows from one of the biggest London-based FX dealers. Our sample period is from January 1994 to February 2014.

4.3.1 Exchange Rate Return Decomposition

We decompose exchange rate returns into carry trade risk premia $c_{t+\tau}^{(\tau)}$ and forward premia $f_t^{(\tau)} - s_t$ components as below[10]:

$$\Delta s_{t+\tau}^{(\tau)} = \underbrace{s_{t+\tau} - f_t^{(\tau)}}_{c_{t+\tau}^{(\tau)}} + \underbrace{f_t^{(\tau)} - s_t}_{r_t^{(\tau),*} - r_t^{(\tau)}} \tag{4.11}$$

If domestic risk-free rate is greater (less) than foreign risk-free rate, $c_{t+\tau}^{(\tau)}$ is the (reverse) carry trade excess return of investing in USD funded by foreign currency. Lustig, Stathopoulos, and Verdelhan (2013) reveal that the term structure of carry trade risk premia is downward sloping because investment currencies tend to have low local sovereign term premia relative to funding currencies. Given that the forward premium component is already known at time t, exchange rate predictability originates from the carry trade risk premia component, which is driven by latent term structure factors.

of CPI.

[9]This series contains U.S., U.K., Europe, Canada, Japan, China, Russia, India. We exclude the U.K. component from the Europe index.

[10]The returns of any security can be decomposed in the same way (see also Koijen, Moskowitz, Pedersen, and Vrugt, 2013).

4.3.2 Dynamic Nelson-Siegel Model

We extend the exponential component extraction approach of Nelson and Siegel (1987) to an international setting to model the term structure of risk premia, i.e. each component of Equation (4.11). For instance, in the circumstance that UIP holds (see Akram, Rime, and Sarno, 2008), the forward (interest rate differential) component can be expressed in a form of (relative) level (L_t^{NS}), slope (S_t^{NS}), and curvature (C_t^{NS}) factors (see Chen and Tsang, 2013). Latent factors of the carry component are extracted in a similar way:

$$c_t^{(\tau)} = L_t^{NS} + \frac{1-\exp(-\lambda\tau)}{\lambda\tau} S_t^{NS} + \left[\frac{1-\exp(-\lambda\tau)}{\lambda\tau} - \exp(-\lambda\tau)\right] C_t^{NS} + \zeta_t^{(\tau)} \quad (4.12)$$

where $\xi_t^{(\tau)}$ is the error term; λ denotes the exponential decay rate, controls the shapes of factor loadings. We also follow Diebold and Li (2006) to assume an autoregressive structure for these factors, which introduces the dynamic Nelson-Siegel (NS) model[11]. We employ Principal Component Analysis (PCA) to determine the number of factors required to explain the cross-section variation of two exchange rate return components. The λ_f for the term structure of forward premia, and the λ_c for the term structure of carry trade risk premia is chosen respectively to maximize the loading on 1-month risk premia in our case. Given that $f_t^{(\tau)} - s_t$ or $r_t^{(\tau),*} - r_t^{(\tau)}$ is already known at time t, we only need to forecast $c_{t+\tau}^{(\tau)}$ recursively to obtain τ-period ahead carry trade (excess returns) risk premia component, which determines the statistical accuracy of exchange rate predictability using extracted term structure factors. We introduce the factor-augmented empirical exchange rate models that the large set of exchange rate predictors is unspanned by the term structure of carry trade risk premia, and allows us to decompose the predictive effects according to the shape of the term structure.

[11] Although no-arbitrage condition is theoretically rigorous, it imposes strong over-identification restrictions and forecasts poorly. Better fit of volatility is at the expense of fitting the cross-section of yields (Creal and Wu, 2015). Christensen, Diebold, and Rudebusch (2011) propose a slighted restricted arbitrage-free version of canonical NS model (see Dai and Singleton, 2000; Duffee, 2002) that not only facilitates estimation but also improves predictive performance. Duffee (2013) demonstrates that Nelson-Siegel approach and alternative no-arbitrage constraint are equivalent to characterize the term structure.

4.3.3 Factor-Augmented Empirical Exchange Rate Models with Time-Varying Parameters

Given that forecasting carry trade risk premium component is equivalent to forecasting exchange rate returns, we can investigate the origins and term structure of exchange rate predictability by incorporating the term structure information of carry trade risk premia into a joint dynamic framework of exchange rates and "scapegoat" variables, including those from canonical empirical exchange rate models, in a setting of time-varying parameter vector autoregression (TVP-VAR):

$$z_t = \beta_{0,t} + \beta_{1,t} z_{t-1} + \cdots + \beta_{n,t} z_{t-n} + u_t \tag{4.13}$$

where $z_t = [L_t^{NS}, S_t^{NS}, C_t^{NS}, x_t]^\top$, consists of three NS factors and a $1 \times k$ vector of "scapegoat" variables x_t. $\beta_{0,t}$ is a $(k+3) \times 1$ vector, and $\beta_{i,t}$ is a $(k+3) \times (k+3)$ matrix for $i = 1, \cdots, n$, lag order. $u_t \sim \mathcal{N}(0, \Sigma_{u,t})$, and $\Sigma_{u,t} \sim \text{inv}\,\mathcal{W}(h_t, g_t)$. h_t, and g_t denotes the degrees of freedom, and the scale matrix of inverse Wishart distribution, respectively. $g_t = \delta g_{t-1} + 1$ and $h_t = (1 - g_t^{-1})\, h_{t-1} + g_t^{-1}(h_{t-1}^{1/2} \Sigma_{u,t-1}^{-1/2} u_t u_t^\top \Sigma_{u,t-1}^{-1/2} h_{t-1}^{1/2})$. $\delta \in (0,1)$ is the decay rate and set to 0.95. The estimation for h_t is numerically equivalent to the Exponentially Weighted Moving Average (EWMA) $h_t = \delta h_{t-1} + (1-\delta) u_t u_t^\top$. Doing so, we can approximate the full posterior distribution of $\Sigma_{u,t}$. We then describe the law of motion of the vector of time-varying β as $\beta_t = \beta_{t-1} + v_t$, where $v_t \sim \mathcal{N}(0, \Sigma_{v,t})$. Bayesian inference for β_t involves state-space model with Kalman filter. We set $\Sigma_{v,t} = (\rho^{-1} - 1)\, \Sigma_{\beta,t-1|t-1}$ based on the information set Ω_{t-1} as in Koop and Korobilis (2013), where $\rho \in (0,1]$ is a "forgetting factor" that discounts past observations and is set to 0.99. This specification of TVP-VAR with drift in coefficients and stochastic volatility allows for structural instabilities and regime shifts. Conducting Bayesian inference entails Markov Chain Monte Carlo (MCMC) technique, which is computationally onerous especially in a recursive context. Their methodology provides accurate and efficient estimation that largely boosts the speed. The Bayesian method to update a vector of coefficients β_t takes the form as below:

$$
\begin{aligned}
p(\beta_t|\Omega_t) &\propto \mathbf{L}(z_t;\beta_t, z_{t-1},\cdots, z_{t-n}, \Omega_{1:t-1})\, p(\beta_t|\Omega_{t-1}) \\
p(\beta_t|\Omega_{t-1}) &= \int_{\wp} p(\beta_t|\Omega_{1:t-1}, \beta_{t-1})\, p(\beta_{t-1}|\Omega_{t-1})\, \mathrm{d}\beta_t
\end{aligned} \tag{4.14}
$$

where $\wp$ is the support of β_t, and $\Omega_{1:t-1}$ denotes the data information up to time $t-1$. The solution to the above problem is using Bayesian generalization of Kalman filter with an algorithm of forward recursions[12] (see Koop, Poirier, and Tobias, 2007, for details).

Castle, Clements, and Hendry (2013) find that factor models perform better at nowcasts and short-term forecasts while individual predictors excel at forecasts of long horizons. Using shrinkage estimators, any factor-augmented empirical exchange rate model that excludes individual predictors essentially collapses to a factor-only model. The importance of the inclusion of the term structure information of carry trade risk premia can be verified explicitly through the forecasting performance and implicitly via the comparisons of probability weighting between factor-only model and factor-augmented models. This framework also allows us to study the time-varying issue of unspanned (business cycle and non-fundamental) risks and the feedback effects between factors and predictors (using impulse response analysis). It is worth accentuating that we assume, beyond the factors, there is no other sources of predictability — $\zeta_t^{(\tau)}$ in Equation (4.12) by x_{t-n}[13] as we focus on the information commonality in the term structure of exchange rate predictability in this chapter.

[12]This approach is convenient for real-time policy analysis.

[13]Yet, full/direct factor-augmented forecasts of the carry component (vis-à-vis partial/indirect forecasts concentrating solely on the common dynamics of the term structure of risk premia) could be more informative if $\mathrm{cov}[x_{t-n}, \zeta_t^{(\tau)}] \neq 0$, and it generates economically meaningful horizon-dependent probability weighting, which only varies with the predictive power of x_{t-n} on $\zeta_t^{(\tau)}$. Implementing forecasts beyond 1-month horizon requires recursive forecasts of the term structure factors so that the DMA probability weighting is optimized at 1-month horizon. In other words, the forecasting power of the "scapegoat" variables on factors are the same across horizons. Whilst $\zeta_t^{(\tau)}$ can be forecast by x_{t-n} separately from the factor component, although it requires repeated implementations of estimation procedure for each (carry trade, or equivalently, forecasting) horizon. It is even more flexible because it nests models without latent factors and also a driftless random walk. As a result, it is compatible with the kitchen-sink model and can be estimated by various shrinkage methods.

4.3.4 Dynamic (Bayesian) Model Averaging and Disagreement

The kitchen-sink regression (see Welch and Goyal, 2008) is broached to merge a large set of predictors into a single predictive regression. However, a model with many regressors but small sample size is often plagued by parameter estimation errors, which result in poor predictive performance in terms of mean squared (forecasting) errors (MSE)[14]. More sophisticated and efficient shrinkage techniques, e.g. ridge (Hoerl and Kennard, 1970), LASSO[15] (Tibshirani, 1996), bagging (Breiman, 1996) and bumping (Tibshirani and Knight, 1999) regressions, Bayesian model selection (Madigan and Raftery, 1994) and averaging (Raftery, Madigan, and Hoeting, 1997), elastic net method (Zou and Hastie, 2005) based on penalized least squares (PLS), and complete subset regressions (Elliott, Gargano, and Timmermann, 2013), among others, have been advanced to alleviate the overfitting problem.

Rapach, Strauss, and Zhou (2010) endorse combined forecasting of alternative predictive regressions because it not only improves predictive preformation (less volatile) but also is more realistic about the economic activities. Bayesian Model Averaging (BMA) is a useful tool for forecast combination of various models/variables (see Avramov, 2002; Cremers, 2002; Wright, 2008; Della Corte, Sarno, and Tsiakas, 2009). We follow the Dynamic Model Averaging (DMA) method of Koop and Korobilis (2012), which dynamically assigns weights to each empirical model or "scapegoat" variable using the probabilities updated on the arrival of new information according to the predictive accuracy. This probability weighting scheme potentially reflects the switches of forecasting rules, at aggregate level, by the heterogeneous agents who learn to forecast exchange rates and deal with model uncertainty in an evolving economy. The posterior probabilities of the coefficients is given by:

[14] The MSE of an estimator equals to the sum of (i) the variance of residuals and (ii) the MSE of estimated coefficients (of the predictive variables). The MSE of $\hat{\beta}$ can be further decomposed into the bias and variance of $\hat{\beta}$. The OLS estimator is unbiased but its variance is usually higher than shrinkage estimators. An extreme case of zero variance is a random walk without drift. Any improvement in the bias-variance trade-off may lead to a gain in predictive accuracy, even though shrinkage estimators push all coefficients towards zero.

[15] It is the abbreviation for Least Absolute Shrinkage and Selection Operator.

$$p(\beta_{t-1}|z_{t-1}) = \sum_{j=1}^{l} p(\beta_{j,t-1} \mid L_{t-1} = j, z_{t-1}) \Pr(L_{t-1} = j \mid z_{t-1}) \tag{4.15}$$

where $p(\beta_{j,t-1} \mid L_{t-1} = j, z_{t-1})$ is estimated by Kalman filter, and $L_{t-1} = j$ representing that the j^{th} model/variable is selected at time $t-1$.

$$\Pr(L_t = j \mid z_{t-1}) = \frac{[\Pr(L_{t-1} = j \mid z_{t-1})]^{\alpha}}{\sum_{j=1}^{l}[\Pr(L_{t-1} = j \mid z_{t-1})]^{\alpha}} \tag{4.16}$$

where $\alpha \in (0, 1]$ is the forgetting factor[16] and set to 0.99. The model is then updated by:

$$\Pr(L_t = j \mid z_t) = \frac{\Pr(L_t = j \mid z_{t-1}) p_j(z_t|z_{t-1})}{\sum_{j=1}^{l} \Pr(L_t = j \mid z_{t-1}) p_j(z_t|z_{t-1})} \tag{4.17}$$

where $p_j(z_t|z_{t-1})$ is the predictive likelihood. In addition, we implement Dynamic Model Selection (DMS) method that chooses the model with best predictive performance (highest probability weight) at any point of time.

To proceed with Bayesian estimation, we also need to specify the prior distribution. The shrinkage level of the hyper-parameters of priors is optimally chosen based on the criteria of Dynamic Prior Selection (DPS) at each point of time. We adopt the Minnesota class of prior by setting, at time $t = 0$, the prior expectation of β_t to a vector of zeroes and the prior variance-covariance matrix $\Sigma_{\beta,t}$ to a diagonal matrix with diagonal elements $\Sigma_{i,0}$ defined as in Koop and Korobilis (2013):

$$\Sigma_{i,0} = \begin{cases} \psi/i^2 & \text{for coefficients on lag } i \text{ where } i = 1, \cdots, n; \\ 1 & \text{for the intercept, } i = 0. \end{cases} \tag{4.18}$$

where ψ controls the degree of shrinkage on β_t. The larger the ψ, the lower the shrinkage level, and hence the more flexible the forecasting results. We consider a reasonable grid of candidate values: 10^{-10}, 10^{-6}, 10^{-4}, 5^{-4}, 0.01, 0.05, 0.1. We also restrict the maximum value of ψ to obtain stable estimates of coefficients and dynamically select ψ according to predictive accuracy.

[16] The advantage of using forgetting factor is no requirement for an MCMC algorithm.

If there is no disagreement across the models which the agents employ to forecast exchange rates or carry trade risk premia, the probability weighting of each model will be equal. Model disagreement may not be a source of forecasting errors. Nevertheless, as argued by Carlin, Longstaff, and Matoba (2014) and Andrei, Carlin, and Hasler (2014), model disagreement affects the dynamics of asset prices, return volatility, and trading volume in the market. Instead of using privilege database, e.g. Survey of Professional Forecasters, in previous literature to measure model disagreement, we resort to the DMA probability weighting generated via a Bayesian forecasting error optimization procedure as a model-implied proxy for the dispersion of forecasts.

$$MD_t = \sqrt{\frac{1}{l}\sum_{j=1}^{l}\left[\Pr(L_t = j \mid z_t) - \frac{1}{l}\right]^2} \tag{4.19}$$

We adopt the AR(1) innovations to MD_t as a pricing factor, then regress carry trade excess returns and the AR(1) innovations to FX volatility, respectively, on ΔMD_t to investigate how increased currency risk premia and volatility are associated with the degree of model disagreement.

4.3.5 Scapegoat Variables

We consider a wide range of empirical exchange rate models or "scapegoat" variables, some of them are nested in Engel and West (2005) present value model, including PPP, $p_t^* - p_t - s_t$; MOF, $(m_t^* - m_t) - (y_t^* - y_t) - s_t$; and TRI that, for simplicity, we assume both domestic and foreign countries share the same interest rate and inflation rate targets, which gives a symmetric[17] Taylor rule (in difference form) of $1.5\,[\pi_t^{(\tau),*} - \pi_t^{(\tau)}] + 0.1\,[\tilde{y}_t^{(\tau),*} - \tilde{y}_t^{(\tau)}]$, and $\tau = 1$. CIP and its term structure are captured by the relative NS yield curve factors (YCF) (Chen and Tsang, 2013)[18]. We then extend

[17]It is asymmetric if they have different target. In reality, if central banks also targets the real exchange rate and/or smooths interest rate, $0.1\,(s_t + p_t - p_t^*)$ and/or $0.1\,[r_{t-\tau}^{(\tau),*} - r_{t-\tau}^{(\tau)}]$ should be appended to formulate Taylor rules (see Clarida, Galí, and Gertler, 1998; Molodtsova and Papell, 2009, for alternative specifications). Backus, Gavazzoni, Telmer, and Zin (2010) also find empirical evidence in favour of asymmetric settings.

[18]The τ-period UIP regression is essentially a constrained version of the factor model, and Chen and Tsang (2013) find empirical evidence against the restrictions imposed by UIP. One may also consider Cochrane and Piazzesi (2005, 2009) forward-rate and Ludvigson and Ng (2009) macroeconomic-

the macro-based model to incorporate signals generated from two types of technical trading rules, from which most of other popular indicators[19] derive, as follows.

Moving Average Convergence Divergence (MACD), in the form of Percentage Price Oscillate (PPO), as a trend indicator:

$$\begin{aligned} DIF_t &= \frac{EMA_t[s_t, T_1] - EMA_t[s_t, T_2]}{EMA_t[s_t, T_2]} \cdot 100\% \\ DEA_t &= EMA_t[DIF_t, T_3] \\ HTG_t &= DIF_t - DEA_t \end{aligned} \tag{4.20}$$

KDJ Stochastic Oscillator as a momentum and mean reversion indicator:

$$\begin{aligned} K_t &= EMA_t[RSV_t, T_4] \\ D_t &= EMA_t[K_t, T_5] \\ J_t &= 3D_t - 2K_t \end{aligned} \tag{4.21}$$

where $RSV_{t,T}$, $s^H_{t,T}$, $s^L_{t,T}$, and $EMA_t[\cdot, T]$ denotes the raw stochastic value, highest high of s_t, lowest low of s_t, and exponential moving average, respectively (over a past period of T); $RSV_t = (s_t - s^L_{t,T_7})/(s^H_{t,T_7} - s^L_{t,T_7}) \cdot 100\%$. DIF_t, DEA_t, and HTG_t is the MACD line, signal line, and histogram, respectively. In a standard daily setting, $T_1 = 12$,

fundamental factors that contain additional information about future yield curve movements and bond excess returns unspanned by the yield curve factors of most affine term structure models. Ludvigson and Ng (2009) find that, among a large set of macroeconomic aggregates, real and inflation factors have significant predictive power, implying the importance of the inclusion of estimated macro factors to generate countercyclical risk premia. The macro-finance linkage stressing the roles of expectations and uncertainty in monetary policy, inflation, and output/consumption growth has received much attention as a driver of bond risk premia (see Ang and Piazzesi, 2003; Buraschi and Jiltsov, 2005; Piazzesi and Scheider, 2007; Rudebusch and Wu, 2008; Christensen, Lopez, and Rudebusch, 2010; Chun, 2011; Wright, 2011; Joslin, Priebsch, and Singleton, 2014). Habit formation as in Campbell and Cochrane (1999) is also a key to understand the time-varying price of risk in the consumption-based (equilibrium) term structure models of interest rates (see Wachter, 2006; Buraschi and Jiltsov, 2007).

[19]There is another important type of indicators — bias and volatility measures, such as Bollinger Band ® (BB) and Commodity Channel Index (CCI). But their information is mostly overlapped by moving average (trend), momentum and mean-reversion indicators.

$T_2 = 26$, $T_3 = T_7 = 9$, and $T_4 = T_5 = 3$ trading days[20]. Shorter or faster MA settings are essential for using weekly and monthly charts to determine the broad trends, and daily chart is harnessed for timing entry-exit strategies. Although momentum and trend following are often used interchangeably in the literature, they contribute to asset allocation distinctively. Investors can achieve higher returns with momentum portfolios but lower volatility and drawdown with trend-following strategy.

We go long (short) the home currency against the foreign currency if the MACD line crosses its signal lines from below (above), and the signal is stronger when accompanied with a large swing below (above) zero. A positive (negative) MACD indicator means an increasing upward (downward) momentum. Price reversal can be confirmed by the bullish (bearish) divergence, particularly a crossover at the resistance (support) breakout. We simply adopt the trend-strength indicator HTG_t[21] as a predictor of exchange rate returns, denoted by MAT.

K_t, $D_t \in [0, 100]$, while J_t can go beyond this range. It gives an overbought (oversold) signal to establish a short (long) position of USD against the foreign currency if $K_t > 90$, $D_t > 80$, and $J_t > 100$ ($K_t < 10$, $D_t < 20$, and $J_t < 0$)[22]. The market is in the balance of long-short power when their values are around 50. Similarly, we go long (short) when K_t rises above (falls below) D_t in the bottom (top) area. We utilize the features of the KDJ trading rule to construct a predictor of exchange rate returns MMR:

$$MMR_t = [\varphi_{MMT}(K_t - D_t) + \varphi_{MRV}(100 - J_t)\iota_{OB} + \varphi_{MRV}(0 - J_t)\iota_{OS}] \cdot 100\% \quad (4.22)$$

where ι_{OB} equals to 1 if $J_t > 100$ and 0 otherwise, and ι_{OS} equals to 1 if $J_t < 0$,

[20]For MACD, given that the setting of "5/35/5" has shorter short-term MA and longer long-term MA, it is more sensitive than that of "12/26/9". Less sensitive setting results in less frequent crossovers. For KJD, T_4 can be selected within the range from 5 to 14.

[21]Investors should be aware of the whipsaws, which usually generate false or lagging signals. To mitigate this problem, we resort to the PPO approach.

[22]It is similar to Relative Strength Indicator (RSI) but more sophisticated and performs better, particularly in the identification of overbought and oversold levels, at which MACD does not excel. However, KDJ indicator normally becomes insensitive at high or low level of values owing to its high sensitivity to price changes.

and 0 otherwise; φ_{MMT}, and φ_{MRV} measures the persistence of momentum, and the rate of mean reversion, respectively. K_t and D_t are not as sensitive as J_t to the overbought/oversold activities, and the corresponding crossovers are more robust for the identification of trends. When an overbought/oversold signal is generated, the mean-reversion component tends to offset or even dominate the momentum component.

We further consider option-implied information and crash sensitivity from the perspective of quantitative risk management. Specifically, the volatility risk premium (VRP_t) as a measure of hedging demand imbalances (Garleanu, Pedersen, and Poteshman, 2009), and hence can be interpreted as a proxy for (relative) downside insurance cost (Della Corte, Ramadorai, and Sarno, 2013). According to Huang and MacDonald (2013b), the skew risk premium (SRP_t) measures the expected change in the probability of UIP to hold, and therefore can be interpreted as a proxy for crash risk premia of investment currencies relative to funding currencies, and the kurtosis risk premium (KRP_t) naturally reflects tail risk premium. The formula for moment risk premia is given by: $MRP_t = \mathbb{E}_t^{\mathbb{P}}[RM_t] - \mathbb{E}_t^{\mathbb{Q}}[RM_t]$, where $\mathbb{E}_t^{\mathbb{P}}[\,\cdot\,]$, $\mathbb{E}_t^{\mathbb{Q}}[\,\cdot\,]$ is the conditional expectation operator under physical measure $\mathbb{P}$, and risk-neutral measure $\mathbb{Q}$, respectively. Hence, the moment risk premia are computed as the realized moment[23] subtracted by model-free option-implied moment (see Carr and Wu, 2009; Kozhan, Neuberger, and Schneider, 2013; Huang and MacDonald, 2013b, for details).

Copula (lower) tail dependence CTD_t between the returns of a currency and that of the global FX market as a measure of the crash sensitivity:

$$CTD_t = \lim_{q \to 0^+} \frac{\Pr\left(FX \leq F_{FX,t}^{-1}(q), MKT \leq F_{MKT,t}^{-1}(q)\right)}{\Pr\left(MKT \leq F_{MKT,t}^{-1}(q)\right)} = \lim_{q \to 0^+} \frac{C_t(q,q)}{q} \tag{4.23}$$

where F_t^{-1} is the inverse function of continuous marginal distribution, C_t is the copula function that captures the joint distribution between two margins, and quantile $q = 10\%$ (see Huang and MacDonald, 2013b). ΔCTD_t is taken as a predictor of exchange rate returns, denoted by TCS.

[23] Neuberger (2012) shows that skewness is not integrable. Thus, we use monthly skew of daily returns as the proxy for realized skew.

In the COT report of CFTC, we measure the hedging pressure in currency futures market HPF_t of commercial ($HPF_{c,t}$) and non-commercial ($HPF_{f,t}$) traders as the difference between short and long futures positions normalized by the sum of these positions[24]:

$$HPF_t = \frac{HPF_t^S - HPF_t^L}{HPF_{t-1}^S + HPF_{t-1}^L} \tag{4.24}$$

and winsorize it at 99%. The aggregate hedging pressure is the sum of both commercial and speculative components as in Acharya, Lochstoer, and Ramadorai (2013). Other "scapegoat" variables we consider are: the past 3-month average changes (see also Bakshi and Panayotov, 2013) in commodity ΔCRB_t, volatility ΔVIX_t, and liquidity ΔTED_t indices. As for country-specific economic policy uncertainty indicators ΔEPU_t, we adopt 1-month changes in the indices.

4.3.6 Customer Order Flows

Customer order flows contain predictive information about future exchange rate movements (Evans and Lyons, 2002, 2005b). Order flow imbalances (as a measure of net buying/selling pressure) is informative about the yield curve without announcements and the effect becomes stronger and permanent when market liquidity is low (Brandt and Kavajecz, 2004). From the foreign exchange market microstructure perspective, it is of paramount importance to investigate the secret (unobservable) content of the private information about the term structure (factors) of currency carry trade risk premia (TSF_t), the yield curve and other "scapegoat" drivers. A direct solution is to test the relationship between customer order flows and the Nelson-Siegel latent factors, and dynamically weighted (by forecast performance-driven probability) "scapegoat" variables or empirical exchange rate models.

$$TSF_t = \varpi_0^{TS} + \varpi_1^{TS} \cdot o_t + \varpi_2^{TS} \cdot o_{t-1} + \nu_t^{TS} \tag{4.25}$$

[24]If the normalization (denominator) of the net position equals to zero, we use the non-zero value of previous period.

$$o_t = \varpi_0^{SG} + \sum_{j=1}^{k} \varpi_j^{SG} \cdot \Pr(L_t = j \mid z_t) \cdot x_{j,t} + \nu_t^{SG} \tag{4.26}$$

$$o_t = \varpi_0^{MD} + \varpi_1^{MD} \cdot \Delta MD_t + \varpi_2^{MD} \cdot \Delta MD_{t-1} + \nu_t^{MD} \tag{4.27}$$

where o_t denotes the aggregate order flow, which can be disaggregated into o_t^{AM}, o_t^{CC}, o_t^{HF}, and o_t^{PC} — order flows from asset managers, corporate (commercial) clients, hedge funds, and private clients, respectively. Asset managers and hedge funds are typical financial clients. Equation (4.25) examines the predictive power of customer order flows on the term structure of currency carry trade excess returns. We do not use a lag in Equation (4.26) because x_t are publicly observable and customer order flows are driven by both public and private information. If the coefficients of model disagreement are statistically significant, Equation (4.27) indicates that model uncertainty drives and/or predicts trading activities. Risk-averse market participants may reduce their exposures to model risk and shift their inventories to assets with low model risk. Thus, it is reasonable to expect negative coefficients.

4.4 Evaluation of the Term Structure of Exchange Rate Predictability

In this section, we evaluate both statistical and economic significance of the out-of-sample forecasts (see also Della Corte, Sarno, and Thornton, 2008) of the term structure of exchange rate predictability with a large set of empirical models or potential "scapegoat" variables using DMA approach in comparison with the best known alternative model, random walk without drift[25], as a parsimonious benchmark.

[25] Engel and Hamilton (1990); Engel, Mark, and West (2007) find that driftless random walk is a better forecaster than random walk with drift.

4.4.1 Statistical Accuracy

We assess the term structure of exchange rate predictability via a series of pseudo out-of-sample forecasting exercise as in Stock and Watson (2003). We compute Campbell and Thompson (2008) out-of-sample R-squared (R^2_{OOS}) which compares unconditional τ-step-ahead RW forecasts $\Delta\bar{s}^{(\tau)}_{t+\tau|t}$ with conditional τ-step-ahead DMA forecasts of our factor-augmented empirical exchange rate model with time-varying parameters, $\Delta\hat{s}^{(\tau)}_{t+\tau|t}$:

$$R^2_{OOS} = 1 - \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2} \tag{4.28}$$

The number of forecasts made by the term structure model of exchange rate predictability is $T_F = T_{OOS} - T_{IS} - \tau$. The in-sample (out-of-sample) period is from January 1994 to January 2004 (February 2004 to February 2014). We then compute the difference of Root Mean Squared Error (RMSE) between our term structure model and parsimonious benchmark RW as in Welch and Goyal (2008):

$$\Delta RMSE = \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} - \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} \tag{4.29}$$

A positive R^2_{OOS} or $\Delta RMSE$ implies that our alternative model outperforms the benchmark RW. We also use the Diebold-Mariano-West test for comparison of two non-nested models[26] with mean quadratic loss differential:

[26] Clark and McCracken (2001), McCracken (2007) illuminate that although the statistics of Diebold and Mariano (1995) and West (1996) perform well in the tests for equal predictability of non-nested models, they severely underestimate the critical values when used for comparing nested models owing to the fact that they do not have a standard normal distribution. To correct this distortion, Clark and McCracken (2001), McCracken (2007) derive non-standard asymptotic distributions for a number of statistical tests on nested models. If the alternative models are not correctly specified, the forecasting errors will be serially correlated and exhibit conditional heteroskedasticity. These methods cannot numerically generate asymptotic critical values, so we must resort to a bootstrapping procedure to compute valid critical values. When estimating a vector of parameters, some of which may not help to forecast, we inevitably introduce noise into the forecasting procedures. In this case, the MSE is expected to be greater than that of a RW. As a result, we may reach a conclusion in favour of the null hypothesis of equal predictability of two nested models. Clark and West (2006, 2007) suggest to modify the MSE.

$$\bar{d}_t = \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s_{t+\tau}^{(\tau)} - \Delta \bar{s}_{t+\tau|t}^{(\tau)}\right)^2 - \sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s_{t+\tau}^{(\tau)} - \Delta \hat{s}_{t+\tau|t}^{(\tau)}\right)^2}{T_F} \tag{4.30}$$

The statistic for the null hypothesis of equal predictive accuracy under the assumptions of $\mathbb{E}[d_t] = \mu_d$; $\sigma_{d_t}^2 < \infty$; and $\mathrm{cov}[d_t, d_{t-\tau}] = \vartheta(\tau), \forall t$:

$$DMW = \frac{\bar{d}_t}{\hat{\sigma}_{\bar{d}_t}} \xrightarrow{d} \mathcal{N}(0,1) \tag{4.31}$$

where $\hat{\sigma}_{\bar{d}_t} = \sqrt{\hat{b}(0)/T_F}$ and $\hat{b}(0)$ is a consistent estimator of the loss differential spectrum at frequency zero. We reject the null hypothesis (in favour of our term structure model) at 1%, 5%, or 10% significant level with a $p-value$ of DMW statistic lower than 0.01, 0.05, or 0.10, respectively.

4.4.2 Economic Value

We assess the economic value of our model in a mean-variance dynamic asset allocation framework[27] that exploits the term structure of exchange rate predictability. We consider a U.S. investor who dynamically rebalances his/her international bond portfolio at monthly or at a lower frequency. The only risk he/she is exposed to is currency risk. The U.S. investor updates the optimal weights according to the expected τ-period-ahead FX returns predicted by the factor-augmented empirical exchange rate model, which offers a projection of information structure via return decomposition. This design allows us to study which forecasting horizon and portfolio rebalance solution yields a better asset allocation result than RW. In active currency management, investors often focus on a strategy that maximizes expected excess return $\mu_{p,t+\tau}$ for a given target of conditional volatility $\bar{\sigma}_p$:

[27] See also Abhyankar, Sarno, and Valente (2005); Thornton and Valente (2012); Sarno, Schneider, and Wagner (2014); Gargano, Pettenuzzo, and Timmermann (2014).

$$
\max_{\omega_t} \left\{ \mu_{p,t+\tau} = \underbrace{\omega_t^\top (\mathbb{E}_t[\Delta s_{t+\tau}^{(\tau)}] + r_t^{(\tau),*})}_{Foreign\ Investment} + \underbrace{(1 - \omega_t^\top \iota)\, r_t^{(\tau)}}_{Domestic\ Investment} - \underbrace{r_t^{(\tau)}}_{Benchmark} \right\}
$$

$$
\text{s.t. } \bar{\sigma}_p^2 = \omega_t^\top \Sigma_{t+\tau|t}\, \omega_t \tag{4.32}
$$

where $\Sigma_{t+\tau|t}$ is the conditional variance-covariance matrix of exchange rate returns using information at time t, which entails modeling the dynamics of return volatilities and correlations then forecasting using the information available at time t. We assume that $\Sigma_{t+\tau|t} = \overline{\Sigma}_t$, the unconditional variance-covariance matrix using the information available at time t[28]. Both RW and our term structure model share the same variance-covariance matrix specification for reasons of comparison. Then the optimal weights vary with the forecasting models only to the extent that predictive regressions produce better forecasts of carry trade risk premia and exchange rate returns. ω_t, $\mathbb{E}_t[\Delta s_{t+\tau}^{(\tau)}]$, and $r_t^{(\tau),*}$ are all $K \times 1$ vectors, ι is a $K \times 1$ vector with all elements equal to unity, and $r_t^{(\tau)}$ is a scalar. Exchange rate in this framework is defined as the domestic value (USD) of foreign currency, so-called "direct quote". The solution of the above problem faced by a representative agent gives the optimal weight matrix of risky assets (currencies):

$$
\omega_t = \frac{\bar{\sigma}_p}{\sqrt{\varrho}} \cdot \Sigma_{t+\tau|t}^{-1}\, \mathbb{E}_t[c_{t+\tau}^{(\tau)}] \tag{4.33}
$$

where $\varrho = \mathbb{E}_t[c_{t+\tau}^{(\tau)}]^\top\, \Sigma_{t+\tau|t}^{-1}\, \mathbb{E}_t[c_{t+\tau}^{(\tau)}]$, and $\mathbb{E}_t[c_{t+\tau}^{(\tau)}] = \mathbb{E}_t[\Delta s_{t+\tau}^{(\tau)}] + r_t^{(\tau),*} - \iota r_t^{(\tau)}$ under direct quote. Then this framework can be simplified to match the forecasts of the term structure of carry trade risk premia so that measuring the economic value of the carry component predictability is equivalent to measuring that of the exchange rate predictability. This leads to an optimal portfolio on the efficient frontier. The performance fee is a measure of economic values to investors introduced by Fleming, Kirby, and Ostdiek (2001, 2003) in evaluating portfolio management. More accurate forecasts result in better portfolio rebalance decisions, and therefore better asset

[28]We find that the forecasting performances are robust to the specification of volatility and correlation dynamics, such as Asymmetric Dynamic Conditional Correlation (A-DCC) model developed by Cappiello, Engle, and Sheppard (2006), and volatility-correlation timing improves asset allocation results.

allocation performance under mean-variance scheme.

The maximum performance fee is determined by a state when a representative agent with a quadratic utility of wealth is indifferent between using term structure (TS) predictive regressions and assuming RW in asset allocation. A performance fee lower than this threshold induces investors to switch from a RW to the alternative TS model. The maximum performance fee $\mathcal{F}$ is estimated by satisfying the out-of-sample condition of average utility with relative risk aversion (RRA) γ as below:

$$\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})^2\right]$$
$$=\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{RW})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{RW})^2\right] \tag{4.34}$$

Goetzmann, Ingersoll, Spiegel, and Welch (2007) further define a manipulation-proof performance measure $\mathcal{P}$ robust to return distributions as follows:

$$\mathcal{P}=\frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{TS}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right]$$
$$-\frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{RW}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right] \tag{4.35}$$

It does not require to specify a utility function but shares the same economic intuition as the maximum performance fee. We can interpret it as certainty equivalent portfolio excess returns. Both $\mathcal{F}$ and $\mathcal{P}$ are reported in percentage. We also report performance measures such as Sharpe ratio $\mathcal{SR}$ and Sortino ratio $\mathcal{SR}_{\mathcal{DR}}$[29]. Transaction cost is adjusted by time-varying bid-ask spread.

Moreover, besides active trading in currency market to acquire absolute returns, we extend this framework for passive, tactic (dynamic portfolio rebalance in anticipation of

[29]Sharpe ratio tends to overestimate the conditional risk of dynamic strategies, and thus underestimate the performance (see also Marquering and Verbeek, 2004; Han, 2006).

downside risk or the presence of a large deviation of the forecast made τ-period ago from the updated forecast at each time of review), and strategic (semi-annual or quarterly portfolio rebalance with a long-term investment objective) currency management. The beauty of our term structure model of carry trade risk premia $c^{(\tau)}_{t+\tau|t}$ is that it allows us to further compute the implied forecasts of exchange rate (log) returns at any time interval of the future τ period:

$$\begin{aligned}\Delta\tilde{s}^{(1)}_{t+\tau|t} &= \underbrace{\left(\hat{c}^{(\tau)}_{t+\tau|t} + f^{(\tau)}_t - s_t\right)}_{\Delta\hat{s}^{(\tau)}_{t+\tau|t}} - \underbrace{\left(\hat{c}^{(\tau-1)}_{t+\tau-1|t} + f^{(\tau-1)}_t - s_t\right)}_{\Delta\hat{s}^{(\tau-1)}_{t+\tau-1|t}} \\ &= \left(\hat{c}^{(\tau)}_{t+\tau|t} - \hat{c}^{(\tau-1)}_{t+\tau-1|t}\right) + \left(f^{(\tau)}_t - f^{(\tau-1)}_t\right) \end{aligned} \tag{4.36}$$

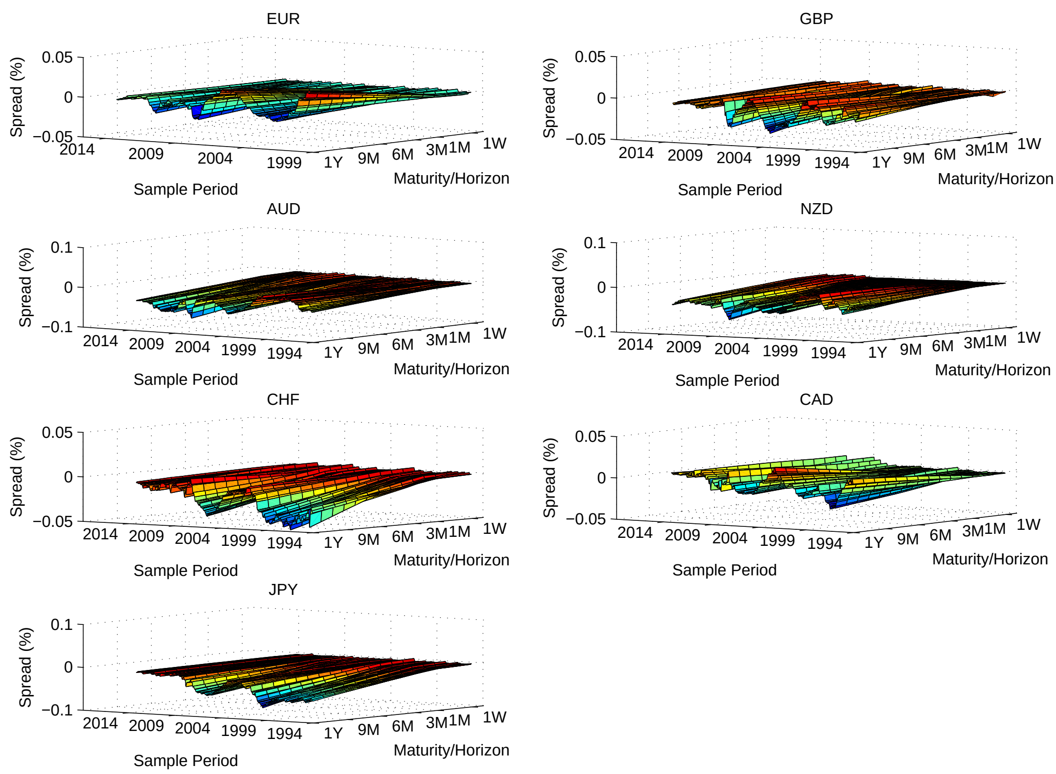
4.5 Empirical Results and Discussion

4.5.1 Preliminary Analysis

Figure 4.1. shows the term structure of the forward points with maturities from 1-week to 1-year (raw data) we utilize to decompose exchange rate returns. We annualize the carry trade risk premium component for the extraction of term structure factor, which is our forecasting focus at any time t. Once the forecasts of the term structure of carry component is done, we match them with the term structure of forward component already known at time t to obtain the forecasts of the term structure of exchange rate returns.

The descriptive statistics of the term structure of carry trade risk premia are shown in Figure 4.2. Both the mean and standard deviation of the carry trade risk premia, the excess returns of investments in foreign currencies financed by USD, are downward sloping, e.g. EURUSD, GBPUSD, AUDUSD, and NZDUSD. As for USDCHF, USDCAD, and USDJPY, the shape of the mean (and skewness) should be inversed.

Figure 4.1 The Term Structure of Forward Risk Premia

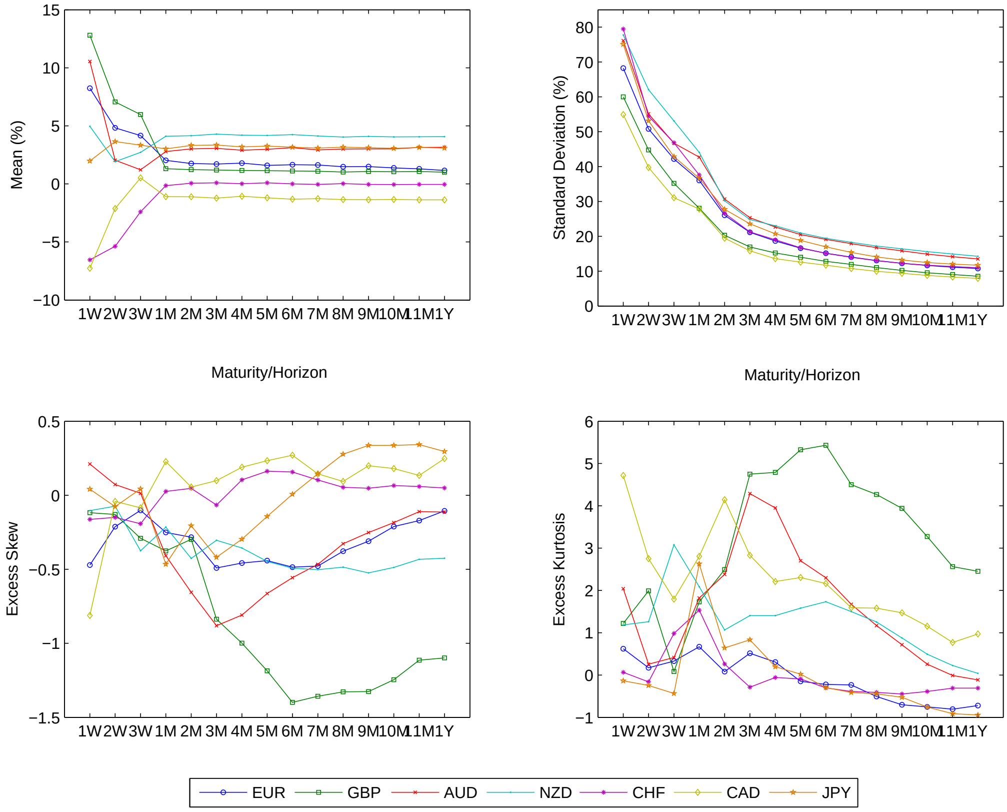


This figure shows the term structure of forward risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-week to 1-year (raw data). For the extraction of term structure factors, the data are annualized. The sample is from January 1994 (except for EURUSD which is available from December 1998) to February 2014 (Tick Label: End of Year).

We extract the Nelson-Siegel factors from the term structure of the carry component. As shown in Figure 4.3 below, all level, slope, and curvature factors experience dramatic fluctuations during the global financial crises, especially the recent Subprime Mortgage Crisis. For investment currencies such as AUD, there are sudden shoots up in the level factors (levels of risk premia) followed by plummets into the negative-value zone after the outbreak of Lehman Brothers' bankruptcy, while the slope factors rise up and remain in the positive-value zone during the crisis, implying that the term structure of risk premia is reversed. Vice versa for the funding currencies such as JPY. This situation lasts until the mid of 2009.

Figure 4.4. provides the time-series and cross-sectional goodness of fit of the term structure of carry components with contemporaneous Nelson-Siegel factors and

Figure 4.2 The Term Structure of Carry Trade Risk Premia: Descriptive Statistics

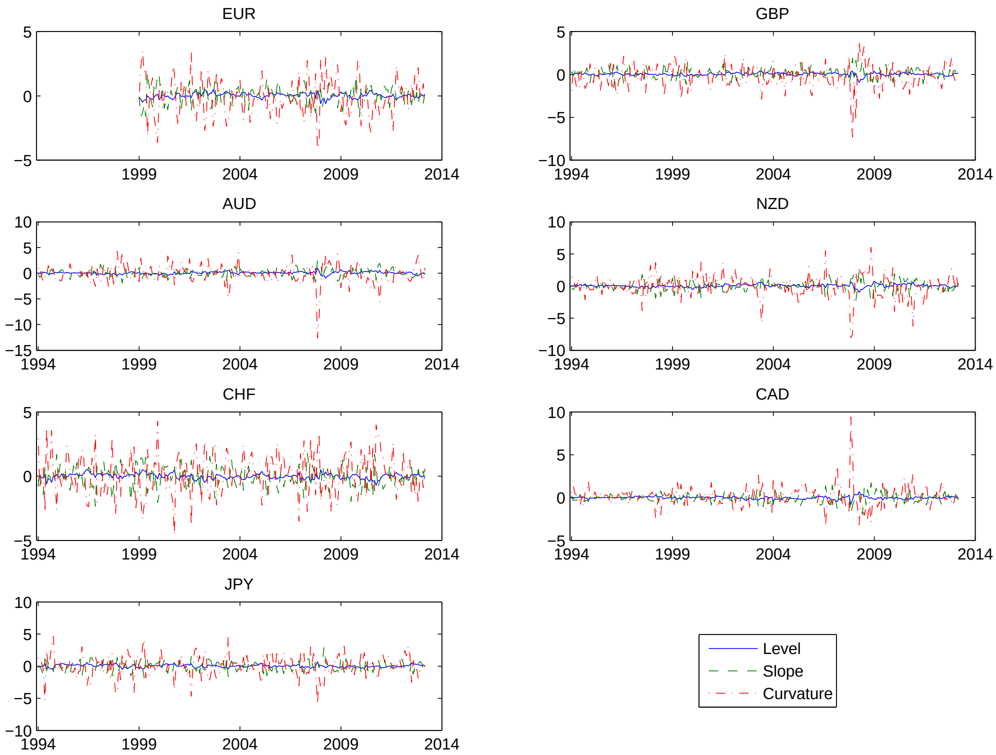


This figure shows the descriptive statistics for the term structure of carry trade risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-week to 1-year (annualized data). The sample is from January 1994 (except for EURUSD which is available from December 1998) to February 2014.

scapegoats. The Nelson-Siegel factors, on average, capture over 90% variations of the whole term structure across all studied currencies, and in particular, over 99% variations in 1-month carry trade risk premia. The scapegoats barely explain the remaining variations of the term structure (with an average adjusted R^2 lower than 1% across all 7 currencies). However, they seem to play a role in the long end (12-month horizon) of the curve in terms of an adjusted R^2 over 3%.

Figure C.1., Figure C.2., Figure C.3., Figure C.4., Figure C.5., Figure C.6., and Figure C.7. in Appendix .C reveal the probability weighting of each empirical exchange rate model or "scapegoat" variable in forecasting the term structure of currency carry trade risk premia. We find that, for all currencies studied in this chapter, the term structure model (factors only) without any other predictors only accounts for a small proportion of the total weight of probability in the forecasts of the term structure of

Figure 4.3 The Term Structure of Carry Trade Risk Premia: Nelson-Siegel Factors



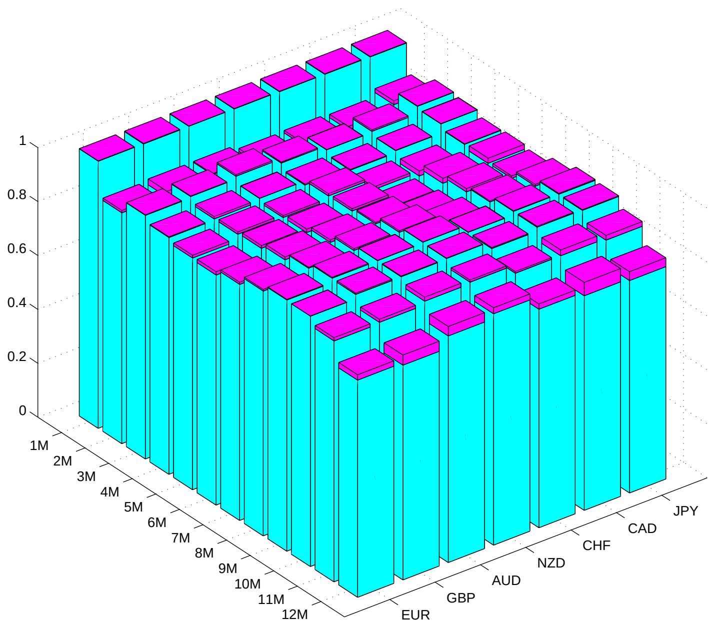
This figure shows the Nelson-Siegel factors extracted from the term structure of carry trade risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-week to 1-year (annualized data). The sample is from January 1994 (except for EURUSD which is available from December 1998) to February 2014. Tick Label: End of Year.

carry component, and the weight drops remarkably after the crisis, indicating that the empirical exchange rate models or "scapegoat" variables, especially the model of yield curve factors, pick up weights in the financial turmoil and become more important in the dynamics with term structure factors. We select some stylized predictors of the term structure of carry trade risk premia to discuss.

4.5.2 Term-Structural Effects of Exchange Rate Predictors

Figure 4.5. demonstrates the time-varying effects of exchange rate predictors on the term structure of carry trade risk premium component of EURUSD. After the crisis, Taylor rule (TRI), volatility risk premia as the proxy for position insurance cost (VRP), and economic policy uncertainty (EPU) pick up weights considerably and

Figure 4.4 The Time-Series & Cross-Sectional (Contemporaneous) Goodness of Fit with Nelson-Siegel Factors & Scapegoats



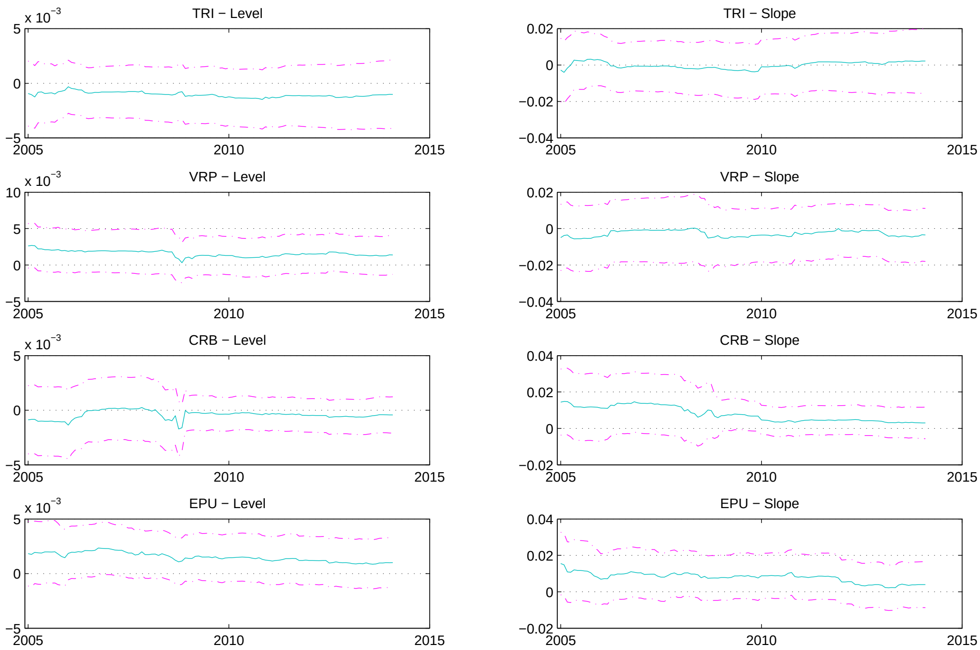
This figure shows the time-series and cross-sectional variations in the term structure of carry trade risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-month to 12-month (annualized data) explained by contemporaneous Nelson-Siegel factors (cyan), and by scapegoats (magenta) *additionally*, which capture some additional variations.

they all exert positive impacts on the level factor except for TRI. Both commodity risk (CRB) and EPU raise the short-term risk premia more than the long-term risk premia.

Both moving average trend (MAT) and hedging pressure in futures market (HPF) play pivotal roles in forecasting the term structure of carry component of GBPUSD and impose positive effects on both level and slope factors, lifting up the short-term side of risk premia relative to the long-term side (see Figure 4.6.). After the crisis, CRB rises remarkably as a key predictor with a negative effect on the level of risk premia.

MAT as a predictor of the term structure of AUDSUD carry trade risk premia lowers the future level of risk premia and flattens the slope of the term structure, with a sudden drop and a quick rebound during the crisis. After the crisis, the impacts of VRP on the level and slope factors become persistently positive, and the effect of

Figure 4.5 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): EUR

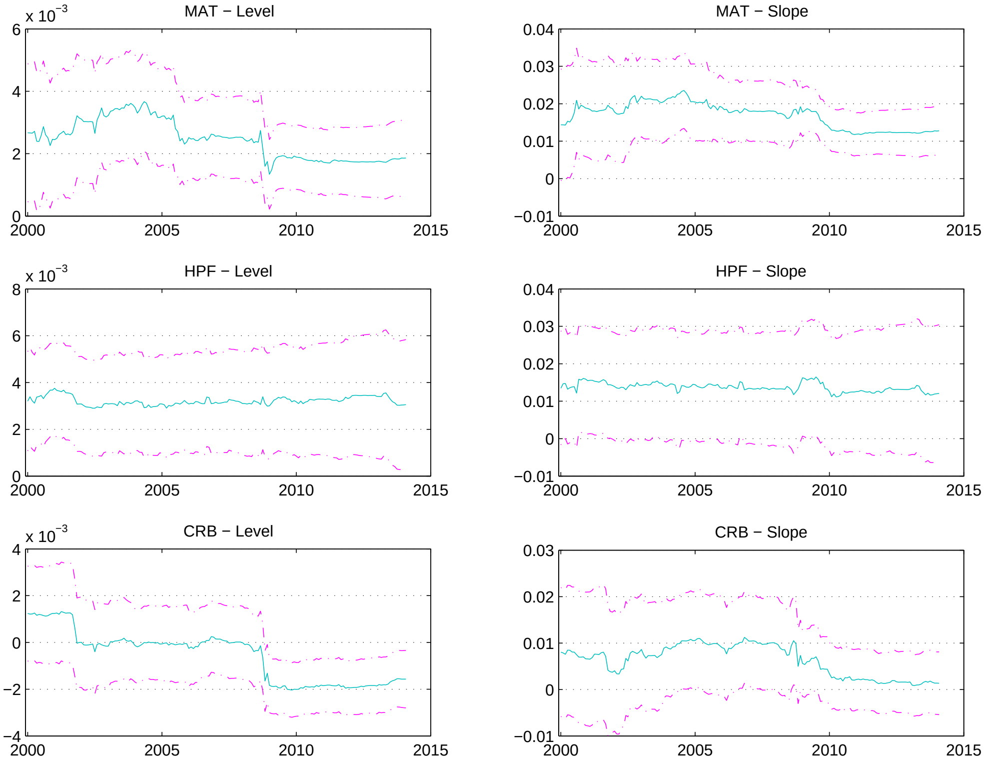


This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for EURUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

CRB on the level of risk premia declines notably and becomes negative, and this effect emphasizes the short-term risk premia relative to the long-term risk premia after the crisis (see Figure 4.7.).

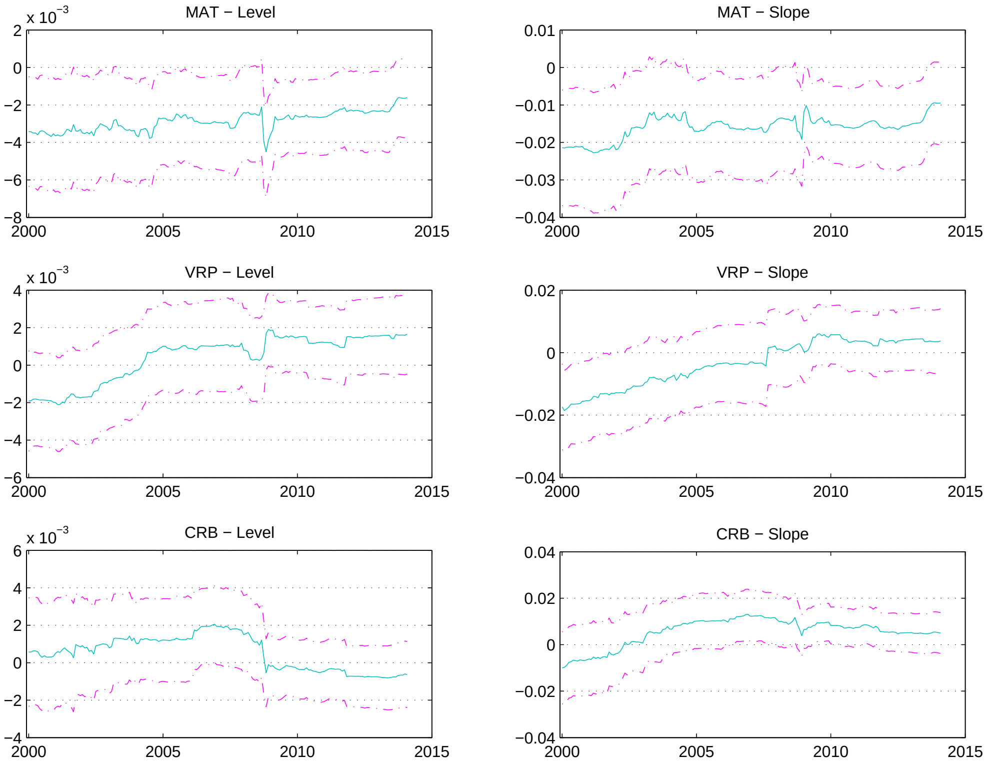
TRI tends to drive up the level of risk premia and its flattening effect on the slope of the term structure of NZDUSD carry trade risk premia becomes smaller after the crisis. The influences of VRP have been diminishing in the past decade. MAT picks up weight significantly after the crisis, and negatively affects both the level and slope factors. The impacts of CRB on these factors are similar to the case of AUDUSD (see Figure 4.8.) as they are both characterized by commodity currencies.

Figure 4.6 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): GBP



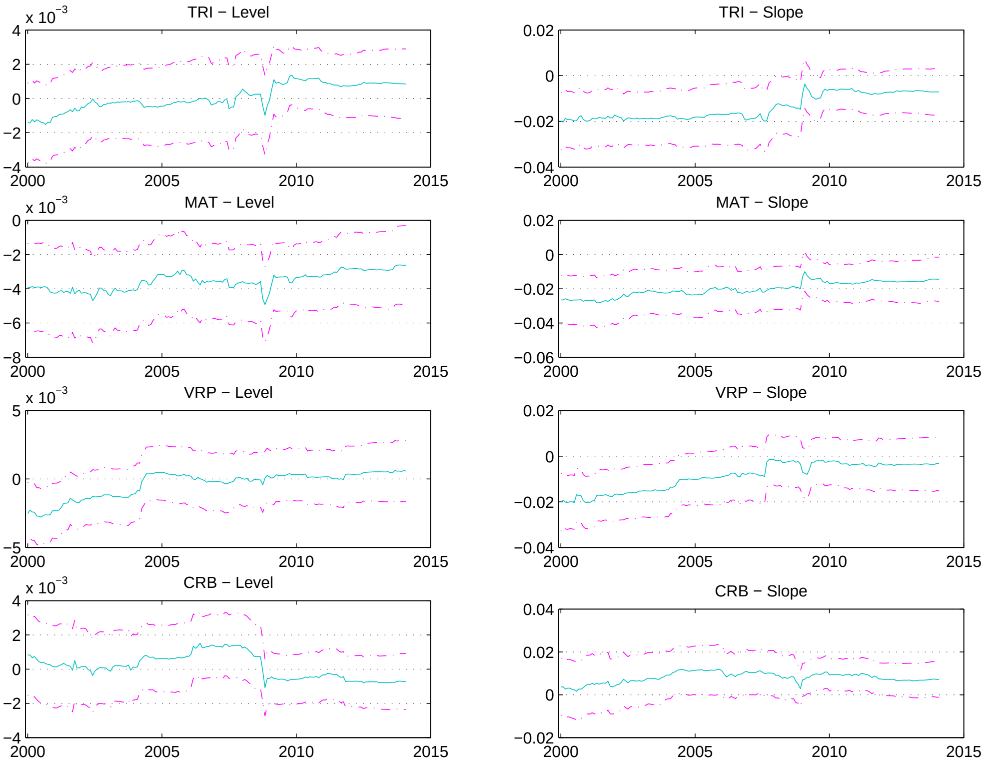
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for GBPUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

Figure 4.7 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): AUD



This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for AUDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for AUDUSD. The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

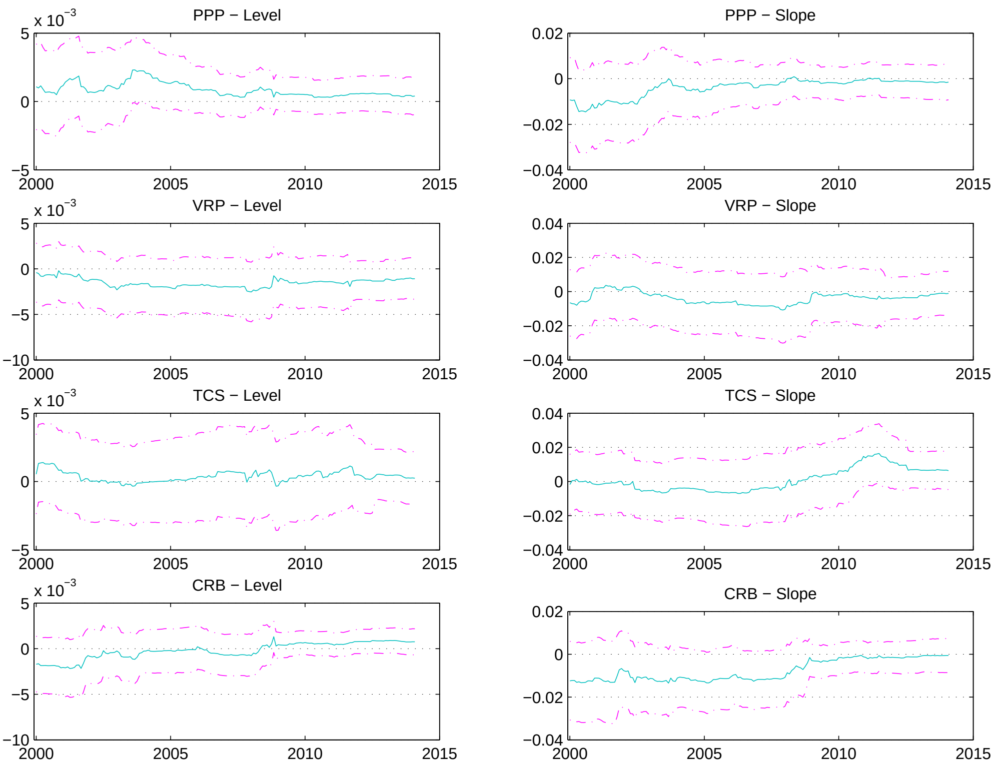
Figure 4.8 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): NZD



This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for NZDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for NZDUSD. The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

Before the NBER recession period, a substantial weight is attached to purchasing power parity (PPP) in the forecasts of the term structure of USDCHF carry trade risk premia. The influences of PPP, VRP, the copula-based tail dependence measure of crash sensitivity (TCS), and CRB on the level and slope factors have also been diminishing in the past decade. After the outbreak of European Debt Crisis, CRB positively affects the level of risk premia while TCS tilts the slope of the term structure (see Figure 4.9.).

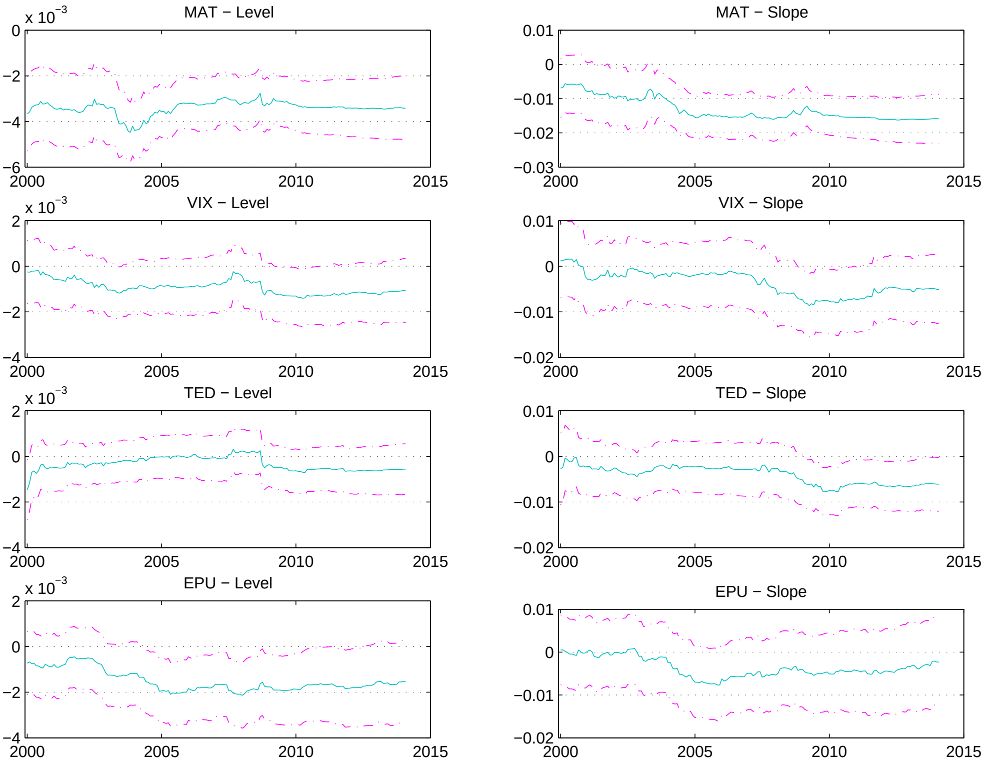
Figure 4.9 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): CHF



This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDCHF via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for USDCHF. The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

Monetary fundamentals (MOF), VRP, volatility risk (VIX), and liquidity risk (TED) pick up substantial weights after the crisis in the forecasts of the term structure of USDCAD carry trade risk premia. MAT lowers the future level of risk premia and tilts the slope of the term structure. In particular, the impacts VIX and TED are stronger (in magnitude) after the crisis. EPU also negatively affects the level and slope factors, but its impact on the slope of the term structure gradually becomes smaller after the crisis (see Figure 4.10.).

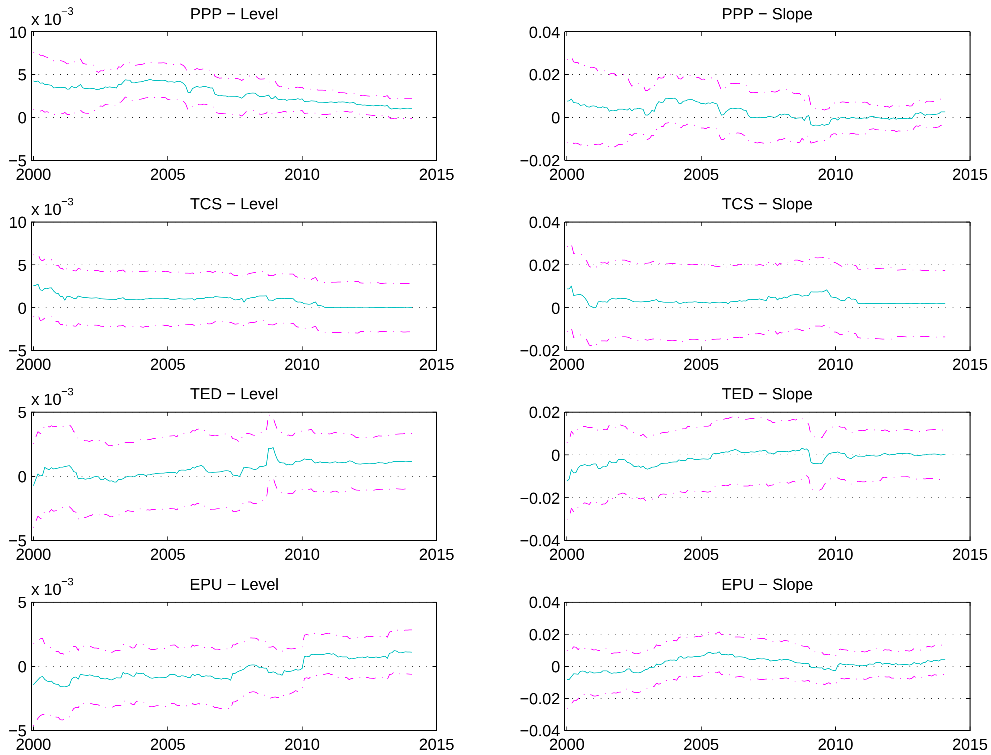
Figure 4.10 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): CAD



This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDCAD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

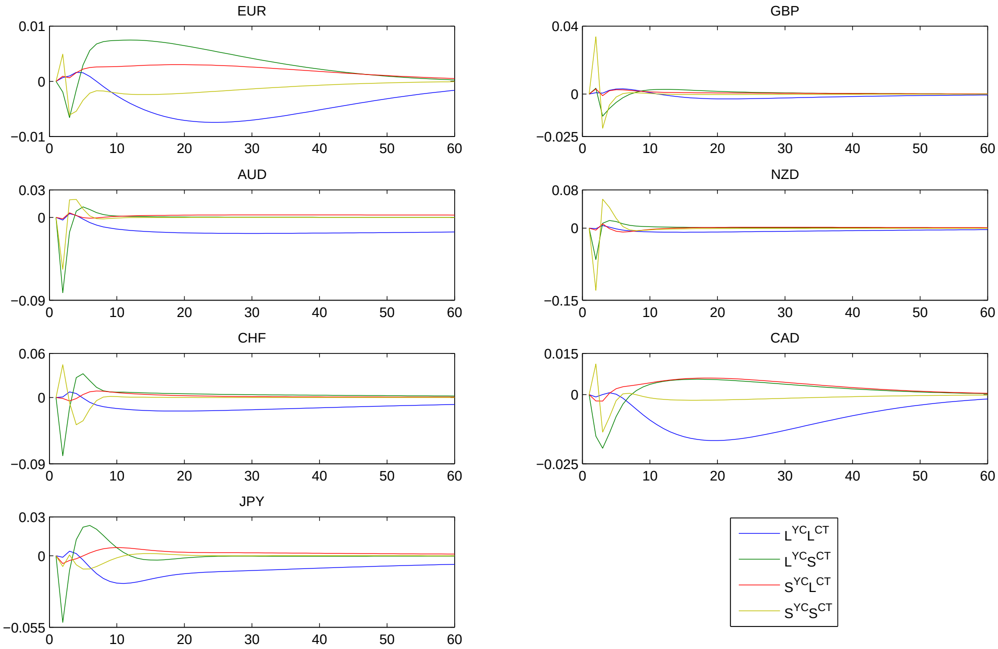
PPP, TRI, and CRB account for large proportions of the probability weighting in the forecasts of the term structure of USDJPY carry trade risk premia, and PPP raises the level of risk premia. The predictive power of TCS suddenly surges up during the crisis due to its temporarily enhanced influences on both level and slops factors. TED and EPU both play increasingly important roles in the association with the level of risk premia after the crisis. However, these predictors are not helpful in forecasting the slope of the term structure (see Figure 4.11.).

Figure 4.11 Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): JPY



This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDJPY via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The dash lines surrounding the posterior mean plots present 95% frequentist confidence intervals.

Figure 4.12 Impulse Response of the Term Structure of Carry Trade Risk Premia to the Yield Curve



This figure shows the impulse response of the term structure of carry trade risk premia to the Nelson-Siegel level & slope factors of relative yield curve (as in September 2008). L, and S is the level, and slope factor, respectively; the subscript YC, and CT denotes the yield curve, and carry trade risk premia, respectively.

Figure 4.12. shows the impulse response of the term structure of carry trade risk premia to the relative yield curve[30], which accounts for the largest share of DMA probability weighting for all 7 currencies. For EUR, GBP, AUD, and NZD, the level of risk premia of the term structure (L^{CT}) positively reacts to the shocks to both relative yield curve level (L^{YC}) and slope (S^{YC}) factors in the first few months, then the reactions diverge from each other and the net effect remains negative, which is the case for other currencies all the time. The impulse response of the L^{CT} to the L^{YC} is quite persistent for AUD — a typical investment currency[31]. Overshooting of the slope factor (S^{CT}) of carry trade term structure in response to the L^{YC} and S^{YC} is common and significant across currencies but is stabilized (net effect) within 12 months

[30] Bekaert, Wei, and Xing (2007) find the deviations from Expectations Hypothesis (EH) cannot well explain deviations from UIP at long horizons.

[31] Ferreira Filipe and Suominen (2013) reveal that funding liquidity risk (see also Brunnermeier and Pedersen, 2009) explains a large proportion of AUD versus JPY speculative positions in currency futures market.

except for EUR. In the first few months, the S^{CT} of GBP (AUD, NZD, and the typical funding currency JPY) positively (negatively) responds to the yield curve movements (both L^{YC} and S^{YC}), followed by a negative (positive[32]) adjustment which implies a flattened term structure. The opposite reactions of L^{CT} and of S^{CT} to L^{YC} and S^{YC} cannot offset each other, as the level of interest rate differential over the yield curves L^{YC} exerts greater impact on L^{CT} and S^{CT} than the slope factor of the relative yield curve S^{YC}, e.g. the case of CHF. EUR and CAD share similar impulse response to the relative yield curve shocks.

4.5.3 Probability Weighting and Model Disagreement

Table 4.1 below reports the descriptive statistics of the probability weighting of each empirical model or "scapegoat" variable for all currencies. The mean μ_m, and standard deviation σ_m measures the significance, and stability of the probability weighting, respectively. Then the ratio of these two moments $\mathcal{SR}_{\mathcal{PW}}$ captures the instability-adjusted average probability weighting. We find that our term structure model without any exchange rate predictors, and with purchasing power parity (PPP), monetary fundamentals (MOF), Taylor rule (TRI), volatility risk premia (VRP), or commodity risk (CRB) are the most stable and influential predictors for nearly all currencies; the model with relative yield curve factors (YCF) has a very high forecasting performance for all currencies during financial crises but its predictive power is instable (low in tranquil periods); momentum and mean-reversion indicator (MMR), crash and tail risk premia (SRP and KRP), hedging pressure in futures market (HPF), copula-based tail dependence (TCS), volatility risk (VIX), and liquidity risk (TED) are stable predictors for GBP and CAD with relatively low significance; economic policy uncertainty (EPU) possesses a very stable predictive power on CAD.

Figure 4.13. reveals the evolving importance of each empirical exchange rate model or "scapegoat" variable over time, measured by the average (out-of-sample) time-varying probability weighting across the sample currencies. It is noteworthy that YCF arises as an important predictor of exchange rates at the outbreak of each financial

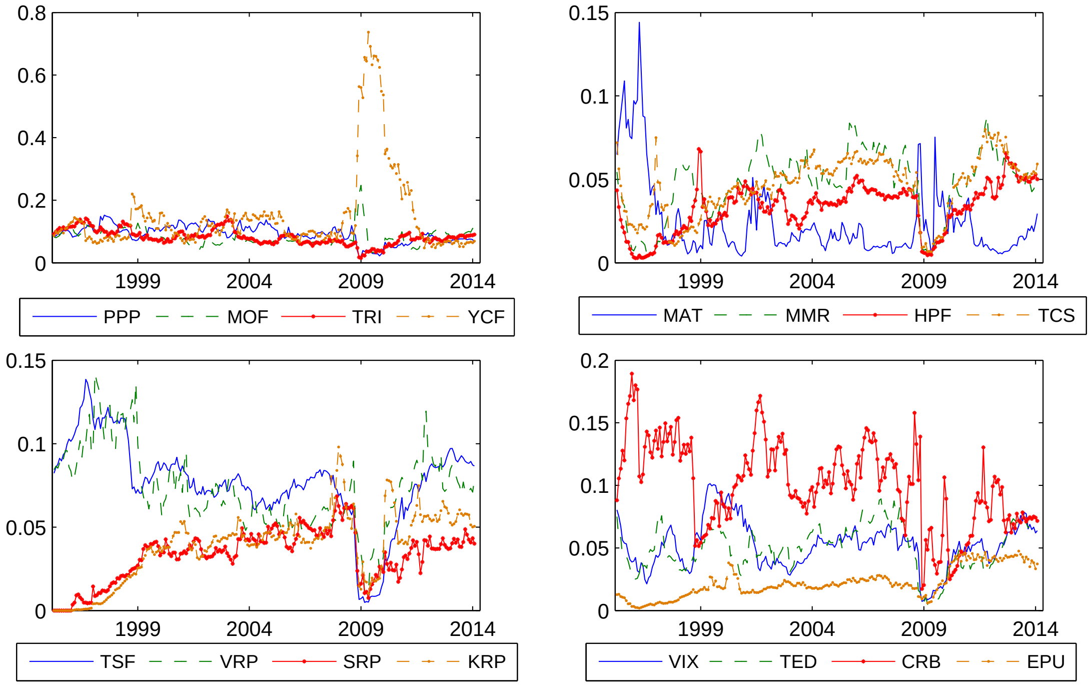
[32]This indicates a greater reaction of the short-term risk premium to the yield curve movements than that of the long-term risk premium.

Table 4.1 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: All Currencies

FX	DS	Empirical Models / Scapegoat Variables															
		TSF	PPP	MOF	TRI	MAT	MMR	VRP	SRP	KRP	HPF	TCS	VIX	TED	CRB	EPU	YCF
EUR	$\mu_m(\%)$	**8.45**	**12.59**	**9.52**	**7.42**	0.05	3.15	5.48	2.68	3.82	2.69	4.76	3.36	4.81	**9.34**	3.54	**18.35**
	$\sigma_m(\%)$	3.38	7.75	5.62	4.72	0.14	3.75	4.09	1.89	2.98	2.76	2.68	2.47	3.47	5.88	2.86	21.51
	$\mathcal{SR}_{\mathcal{PW}}$	**2.50**	**1.62**	**1.69**	**1.57**	0.36	0.84	1.34	1.42	1.28	0.97	**1.77**	1.36	1.38	**1.59**	1.24	0.85
GBP	$\mu_m(\%)$	**7.62**	**8.06**	**6.68**	**7.17**	2.57	6.24	**10.70**	4.34	3.84	4.16	5.04	5.72	5.29	**7.93**	4.09	**11.68**
	$\sigma_m(\%)$	2.91	3.47	2.56	3.09	5.89	3.71	7.26	2.18	2.40	2.12	2.26	2.57	2.60	4.47	3.80	15.37
	$\mathcal{SR}_{\mathcal{PW}}$	**2.62**	**2.32**	**2.61**	**2.32**	0.44	**1.68**	1.47	**1.99**	1.50	**1.96**	**2.22**	**2.23**	**2.03**	**1.77**	1.08	0.76
AUD	$\mu_m(\%)$	**8.28**	**8.65**	**8.44**	**8.67**	0.73	4.55	**8.30**	4.09	4.50	4.05	5.34	6.02	5.30	**7.92**	—	**15.67**
	$\sigma_m(\%)$	3.94	3.72	5.88	4.03	1.92	2.76	4.19	2.77	2.70	3.01	3.27	4.93	3.12	3.68	—	19.62
	$\mathcal{SR}_{\mathcal{PW}}$	**2.10**	**2.33**	1.43	**2.15**	0.38	1.64	**1.98**	1.47	1.66	1.35	1.63	1.22	**1.70**	**2.15**	—	0.80
NZD	$\mu_m(\%)$	**7.80**	**7.40**	**9.55**	**10.09**	**6.95**	5.35	**7.22**	3.89	5.21	—	4.94	5.39	5.21	**7.10**	—	**14.41**
	$\sigma_m(\%)$	3.43	3.13	8.54	5.92	7.38	4.50	3.57	2.52	4.71	—	2.98	2.77	3.19	3.07	—	19.33
	$\mathcal{SR}_{\mathcal{PW}}$	**2.28**	**2.37**	1.12	**1.70**	0.94	1.19	**2.02**	1.55	1.11	—	1.66	**1.94**	1.64	**2.31**	—	0.75
CHF	$\mu_m(\%)$	**7.67**	**12.37**	**8.95**	**7.72**	0.30	4.85	4.71	3.15	4.19	4.10	5.08	5.03	4.24	**7.70**	—	**20.36**
	$\sigma_m(\%)$	3.61	8.74	5.27	4.20	1.13	4.39	2.49	2.38	3.36	3.52	3.46	2.81	2.71	4.00	—	20.57
	$\mathcal{SR}_{\mathcal{PW}}$	**2.13**	1.41	**1.70**	**1.84**	0.26	1.11	**1.89**	1.32	1.25	1.16	1.47	**1.79**	1.56	**1.92**	—	0.99
CAD	$\mu_m(\%)$	**7.18**	**7.18**	**7.63**	**7.45**	1.48	5.52	**7.73**	5.03	5.32	5.51	4.70	5.49	5.39	**7.98**	5.50	**11.51**
	$\sigma_m(\%)$	2.22	2.59	4.96	2.84	4.44	1.89	2.96	2.10	1.94	2.17	2.40	1.64	2.86	3.44	1.76	8.80
	$\mathcal{SR}_{\mathcal{PW}}$	**3.24**	**2.77**	1.54	**2.62**	0.33	**2.92**	**2.61**	**2.40**	**2.74**	**2.54**	**1.96**	**3.34**	**1.89**	**2.32**	**3.12**	1.31
JPY	$\mu_m(\%)$	**6.30**	**8.88**	**5.82**	**8.37**	3.76	3.13	5.67	1.35	1.95	2.68	2.48	4.99	4.77	**21.72**	3.53	**14.79**
	$\sigma_m(\%)$	2.48	5.57	2.93	5.36	4.80	2.21	2.42	1.00	1.36	1.72	1.94	2.96	3.20	13.65	3.16	14.45
	$\mathcal{SR}_{\mathcal{PW}}$	**2.54**	**1.60**	**1.98**	**1.56**	0.78	1.42	**2.34**	1.35	1.43	1.55	1.28	**1.69**	1.49	**1.59**	1.11	1.02

This table reports descriptive statistics (mean - μ_m in percentage; standard deviation - σ_m in percentage; stability ratio - $\mathcal{SR}_{\mathcal{PW}}$, which measures instability-adjusted average probability weighting) of the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia / exchange rate returns for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The sample is from January 1995 to February 2014.

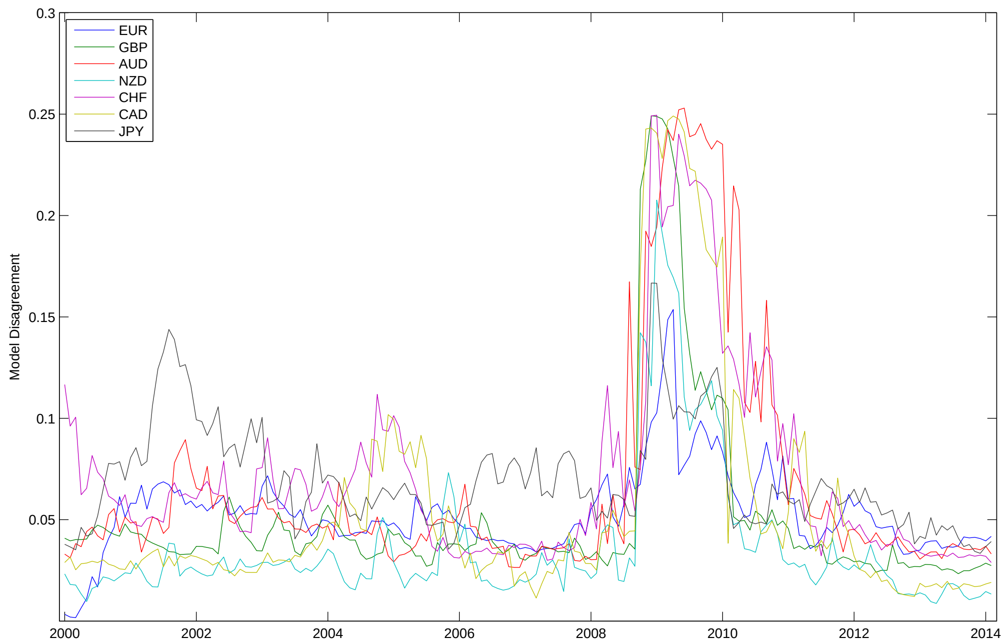
Figure 4.13 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: Average across Currencies



This figure shows the average probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia / exchange rate returns across G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The sample is from January 1995 to February 2014.

crisis in the sample period (September 2008 in particular) and drop in its probability weighting gradually during the economic recovery. And its probability weighting has a correlation of -0.93 with that of TFS — the factor-only model, and also low negative correlations with most of other predictors. This implies that the relative yield curve factors provide superior complementary information. So do MOF, MAT, CRB, and EPU but to a lesser extent. TSF is as important as VRP and HPF, which are shown to be non-trivial predictors of exchange rates (Della Corte, Ramadorai, and Sarno, 2013).

Figure 4.14 DMA-Implied Model Disagreements (All Currencies)

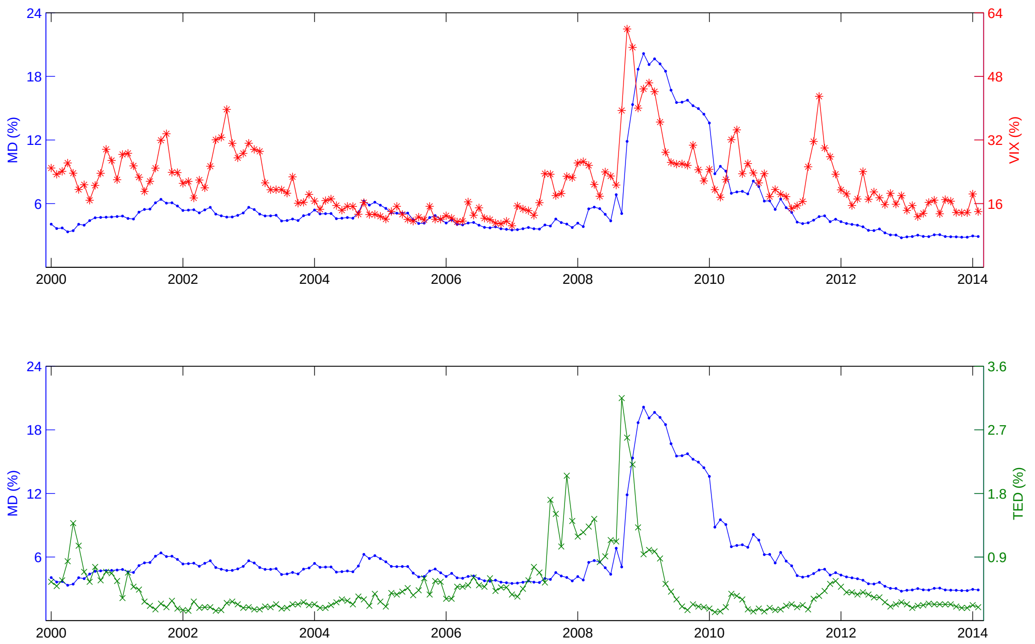


This figure shows the model disagreements implied by the probability weighting of the Dynamic Model Averaging (DMA) method (see Koop and Korobilis, 2012) for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK). The sample is from January 2000 to February 2014.

The DMA probability weighting is computed according to the forecasting accuracy of each empirical exchange rate model or "scapegoat" variable, and thereby can be used to construct a regression-based (rather than survey-based) measure model disagreement. Figure 4.14. shows the DMA-implied 1-month horizon model disagreements (MD) of individual currencies. The corresponding index in the foreign exchange market as the average across all currencies is closely associated with volatility (VIX) and liquidity (TED) risks (see Figure 4.15.).

Table 4.2 reveals that the series of AR(1) innovations to DMA-implied 1-month horizon model disagreement (ΔMD) has both predictive and contemporaneous relations with 1-month carry trade excess returns and the term structure (level and slop factors), FX (realized) volatility, and customer order flows across currencies. A positive shock to model disagreement predicts a higher (lower) level of currency risk premia of EUR, AUD, NZD, and CHF (GBP), a tilted slope of the term structure of GBP, CHF, CAD, and JPY. In the contemporaneous period, it induces a decline (rise) in level of the

Figure 4.15 Model Disagreement (Risk) Index vs. Volatility & Liquidity Risk Indices



This figure shows the model disagreement (risk) index (MD) as the average model disagreement across all 7 currencies implied by the probability weighting of the Dynamic Model Averaging (DMA) method (see Koop and Korobilis, 2012) versus volatility (VIX) and liquidity (TED) risk indices. The sample is from January 2000 to February 2014.

excess returns of GBP, CHF, and JPY (AUD, NZD, and CAD), and a tilted (flattened) slope of the term structure of AUD, NZD, and CAD (GBP, CHF, and JPY). A positive ΔMD also leads to an increase in contemporaneous FX volatility, and predicts a drop in this realized volatility in the next period for almost all studied currencies. This is possibly due to the volatility overshooting. These findings are compelling for GBP, NZD, CHF, and JPY. Furthermore, a higher level of MD induces financial clients, such as hedge funds, to speculate in future exchange rate returns meanwhile reduce current exposures to risky currencies by shifting a part of the overall investments to less risky USD and safe-haven currency such as JPY in a dynamic way (except for EUR). There are negative (positive) predictive and contemporaneous correlations of ΔMD with the order flows from private and corporate clients of risky currencies (safe-haven currencies CHF and JPY). In general, when confronting model uncertainty, asset managers tend to invest in foreign currencies funded by USD. Overall, the aggregate customer order flows are partially driven and predicted by model disagreement.

Table 4.2 Model Disagreement Effects: Carry Trade Excess Return, Volatility, Term Structure, and Customer Order Flows

FX	REG	Carry Trade Excess Returns, Volatility, Term Structure, and Customer Order Flows								
		xr	Δvol	L^{CT}	S^{CT}	AGG	AM	CC	HF	PC
	ϖ			2.24*			45.70**	-11.84**		
	s.e.			(1.16)			(22.53)	(5.98)		
EUR	ϖ_{-1}	3.59**	-0.37*	3.05**		-56.37***			-31.58**	-7.91**
	s.e.	(1.65)	(0.19)	(1.45)		(27.34)			(13.89)	(3.94)
	$Adj-R^2$	0.01	0.02	0.03	—	0.04	0.05	0.01	0.03	0.01
	ϖ	-4.47***	0.63***	-1.26*	-5.44*	10.87*	9.39*		-18.18***	-3.28**
	s.e.	(1.47)	(0.13)	(0.76)	(3.14)	(5.77)	(4.86)		(6.77)	(1.37)
GBP	ϖ_{-1}	-2.58***	-0.34***	-1.06**	10.22***	15.07*	15.30***		16.28***	-4.55***
	s.e.	(0.80)	(0.13)	(0.53)	(2.89)	(8.74)	(3.45)		(5.27)	(1.45)
	$Adj-R^2$	**0.09**	**0.19**	0.03	0.05	0.04	0.04	—	**0.21**	0.03
	ϖ	5.22***	0.76***	5.00**	10.46**	4.74*	6.67***	-1.50***		
	s.e.	(1.77)	(0.26)	(2.13)	(4.22)	(2.81)	(2.15)	(0.56)		
AUD	ϖ_{-1}	2.79*		5.54***			-9.19***		3.98**	-3.38***
	s.e.	(1.48)		(1.05)			(3.15)		(2.00)	(1.20)
	$Adj-R^2$	0.05	**0.10**	**0.20**	**0.06**	0.01	**0.13**	0.01	0.01	0.04
	ϖ	8.78*	0.73**	3.27*	8.41**		-1.28*			
	s.e.	(4.93)	(0.31)	(1.68)	(4.18)		(0.70)			
NZD	ϖ_{-1}	4.06***	-0.69*	2.02*		1.74***	1.48*			
	s.e.	(1.39)	(0.42)	(1.10)		(0.53)	(0.87)			
	$Adj-R^2$	**0.09**	**0.10**	**0.06**	0.03	0.02	0.01	—	—	—
	ϖ	-6.71***	0.71***	-3.72***	-8.66***				-11.17***	-3.36*
	s.e.	(2.01)	(0.26)	(1.16)	(2.81)				(3.17)	(1.97)
CHF	ϖ_{-1}	3.21*	-0.36**	2.74***	6.92**	9.22*		4.75**	6.02**	-3.26*
	s.e.	(1.84)	(0.18)	(0.82)	(2.97)	(5.51)		(2.17)	(2.40)	(1.78)
	$Adj-R^2$	**0.10**	**0.19**	**0.11**	**0.07**	0.01	—	0.01	**0.07**	0.01
	ϖ	2.46*	0.33***		7.70***	14.22***	17.86***	-1.50**	-4.52*	
	s.e.	(1.29)	(0.11)		(2.42)	(2.30)	(2.51)	(0.58)	(2.54)	
CAD	ϖ_{-1}				5.69***					-6.16**
	s.e.				(1.92)					(2.85)
	$Adj-R^2$	0.02	**0.06**	—	**0.09**	0.05	**0.10**	0.02	0.01	**0.11**
	ϖ	-7.09***	0.38**	-6.71**	-29.55*	93.91***	45.52***	4.21*	58.02***	
	s.e.	(1.55)	(0.17)	(2.81)	(15.43)	(21.22)	(16.75)	(2.13)	(15.08)	
JPY	ϖ_{-1}				19.49**				40.39***	-9.15**
	s.e.				(8.24)				(12.81)	(4.11)
	$Adj-R^2$	**0.10**	0.01	0.05	**0.07**	**0.11**	0.04	0.02	**0.08**	0.02

This table reports the effects of model disagreement on carry trade excess returns (xr), AR(1) innovations to FX volatility (Δvol), Nelson-Siegel level (L^{CT}) and slope (S^{CT}) factors, and customer order flows (both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC)). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

4.5.4 Model Evaluation and Term-Structural Commonality of Forecasts

The statistical accuracy of our term structure model in the out-of-sample forecasts of carry trade risk premia (or equivalently, exchange rate returns) are reported in Table 4.3, respectively. Our term structure model statistically outperforms the random walk in terms of R^2_{OOS} up to 20% (12-month forecasting horizon), $\Delta RMSE$ up to 4.5% (1-month forecasting horizon), and rejecting the null hypothesis of equal predictability of the Diebold-Mariano-West test with up to 5% significance level ($p - value$ of the $DMW - test$) for all currencies. All these indicate that our term structure model is able to beat the random walk in 1-month forecasting horizon at minimum. NZD and CAD are typically difficult to forecast at horizons from 3-month to 12-month. It is noteworthy that our term structure model performs the best for safe-haven currencies CHF and JPY. Our term structure model consistently beats RW at 1-month and 12-month horizons for all studied currencies, and better short-run (1-month horizon) forecasts of NZD, GBP, and CAD seem to be achieved at the cost of medium and long run predictive accuracy, whereas CHF and JPY are the best predicted currencies at the 12-month horizon.

These statistical results are economically intuitive and concordant with the "scapegoat" theory and mean-reverting story: The weights attached to the "scapegoat" variables change over time and investors switch their currency trading rules according to the model/varliable's contemporaneous predictive accuracy so that the predictive power of our term structure model varies with the forecasting horizon, i.e. the current model/variable to which a high weight is attached for the forecasts at 1-month horizon may not provide a full projection of information far into the future, but it does contain predictive information to evaluate a currency's long-run intrinsic value toward which its price reverts back. Purchasing power parity (PPP) is an important long-run mean-reverting predictor of exchange rates (Taylor, Peel, and Sarno, 2001; Taylor, 2002; Imbs, Mumtaz, Ravn, and Rey, 2005). The forecasting performance of our term structure model is impressive and robust on currencies with high weights of probabilities attached to PPP, e.g. EUR, CHF, and JPY; but is not stable on currencies with low weights

Table 4.3 Statistical Accuracy of the Term Structure Model: Out-of-Sample Predictability of Carry Trade Risk Premia / Exchange Rate Returns

FX	SA	Forecasting Horizons				
		1M	3M	6M	9M	12M
	$R^2_{OOS}(\%)$	3.78	1.75	13.16	15.32	8.61
EUR	$\Delta RMSE(\%)$	0.73	0.16	0.78	0.74	0.36
	$DMW-test$	*	—	—	—	—
	$R^2_{OOS}(\%)$	14.36	-2.04	-12.69	-3.20	8.37
GBP	$\Delta RMSE(\%)$	2.12	-0.13	-0.53	-0.10	0.19
	$DMW-test$	**	—	—	—	—
	$R^2_{OOS}(\%)$	4.88	-6.60	3.79	5.20	6.18
AUD	$\Delta RMSE(\%)$	1.18	-0.48	0.29	0.35	0.35
	$DMW-test$	*	—	—	—	—
	$R^2_{OOS}(\%)$	17.98	-10.80	-13.12	-10.52	-6.86
NZD	$\Delta RMSE(\%)$	4.54	-1.04	-0.73	-0.48	-0.27
	$DMW-test$	**	—	—	—	—
	$R^2_{OOS}(\%)$	2.61	16.93	13.50	16.64	20.07
CHF	$\Delta RMSE(\%)$	0.55	1.96	1.12	1.18	1.27
	$DMW-test$	*	—	—	—	—
	$R^2_{OOS}(\%)$	9.34	-11.27	-11.93	-14.53	-14.07
CAD	$\Delta RMSE(\%)$	1.32	0.66	-0.46	-0.44	-0.35
	$DMW-test$	**	—	—	—	—
	$R^2_{OOS}(\%)$	3.66	18.45	15.82	18.05	18.11
JPY	$\Delta RMSE(\%)$	0.57	2.05	1.41	1.37	1.28
	$DMW-test$	**	—	—	—	—

This table reports the statistical accuracy (SA) of the term structure of carry trade risk premium / exchange rate return predictability for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-month to 12-month forecasting horizons: R^2_{OOS}, pseudo out-of-sample R^2 (in percentage); $\Delta RMSE$, difference of Root Mean Squared Error between our term structure model and RW (in percentage); and $DMW-test$, '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level ($p-value$) of Diebold-Mariano-West test for equal predictive accuracy between two non-nested models, respectively. Note that we do not perform the Diebold-Mariano-West test for the overlapping forecasts. The out-of-sample period is from February 2004 (February 2010 for EURUSD) to February 2014.

of probabilities, e.g. NZD and CAD. As a result, the robustness of the term structure model depends on (i) the speed of exchange rate mean reversion[33], and (ii) the predictive information set that is common to both short-run and long-run forecasting.

To assess the information commonality in the term structure of exchange rate predictability, we run pooled-OLS[34] regressions of the absolute forecasting errors (AFE)

[33]It can be obtained from an Ornstein-Uhlenbeck process $\mathrm{d}S_t = \upsilon(\mu - S_t)\mathrm{d}t + \sigma \mathrm{d}W$, where υ is the speed of mean reversion. It can be re-written as $\mathrm{d}S_t = [1 - \exp(-\upsilon \mathrm{d}t)](\mu - S_{t-1}) + \epsilon_t$ applying Itô's lemma. Once the long-run mean is determined, we can easily solve for υ from the coefficient estimated by the regression of $\mathrm{d}S_t$ on $\mu - S_{t-1}$. We leave this point for future studies.

[34]The likelihood ratio (LR) test, and Lagrange multiplier (LM) test is in favor of pooled-OLS method

Table 4.4 Information Commonality in the Term Structure of Exchange Rate Predictability

FX	IC	Empirical Models / Scapegoat Variables							
		TSF	PPP	MOF	TRI	MAT	MMR	VRP	SRP
	b	-3.14***	-2.51***	-1.68***	-1.84***	46.38***	-0.31	-1.15**	-1.06
1M	s.e.	(0.53)	(0.66)	(0.37)	(0.44)	(5.54)	(0.34)	(0.45)	(0.74)
	R^2	**0.12**	**0.06**	**0.07**	**0.06**	**0.22**	0.00	0.03	0.01
	b	-1.13***	-0.91***	-0.26	-0.97***	-4.67	0.44***	-0.16	-0.71**
3M	s.e.	(0.25)	(0.30)	(0.18)	(0.20)	(2.85)	(0.15)	(0.21)	(0.34)
	R^2	**0.07**	0.03	0.00	**0.09**	0.01	0.03	0.00	0.02
	b	-0.06	-0.33*	-0.36***	0.22*	-2.33	0.16*	-0.08	0.62***
6M	s.e.	(0.15)	(0.18)	(0.10)	(0.12)	(1.64)	(0.09)	(0.12)	(0.19)
	R^2	0.00	0.01	0.05	0.01	0.01	0.01	0.00	0.04
	b	-0.40***	-0.68***	-0.73***	0.18*	-1.21	0.00	-0.35***	1.13***
9M	s.e.	(0.13)	(0.16)	(0.08)	(0.11)	(1.49)	(0.08)	(0.11)	(0.16)
	R^2	0.04	**0.07**	**0.25**	0.01	0.00	0.00	0.04	**0.16**
	b	0.01	-0.12	-0.58***	0.29***	-3.24***	0.04	-0.04	0.98***
12M	s.e.	(0.10)	(0.12)	(0.06)	(0.08)	(1.11)	(0.06)	(0.08)	(0.12)
	R^2	0.00	0.00	**0.28**	0.05	0.03	0.00	0.00	**0.22**
		KRP	HPF	TCS	VIX	TED	CRB	EPU	YCF
	b	1.60**	-1.49***	-0.59	-2.30	-2.02**	-0.84*	-2.48***	0.33***
1M	s.e.	(0.65)	(0.43)	(0.50)	(2.37)	(0.90)	(0.45)	(0.85)	(0.07)
	R^2	0.02	0.05	0.01	0.00	0.02	0.01	**0.06**	**0.08**
	b	0.34	-0.77***	-0.25	-2.53**	-1.95***	0.05	-1.29***	0.14***
3M	s.e.	(0.30)	(0.20)	(0.23)	(1.08)	(0.40)	(0.21)	(0.38)	(0.03)
	R^2	0.00	**0.07**	0.00	0.02	**0.09**	0.00	**0.08**	**0.06**
	b	-0.01	-0.41***	-0.29**	1.14*	-0.86***	0.29**	-0.09	0.02
6M	s.e.	(0.17)	(0.11)	(0.13)	(0.62)	(0.23)	(0.12)	(0.23)	(0.02)
	R^2	0.00	**0.06**	0.02	0.01	0.05	0.02	0.00	0.00
	b	-0.76***	-0.78***	-0.64***	0.19	-1.15***	-0.25**	0.05	0.10***
9M	s.e.	(0.15)	(0.09)	(0.11)	(0.57)	(0.21)	(0.11)	(0.21)	(0.02)
	R^2	**0.09**	**0.25**	**0.11**	0.00	**0.11**	0.02	0.00	**0.12**
	b	-0.49***	-0.75***	-0.49***	0.90**	-1.13***	-0.09	0.26	0.05
12M	s.e.	(0.11)	(0.06)	(0.08)	(0.42)	(0.15)	(0.08)	(0.16)	(0.01)
	R^2	**0.07**	**0.41**	**0.12**	0.02	**0.19**	0.00	0.02	0.05

This table reports information commonality in the term structure of exchange rate predictability using pooled-OLS regressions. The dependent variable is Absolute Forecasting Error (AFE) in the forecasts of the term structure of carry trade risk premia / exchange rate returns for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK). The explanatory variable is the Dynamic Model Averaging (DMA) probability weighting (Koop and Korobilis, 2012) of each empirical exchange rate model or "scapegoat" variable. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates using using panel-corrected standard errors (PCSE). The out-of-sample period is from February 2004 (February 2010 for EURUSD) to February 2014.

across countries on the DMA probability weighting for each forecasting horizon in the out-of-sample forecasting period using panel-corrected standard errors (PCSE): $|\Delta s_{i,t+\tau}^{(\tau)} - \Delta\hat{s}_{i,t+\tau|t}^{(\tau)}| = a_i + b \cdot \Pr(L_{i,t} = j \mid z_{i,t}) + \epsilon_{i,t}$. Then the information commonality over the term structure of exchange rate predictability can be assessed by two principles: (i) the coefficients of stable exchange rate predictors are expected to be negative — an increase in the corresponding DMA probability weighting lowers the AFE, and vice versa for those of "scapegoat" variables; and (ii) the coefficients are statistically significant across forecasting horizons. As shown in Table 4.4, overall, hedging pressure in futures market (HPF) and liquidity risk (TED) contain the common information that possesses stable predictive power on exchange rate returns over a range of horizons. Policy-related predictors, such as monetary fundamentals (MOF), Taylor rule (TRI) and economic policy uncertainty (EPU), provide important information for short-run forecasting up to 3 months, while crash risk indicators, such as tail risk premia (KRP) and crash sensitivity (TCS), matter for long-run forecasting from 9 months to 12 months. The empirical results in Table 4.4 also confirm the existence of "scapegoat" effects of exchange rate predictors.

Table 4.5 reports the economic values of our term structure model for a full spectrum of currency management from 1-month to 12-month investment horizons. We are able to achieve a performance fee over 6% excess return per annum ($\mathcal{F}$: 6.69% p.a.; $\mathcal{P}$: 6.05% p.a.) with an annualized Sharpe ratio ($\mathcal{SR}$) of 1.30 in active investment management. The economic significance of passive (12-month portfolio rebalance) investment management is also about 6% p.a. on average ($\mathcal{F}$: 5.66% p.a.; $\mathcal{P}$: 6.51% p.a.) with a $\mathcal{SR}$ of 1.18. Tactic investment management also yields considerable performance fees of over 4% p.a. ($\mathcal{F}$: 4.01% p.a.; $\mathcal{P}$: 4.46% p.a.) with a $\mathcal{SR}$ of 1.15, and approximately 4% p.a. ($\mathcal{F}$: 3.94% p.a.; $\mathcal{P}$: 3.91% p.a.) with a $\mathcal{SR}$ of 1.10 for quarterly (3-month), and bi-annual (6-month) portfolio rebalance style, respectively. In strategic investment management, we rebalance the portfolio every 9-month with dynamic

over panel data methods — fixed effect, and random effect, respectively. Hausman (1978) test indicates that there is no statistically significant difference in the coefficient estimates between fixed effect model and random effect model. So, considering that priority should be given to efficiency in this case, a random effect model using Swamy and Arora's (1972) method for the estimates of variance-covariance matrix of error terms is preferable. However, a key drawback of random effect method is that it assumes strict exogeneity (zero correlation between regressors and residuals), we choose pooled-OLS method, which guarantees consistency of the estimator in case of sequential exogeneity.

Table 4.5 Economic Value of the Term Structure Model: Out-of-Sample Predictability of Carry Trade Risk Premia / Exchange Rate Returns

EV	Investment Management				
	Active (1M)	Tactic (3M)	(6M)	Strategic (Dynamic)	Passive (12M)
$\mu_p(\%)$	15.46	13.77	13.25	12.57	15.52
$\sigma_p(\%)$	11.85	11.93	12.10	9.88	13.18
$\mathcal{SR}$	1.30	1.15	1.10	1.27	1.18
$\mathcal{SR}_{\mathcal{DR}}$	2.49	2.46	2.89	2.64	2.70
$\mathcal{F}(\%)$	6.69	4.01	3.94	3.08	5.66
$\mathcal{P}(\%)$	6.05	4.46	3.91	3.29	6.51

This table reports the economic value of the term structure of carry trade risk premium / exchange rate predictability for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from active (monthly rebalance), strategic (semi-annual or quarterly rebalance), tactic (dynamic rebalance in the anticipation of downside risk or the presence of a large deviation of the forecast made τ-period ago from the current updated forecast), to passive (annual rebalance) investment management: μ_p, portfolio mean of monthly **excess returns** by asset allocation (in percentage); σ_p, portfolio volatility of monthly excess returns by asset allocation (in percentage); $\mathcal{SR}$, Sharpe ratio; $\mathcal{SR}_{\mathcal{DR}}$, Sortino ratio; $\mathcal{F}$, performance fee that a risk-averse investor is willing to pay for switching from RW to our term structure model (in percentage); $\mathcal{P}$, manipulation-proof performance measure (in percentage). The optimal weights are computed using unconditional variance-covariance matrix of the whole sample. The conditional volatility target, and the degree of relative risk aversion is set to 10%, and 6, respectively. All data are annualized. The reported economic value is computed as the average of economic values estimated with **non − overlapping data** and **rolling starting points**. The out-of-sample period is from February 2004 (February 2010 for EURUSD) to February 2014.

scrutiny and adjustment every 3-month if the deviation of the initial forecast from the updated forecast is over 5% in strategic investment management, which generates a performance fee of over 3% p.a. ($\mathcal{F}$: 3.08% p.a.; $\mathcal{P}$: 3.29% p.a.) with a $\mathcal{SR}$ of 1.27. The reported economic value is computed as the average of economic values estimated with non-overlapping data and rolling starting points. These empirical findings are both qualitatively and quantitatively insensitive to different settings of RRA and portfolio risk constraint. Our term structure model achieves superb performance fees (economic values) with very well bounded volatility[35] (target at 10%) in the existing literature of exchange rate forecasting.

[35]The volatility of the portfolio is found to increase with the forecasting horizon except for the strategic investment management that achieves volatility slightly lower than the target, which possibly benefits from the dynamic rebalance for forecasting deviations.

4.5.5 Information Term Structure and Scapegoat Drivers of Customer Order Flows

From the perspective of foreign exchange market microstructure, we find that customer order flows are informative about the term structure of carry trade risk premia as well. As shown in Table 4.6, aggregate order flows predict a rise in the level of risk premia of EUR and JPY, tilts the slope of the term structure of GBP while flattens that of AUD in next period. More specifically, the predictive power origins from the order flows of financial clients such as asset managers and hedge funds. The order flows from private clients predict that the long-term risk premia will increase more than the short-term risk premia of EUR. We do not discuss about the contemporaneous relations here. As the relative yield curve factors has significant predictive implications on currency carry trade risk premia (Chen and Tsang, 2013), it is of interest to study the yield curve driver of customer order flows. Table 4.7 demonstrates that an increase in the level of relative yield curve (interest rate differentials) leads to speculative trading of the financial clients that bets on high interest-rate currency to appreciate against low interest-rate currency. Non-financial clients tend to follow the UIP rule on high interest-rate and commodity currencies such as AUD and CAD but not on low interest-rate and the safe-haven currency JPY. A flattened upward or tilted downward sloping relative yield curve induces financial clients to invest in foreign currencies funded USD.

Moreover, we identify the “scapegoat” drivers by running regressions of Equation (4.26) on each currency. The selection procedure is as follows: (i) We search for the stable drivers of customer order flows (COF) — those with statistically significant correlations with COF within the basket of exchange rate predictors — market participants routinely trade foreign exchanges on these predictors; (ii) We replace those statistically insignificant with the products of the predictors per se and the corresponding weights of the DMA probabilities, and the statistically significant surrogates are treated as potential “scapegoat” variables; (iii) We refine the pool of “scapegoat” variables by excluding drivers that are statistically dominated by others.

As shown in Figure 4.16., we find that almost all of the exchange rate predictors play a role of “scapegoat” variable to different types of clients across currencies. In

Table 4.6 Predictive Power of Customer Order Flows on the Term Structure of Currency Carry Trade Risk Premia

COF	REG	Nelson-Siegel Term Structure Factors													
		EUR		GBP		AUD		NZD		CHF		CAD		JPY	
		L^{CT}	S^{CT}	L^{CT}	S^{CT}	L^{CT}	S^{CT}	L^{CT}	S^{CT}	L^{CT}	S^{CT}	L^{CT}	S^{CT}	L^{CT}	S^{CT}
	ϖ	1.94***				3.09*									-8.03*
	s.e.	(0.44)				(1.79)									(4.64)
AGG	ϖ_{-1}	1.09***			9.13**		-18.38**							1.80***	
	s.e.	(0.41)			(4.45)		(8.51)							(0.67)	
	$Adj-R^2$	**0.13**			0.05	0.01	0.05							0.03	0.02
	ϖ	2.96***		2.58***		8.96***		19.24**				4.51**			-12.39**
	s.e.	(0.66)		(0.91)		(3.24)		(8.57)				(2.04)			(6.13)
AM	ϖ_{-1}	0.77*			11.41**		-27.49*							3.64***	
	s.e.	(0.40)			(4.57)		(14.24)							(0.65)	
	$Adj-R^2$	0.02		0.01	0.05	0.05	0.04	0.02				0.02		**0.08**	0.04
	ϖ	-4.06**								-8.20***					
	s.e.	(1.78)								(2.24)					
CC	ϖ_{-1}														
	s.e.														
	$Adj-R^2$	0.03								**0.08**					
	ϖ	3.43***				6.35**					-20.30***		-30.37*		-9.17*
	s.e.	(0.84)				(2.88)					(7.09)		(16.85)		(4.83)
HF	ϖ_{-1}	2.91***					-25.63*								
	s.e.	(0.84)					(14.53)								
	$Adj-R^2$	**0.12**				0.01	0.03				0.04		0.03		0.01
	ϖ		17.32***		19.19*	-17.30***	40.43***	-45.43*			40.07**	-21.82***			57.47***
	s.e.		(5.04)		(10.03)	(3.48)	(13.01)	(26.13)			(17.17)	(7.00)			(15.28)
PC	ϖ_{-1}		9.87*												
	s.e.		(5.64)												
	$Adj-R^2$		**0.10**		0.01	**0.08**	0.03	0.01			0.04	**0.06**			**0.08**

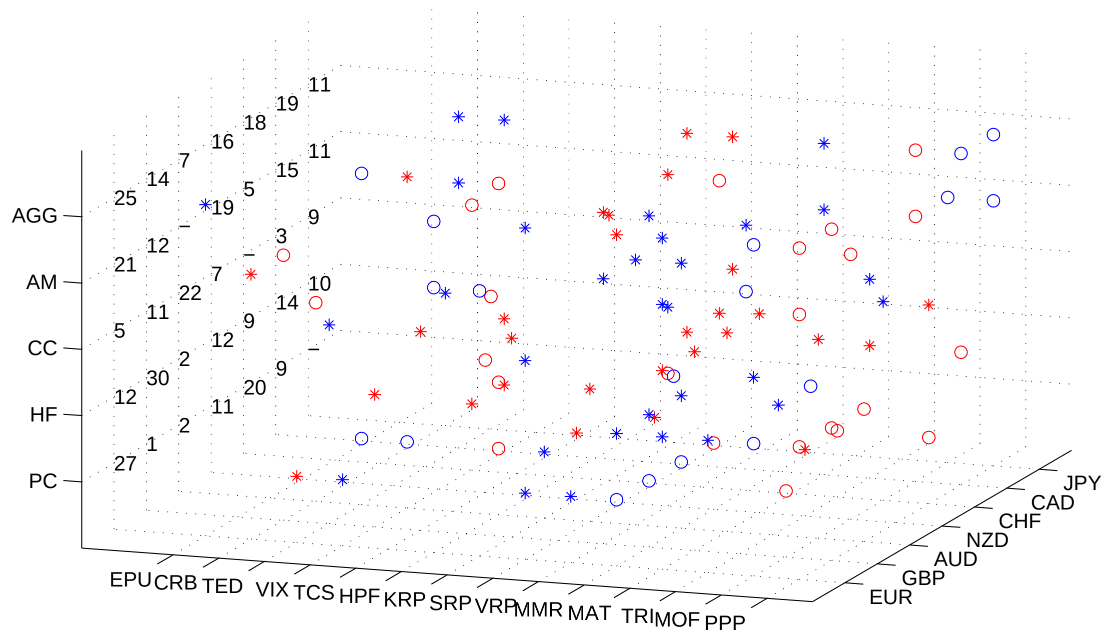
This table reports the predictive power of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC), on the term structure of currency carry trade risk premia — Nelson-Siegel level (L^{CT}) and slope (S^{CT}) factors for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK). Subscript -1 is 1-period lag. HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table 4.7 Yield Curve Driver of Customer Order Flows

FX	YCF	Customer Order Flows				
		AGG	AM	CC	HF	PC
	L^{YC}	59.58**	46.62***			
		(30.93)	(17.00)			
EUR	S^{YC}		15.67*			
			(8.92)			
	$Adj-R^2$	0.03	**0.06**	—	—	—
	L^{YC}	28.74***		-8.36**	10.93**	
		(9.30)		(3.44)	(4.45)	
GBP	S^{YC}		6.40*			
			(3.26)			
	$Adj-R^2$	0.03	0.01	0.04	0.01	—
	L^{YC}			-2.98*	**7.58***	
				(1.76)	(4.19)	
AUD	S^{YC}					
	$Adj-R^2$	—	—	0.01	0.01	—
	L^{YC}					-2.64*
						(1.36)
NZD	S^{YC}	1.96*	1.92**	**-0.77***		
		(1.04)	(0.89)	(0.45)		
	$Adj-R^2$	0.03	0.05	0.01	—	**0.07**
	L^{YC}					
CHF	S^{YC}	13.40**	**78.63****		6.51**	
		(5.19)	(32.21)		(2.71)	
	$Adj-R^2$	**0.06**	0.04	—	0.03	—
	L^{YC}			-5.69***		
				(1.74)		
CAD	S^{YC}	2.96**	3.74***			
		(1.42)	(1.25)			
	$Adj-R^2$	0.03	0.05	0.03	—	—
	L^{YC}	24.26*	18.39**	4.30**		
		(13.69)	(8.86)	(1.89)		
JPY	S^{YC}					**-19.81***
						(10.23)
	$Adj-R^2$	0.03	0.03	0.04	—	0.01

This table reports the information content about the relative yield curve in customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The "scapegoat" effect is reported in highlight where the variable is the product of the yield curve factor per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for USDJPY via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Figure 4.16 Scapegoat Drivers of Customer Order Flows



This figure shows the drivers (explanatory varliables) of customer order flows (dependent variables), both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variables include Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), and Economic Policy Uncertainty (EPU) indices; and those highlighted in red color are identified as "scapegoat" drivers — the products of the values per se and the corresponding weights of probabilities obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). 'o', and '*' denotes positive, and negative (statistically significant) parameter estimates, respectively. The numbers are $adjusted - R^2s$ in percentage. '-' means that none of the variables considered in this paper explains certain customer order flows. The sample period is from January 2001 to February 2014.

particular, country-specific risk, such as macroeconomic fundamentals associated with long-run business cycle risk — purchasing power parity (PPP) to the investors of EUR, GBP, AUD, and CHF; monetary fundamentals (MOF) to those of GBP, AUD, NZD, and CAD; option-implied moment risk premia (VRP, SRP, and KRP) to GBP, NZD, CHF, CAD, and JPY; global risk such as market sentiment volatility index (VIX) to GBP, AUD, CHF, CAD, and JPY; and commodity index (CRB) to EUR and GBP are pronounced "scapegoat" variables because they are not stable drivers of customer order flows and the relevance is judged by the contemporaneous predictive power of the variable of interest. Market participants of AUD are found to trade on the hedging pressure in futures market (HPF) occasionally. The short-run non-fundamental risk — technical indicators (MAT and MMR) play the roles of either stable or "scapegoat" drivers of customer order flows across currencies. After the adjustments by the DMA probability weighting, these hidden (seemly unrelated) variables come into the spotlights and the signs of the coefficients are consistently reasonable[36]. The DMA probability weighting works well as a good proxy of estimates for the weights of probabilities the market participants attach to multiple forecasting models.

4.6 Conclusion

We investigate the origins and the term structure of exchange rate predictability from 1-month to 12-month horizons by the decomposition of exchange rate returns into carry trade risk premia and forward risk premium components that allows us to forecast exchange rate indirectly via its carry component, for which we propose a term structure model with Nelson-Siegel (level, slope, and curvature) factors extracted from the carry curve and incorporate them into the dynamics between carry trade excess returns and a large set of exchange rate predictors in a TVP-VAR setting. We then employ the (Bayesian) Dynamic Model Averaging method to handle model uncertainty in the forecasts of the term structure of carry trade risk premia.

We reveal that hedging pressure and liquidity contain predictive information that is common to a range of forecasting horizons. Policy-related predictors are important for short-term forecasts up to 3 months while crash risk indicators matter for long-term forecasts from 9 months to 12 months. We then comprehensively evaluate the statistical and economic significance of the term structure predictive power of our model in a framework allowing for a full spectrum of currency investment management. Our term structure model is able to beat the random walk remarkably and consistently in

[36] See Table C.1., Table C.2., Table C.3., Table C.4., Table C.5., Table C.6., Table C.7. in Appendix ??.

the forecasts up to 12-month horizon for 7 most traded currencies (in terms of R^2_{OOS} up to 20% at 12-month horizon, $\Delta RMSE$ up to 4.5% at 1-month horizon, and rejection of equal predictability at up to 5% significance level in the Diebold-Mariano-West test for 1-month horizon), and generates substantial performance fees up to approximately 6.5% per annum

We further utilize the time-variations in the probability weighting of each group of factor-augmented empirical exchange rate models or "scapegoat" variables to measure regression-based (vis-à-vis survey-based) model disagreement, which is dynamically related to currency risk premia (and the term structure), volatility, and customer order flows. From the perspective of foreign exchange market microstructure, customer order flows are also informative about the term structure of carry trade risk premia. Moreover, we apply the DMA probability weighting to examine the "scapegoat" drivers of customer order flows. To summarize, our findings confirm that heterogeneous agents learn to forecast exchange rates and switch trading rules over time, resulting in the dynamic country-specific and global exposures of exchange rates to short-run non-fundamental risk and long-run business cycle risk.

Chapter 5

Conclusion

This Ph.D. thesis is constituted by three essays that address two mysteries in international money and finance — the forward premium puzzle and the Meese-Rogoff puzzle. Chapter 2 and Chapter 3 examine the former puzzle and the relevant currency risk premia associated with carry trades that exploit the deviations from the UIP in the field of empirical asset pricing, and in Chapter 4 we investigate the latter, also as known as "exchange-rate disconnect" puzzle from the perspectives of forecasting method (e.g. term structure model and dynamic model averaging) and market microstructure. This chapter summarises the contributions of this Ph.D. thesis to the existing literature and how future work can be developed, as well as sketches out some policy implications.

In Chapter 2 and Chapter 3, we adopt sovereign CDS spreads, misalignments implied by Fundamental Equilibrium Exchange Rate (FEER) and Behavior Equilibrium Exchange Rate (BEER) approaches, and skew risk premia computed by a model-free method from currency option prices as the proxies for sovereign credit risk, equilibrium exchange rate misalignment risk, and speculative risk, respectively. We sort currencies into portfolios based on the ranks of these characteristics of 34 global currencies, and accordingly construct high-minus-low factors from these currency portfolios. This is deemed as a data-driven approach. Using standard empirical asset pricing procedures — Generalized Method of Moments (GMM) and Fama-MacBeth (FMB) two-step OLS approach, we show that high interest-rate currencies load up positively on these risks while the low interest-rate currencies provide a hedge against them, the factor prices are statistically significant, and the models pass the zero pricing error test and Hansen-Jagannathan distance test. We argue that the profitability of currency carry trades can be rationalized as a compensation for these three types of risks, as these factors explain over 90% of the cross section of carry trade portfolios, and the beta-sorted currency portfolios all exhibit similar descriptive statistics to carry trade portfolios.

The pricing power of sovereign default risk does not reflect a "Peso problem", and it is robust to alternative measures by sovereign bond total return indices and the innovations to global (aggregate level) sovereign CDS spreads. The sovereign credit premia not only reflects a country's medium to long-run fundamental risk, but also response to short-run rollover risk of maturing debt and liquidity constraint of the state. Therefore, interest rates embody a market liquidity premium component and a sovereign credit premium component. A country with high sovereign default risk displays a high propensity to issue debts denominated by foreign (safe) currencies to make them more appealing to investors, and inclines to offer high interest rate to attract foreign savings for funding its external deficit. The destabilizing effect on the debtor's currency drives the currency risk premia, which should be taken into account for measuring the "effective" forward premia. Furthermore, we show that both the cross sections of currency portfolios sorted by momentum and position insurance costs (volatility risk premia) can be understood as a compensation for sovereign credit risk as well. 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.

We also drive the position-unwinding risk of carry trades from currency option pricing model. In the Black-Scholes-Merton universe, the cross-sectional variation of currency risk premia is naturally driven by interest rate differential and currency volatility, and the construction of position-unwinding likelihood indicator implies empirical asset pricing results of Lustig, Roussanov, and Verdelhan (2011); Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). Thus, it is also priced in the cross section of carry trade portfolios, and its factor-mimicking portfolio confirms that position-unwinding risk is an arbitrage-free traded asset, and it is fed by the forward bias risk in both linear and nonlinear Granger causality tests, in which complicated global contagion channels are highlighted. This explains the "self-fulfilling" nature of currency carry trades. We reveal that high interest-rate currencies are exposed to higher position-unwinding (crash) risk than low interest-rate currencies, owing to the global liquidity transfer brought by carry trades themselves. Once the risk-bearing capacity (e.g. market risk sentiment and funding liquidity constraint) of the financial intermediaries is unable to sustain the "global liquidity imbalance", the global liquidity reversal/withdrawal triggers currency crashes (Brunnermeier et al., 2009; Gabaix and Maggiori, 2015). Accordingly, we propose a threshold carry trade strategy that is immunized from currency crash risk and earns a much higher annualized excess return than the plain vanilla one. Our threshold carry trades is a risk-managed strategy, and increases the Sharpe ratio substantially (approximately twice as big as its original version). It works because of the crash timing capacity of the position-unwinding likelihood indicator. However, this presents a new challenge to theories that attempt to explain currency carry trade excess returns.

Given that sovereign credit premia is priced in the cross section of carry trade portfolios and accounts for the largest proportion of the variation in position-unwinding likelihood indicator among other factors, policy-makers should primarily target the sovereign default risk, e.g. debt maturity management, to avoid currency crashes. Moreover, To examine the crash story of currency risk premia, we employ the copula method to capture the tail sensitivity of currencies to the global market. we find that high (low) interest rate currencies tend to be overvalued (undervalued) with respect to real effective exchange rate (REER), crash sensitive (insensitive), relative cheap (expensive) to hedge, and exposed to high (low) speculative inclination of the market. This is what the policy-makers should concern about. They should control the exchange rate misalignment within a reasonable range to avoid speculative attacks by the investors, who can also take the advantage of the mispricing in currency options as highly crash sensitive currencies are relatively cheap to insure.

We also find notable risk reversals in currency premia in pre-crisis and post-crisis periods with respect to both crash sensitivities and volatility risk premia (position insurance costs), and intriguing patterns in the average excess returns of currency portfolios doubly sorted by these two dimensions. We then propose a novel trading strategy that makes a 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, higher than any other 7 simple currency investment strategies over the sample period) and an alpha that cannot be explained by canonical risk factors, or by hedge fund and betting-against-beta risk factors, government policy uncertainty, and other financial indices. Unlike other currency investment strategies, its cumulative wealth is driven by both exchange rate and yield components. So, it actually works as a currency filtering procedure that selects high (low) interest-rate currencies that are about to appreciate (depreciate).

From the asset allocation perspective, a crash-averse investor would optimally choose a relatively diversified portfolio by allocating over 40% of the wealth to currency misalignment strategy over the sample period, about 40% to crash sensitivity strategy and about 10% to skew risk premium strategy in the tranquil period. While during the financial turmoil, the investor would be better-off by reallocating his/her portfolio holdings dramatically to currency volatility risk premium strategy with a weight of over 60% of the wealth. Trading strategies that exploit the properties such as currency misalignment, crash sensitivity, and moment risk premia also offer remarkable diversification benefits for risk management purpose in terms of considerable reductions in conditional value-at-risk (expected shortfall) of the efficient frontiers.

We also utilize the generalized dynamic factor model to identify an additional important factor that accounts for extra 14% of the cross-sectional variation in the whole FX market but omitted in the literature using the standard portfolio approach. It is related to the payoff of the currency strategy trading on volatility risk premia and priced in the cross section of currency value portfolios (explaining over 90% of the variations). The risk attributes and factor structure of the investments in currencies and relevant strategies are studied. Sovereign credit risk is the key driver to the factors that capture the common dynamics of the global currencies and also the FX trading strategies studied in this Ph.D. thesis. Beyond the systematic (dollar) risk, there are two types of diversifiable risks implied in these investment strategies — one is intimately associated with currency interest rate differentials, REER misalignments, and skew (speculative) risk premia while the another with highly correlated with currency values, crash sensitivities, and volatility risk premia.

Our next step is to extend the sample period as now we have obtained a currency option data set with longer time span (back to 1995). A lot of future work can be done, e.g. (i) building an international macro-finance pricing model to rationalize the findings mentioned above; (ii) extending Merton's (1974) model to a sovereign version or the analytical framework of Friewald, Wagner, and Zechner (2014) so that we can explore the information about macroeconomic fundamentals implied in the currency option pricing model; (iii) linking the time variation in "limit to arbitrage" (Acharya, Lochstoer, and Ramadorai, 2013) to the hedgers and speculators' motivations for portfolio constructions with currency risk under informational ambiguity (see Epstein and Schneider, 2007, 2008; Leippold, Trojani, and Vanini, 2008; Condie and Ganguli, 2011; Ilut, 2012; Ju and Miao, 2012; Branger, Larsen, and Munk, 2013; Maccheroni, Marinacci, and Ruffino, 2013, among others) and learning process (see Guidolin and Timmermann, 2007; Chakraborty and Evans, 2008; Carceles-Poveda and Giannitsarou, 2008; Branch and Evans, 2010, 2011, among others), etc.; (iv) evaluating the option-implied sovereign default premia and CDS-implied systemic risk in a joint framework of sovereign CDS and currency option as in Carr and Wu (2007, 2010); (v) Backus, Gavazzoni, Telmer, and Zin (2010) show that a certain specification of Taylor rule can give rise to the failure of UIP, and this may also explain why Taylor rule fundamentals perform better than other economic fundamentals among empirical exchange rate models. Furthermore, recent literature no long supports the view of monetary and fiscal policy dichotomy, i.e. the maturity structure of nominal government debt affects the optimal monetary and fiscal policy decisions (Leeper, 1991; Davig and Leeper, 2011; Leeper and Zhou, 2013). So, a theoretical framework that models the interactions between monetary (Taylor rule) and fiscal (sovereign credit) policies may help to rationalize the major puzzles in international macroeconomics.

In Chapter 4, we study the origins of exchange rate predictability via return decomposition so that exchange rate returns over a range of forecasting horizons can be modelled as a function of common (term structure) factors. for which we propose a dynamic Nelson-Siegel model with level, slope, and curvature factors extracted from the carry curve and incorporate them into the dynamics between carry trade excess returns and a large set of exchange rate predictors in a TVP-VAR setting. We then employ (Bayesian) Dynamic Model Averaging method to handle model uncertainty in the forecasts of the term structure of carry trade risk premia.

We illustrate that hedging pressure and liquidity contain predictive information that is common to a range of forecasting horizons. Policy-related predictors are important for short-term forecasts up to 3 months while crash risk indicators matter for long-term forecasts from 9 months to 12 months. This provides some new insights on the informational commonality and projection of exchange predictors over the term structure that the policy-makers can harness to monitor and intervene the foreign exchange market, especially, to design both short-term and long-term exchange rate policy tools. We then comprehensively evaluate the statistical and economic significance of the term structure predictive power of our model in a framework allowing for full spectrum of currency investment management. Our term structure model is able to beat random walk remarkably and consistently in the forecasts up to 12-month horizon for 7 most traded currencies (in terms of R^2_{OOS} up to 20% at 12-month horizon, $\Delta RMSE$ up to 4.5% at 1-month horizon, and rejection of equal predictability at up to 5% significance level in the Diebold-Mariano-West test for 1-month horizon), and generates substantial performance fees up to approximately 6.5% per annum.

We further utilize the time-variations in the probability weighting of each group of factor-augmented empirical exchange rate model or "scapegoat" variable to measure regression-based (vis-à-vis survey-based) model disagreement, which is dynamically related to currency risk premia (and the term structure), volatility, and customer order flows. Customer order flows are also informative about the term structure of carry trade risk premia. Moreover, we apply the DMA probability weighting to examine the "scapegoat" drivers of customer order flows. To summarize, our findings confirm that heterogeneous agents learn to forecast exchange rates and switch trading rules over time, resulting in the dynamic country-specific and global exposures of exchange rates to short-run non-fundamental risk and long-run business cycle risk. The model disagreement index may capture a part of this mechanism. It not only explains market volatility and liquidity, but also works as a leading indicator. Thereby, policy-makers may consider adding it to their surveillance scope for exchange rate management.

Our term structure model of the carry component can be extended to other asset classes using return decomposition into carry and expected price depreciation components (see Koijen, Moskowitz, Pedersen, and Vrugt, 2013). Future research in this area could include the following: (i) to examine the economic value of our term structure model using its implied forecasts of exchange rate returns in any time interval of the future τ period without implementing further forecasts in this period; (ii) to decompose the forecasting variance (into short-run and long-run components) that can be attributed to important state variables of exchange rate at different horizons, and this may improve the predictive accuracy and provide rich analysis of the structure of the shocks to exchange rate determinants (see Doshi, Jacobs, and Liu, 2014, for the analysis of the term structure of interest rates); (iii) to endogenize the probability weighting according to forecasting performance over a range of horizons for the investigation of whether or not the predictive power of each model/variable varies with the term structure of the carry component, which allows us to understand, at the aggregate level, how disappointment-averse[1] agents with heterogeneous beliefs optimally choose forecasting rules and shift "scapegoat" variables not only over the time but also over a span of horizons, and this can also be achieved by direct forecasts of the term structure of carry trade risk premia; (iv) to propose an arbitrage-free framework for the study of the joint term structure of bond and currency (carry trade) risk premia based on the analytical framework of Lustig, Stathopoulos, and Verdelhan (2013), or even extend it to other asset classes; (v) to bridge the term structure of forecast disagreements in a factor model with the information content of customer order flows in a Bayesian learning and model averaging framework (see Xia, 2001; Lahiri and Sheng, 2008, 2010; Banerjee and Kremer, 2010; Banerjee, 2011; Evans, Honkapohja, Sargent, and Williams, 2012; Collin-Dufresne, Johannes, and Lochstoer, 2013; Banerjee and Green, 2014, among others). Moreover, given the close linkage between the probabilities of financial crises and the term structure of currency risk premia, our analysis can be extended to measure the term structure of systemic risk in

[1]The use of (generalized) disappointment aversion risk preference that attaches a higher weight to lower tail events than expected utility theory helps to explain consumption-based asset pricing puzzles (see Routledge and Zin, 2010; Bonomo, Garcia, Meddahi, and Tédongap, 2011).

currency market as well.

Appendix

.A Supporting Documentation: Chapter 2

.A.1 Currency Option Pricing Model

It is assumed that the spot rates S_t of a currency pair (indirect quotes[2]) follows a geometric Brownian motion (GBM) of the form with an instantaneous drift μ and an instantaneous volatility σ:

$$\mathrm{d}S_t = \mu\, S_t\, \mathrm{d}t + \sigma\, S_t\, \mathrm{d}W \tag{1}$$

where W is the standard Wiener process. Then the value of the spot rates at any time $t+T$ is given by:

$$\ln S_{t+T} = \ln S_t + \left(\mu - \frac{\sigma^2}{2}\right) T + \sigma \sqrt{T}\, \varepsilon_{t+T} \tag{2}$$

where

$$\varepsilon_{t+T} = \frac{W(t+T) - W(t)}{\sqrt{T}} \quad \text{and} \quad \varepsilon_{t+T} \sim \mathcal{N}(0,1) \tag{3}$$

$\mathcal{N}(0,1)$ is the Gaussian *i.i.d.* standard normal distribution. The value of a call option for a currency pair with the strike price of X_t and the time to maturity of T at time t is:

[2]Units of foreign currency per unit of domestic currency (USD).

$$c_t = S_t \exp(-r_t T)\, \mathbb{N}(d_1) - X_t \exp(-r_t^* T)\, \mathbb{N}(d_2) \tag{4}$$

For the put option:

$$p_t = X_t \exp(-r_t^* T)\, \mathbb{N}(-d_2) - S_t \exp(-r_t T)\, \mathbb{N}(-d_1) \tag{5}$$

where

$$d_1 = \frac{\ln(S_t/X_t) + \left(r_t^* - r_t + \frac{1}{2}\sigma^2\right) T}{\sigma\sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma\sqrt{T} \tag{6}$$

r_t, r_t^* denotes domestic (U.S.) risk-free interest rate, and foreign risk-free interest rate, respectively. $\mathbb{N}(\cdot)$ is the cumulative density function of standard normal distribution. We can reproduce the currency prices for hedging the carry trade positions by setting $X_t = F_t$ and the implication of CIP, then Equation (6) is simplified as $d_{1,2} = \pm\frac{1}{2}\sigma\sqrt{T}$. Now, we turn to the application of this model for evaluating the position-unwinding risk.

.A.2 Gram-Charlier Expansion by Hermite Polynomial

The standard definition of Hermite Polynomials (Stuart and Ord, 2009) series is truncated after its fourth term for the skewness-and-kurtosis augmented probability density function of standard normal distribution (see Backus, Foresi, and Wu, 2004):

$$h(z) = n(z)\left[1 - \frac{\varsigma}{3!}\,H_3(z) + \frac{\kappa}{4!}\,H_4(z)\right] \tag{7}$$

where

$$H_a(z)\,n(z) = (-1)^a\,\frac{\mathrm{d}^a n(z)}{\mathrm{d}z^a} \tag{8}$$

Equation (7) can be rewritten as:

$$h(z) = n(z)\left[\,1 - \frac{\varsigma}{3!}(z^3 - 3z) + \frac{\kappa}{4!}(z^4 - 6z^2 + 3)\,\right] \tag{9}$$

where $n(z)$ is the probability density function of standard normal distribution. a represents the order of the moment. ς, κ denotes the excess skewness, and excess kurtosis, respectively. These terms are estimated by the methods of realized moments similar to realized volatility (see e.g. Andersen, Bollerslev, Diebold, and Labys, 2001). The details will be discussed in Section 2.5. z here is actually the values of DB_{t+T}. Hence, the skewness-and-kurtosis adjusted $\Pr\left(DB_{t+T}\right)$ is:

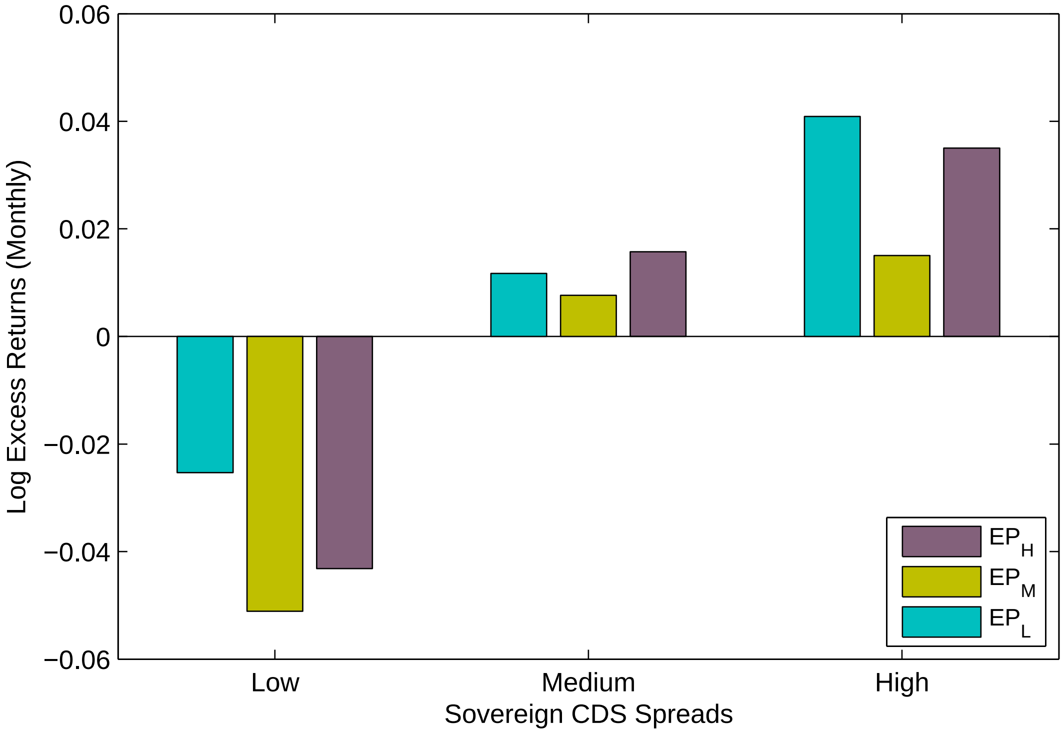
$$\Pr\left(z\right) = \int_{-\infty}^{z} h(z)\mathrm{d}z = \mathbb{N}(z) + \left[\,\frac{\varsigma}{3!}(z^2 - 1) + \frac{\kappa}{4!}(3z - z^3)\,\right]\cdot n(z) \tag{10}$$

.A.3 Global Currency, Bond, and Equity Portfolios

Figure A.1 Cumulative Excess Returns of Currency Carry Portfolios Sorted on Forward Discounts

This figure shows the cumulative excess returns of currency carry portfolios sorted on forward discounts and in long positions from September 2005 to January 2013. PFL_1, PFL_2, and PFL_3, PFL_4, and PFL_5 denotes the currency carry portfolios with lowest, lower medium, medium, higher medium, and highest forward discounts, respectively.

Figure A.2 Currency Portfolios Doubly Sorted on Sovereign CDS Spreads and Equity Premia



This figure shows the average monthly excess returns of nine currency portfolios (the vertical axis) that are sorted on both sovereign CDS spreads and equity premia over U.S. market from September 2005 to January 2013. EP_L, EP_M, and EP_H denotes the low, medium, and high equity-premium currency portfolios, respectively. The horizontal axis represents the level of sovereign CDS spreads of currency portfolios in ascending order.

Table A.1. Descriptive Statistics of Government Bond Portfolios

All Countries without Transaction Costs							
Portfolios	B_1	B_2	B_3	B_4	B_5	Avg.	H/L
Mean (%)	3.87	3.93	5.50	5.75	7.62	5.34	3.76
Median (%)	3.55	7.53	8.82	10.14	10.54	8.12	7.05
Std.Dev. (%)	6.30	8.45	8.28	12.57	16.72	10.46	15.54
Skewness	0.07	-0.20	-0.13	-0.37	-0.27	-0.18	-0.36
Kurtosis	0.02	0.19	0.14	0.38	0.53	0.25	0.60
Sharpe Ratio	0.61	0.47	0.70	0.44	0.46	0.53	0.24
AC(1)	-0.09	-0.18	-0.09	-0.01	0.04	-0.06	0.08

This table reports descriptive statistics of the excess returns in USD of government bond (total return) indices portfolios with 5-year maturity sorted on 1-month lagged redemption yield. The 20% equity indices with the lowest lagged redemption yields are allocated to Portfolio B_1, and the next 20% to Portfolio B_2, and so on to Portfolio B_5 which contains the highest 20% lagged redemption yields. The portfolios are rebalanced simultaneously with the the currency portfolios, hence the excess returns have the same duration. 'Avg.', and 'H/L' denotes the average excess returns of five portfolios, and difference in the excess returns between Portfolio B_5 and Portfolio B_1 respectively. All excess returns are monthly and unadjusted for transaction costs with the sample period from September 2005 to January 2013 with daily availability. 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 coefficient of the monthly excess returns in monthly frequency.

Table A.2. Descriptive Statistics of Equity Momentum Portfolios

All Countries without Transaction Costs							
Portfolios	E_1	E_2	E_3	E_4	E_5	Avg.	H/L
Mean (%)	1.33	1.59	2.98	4.44	4.74	3.01	3.41
Median (%)	9.80	14.85	15.68	15.60	16.99	14.58	5.03
Std.Dev. (%)	25.62	25.60	26.06	26.52	30.88	26.94	15.27
Skewness	-0.28	-0.40	-0.46	-0.47	-0.46	-0.04	-0.17
Kurtosis	0.25	0.45	0.63	0.67	0.67	0.53	0.33
Sharpe Ratio	0.05	0.06	0.11	0.17	0.15	0.11	0.22
AC(1)	0.10	0.22	0.20	0.20	0.19	0.20	-0.18

This table reports descriptive statistics of the excess returns in USD of equity momentum portfolios sorted on 1-month lagged equity-index excess returns. The 20% equity indices with the lowest lagged excess returns are allocated to Portfolio E_1, and the next 20% to Portfolio E_2, and so on to Portfolio E_5 which contains the highest 20% lagged excess returns. The portfolios are rebalanced simultaneously with the the currency portfolios, hence the excess returns have the same duration. 'Avg.', and 'H/L' denotes the average excess returns of five portfolios, and difference in the excess returns between Portfolio E_5 and Portfolio E_1 respectively. All excess returns are monthly and unadjusted for transaction costs with the sample period from September 2005 to January 2013 with daily availability. 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 coefficient of the monthly excess returns in monthly frequency.

.A.4 Principal Components and Correlation Matrix

Table A.3. Principal Component Analysis of Asset Excess Returns

Currency Carry Portfolios						
	C_1	C_2	C_3	C_4	C_5	Variance (%)
PC_1	0.876	0.946	0.959	0.952	0.904	86.120
PC_2	0.442	0.143	-0.043	-0.157	-0.368	7.552
Total						93.672
Government Bond Portfolios						
	B_1	B_2	B_3	B_4	B_5	Variance (%)
PC_1	0.741	0.932	0.951	0.919	0.831	77.120
PC_2	0.635	0.111	0.049	-0.252	-0.469	14.035
Total						91.155
Equity Momentum Portfolios						
	E_1	E_2	E_3	E_4	E_5	Variance (%)
PC_1	0.956	0.976	0.977	0.974	0.958	93.730
PC_2	0.259	0.066	-0.015	-0.067	0-.242	2.699
Total						96.429

This table reports the principal component coefficients of currency carry, government bonds, equity momentum portfolios. PC_1, PC_2 denotes the first principal component, and the second principal component, respectively. The last column shows the share of the total variance (in %) explained by each common factor. The last row provides the cumulative share of the total variance (in %) explained by the first two common factors. The sample period is from September 2005 to January 2013.

Table A.4. Correlations between Risk Factors and Principal Components

	Currency		Bond		Equity	
	PC_1	PC_2	PC_1	PC_2	PC_1	PC_2
GDR	0.999	0.047	0.915	0.205	0.837	0.047
PUW	-0.750	-0.243	-0.396	-0.196	-0.485	-0.184
GSQ	-0.837	-0.019	-0.785	-0.146	-0.697	-0.003
GKT	0.158	0.041	0.127	0.080	0.123	-0.118
HML_{FB}	0.390	0.904	0.156	0.820	0.566	-0.088
HML_{SC}	-0.082	0.712	-0.106	0.697	0.287	0.038
GSI	-0.722	-0.310	-0.443	-0.310	-0.630	-0.211
HML_{GB}	0.693	0.551	0.561	0.752	0.829	0.005
HML_{EM}	0.329	0.203	0.307	0.128	0.340	0.925
GVI	-0.629	-0.369	-0.443	-0.369	-0.582	0.065
ΔVIX	-0.541	-0.431	-0.374	-0.475	-0.703	-0.122
GLR	-0.268	-0.178	-0.205	-0.218	-0.299	0.048
ΔTED	-0.084	-0.176	-0.092	-0.115	-0.201	-0.087

This table reports the correlations between risk factors and the principal components of currency carry, government bonds, equity momentum portfolios. PC_1, PC_2 denotes the first principal component, and the second principal component, respectively. The sample period is from September 2005 to January 2013.

.A.5 Contagion and Threshold Trading

The existing literature in empirical asset pricing of currency carry trades do not highlight the spillover effect of country-specific fundamental risk to the global economy nor test the impulsive country-specific risk that drives others of its kind. The contagion channels can be international trade linkages (e.g. Krugman, 1979; Eichengreen, Rose, and Wyplosz, 1996), international bank lending (e.g. Kaminsky and Reinhart, 1999, 2000; Allen and Gale, 2000; Van Rijckeghem and Weder, 2001), international portfolio holdings and rebalancing (e.g. Kodres and Pritsker, 2002; Pericoli and Sbracia, 2003), or more generally speaking, international capital flows, such as sudden stop and flight-to-quality (see Calvo, 1998; Forbes and Warnock, 2012). There are various econometric techniques that can be employed for testing factor dynamics, which, however, is not the main purpose of this chapter. Therefore, we only choose both linear and nonlinear Granger causality test.

The interactions between the global risk factor and country-specific factor is the principal concern of testing contagion. Position-unwinding likelihood indicator is embedded with the global risk aversion. At the early stage of the financial crisis, global risk aversion is a significant factor influencing sovereign CDS spreads; and at the later stage, country-specific factor, such as short-term refinancing constaint and long-term fiscal sustainability, becomes more important and begins to feed back into broader financial instability (Caceres, Guzzo, and Segoviano Basurto, 2010). Furthermore, hedging design of currency portfolios against idiosyncratic risk can be oriented by testing the stimulative source of risk among the country-specific factors.

Contagion among Risk Factors

We employ both linear and nonlinear Granger causality tests to identify which factor drives the cross-sectional risk, and to investigate the dynamic propagation between global risk and country-specific risk, especially the spillover of the country-specific risk to the global economy, because the degree of Granger causality in the asset return-based risk factors can also be viewed as a proxy for the spillover of information among market participants as suggested by some recent relevant research, e.g. Daníelsson,

Table A.5. Linear & Nonlinear Granger Causality Tests for Impulsive Country-specific Risk

	Linear	Nonlinear
HML_{SC} does not Granger cause HML_{FB}	0.01	0.02
HML_{FB} does not Granger cause HML_{SC}	0.37	0.03
HML_{SC} does not Granger cause GSI	0.00	0.20
GSI does not Granger cause HML_{SC}	0.40	0.39
HML_{SC} does not Granger cause GVI	0.03	0.04
GVI does not Granger cause HML_{SC}	0.63	0.73
HML_{SC} does not Granger cause ΔVIX	0.04	0.07
ΔVIX does not Granger cause HML_{SC}	0.92	0.41
HML_{SC} does not Granger cause ΔTED	0.00	0.03
ΔTED does not Granger cause HML_{SC}	0.29	0.05
HML_{SC} does not Granger cause GLR	0.25	0.07
GLR does not Granger cause HML_{SC}	0.44	0.10
HML_{SC} does not Granger cause HML_{GB}	0.03	0.05
HML_{GB} does not Granger cause HML_{SC}	0.65	0.12
HML_{SC} does not Granger cause HML_{EM}	0.04	0.22
HML_{EM} does not Granger cause HML_{SC}	0.70	0.19

This table reports the $p-values$ of linear and nonlinear Granger causality tests (see Hiemstra and Jones, 1994; Diks and Panchenko, 2006 for details) for the impulsive country-specific risk. The first column lists the null hypotheses to be tested. Due to the limited sample size, Akaike's Final Prediction Error (also as known as AIC) is chosen as the lag-length selection procedure rather than Schwarz (Bayesian) Information Criterion (SIC) or Hannan-Quinn Information Criterion (see Anderson, 2004 for details). The bandwidth of 1.50 is chosen according to the sample size. The sample period is from September 2005 to January 2013.

Table A.6. Linear & Nonlinear Granger Causality Tests for Global Contagion

	Linear	Nonlinear		Linear	Nonlinear
HML_{SC} does not Granger cause GDR	0.08	0.06	HML_{FB} does not Granger cause GDR	0.02	0.13
GDR does not Granger cause HML_{SC}	0.43	0.41	GDR does not Granger cause HML_{FB}	0.54	0.27
GVI does not Granger cause GDR	0.36	0.05	ΔVIX does not Granger cause GDR	0.00	0.04
GDR does not Granger cause GVI	0.64	0.10	GDR does not Granger cause ΔVIX	0.35	0.11
GLR does not Granger cause GDR	0.85	0.69	ΔTED does not Granger cause GDR	0.00	0.54
GDR does not Granger cause GLR	0.05	0.38	GDR does not Granger cause ΔTED	0.03	0.75
HML_{SC} does not Granger cause PUW	0.89	0.08	HML_{FB} does not Granger cause PUW	0.42	0.08
PUW does not Granger cause HML_{SC}	0.15	0.57	PUW does not Granger cause HML_{FB}	0.94	0.33
GVI does not Granger cause PUW	0.66	0.43	ΔVIX does not Granger cause PUW	0.01	0.08
PUW does not Granger cause GVI	0.37	0.09	PUW does not Granger cause ΔVIX	0.42	0.09
GLR does not Granger cause PUW	0.49	0.10	ΔTED does not Granger cause PUW	0.29	0.75
PUW does not Granger cause GLR	0.04	0.22	PUW does not Granger cause ΔTED	0.06	0.17
HML_{SC} does not Granger cause GSQ	0.24	0.06	HML_{FB} does not Granger cause GSQ	0.04	0.06
GSQ does not Granger cause HML_{SC}	0.22	0.14	GSQ does not Granger cause HML_{FB}	0.27	0.16
GVI does not Granger cause GSQ	0.46	0.68	ΔVIX does not Granger cause GSQ	0.03	0.02
GSQ does not Granger cause GVI	0.06	0.07	GSQ does not Granger cause ΔVIX	0.13	0.08
GLR does not Granger cause GSQ	0.86	0.22	ΔTED does not Granger cause GSQ	0.17	0.43
GSQ does not Granger cause GLR	0.34	0.28	GSQ does not Granger cause ΔTED	0.22	0.50

This table reports the $p-values$ of linear and nonlinear Granger causality tests (see Hiemstra and Jones, 1994; Diks and Panchenko, 2006 for details) for global contagion. The first column lists the null hypotheses to be tested. Due to the limited sample size, Akaike's Final Prediction Error (also as known as AIC) is chosen as the lag-length selection procedure rather than Schwarz (Bayesian) Information Criterion (SIC) or Hannan-Quinn Information Criterion (see Anderson, 2004 for details). The bandwidth of 1.50 is chosen according to the sample size. The sample period is from September 2005 to January 2013.

Shin, and Zigrand (2009), Battiston, Delli Gatti, Gallegati, Greenwald, and Stiglitz (2012), and Billio, Getmansky, Lo, and Pelizzon (2012). Hiemstra and Jones (1994) propose a nonparametric test for general (both linear and nonlinear) Granger non-causality (HJ-test), which is questioned by Diks and Panchenko (2006). They show that HJ-test tends to incur spurious discovery of nonlinear Granger causality, and the probability to reject the Granger non-causality increases with the sample size. Instead, they provide an alternative nonparametric test for nonlinear Granger causality that circumvents the problem in HJ-test through replacing the global statistic by the average of local conditional dependence measures. We follow their method to test the nonlinear Granger causality among risk factors. The bandwidth of 1.50 is chosen to accommodate the sample size. We adopt Akaike's Final Prediction Error (as known as AIC) as the lag-length selection criterion because Anderson (2004) find that Akaike's Final Prediction Error[3] works quite well for small samples even if the true model is nonlinear, and contrarily, Schwarz (Bayesian) Information Criterion (SIC) and Hannan-Quinn Information Criterion performs poorly unless the sample size is large enough.

Table A.5. shows that sovereign credit risk seems to be the impetus of other country-specific factors: HML_{SC} both linearly and nonlinearly Granger causes HML_{FB}, GVI, ΔVIX, and ΔTED. And the reverse is not true except that HML_{FB} and ΔTED feedback into HML_{SC} nonlinearly. The relationship between HML_{SC} and GLR seems to be dynamic and nonlinear. From the aspect of market microstructure, liquidity spreads (bid-ask spreads) are set by the market maker, whose reaction function to perceived sovereign credit risk should be nonlinear. All these with the asset pricing tests vindicate that sovereign credit risk is the dominant country-specific fundamental risk. Table A.6. reveals the spillover of country-specific risk to the global economy. Sovereign default risk (HML_{SC}) is contagious to the global money market (GDR) and drives the currency crash risk (GSQ), which in turn amplifies the global volatility risk (both GVI and ΔVIX).

Baek, Bandopadhyaya, and Du (2005) find that the market risk appetite imposes larger impact on the bond yield spreads than the economic fundamentals. The

[3]Although nonlinear techniques suggested by Tjøstheim and Auestad (1994) might improve the accuracy, they're very difficult to implement.

mechanism is reverse in currency market that the market risk sentiment, e.g. the FX market volatility (GVI), broad market volatility (ΔVIX), and position-unwinding likelihood indicator (PUW) are driven by the sovereign credit risk measured directly in the currency excess returns. Moreover, GVI is naturally triggered by the position-unwinding risk, which measures the precautionary risk attitude of the investors. PUW is also fed into ΔVIX. We also find that position-unwinding risk of the currency carry trades is driven by ΔVIX and by the forward bias risk (HML_{FB}).

Threshold Trading

We can continue to profit from forward bias risk as long as the carry trade positions are not forced unwound. PUW not only represents the systematic risk in terms of high correlation with the market portfolio of the foreign exchange market and with the global skewness risk (GSQ) but also is priced in the cross section of currency carry trade portfolios. It has correlations of -0.76 with GDR and of -0.48 with HML_{FB}. However, once the currency crashes in the opposite direction of the carry trade positions, the risk reverses and we suffer losses by taking up any more forward bias risk. Given that the position-unwinding likelihood indicator measures the probability of the currency crashes against the speculative carry trade positions taken by the investors, focusing on the position-unwinding risk is the principal concern of currency carry trades.

In this section, we propose an alternative carry trade strategy that is immunized from currency crash risk by identifying the threshold level of the position-unwinding likelihood indicator. Brunnermeier and Pedersen (2009), Clarida, Davis, and Pedersen (2009) reveal the regime-sensitivity of Fama regression parameters that the βs are much smaller than unity or even negative during the tranquil period and shift to positive values or even become greater than unity during the turmoil period. Thus, we can gain both statistical and economic significance by analyzing the transition dynamics between regimes, e.g. reverse the carry trade positions during the currency crashes. And according to the reality observed in our data, the position-unwinding behavior would be triggered when PUW exceeds a certain precautionary threshold. The procedure to search for the threshold level could be done using a Smooth Transition Model

(STR) that specifies a nonlinear model of carry trade excess returns with HML_{FB} and GDR. The nonlinear relationship is dependent on the level of PUW. More generally, our model is given by $xr_{j,t} = (\alpha_j^0 + \beta_j^0\ xf_t^0) + (\alpha_j^1 + \beta_j^1\ xf_t^1) \cdot \omega(\nu_t; \gamma_j, c_j) + \zeta_{j,t}$. where $\zeta_{j,t}$ is $i.i.d.$ $(0, \sigma_{j,\zeta}^2)$. PUW acts as the transition variable ν_t and $\omega(\cdot)$ is the transition function which is conventionally bounded by zero and one. $\gamma_j > 0$ denotes the slope parameter that determines the smoothness[4] of the transition from one regime to the other. When γ_j approaches zero, the STR process reduces to a linear model; and as γ_j goes to infinity, the STR process becomes an absolute two-regime threshold model with abrupt transition (Tong, 1990). c_j is the threshold level of the abruptness in transitional dynamics. xf_t^0, xf_t^1 are vectors of risk factors that enter the linear, nonlinear part of the STR model[5], respectively. We follow Teräsvirta's (1994) methodology to choose the appropriate STR model and utilize $LM - test$ for examining the null hypothesis of no remaining nonlinearity (Eitrheim and Teräsvirta, 1996). That no residual autocorrelation in the STR model is confirmed by Teräsvirta's (1998) procedure.

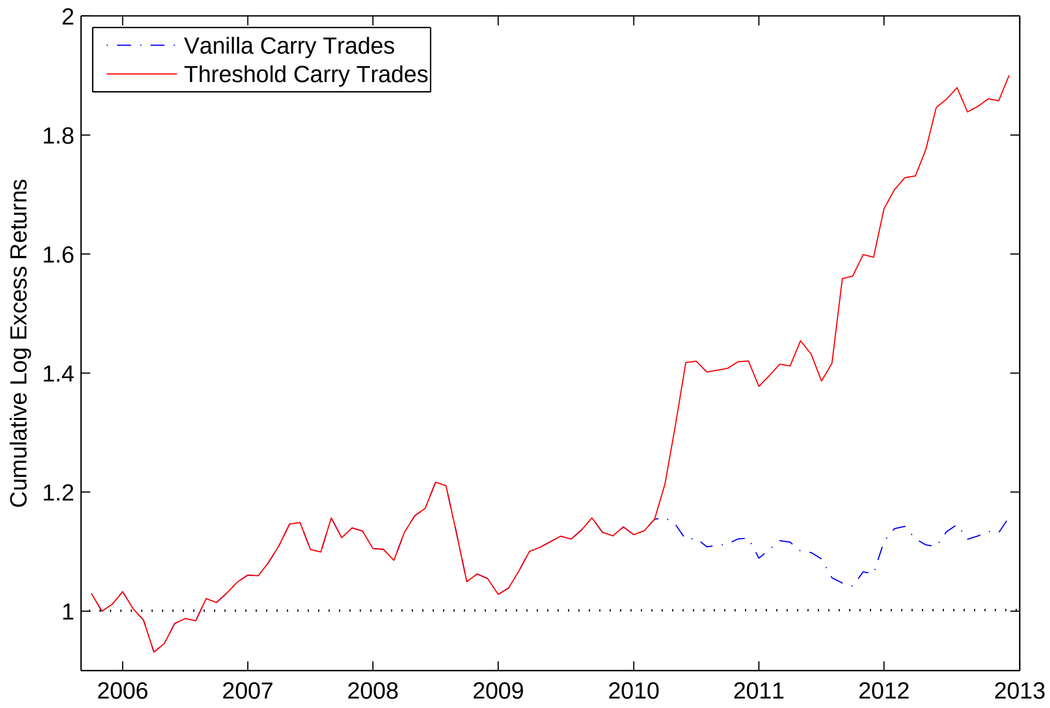
Both the investment and funding legs share the same threshold level of the position-unwinding risk in-sample (2005 September - 2009 September) — 58.289%, and it works as a signal for reversing the positions of conventional carry trades. In our principal trading rule, we use ex-ante 1-quarter moving average of PUW for comparison with the threshold level. Besides the level, we note that the volatility of PUW becomes persistent during the recent financial crisis. As a result, we set the ex-ante 1-year PUW volatility as the complementary trading rule, which also suddenly exceeds a certain level at the outbreak point and remains above this level in the aftermath of the financial crunch. This may be related to the funding liquidity risk of the financial intermediaries (Gabaix and Maggiori, 2015). If it drops below the outbreak point level, the funding positions are reverted back to the plain vanilla carry trade strategy.

Figure A.3. show that the cumulative excess returns of the threshold carry trade

[4] This implies that there exists a continuum of states between two polar regimes.

[5] Two types of widely used transition functions (Teräsvirta and Anderson, 1992) are: Logistic STR Model (LSTR) — $\omega(\nu_t; \gamma_j, c_j) = \{1 + \exp[-\gamma_j(\nu_t - c_j)]\}^{-1}$, and Exponential STR Model (ESTR) — $\omega(\nu_t; \gamma_j, c_j) = 1 - \exp[-\gamma_j(\nu_t - c_j)^2]$. Unlike the ESTR model, the LSTR specification accounts for asymmetric realizations of the transition variable at two sides of the threshold level.

Figure A.3 Cumulative Excess Returns of the Alternative Currency Carry Portfolio: Threshold Trading on *PUW*



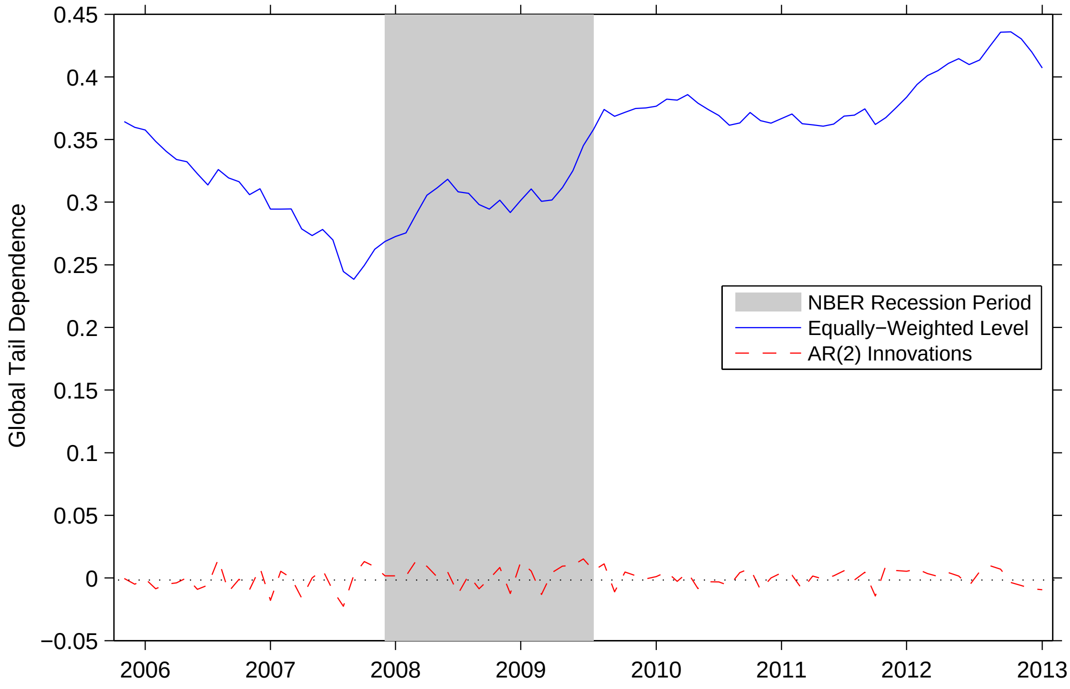
This figure shows the cumulative excess returns of an alternative carry trade strategy that is immunized from currency crashes, in comparison of the traditional long-short strategy. It trades on the threshold level of position-unwinding risk that investing in the highest interest-rate currencies funded by the lowest interest-rate currencies during the tranquil period and reverse the positions once the threshold level of position-unwinding likelihood indicator is reached. The out-of-sample period is from October 2009 to January 2013.

strategy is immunized from currency crashes, in comparison with the plain vanilla one. The out-of-sample performance (2009 October - 2013 January) of this trading strategy is better. The annualized (compounded) excess return of the threshold carry trading strategy is about 9.04%, which is much higher than that of the plain vanilla one (2.00%). And it has a Sharpe ratio of 0.95, more than three times as big as its original version. The success of our novel strategy lies in the fact that the risk of currency carry trades is highly predictable by our position-unwinding likelihood indicator.

.B Supporting Documentation: Chapter 3

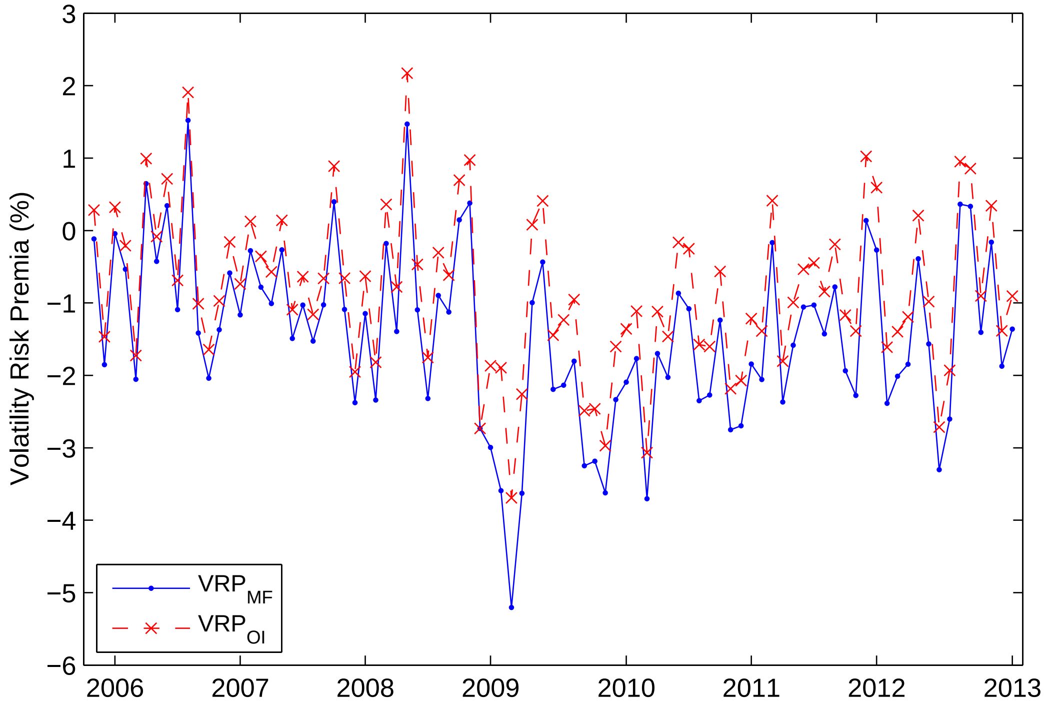
.B.1 Crash Risk, Insurance Cost, and Speculative Inclination

Figure B.1 Global Lower Tail Dependence: Aggregate Level & Shocks



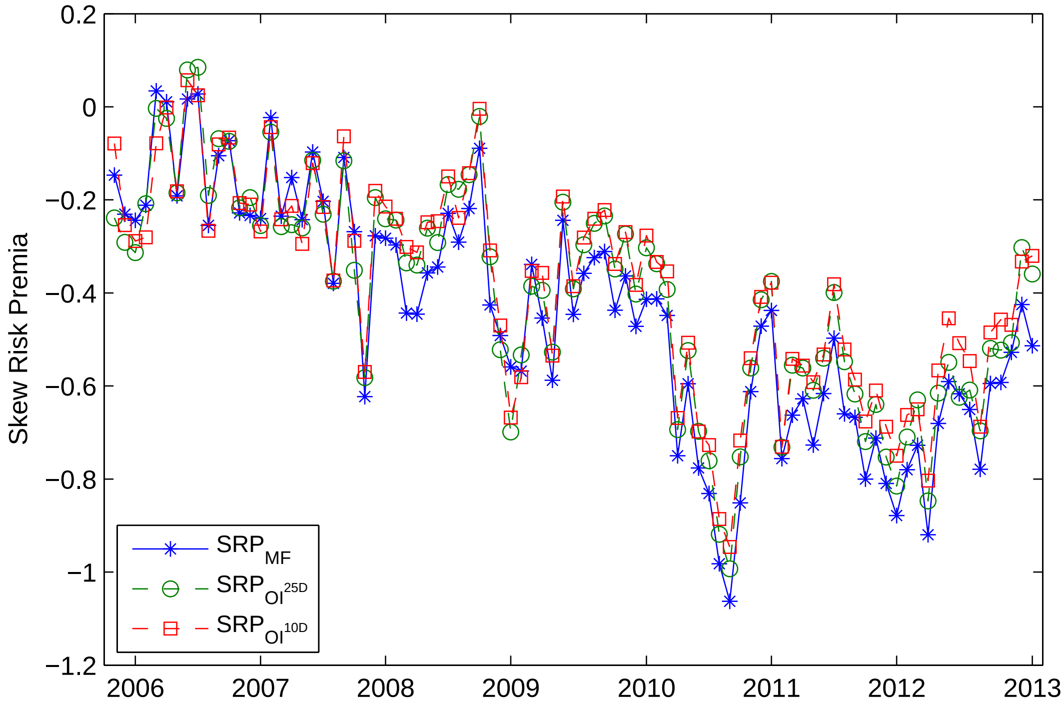
This figure shows global crash sensitivity at aggregate level of the whole sample countries with equal weights (GTD), and the innovations of its AR(2) process without a constant (GTI) from September 2005 to January 2013.

Figure B.2 Global 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 period is from September 2005 to January 2013.

Figure B.3 Global 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 period is from September 2005 to January 2013.

.B.2 Portfolios of Currency Investment Strategies

Table B.1. Descriptive Statistics of Currency Portfolios (Momentum, Value, and 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)

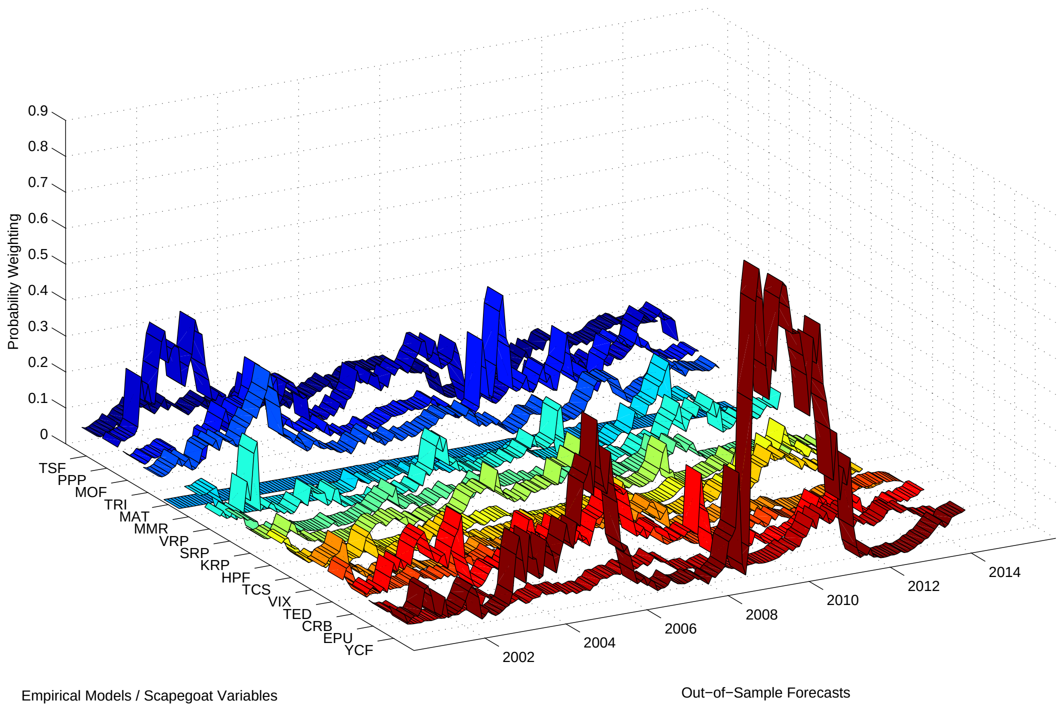
All Countries with Bid-Ask Spreads					
Portfolios	$P_{1,VRP}$	$P_{2,VRP}$	$P_{3,VRP}$	$P_{4,VRP}$	$P_{5,VRP}$
Mean (%)	4.99	1.60	1.15	1.64	2.49
Median (%)	9.22	9.07	10.17	11.63	11.60
Std.Dev. (%)	7.98	8.07	2.51	2.45	6.42
Skewness	-0.10	-0.38	-0.30	-0.89	-0.54
Kurtosis	0.02	0.29	0.37	1.55	0.76
Sharpe 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.

.C Supporting Documentation: Chapter 4

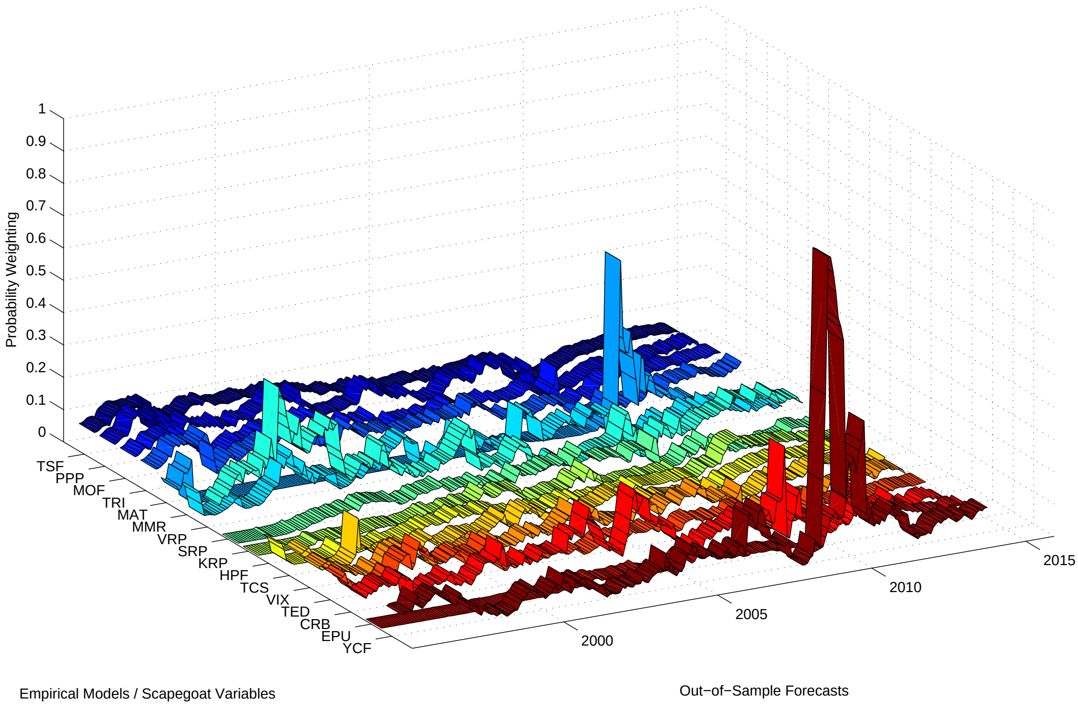
.C.1 DMA Probability Weighting of TVP-FAVAR Models: Sample Countries

Figure C.1 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: EUR



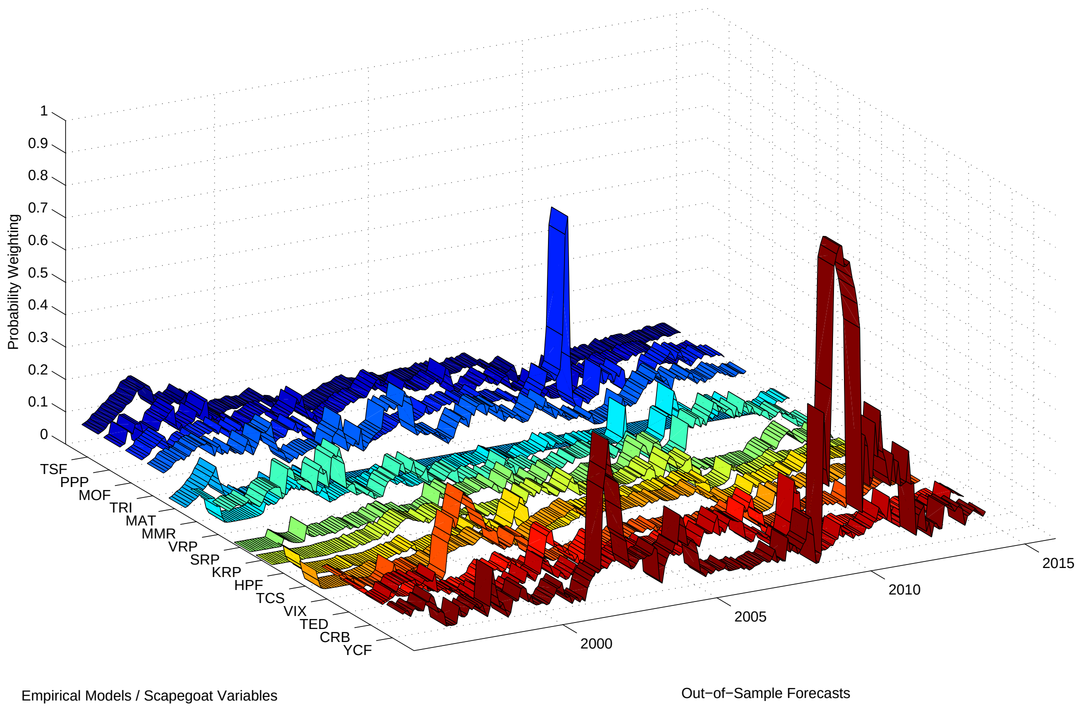
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for EURUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.2 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: GBP



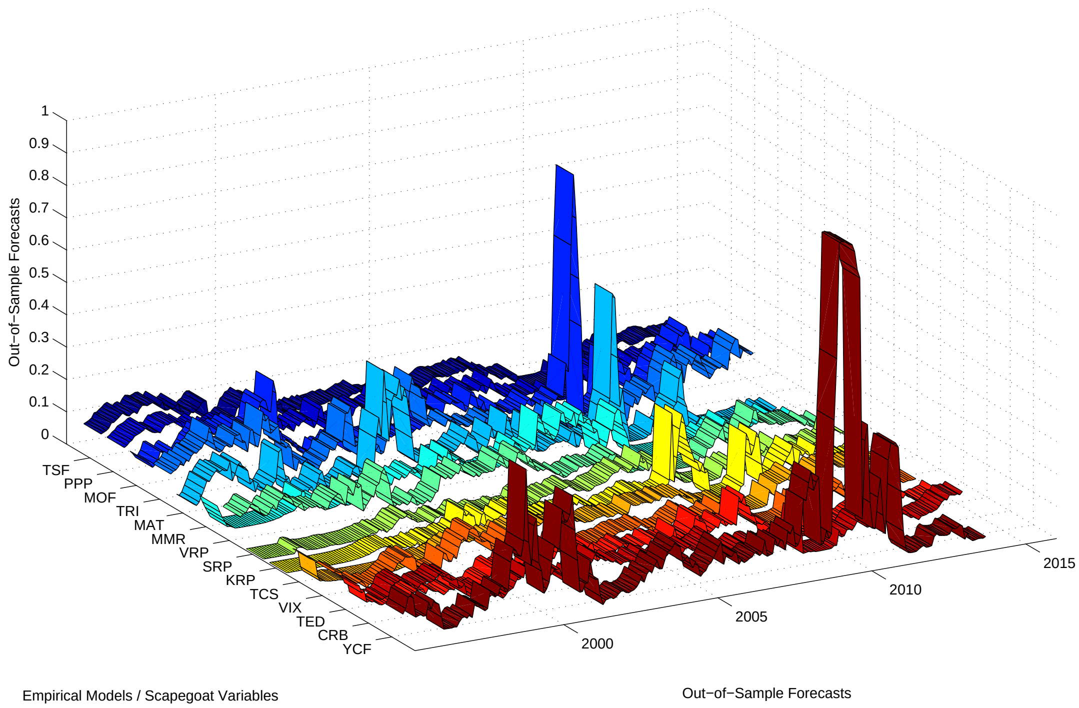
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for GBPUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.3 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: AUD



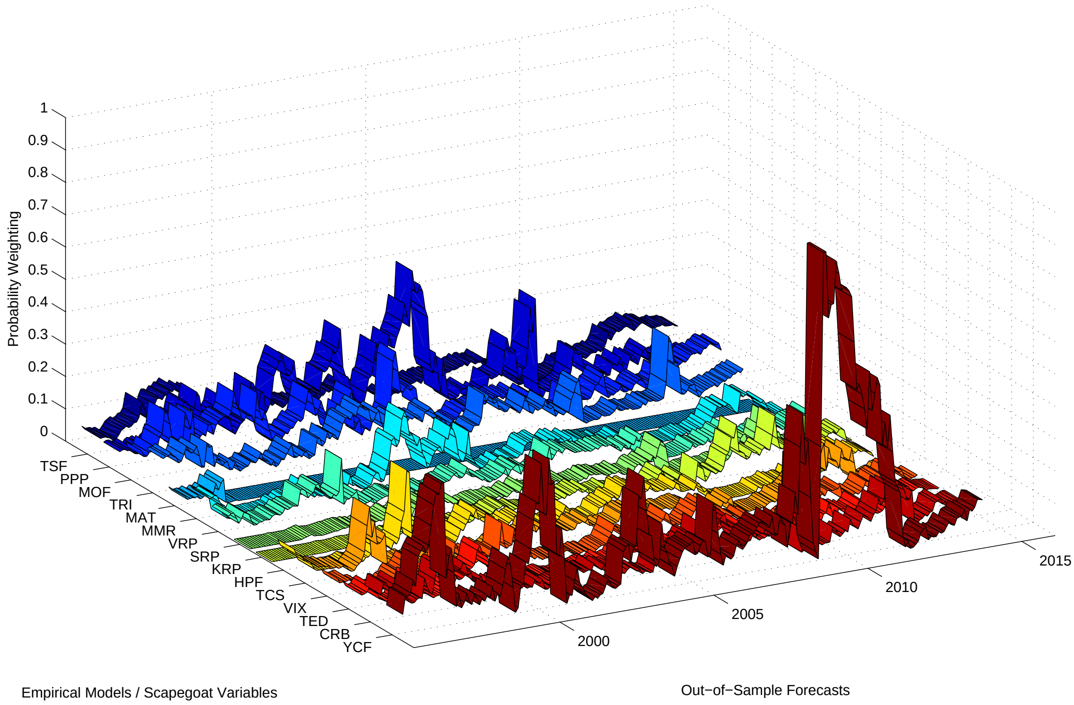
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for AUDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for AUDUSD. All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.4 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: NZD



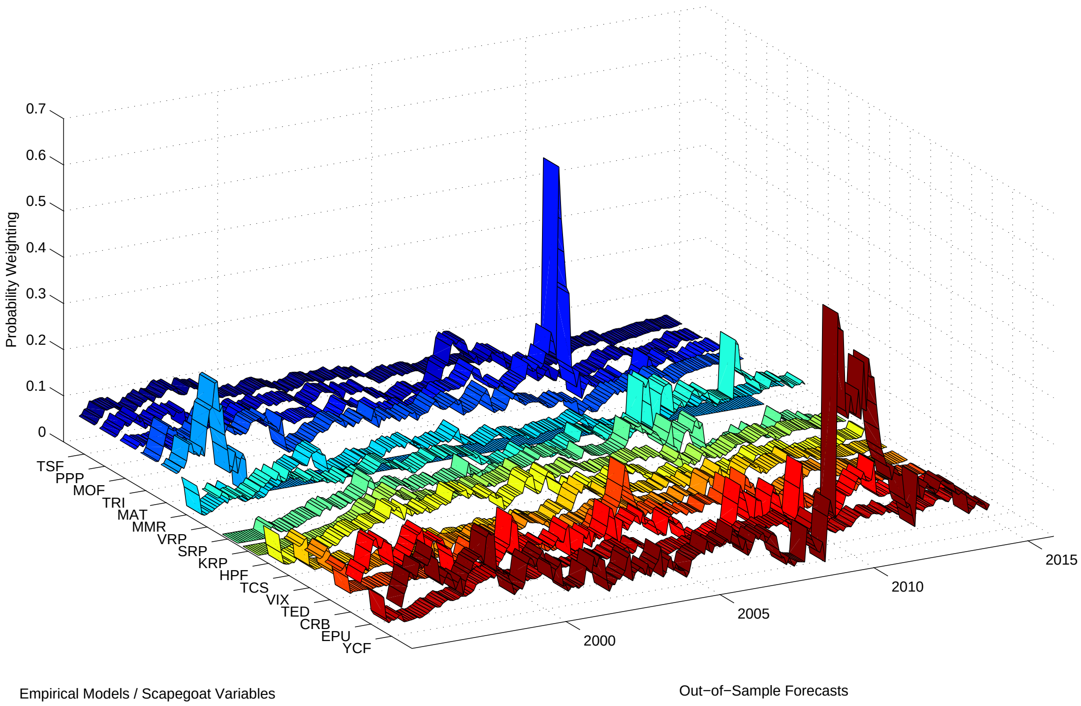
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for NZDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for NZDUSD. All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.5 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: CHF



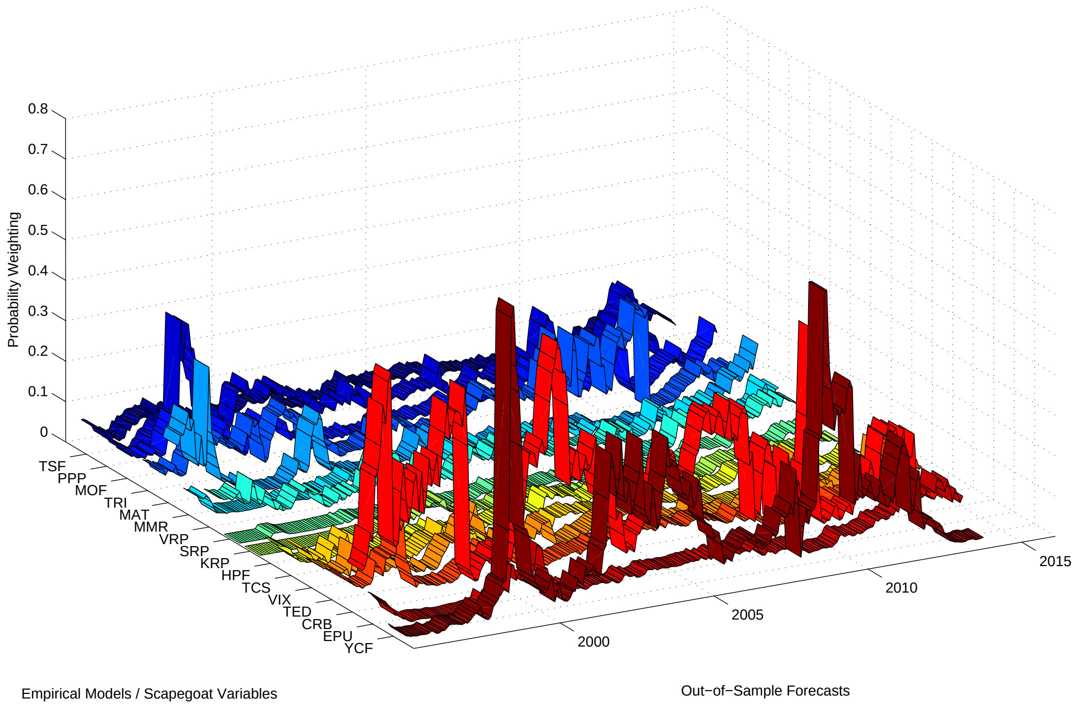
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDCHF via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). The Economic Policy Uncertainty (EPU) index is not available for USDCHF. All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.6 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: CAD



This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDCAD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

Figure C.7 Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: JPY



This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor Rule (TRI); Technical Indicators: MACD Trend Indicator (MAT), KDJ Momentum & Mean-Reversion Indicator (MMR); Option-implied Information: Volatility Risk Premia (Insurance Cost, VRP), Skew Risk Premia (SRP), Kurtosis Risk Premia (KRP); Copula-based Crash Sensitivity (TCS) and Hedging Pressure in Futures Market (HPF); Volatility Risk (VIX), Liquidity Risk (TED), Commodity Risk (CRB), Economic Policy Uncertainty (EPU) indices, and relative Yield Curve Factors (YCF), in the forecasting of the term structure of carry trade risk premia for USDJPY via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). All empirical exchange rate models take the form of incorporating corresponding predictor(s) into the dynamics of TSF in a TVP-VAR system. The lag number is selected according to information criteria. The in-sample (out-of-sample) period is from January 1995 to December 2004 (January 2005 to February 2014). Tick Label: Beginning of Year.

.C.2 Scapegoat Drivers of Customer Order Flows: Sample Countries

Table C.1. Scapegoat Drivers of Customer Order Flows: EUR

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP	**1.46****	**1.54****		**0.89*****	
	(0.73)	(0.68)		(0.29)	
MOF	0.38**		-0.13***	0.23*	
	(0.18)		(0.05)	(0.13)	
TRI				-0.15***	
				(0.05)	
MAT	-2.01**	-1.88***	**-0.28****	-1.19***	
	(0.82)	(0.58)	(0.11)	(0.38)	
MMR	**-0.75E-2***			-0.53E-2**	0.59E-2***
	(0.39E-2)			(0.23E-2)	(0.14E-2)
VRP					-0.15**
					(0.06)
SRP	-0.03***		-0.91E-2***		-0.49E-2**
	(0.01)		(0.27E-2)		(0.21E-2)
KRP		1.58E-2**			
		(0.63E-2)			
HPF	1.43E-2*	2.51E-2***			
	(0.80E-2)	(0.41E-2)			
TCS					
VIX					-0.02*
					(0.01)
TED					**-0.57E-2*****
					(0.29E-2)
CRB		**-3.99E-2*****			
		(0.74E-2)			
EPU	-0.03***				
	(0.01)				
$Adj-R^2$	0.27	0.30	0.22	0.19	0.18

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for EURUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.2. Scapegoat Drivers of Customer Order Flows: GBP

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP	**0.15****			**0.11*****	
	(0.07)			(0.03)	
MOF					**0.05E-2****
					(0.02E-2)
TRI					
MAT			**-0.53E-2***		
			(0.32E-2)		
MMR	-0.56E-2**			-0.33E-2***	0.18E-2***
	(0.26E-2)			(0.12E-2)	(0.06)
VRP	**-0.30*****	-0.17***			
	(0.10)	(0.05)			
SRP					
KRP			**-0.05E-2****		
			(0.02E-2)		
HPF					
TCS			**-0.40E-2***		
			(0.21E-2)		
VIX				**-0.81E-2****	
				(0.33E-2)	
TED			-0.36E-2*		
			(0.21E-2)		
CRB		**0.14E-2*****			
		(0.05E-2)			
EPU					
$Adj-R^2$	0.09	0.10	0.05	0.12	0.07

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for GBPUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.3. Scapegoat Drivers of Customer Order Flows: AUD

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP				**0.70***** (0.26)	
MOF			**-0.37E-2*** (0.21E-2)		
TRI					
MAT			**-0.20E-2***** (0.06E-2)		
MMR		-0.14E-2* (0.08E-2)		-0.20E-2** (0.10E-2)	0.21E-2*** (0.04E-2)
VRP		-0.06** (0.03)			
SRP				**-0.19E-2*** (0.11E-2)	
KRP					-0.31E-2** (0.13E-2)
HPF	**0.22E-2***** (0.08E-2)			**0.12E-2**** (0.05E-2)	**0.06E-2**** (0.03E-2)
TCS					
VIX	**-1.33E-2**** (0.61E-2)				0.70E-2** (0.30E-2)
TED	0.02** (0.01)				0.46E-2* (0.28E-2)
CRB			**0.20E-2*** (0.10E-2)		
$Adj-R^2$	0.11	0.09	0.03	0.11	0.25

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for AUDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.4. Scapegoat Drivers of Customer Order Flows: NZD

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP					
MOF		**0.10E-2***** (0.04E-2)			
TRI					**-0.06E-2***** (0.02E-2)
MAT			**-0.12E-2***** (0.04E-2)		
MMR					**1.19E-4***** (0.35E-4)
VRP	**-0.14E-2***** (0.05E-2)		-0.40E-2*** (0.12E-2)	**-0.12E-2***** (0.04E-2)	
SRP					
KRP					**-0.55E-4***** (0.10E-4)
HPF					
TCS				**0.20E-2**** (0.09E-2)	
VIX					
TED					
CRB					
$Adj-R^2$	0.01	0.02	0.07	0.05	0.19

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for NZDUSD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.5. Scapegoat Drivers of Customer Order Flows: CHF

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP			**-4.29E-2****		**3.93E-2****
			(1.84E-2)		(1.77E-2)
MOF			-0.05**		
			(0.02)		
TRI					**0.14*****
					(0.03)
MAT					
MMR		-0.28E-2**	0.40E-2***		
		(0.13E-2)	(0.09E-2)		
VRP					
SRP					**-0.15E-2****
					(0.07E-2)
KRP		**-1.11E-4****			
		(0.43E-4)			
HPF					
TCS					
VIX		**0.98E-2*****			**-0.70E-2*****
		(0.35E-2)			(0.16E-2)
TED					
CRB					
$Adj-R^2$	—	0.12	0.11	—	0.16

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for USDCHF via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.6. Scapegoat Drivers of Customer Order Flows: CAD

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP	0.56***			**0.13*** **	
	(0.16)			(0.04)	
MOF	**1.44E-2*** **	**1.30E-2** **			
	(0.38E-2)	(0.54E-2)			
TRI			-0.02*	**-0.03** **	
			(0.01)	(0.01)	
MAT	-0.36**	-0.52**			
	(0.18)	(0.20)			
MMR					-0.88E-3**
					(0.37E-3)
VRP	**-3.04E-2*** **		**-1.21E-2*** **		
	(1.09E-2)		(0.46E-2)		
SRP	**-1.09E-2** **			**-1.19E-2*** **	
	(0.46E-2)			(0.26E-2)	
KRP					
HPF					
TCS					
VIX	-1.35E-2*				**-0.06E-2** **
	(0.75E-2)				(0.02E-2)
TED	-1.20E-2**				
	(0.48E-2)				
CRB					
EPU					
$Adj-R^2$	0.20	0.14	0.09	0.21	0.14

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for USDCAD via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Table C.7. Scapegoat Drivers of Customer Order Flows: JPY

PW	Customer Order Flows				
	AGG	AM	CC	HF	PC
PPP	1.02**	0.81**			
	(0.51)	(0.33)			
MOF		0.07***			
		(0.03)			
TRI					
MAT					
MMR					0.24E-2***
					(0.05E-2)
VRP					
SRP		**0.64E-2****		**-0.81E-2****	
		(0.29E-2)		(0.38E-2)	
KRP					0.17E-2*
					(0.09E-2)
HPF					
TCS					
VIX				**-0.08****	
				(0.03)	
TED		-0.02***		**0.11E-2****	
		(0.01)		(0.06E-2)	
CRB				-0.14***	
				(0.05)	
EPU					
$Adj-R^2$	0.02	0.12	—	0.15	0.11

This table reports the drivers of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC). The candidate "scapegoat" variable reported in highlight is the product of the value per se and the corresponding probability weighting obtained from the forecasting of the term structure of carry trade risk premia / exchange rate returns for USDJPY via implementing the Dynamic Model Averaging (DMA) procedure of Koop and Korobilis (2012). HAC standard errors with optimal lag selection are reported in the parentheses. '*', '**', and '***' represents statistical significance at 10%, 5%, and 1% level of parameter estimates. The sample period is from January 2001 to February 2014.

Bibliography

Abhyankar, A., A. Gonzalez, and O. Klinkowska (2011). Salvaging the C-CAPM: Currency carry trade risk premia and conditioning information. *Available at SSRN No.1927265*.

Abhyankar, A., L. Sarno, and G. Valente (2005). Exchange rates and fundamentals: Evidence on the economic value of predictability. *Journal of International Economics 66*(2), 325–348.

Abreu, D. and M. Brunnermeier (2003). Bubbles and crashes. *Econometrica 71*(1), 173–204.

Acharya, V., D. Gale, and T. Yorulmazer (2011). Rollover risk and market freezes. *Journal of Finance 66*(4), 1177–1209.

Acharya, V., L. Lochstoer, and T. Ramadorai (2013). Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics 109*(2), 441–465.

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

Aghion, P., P. Bacchetta, R. Ranciere, and K. Rogoff (2009). Exchange rate volatility and productivity growth: The role of financial development. *Journal of Monetary Economics 56*(4), 494–513.

Ahn, D.-H. (2004). Common factors and local factors: Implications for term structures and exchange rates. *Journal of Financial and Quantitative Analysis 39*(1), 69–102.

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.

Albuquerque, R., G. Bauer, and M. Schneider (2009). Global private information in international equity markets. *Journal of Financial Economics 94*(1), 18–46.

Albuquerque, R., E. De Francisco, and L. Marques (2008). Marketwide private information in stocks: Forecasting currency returns. *Journal of Finance 63*(5), 2297–2343.

Allen, F. and D. Gale (2000). Financial contagion. *Journal of Political Economy 108*(1), 1–33.

Almeida, A., C. Goodhart, and R. Payne (1998). The effects of macroeconomic news on high frequency exchange rate behavior. *Journal of Financial and Quantitative Analysis 33*(3), 383–408.

Alvarez, F., A. Atkeson, and P. Kehoe (2009). Time-varying risk, interest rates, and exchange rates in general equilibrium. *Review of Economic Studies 76*(3), 851–878.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y. and H. Mendelson (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics 17*(2), 223–249.

Andersen, T., T. Bollerslev, F. Diebold, and P. Labys (2001). The distribution of realized exchange rate volatility. *Journal of the American Statistical Association 96*(453), 42–55.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review 93*(1), 38–62.

Anderson, H. (2004). Choosing lag lengths in nonlinear dynamic models. *Advances in Economics and Econometrics, Cheltenham: Edward Elgar Press*, 176–204.

Andrei, D., B. Carlin, and M. Hasler (2014). Model disagreement and economic outlook. *NBER Working Paper No.20190*.

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

Ang, A. (2014). *Asset Management: A Systematic Approach to Factor Investing*. Oxford University Press.

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.

Ang, A. and J. Chen (2010). Yield curve predictors of foreign exchange returns. In *AFA 2011 Denver Meetings Paper*.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *Journal of Finance 61*(1), 259–299.

Ang, A. and F. Longstaff (2013). Systemic sovereign credit risk: Lessons from the U.S. and Europe. *Journal of Monetary Economics 60*(5), 493–510.

Ang, A. and M. Piazzesi (2003). A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. *Journal of Monetary Economics 50*(4), 745–787.

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. *Journal of Finance 68*(3), 929–985.

Augustin, P. (2012). The term structure of CDS spreads and sovereign credit risk. *Available at SSRN No.2172382*.

Augustin, P. and R. Tédongap (2014). Real economic shocks and sovereign credit risk. *Forthcoming in Journal of Financial and Quantitative Analysis*.

Avramov, D. (2002). Stock return predictability and model uncertainty. *Journal of Financial Economics 64*(3), 423–458.

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

Bacchetta, P. and E. Van Wincoop (2004). A scapegoat model of exchange rate fluctuations. *NBER Working Paper No.10245*.

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

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

Bacchetta, P. and E. Van Wincoop (2013). On the unstable relationship between exchange rates and macroeconomic fundamentals. *Journal of International Economics 91*(1), 18–26.

Backus, D., S. Foresi, and C. Telmer (2001). Affine term structure models and the forward premium anomaly. *Journal of Finance 56*(1), 279–304.

Backus, D., S. Foresi, and L. Wu (2004). Accounting for biases in Black-Scholes. *Available at SSRN No.585623*.

Backus, D., F. Gavazzoni, C. Telmer, and S. Zin (2010). Monetary policy and the uncovered interest parity puzzle. *NBER Working Paper No.16218*.

Baek, I., A. Bandopadhyaya, and C. Du (2005). Determinants of market-assessed sovereign risk: Economic fundamentals or market risk appetite? *Journal of International Money and Finance 24*(4), 533–548.

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.

Bakshi, G. and G. Panayotov (2013). Predictability of currency carry trades and asset pricing implications. *Journal of Financial Economics 110*(1), 139–163.

Bandi, F., C. Moise, and J. Russell (2008). The joint pricing of volatility and liquidity. *Manuscript, University of Chicago*.

Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *Review of Financial Studies 24*(9), 3025–3068.

Banerjee, S. and B. Green (2014). Signal or noise? Uncertainty and learning about whether other traders are informed. *Available at SSRN No.2139771*.

Banerjee, S. and I. Kremer (2010). Disagreement and learning: Dynamic patterns of trade. *Journal of Finance 65*(4), 1269–1302.

Bansal, R. and M. Dahlquist (2000). The forward premium puzzle: Different tales from developed and emerging economies. *Journal of International Economics 51*(1), 115–144.

Bansal, R., D. Kiku, and A. Yaron (2010). Long-run risks, the macroeconomy, and asset prices. *American Economic Review 100*(2), 542–546.

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

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

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

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

Battiston, S., D. Delli Gatti, M. Gallegati, B. Greenwald, and J. Stiglitz (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control 36*(8), 1121–1141.

Bauwens, L., W. Ben Omrane, and P. Giot (2005). News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance 24*(7), 1108–1125.

Beber, A. and M. Brandt (2006). The effect of macroeconomic news on beliefs and preferences: Evidence from the options market. *Journal of Monetary Economics 53*(8), 1997–2039.

Beber, A., F. Breedon, and A. Buraschi (2010). Differences in beliefs and currency risk premiums. *Journal of Financial Economics 98*(3), 415–438.

Bekaert, G., M. Wei, and Y. Xing (2007). Uncovered interest rate parity and the term structure. *Journal of International Money and Finance 26*(6), 1038–1069.

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

Berger, D., A. Chaboud, S. Chernenko, E. Howorka, and J. Wright (2008). Order flow and exchange rate dynamics in electronic brokerage system data. *Journal of International Economics 75*(1), 93–109.

Berger, D., A. Chaboud, and E. Hjalmarsson (2009). What drives volatility persistence in the foreign exchange market? *Journal of Financial Economics 94*(2), 192–213.

Berkowitz, J. and L. Giorgianni (2001). Long-horizon exchange rate predictability? *Review of Economics and Statistics 83*(1), 81–91.

Bikbov, R. and M. Chernov (2010). No-arbitrage macroeconomic determinants of the yield curve. *Journal of Econometrics 159*(1), 166–182.

Billio, M., M. Getmansky, A. Lo, and L. Pelizzon (2012). Econometric measures of systemic risk in the finance and insurance sectors. *Journal of Financial Economics 104*(3), 535–559.

Bjønnes, G. and D. Rime (2005). Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics 75*(3), 571–605.

Bjønnes, G., D. Rime, and H. Solheim (2005). Liquidity provision in the overnight foreign exchange market. *Journal of International Money and Finance 24*(2), 175–196.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*(3), 637–654.

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. *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. *Journal of Finance 66*(6), 2165–2211.

Bonomo, M., R. Garcia, N. Meddahi, and R. Tédongap (2011). Generalized disappointment aversion, long-run volatility risk, and asset prices. *Review of Financial Studies 24*(1), 82–122.

Borri, N. and A. Verdelhan (2011). Sovereign risk premia. In *AFA 2010 Atlanta Meetings Paper*.

Branch, W. and G. Evans (2010). Asset return dynamics and learning. *Review of Financial Studies 23*(4), 1651–1680.

Branch, W. and G. Evans (2011). Learning about risk and return: A simple model of bubbles and crashes. *American Economic Journal: Macroeconomics 3*(3), 159–191.

Brandt, M. and K. Kavajecz (2004). Price discovery in the U.S. treasury market: The impact of order flow and liquidity on the yield curve. *Journal of Finance 59*(6), 2623–2654.

Branger, N., L. S. Larsen, and C. Munk (2013). Robust portfolio choice with ambiguity and learning about return predictability. *Journal of Banking and Finance 37*(5), 1397–1411.

Breeden, D., M. Gibbons, and R. Litzenberger (1989). Empirical tests of the consumption-oriented CAPM. *Journal of Finance 44*(2), 231–262.

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

Breedon, F., D. Rime, and P. Vitale (2010). A transaction data study of the forward bias puzzle. *CEPR Discussion Paper No.7791*.

Breedon, F. and P. Vitale (2010). An empirical study of portfolio-balance and information effects of order flow on exchange rates. *Journal of International Money and Finance 29*(3), 504–524.

Breiman, L. (1996). Bagging predictors. *Machine Learning 24*(2), 123–140.

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

Brock, W. and C. Hommes (1997). A rational route to randomness. *Econometrica 65*(5), 1059–1095.

Brock, W., J. Lakonishok, and B. LeBaron (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance 47*(5), 1731–1764.

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.

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

Buraschi, A. and A. Jiltsov (2005). Inflation risk premia and the expectations hypothesis. *Journal of Financial Economics 75*(2), 429–490.

Buraschi, A. and A. Jiltsov (2007). Habit formation and macroeconomic models of the term structure of interest rates. *Journal of Finance 62*(6), 3009–3063.

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

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2011). Do peso problems explain the returns to the carry trade? *Review of Financial Studies 24*(3), 853–891.

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

Burnside, C., M. Eichenbaum, and S. Rebelo (2009). Understanding the forward premium puzzle: A microstructure approach. *American Economic Journal: Macroeconomics 1*(2), 127–154.

Burnside, C., B. Han, D. Hirshleifer, and T. Y. Wang (2011). Investor overconfidence and the forward premium puzzle. *Review of Economic Studies 78*(2), 523–558.

Caballero, R., E. Farhi, and P.-O. Gourinchas (2008). An equilibrium model of global imbalances and low interest rates. *American Economic Review 98*(1), 358–393.

Caceres, C., V. Guzzo, and M. Segoviano Basurto (2010). Sovereign spreads: Global risk aversion, contagion or fundamentals? *IMF Working Paper No.06/194*.

Calvo, G. (1998). Capital flows and capital-market crises: The simple economics of sudden stops. *Journal of Applied Economics 1*(1), 35–54.

Campbell, J. (1993). Intertemporal asset pricing without consumption data. *American Economic Review 83*(3), 487–512.

Campbell, J. and J. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy 107*(2), 205–251.

Campbell, J. and S. Thompson (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies 21*(4), 1509–1531.

Cappiello, L., R. Engle, and K. Sheppard (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics 4*(4), 537–572.

Carceles-Poveda, E. and C. Giannitsarou (2008). Asset pricing with adaptive learning. *Review of Economic Dynamics 11*(3), 629–651.

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

Carlin, B., F. Longstaff, and K. Matoba (2014). Disagreement and asset prices. *Journal of Financial Economics 114*(2), 226–238.

Carlson, J. and C. Osler (2000). Rational speculators and exchange rate volatility. *European Economic Review 44*(2), 231–253.

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 (2007). Theory and evidence on the dynamic interactions between sovereign credit default swaps and currency options. *Journal of Banking and Finance 31*(8), 2383–2403.

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

Carr, P. and L. Wu (2010). Stock options and credit default swaps: A joint framework for valuation and estimation. *Journal of Financial Econometrics 8*(4), 409–449.

Castle, J., M. Clements, and D. Hendry (2013). Forecasting by factors, by variables, by both or neither? *Journal of Econometrics 177*(2), 305–319.

Chakraborty, A. and G. Evans (2008). Can perpetual learning explain the forward-premium puzzle? *Journal of Monetary Economics 55*(3), 477–490.

Chan, K. and W.-M. Fong (2000). Trade size, order imbalance, and the volatility-volume relation. *Journal of Financial Economics 57*(2), 247–273.

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

Chang, B., P. Christoffersen, and K. Jacobs (2013). Market skewness risk and the cross-section of stock returns. *Journal of Financial Economics 107*(1), 46–68.

Chen, Y.-C. and K.-P. Tsang (2013). What does the yield curve tell us about exchange rate predictability? *Review of Economics and Statistics 95*(1), 185–205.

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

Cheung, Y.-W. and M. Chinn (2001). Currency traders and exchange rate dynamics: A survey of the U.S. market. *Journal of International Money and Finance 20*(4), 439–471.

Cheung, Y.-W., M. Chinn, and A. Pascual (2005). Empirical exchange rate models of the nineties: Are any fit to survive? *Journal of International Money and Finance 24*(7), 1150–1175.

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

Chinn, M. and M. Moore (2011). Order flow and the monetary model of exchange rates: Evidence from a novel data set. *Journal of Money, Credit and Banking 43*(8), 1599–1624.

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

Christensen, J., F. Diebold, and G. Rudebusch (2011). The affine arbitrage-free class of Nelson–Siegel term structure models. *Journal of Econometrics 164*(1), 4–20.

Christensen, J., J. Lopez, and G. Rudebusch (2010). Inflation expectations and risk premiums in an arbitrage-free model of nominal and real bond yields. *Journal of Money, Credit and Banking 42*(1), 143–178.

Christiansen, C., A. Ranaldo, and P. Söderlind (2011). The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis 46*(4), 1107–1125.

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. *Journal of Financial and Quantitative Analysis 48*(05), 1371–1404.

Chun, A. L. (2011). Expectations, bond yields, and monetary policy. *Review of Financial Studies 24*(1), 208–247.

Clarida, R., J. Davis, and N. Pedersen (2009). Currency carry trade regimes: Beyond the Fama regression. *Journal of International Money and Finance 28*(8), 1375–1389.

Clarida, R., J. Galí, and M. Gertler (1998). Monetary policy rules in practice: Some international evidence. *European Economic Review 42*(6), 1033–1067.

Clarida, R., J. Galí, and M. Gertler (2002). A simple framework for international monetary policy analysis. *Journal of Monetary Economics 49*(5), 879–904.

Clarida, R., L. Sarno, M. Taylor, and G. Valente (2003). The out-of-sample success of term structure models as exchange rate predictors: A step beyond. *Journal of International Economics 60*(1), 61–83.

Clarida, R. and M. Taylor (1997). The term structure of forward exchange premiums and the forecastability of spot exchange rates: Correcting the errors. *Review of Economics and Statistics 79*(3), 353–361.

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

Clark, T. and M. McCracken (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics 105*(1), 85–110.

Clark, T. and K. West (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics 135*(1), 155–186.

Clark, T. and K. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics 138*(1), 291–311.

Cline, W. (2008). Estimating consistent fundamental equilibrium exchange rates. *Peterson Institute of International Economics Working Paper Series No.08-6*.

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

Cochrane, J. and M. Piazzesi (2005). Bond risk premia. *American Economic Review 95*(1), 138–160.

Cochrane, J. and M. Piazzesi (2009). Decomposing the yield curve. In *AFA 2010 Atlanta Meetings Paper*.

Colacito, R. and M. Croce (2011). Risks for the long run and the real exchange rate. *Journal of Political Economy 119*(1), 153–181.

Collin-Dufresne, P., M. Johannes, and L. Lochstoer (2013). Parameter learning in general equilibrium: The asset pricing implications. *NBER Working Paper No.19705*.

Condie, S. and J. Ganguli (2011). Ambiguity and rational expectations equilibria. *Review of Economic Studies 78*(3), 821–845.

Conrad, J., R. Dittmar, and E. Ghysels (2013). Ex ante skewness and expected stock returns. *Journal of Finance 68*(1), 85–124.

Cont, R., A. Kukanov, and S. Stoikov (2013). The price impact of order book events. *Journal of Financial Econometrics 12*(1), 47–88.

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

Coudert, V. and V. Mignon (2013). The forward premium puzzle and the sovereign default risk. *Journal of International Money and Finance 32*, 491–511.

Cox, J., J. Ingersoll, and S. Ross (1985). A theory of the term structure of interest rates. *Econometrica 53*(2), 385–408.

Creal, D. and J. C. Wu (2015). Estimation of affine term structure models with spanned or unspanned stochastic volatility. *Journal of Econometrics 185*(1), 60–81.

Cremers, M. (2002). Stock return predictability: A Bayesian model selection perspective. *Review of Financial Studies 15*(4), 1223–1249.

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.

Dai, Q. and K. Singleton (2000). Specification analysis of affine term structure models. *Journal of Finance 55*(5), 1943–1978.

Daníelsson, J., H. Shin, and J.-P. Zigrand (2009). Risk appetite and endogenous risk. *Available at SSRN No.1360866*.

Davig, T. and E. Leeper (2011). Monetary-fiscal policy interactions and fiscal stimulus. *European Economic Review 55*(2), 211–227.

De Grauwe, P. and M. Grimaldi (2006). Exchange rate puzzles: A tale of switching attractors. *European Economic Review 50*(1), 1–33.

De Grauwe, P. and A. Markiewicz (2013). Learning to forecast the exchange rate: Two competing approaches. *Journal of International Money and Finance 32*(1), 42–76.

De Long, J. B., A. Shleifer, L. Summers, and R. Waldmann (1990a). Noise trader risk in financial markets. *Journal of Political Economy 98*(4), 703–738.

De Long, J. B., A. Shleifer, L. Summers, and R. Waldmann (1990b). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance 45*(2), 379–395.

De Roon, F., T. Nijman, and C. Veld (2000). Hedging pressure effects in futures markets. *Journal of Finance 55*(3), 1437–1456.

De Santis, G. and B. Gerard (1998). How big is the premium for currency risk? *Journal of Financial Economics 49*(3), 375–412.

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 D. Thornton (2008). The expectation hypothesis of the term structure of very short-term rates: Statistical tests and economic value. *Journal of Financial Economics 89*(1), 158–174.

Della Corte, P., L. Sarno, and I. Tsiakas (2009). An economic evaluation of empirical exchange rate models. *Review of Financial Studies 22*(9), 3491–3530.

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.

Dick, C. and L. Menkhoff (2013). Exchange rate expectations of chartists and fundamentalists. *Journal of Economic Dynamics and Control 37*(7), 1362–1383.

Diebold, F. and C. Li (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics 130*(2), 337–364.

Diebold, F., C. Li, and V. Yue (2008). Global yield curve dynamics and interactions: A dynamic Nelson–Siegel approach. *Journal of Econometrics 146*(2), 351–363.

Diebold, F. and R. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*(3), 253–263.

Diebold, F., M. Piazzesi, and G. Rudebusch (2005). Modeling bond yields in finance and macroeconomics. *American Economic Review 95*(2), 415–420.

Diebold, F., G. Rudebusch, and S. Boragan Aruoba (2006). The macroeconomy and the yield curve: A dynamic latent factor approach. *Journal of Econometrics 131*(1), 309–338.

Diez, A. (2009). Can affine term structure models help us predict exchange rates? *Journal of Money, Credit and Banking 41*(4), 755–766.

Diks, C. and V. Panchenko (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control 30*(9), 1647–1669.

Dittmar, R. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross-section of equity returns. *Journal of Finance 57*(1), 369–403.

Doshi, H., K. Jacobs, and R. Liu (2014). Macroeconomic variables and the term structure: Long-run and short-run dynamics. *Available at SSRN No.2561026*.

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.

Duffee, G. (2002). Term premia and interest rate forecasts in affine models. *Journal of Finance 57*(1), 405–443.

Duffee, G. (2011). Information in (and not in) the term structure. *Review of Financial Studies 24*(9), 2895–2934.

Duffee, G. (2013). Bond pricing and the macroeconomy. In *Handbook of the Economics of Finance*. Eds. Constantinides, G. and Harris, M. and Stulz, R., Elsevier.

Duffie, D. and R. Kan (1996). A yield-factor model of interest rates. *Mathematical Finance 6*(4), 379–406.

Duffie, D. and K. Singleton (1999). Modeling term structures of defaultable bonds. *Review of Financial Studies 12*(4), 687–720.

Dunne, P., H. Hau, and M. Moore (2010). International order flows: Explaining equity and exchange rate returns. *Journal of International Money and Finance 29*(2), 358–386.

Durdu, C., E. Mendoza, and M. Terrones (2013). On the solvency of nations: Cross-country evidence on the dynamics of external adjustment. *Journal of International Money and Finance 32*(1), 762–780.

Easley, D., S. Hvidkjaer, and M. O'Hara (2002). Is information risk a determinant of asset returns? *Journal of Finance 57*(5), 2185–2221.

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.

Ehrmann, M. and M. Fratzscher (2005). Exchange rates and fundamentals: New evidence from real-time data. *Journal of International Money and Finance 24*(2), 317–341.

Eichengreen, B., A. Rose, and C. Wyplosz (1996). Contagious currency crises. *NBER Working Paper No.5681*.

Eitrheim, O. and T. Teräsvirta (1996). Testing the adequacy of smooth transition autoregressive models. *Journal of Econometrics 74*(1), 59–75.

Elliott, G., A. Gargano, and A. Timmermann (2013). Complete subset regressions. *Journal of Econometrics 177*(2), 357–373.

Engel, C. (1996). The forward discount anomaly and the risk premium: A survey of recent evidence. *Journal of Empirical Finance 3*(2), 123–192.

Engel, C. (2011). Currency misalignments and optimal monetary policy: A reexamination. *American Economic Review 101*(6), 2796–2822.

Engel, C. and J. Hamilton (1990). Long swings in the dollar: Are they in the data and do markets know it? *American Economic Review 80*(4), 689–713.

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. *Journal of Political Economy 113*(3), 485–517.

Epstein, L. and M. Schneider (2007). Learning under ambiguity. *Review of Economic Studies 74*(4), 1275–1303.

Epstein, L. and M. Schneider (2008). Ambiguity, information quality, and asset pricing. *Journal of Finance 63*(1), 197–228.

Espinoza, R. and M. Segoviano (2011). Probabilities of default and the market price of risk in a distressed economy. *IMF Working Paper No.11/75*.

Evans, G. and S. Honkapohja (2001). *Learning and Expectations in Macroeconomics.* Princeton, NJ: Princeton University Press.

Evans, G., S. Honkapohja, T. Sargent, and N. Williams (2012). Bayesian model averaging, learning and model selection. *CEPR Discussion Paper No.8917*.

Evans, M. (2010). Order flows and the exchange rate disconnect puzzle. *Journal of International Economics 80*(1), 58–71.

Evans, M. and R. Lyons (2002). Order flow and exchange rate dynamics. *Journal of Political Economy 110*(1), 170–180.

Evans, M. and R. Lyons (2005a). Do currency markets absorb news quickly? *Journal of International Money and Finance 24*(2), 197–217.

Evans, M. and R. Lyons (2005b). Meese-Rogoff redux: Micro-based exchange-rate forecasting. *American Economic Review 95*(2), 405–414.

Evans, M. and R. Lyons (2008). How is macro news transmitted to exchange rates? *Journal of Financial Economics 88*(1), 26–50.

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. *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. *Journal of Political Economy 81*(3), 607–636.

Farhi, E., S. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan (2009). Crash risk in currency markets. *NBER Working Paper No.15062*.

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

Faust, J., J. Rogers, S.-Y. Wang, and J. Wright (2007). The high-frequency response of exchange rates and interest rates to macroeconomic announcements. *Journal of Monetary Economics 54*(4), 1051–1068.

Faust, J., J. Rogers, and J. Wright (2003). Exchange rate forecasting: The errors we've really made. *Journal of International Economics 60*(1), 35–59.

Feldhütter, P. and D. Lando (2008). Decomposing swap spreads. *Journal of Financial Economics 88*(2), 375–405.

Ferreira Filipe, S. and M. Suominen (2013). Currency carry trades and funding risk. In *AFA 2014 Philadelphia Meetings Paper*.

Fleming, J., C. Kirby, and B. Ostdiek (2001). The economic value of volatility timing. *Journal of Finance 56*(1), 329–352.

Fleming, J., C. Kirby, and B. Ostdiek (2003). The economic value of volatility timing using realized volatility. *Journal of Financial Economics 67*(3), 473–509.

Flood, R. and A. Rose (1995). Fixing exchange rates: A virtual quest for fundamentals. *Journal of Monetary Economics 36*(1), 3–37.

Forbes, K. and F. Warnock (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics 88*(2), 235–251.

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 K. Froot (1989). Forward discount bias: Is it an exchange risk premium? *Quarterly Journal of Economics 104*(1), 139–161.

Frankel, J. and K. Froot (1990). Chartists, fundamentalists, and trading in the foreign exchange market. *American Economic Review 80*(2), 181–185.

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.

Fratzscher, M., D. Rime, L. Sarno, and G. Zinna (2015). The scapegoat theory of exchange rates: The first tests. *Journal of Monetary Economics 70*, 1–21.

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

Friewald, N., C. Wagner, and J. Zechner (2014). The cross-section of credit risk premia and equity returns. *Journal of Finance 69*(6), 2419–2469.

Frömmel, M., A. Mende, and L. Menkhoff (2008). Order flows, news, and exchange rate volatility. *Journal of International Money and Finance 27*(6), 994–1012.

Froot, K. and T. Ramadorai (2005). Currency returns, intrinsic value, and institutional-investor flows. *Journal of Finance 60*(3), 1535–1566.

Froot, K. and R. Thaler (1990). Anomalies: Foreign exchange. *Journal of Economic Perspectives 4*(3), 179–192.

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. *Journal of Finance 63*(4), 1777–1803.

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

Gabaix, X. and M. Maggiori (2015). International liquidity and exchange rate dynamics. *Quarterly Journal of Economics 130*(3), 1369–1420.

Gargano, A., D. Pettenuzzo, and A. Timmermann (2014). Bond return predictability: Economic value and links to the macroeconomy. *Available at SSRN No.2471273*.

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. *Journal of Finance 48*(5), 1779–1801.

Glosten, L. and P. Milgrom (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*(1), 71–100.

Goetzmann, W., J. Ingersoll, M. Spiegel, and I. Welch (2007). Portfolio performance manipulation and manipulation-proof performance measures. *Review of Financial Studies 20*(5), 1503–1546.

Gómez, V. and A. Maravall (2000). Seasonal adjustment and signal extraction time series. In *A Course in Time Series Analysis*. Eds. Peña, D. and Tiao, G. and Tsay, R., Wiley Online Library.

Gorton, G., F. Hayashi, and G. Rouwenhorst (2013). The fundamentals of commodity futures returns. *Review of Finance 17*(1), 35–105.

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

Gourinchas, P.-O. and H. Rey (2013). External adjustment, global imbalances and valuation effects. *NBER Working Paper No.19240*.

Gourio, F., M. Siemer, and A. Verdelhan (2013). International risk cycles. *Journal of International Economics 89*(2), 471–484.

Griffin, J., X. Ji, and J. S. Martin (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *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.

Groen, J. (2000). The monetary exchange rate model as a long-run phenomenon. *Journal of International Economics 52*(2), 299–319.

Groen, J. (2005). Exchange rate predictability and monetary fundamentals in a small multi-country panel. *Journal of Money, Credit and Banking 37*(3), 495–516.

Guidolin, M. and A. Timmermann (2007). Properties of equilibrium asset prices under alternative learning schemes. *Journal of Economic Dynamics and Control 31*(1), 161–217.

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.

Han, Y. (2006). Asset allocation with a high dimensional latent factor stochastic volatility model. *Review of Financial Studies 19*(1), 237–271.

Hansen, B. (1992). Tests for parameter instability in regressions with I(1) processes. *Journal of Business and Economic Statistics 20*(1), 45–59.

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

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

Hansen, L. P. and R. Hodrick (1980). Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *Journal of Political Economy 88*(5), 829–853.

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

Harvey, C. and A. Siddique (2000). Conditional skewness in asset pricing tests. *Journal of Finance 55*(3), 1263–1295.

Hassan, T. (2013). Country size, currency unions, and international asset returns. *Journal of Finance 68*(6), 2269–2308.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica 46*(6), 1251–1271.

He, Z. and W. Xiong (2012). Rollover risk and credit risk. *Journal of Finance 67*(2), 391–430.

Hellwig, C., A. Mukherji, and A. Tsyvinski (2006). Self-fulfilling currency crises: The role of interest rates. *American Economic Review 96*(5), 1769–1787.

Hiemstra, C. and J. Jones (1994). Testing for linear and nonlinear Granger causality in the stock price-volume relation. *Journal of Finance 49*(5), 1639–1664.

Hilscher, J. and Y. Nosbusch (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt. *Review of Finance 14*(2), 235–262.

Hodrick, R. and E. Prescott (1997). Postwar U.S. business cycles: an empirical investigation. *Journal of Money, Credit and Banking 29*(1), 1–16.

Hoerl, A. and R. Kennard (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics 12*(1), 55–67.

Hong, H., T. Lim, and J. Stein (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *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.

Hördahl, P., O. Tristani, and D. Vestin (2006). A joint econometric model of macroeconomic and term-structure dynamics. *Journal of Econometrics 131*(1), 405–444.

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

Huang, H. and R. MacDonald (2013b). Global currency misalignments, crash sensitivity, and moment risk premia. *Available at SSRN No.2393105*.

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

Ilut, C. (2012). Ambiguity aversion: Implications for the uncovered interest rate parity puzzle. *American Economic Journal: Macroeconomics 4*(3), 33–65.

Imbs, J., H. Mumtaz, M. Ravn, and H. Rey (2005). Ppp strikes back: Aggregation and the real exchange rate. *Quarterly Journal of Economics 120*(1), 1–43.

Inci, A. C. and B. Lu (2004). Exchange rates and interest rates: Can term structure models explain currency movements? *Journal of Economic Dynamics and Control 28*(8), 1595–1624.

Ivanova, Y., C. Neely, D. Rapach, and P. Weller (2014). Can risk explain the profitability of technical trading in currency markets? *Federal Reserve Bank of St. Louis, Working Paper No.2014-33*.

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

Jarrow, R. and A. Rudd (1982). Approximate option valuation for arbitrary stochastic processes. *Journal of Financial Economics 10*(3), 347–369.

Jeanne, O. and A. Rose (2002). Noise trading and exchange rate regimes. *Quarterly Journal of Economics 117*(2), 537–569.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*(1), 65–91.

Jegadeesh, N. and S. Titman (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance 56*(2), 699–720.

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.

Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press.

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.

Joslin, S., M. Priebsch, and K. Singleton (2014). Risk premiums in dynamic term structure models with unspanned macro risks. *Journal of Finance 69*(3), 1197–1233.

Ju, N. and J. Miao (2012). Ambiguity, learning, and asset returns. *Econometrica 80*(2), 559–591.

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

Kaminsky, G. and C. Reinhart (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review 89*(3), 473–500.

Kaminsky, G. and C. Reinhart (2000). On crises, contagion, and confusion. *Journal of International Economics 51*(1), 145–168.

Kilian, L. (1999). Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? *Journal of Applied Econometrics 14*(5), 491–510.

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.

Killeen, W., R. Lyons, and M. Moore (2006). Fixed versus flexible: Lessons from EMS order flow. *Journal of International Money and Finance 25*(4), 551–579.

Kodres, L. and M. Pritsker (2002). A rational expectations model of financial contagion. *Journal of Finance 57*(2), 769–799.

Koijen, R., T. Moskowitz, L. H. Pedersen, and E. Vrugt (2013). Carry. *NBER Working Paper No.19325*.

Koop, G. and D. Korobilis (2012). Forecasting inflation using dynamic model averaging. *International Economic Review 53*(3), 867–886.

Koop, G. and D. Korobilis (2013). Large time-varying parameter VARs. *Journal of Econometrics 177*(2), 185–198.

Koop, G., D. Poirier, and J. Tobias (2007). *Bayesian Econometric Methods*. Cambridge University Press.

Korajczyk, R. and R. Sadka (2004). Are momentum profits robust to trading costs? *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. *American Economic Review 93*(4), 1216–1239.

Kozhan, R., A. Neuberger, and P. Schneider (2013). The skew risk premium in the equity index market. *Review of Financial Studies 26*(9), 2174–2203.

Kozhan, R. and M. Salmon (2009). Uncertainty aversion in a heterogeneous agent model of foreign exchange rate formation. *Journal of Economic Dynamics and Control 33*(5), 1106–1122.

Kraus, A. and R. Litzenberger (1976). Skewness preference and the valuation of risk assets. *Journal of Finance 31*(4), 1085–1100.

Krugman, P. (1979). A model of balance-of-payments crises. *Journal of Money, Credit and Banking 11*(3), 311–325.

Lahiri, K. and X. Sheng (2008). Evolution of forecast disagreement in a Bayesian learning model. *Journal of Econometrics 144*(2), 325–340.

Lahiri, K. and X. Sheng (2010). Measuring forecast uncertainty by disagreement: The missing link. *Journal of Applied Econometrics 25*(4), 514–538.

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.

LeBaron, B. (1999). Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics 49*(1), 125–143.

Leeper, E. (1991). Equilibria under 'active' and 'passive' monetary and fiscal policies. *Journal of Monetary Economics 27*(1), 129–147.

Leeper, E. and X. Zhou (2013). Inflation's role in optimal monetary-fiscal policy. *NBER Working Paper No.19686*.

Leippold, M., F. Trojani, and P. Vanini (2008). Learning and asset prices under ambiguous information. *Review of Financial Studies 21*(6), 2565–2597.

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

Levich, R. and L. Thomas (1993). The significance of technical trading-rule profits in the foreign exchange market: A bootstrap approach. *Journal of International Money and Finance 12*(5), 451–474.

Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature 35*(2), 688–726.

Li, Y. and L. Yang (2013). Prospect theory, the disposition effect, and asset prices. *Journal of Financial Economics 107*(3), 715–739.

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

Lo, A. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management 30*(5), 15–29.

Lo, A., H. Mamaysky, and J. Wang (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance 55*(4), 1705–1770.

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

Longstaff, F., J. Pan, L. H. Pedersen, and K. Singleton (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*(2), 75–103.

Love, R. and R. Payne (2008). Macroeconomic news, order flows, and exchange rates. *Journal of Financial and Quantitative Analysis 43*(2), 467.

Ludvigson, S. and S. Ng (2009). Macro factors in bond risk premia. *Review of Financial Studies 22*(12), 5027–5067.

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

Lustig, H., A. Stathopoulos, and A. Verdelhan (2013). The term structure of currency carry trade risk premia. *Available at SSRN No.2340547*.

Lustig, H. and A. Verdelhan (2007). The cross-section of foreign currency risk premia and consumption growth risk. *American Economic Review 97*(1), 89–117.

Lyons, R. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics 39*(2), 321–351.

Maccheroni, F., M. Marinacci, and D. Ruffino (2013). Alpha as ambiguity: Robust mean-variance portfolio analysis. *Econometrica 81*(3), 1075–1113.

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 Global Imbalances Workshop Paper, February*.

MacDonald, R. and I. Marsh (1996). Currency forecasters are heterogeneous: Confirmation and consequences. *Journal of International Money and Finance 15*(5), 665–685.

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.

Madigan, D. and A. Raftery (1994). Model selection and accounting for model uncertainty in graphical models using Occam's window. *Journal of the American Statistical Association 89*(428), 1535–1546.

Mark, N. (1995). Exchange rates and fundamentals: Evidence on long-horizon predictability. *American Economic Review 85*(1), 201–218.

Mark, N. (2009). Changing monetary policy rules, learning, and real exchange rate dynamics. *Journal of Money, Credit and Banking 41*(6), 1047–1070.

Mark, N. and D. Sul (2001). Nominal exchange rates and monetary fundamentals: Evidence from a small post-Bretton Woods panel. *Journal of International Economics 53*(1), 29–52.

Marquering, W. and M. Verbeek (2004). The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis 39*(02), 407–429.

McCracken, M. (2007). Asymptotics for out of sample tests of granger causality. *Journal of Econometrics 140*(2), 719–752.

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.

Mendoza, E. and V. Yue (2012). A general equilibrium model of sovereign default and business cycles. *Quarterly Journal of Economics 127*(2), 889–946.

Menkhoff, L., R. Rebitzky, and M. Schröder (2009). Heterogeneity in exchange rate expectations: Evidence on the chartist-fundamentalist approach. *Journal of Economic Behavior and Organization 70*(1), 241–252.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a). Carry trades and global foreign exchange volatility. *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 (2013a). Currency risk premia and macro fundamentals. *Available at SSRN No.2282480*.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2013b). Information flows in dark markets: Dissecting customer currency trades. *Forthcoming in Journal of Finance*.

Menkhoff, L. and M. Taylor (2007). The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature 45*(4), 936–972.

Merton, R. (1973). An intertemporal capital asset pricing model. *Econometrica 41*(5), 867–887.

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance 29*(2), 449–470.

Molodtsova, T., A. Nikolsko-Rzhevskyy, and D. Papell (2008). Taylor rules with real-time data: A tale of two countries and one exchange rate. *Journal of Monetary Economics 55*, 63–79.

Molodtsova, T. and D. Papell (2009). Out-of-sample exchange rate predictability with Taylor rule fundamentals. *Journal of International Economics 77*(2), 167–180.

Moore, M. and R. Payne (2011). On the sources of private information in FX markets. *Journal of Banking and Finance 35*(5), 1250–1262.

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

Neely, C., D. E. Rapach, J. Tu, and G. Zhou (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science 60*(7), 1772–1791.

Neely, C. and P. Weller (2013). Lessons from the evolution of foreign exchange trading strategies. *Journal of Banking amd Finance 37*(10), 3783–3798.

Neely, C., P. Weller, and R. Dittmar (1997). Is technical analysis in the foreign exchange market profitable? a genetic programming approach. *Journal of Financial and Quantitative Analysis 32*(04), 405–426.

Neely, C., P. Weller, and J. Ulrich (2009). The adaptive markets hypothesis: Evidence from the foreign exchange market. *Journal of Financial and Quantitative Analysis 44*(2), 467–488.

Nelson, C. and A. Siegel (1987). Parsimonious modeling of yield curves. *The Journal of Business 60*(4), 473–489.

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.

Obstfeld, M. and K. Rogoff (1995). Exchange rate dynamics redux. *Journal of Political Economy 103*(3), 624–660.

Obstfeld, M. and K. Rogoff (1996). *Foundations of International Macroeconomics.* Cambridge, MA: MIT Press.

Okunev, J. and D. White (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis 38*(2), 425–448.

Orphanides, A. (2001). Monetary policy rules based on real-time data. *American Economic Review 91*(4), 964–985.

Osler, C. (2003). Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis. *Journal of Finance 58*(5), 1791–1820.

Osler, C. (2005). Stop-loss orders and price cascades in currency markets. *Journal of International Money and Finance 24*(2), 219–241.

Osler, C. and V. Vandrovych (2009). Hedge funds and the origins of private information in currency markets. *Available at SSRN No.1484711*.

Pan, J. and K. Singleton (2008). Default and recovery implicit in the term structure of sovereign CDS spreads. *Journal of Finance 63*(5), 2345–2384.

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

Pasquariello, P. and C. Vega (2007). Informed and strategic order flow in the bond markets. *Review of Financial Studies 20*(6), 1975–2019.

Pástor, L. and R. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

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

Pástor, 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. *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.

Payne, R. (2003). Informed trade in spot foreign exchange markets: An empirical investigation. *Journal of International Economics 61*(2), 307–329.

Pericoli, M. and M. Sbracia (2003). A primer on financial contagion. *Journal of Economic Surveys 17*(4), 571–608.

Piazzesi, M. and M. Scheider (2007). Equilibrium yield curves. In *NBER Macroeconomics Annual*, Volume 21, pp. 389–472. MIT Press.

Plantin, G. and H. Shin (2011). Carry trades, monetary policy and speculative dynamics. *CEPR Discussion Papers No.8224*.

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.

Quintos, C. (1998). Stability tests in error correction models. *Journal of Econometrics 82*(2), 289–315.

Raftery, A., D. Madigan, and J. Hoeting (1997). Bayesian model averaging for linear regression models. *Journal of the American Statistical Association 92*(437), 179–191.

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

Ranaldo, A. and P. Söderlind (2010). Safe haven currencies. *Review of Finance 14*(3), 385–407.

Rapach, D., J. Strauss, and G. Zhou (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies 23*(2), 821–862.

Rapach, D. and M. Wohar (2002). Testing the monetary model of exchange rate determination: New evidence from a century of data. *Journal of International Economics 58*(2), 359–385.

Rapach, D. and M. Wohar (2004). Testing the monetary model of exchange rate determination: A closer look at panels. *Journal of International Money and Finance 23*(6), 867–895.

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

Rime, D., L. Sarno, and E. Sojli (2010). Exchange rate forecasting, order flow and macroeconomic information. *Journal of International Economics 80*(1), 72–88.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory 13*(3), 341–360.

Rossi, B. (2005). Testing long-horizon predictive ability with high persistence, and the Meese-Rogoff puzzle. *International Economic Review 46*(1), 61–92.

Routledge, B. and S. Zin (2010). Generalized disappointment aversion and asset prices. *Journal of Finance 65*(4), 1303–1332.

Rudebusch, G. and T. Wu (2008). A macro-finance model of the term structure, monetary policy and the economy. *The Economic Journal 118*(530), 906–926.

Sager, M. and M. Taylor (2008). Commercially available order flow data and exchange rate movements: Caveat emptor. *Journal of Money, Credit and Banking 40*(4), 583–625.

Sager, M. and M. Taylor (2014). Generating currency trading rules from the term structure of forward foreign exchange premia. *Journal of International Money and Finance 44*(1), 230–250.

Sarno, L., P. Schneider, and C. Wagner (2014). The economic value of predicting bond risk premia: Can anything beat the expectations hypothesis? *Available at SSRN No.2005178*.

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.

Schularick, M. and A. Taylor (2012). Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870-2008. *American Economic Review 102*(2), 1029–61.

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

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

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

Spronk, R., W. Verschoor, and R. Zwinkels (2013). Carry trade and foreign exchange rate puzzles. *European Economic Review 60.*

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 (2003). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature 41*(3), 788–829.

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

Stuart, A. and K. Ord (2009). *Kendall's Advanced Theory of Statistics (Volume I): Distribution Theory.* A. Arnold.

Sullivan, R., A. Timmermann, and H. White (1999). Data-snooping, technical trading rule performance, and the bootstrap. *Journal of Finance 54*(5), 1647–1691.

Swamy, P. and S. Arora (1972). The exact finite sample properties of the estimators of coefficients in the error components regression models. *Econometrica 40*(2), 261–275.

Taylor, A. (2002). A century of purchasing power parity. *Review of Economics and Statistics 84*(1), 139–150.

Taylor, J. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester Conference Series on Public Policy*, Volume 39, pp. 195–214. Elsevier.

Taylor, M. and H. Allen (1992). The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance 11*(3), 304–314.

Taylor, M., D. Peel, and L. Sarno (2001). Nonlinear mean-reversion in real exchange rates: Toward a solution to the purchasing power parity puzzles. *International Economic Review 42*(4), 1015–1042.

Teräsvirta, T. (1994). Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association 89*(425), 208–218.

Teräsvirta, T. (1998). Modelling economic relationships with smooth transition regressions. In *Handbook of Applied Economic Statistics.* Eds. Ullah, A. and Giles, D., New York: Dekker.

Teräsvirta, T. and H. Anderson (1992). Characterizing nonlinearities in business cycles using smooth transition autoregressive models. *Journal of Applied Econometrics 7*(1), 119–136.

Thornton, D. and G. Valente (2012). Out-of-sample predictions of bond excess returns and forward rates: An asset allocation perspective. *Review of Financial Studies 25*(10), 3141–3168.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Statistical Methodology) 58*(1), 267–288.

Tibshirani, R. and K. Knight (1999). Model search by bootstrap bumping. *Journal of Computational and Graphical Statistics 8*(4), 671–686.

Tjøstheim, D. and B. Auestad (1994). Nonparametric identification of nonlinear time series: Selecting significant lags. *Journal of the American Statistical Association 89*(428), 1410–1419.

Tong, H. (1990). *Nonlinear Time Series: A Dynamical System Approach.* Oxford University Press.

Van Rijckeghem, C. and B. Weder (2001). Sources of contagion: Is it finance or trade? *Journal of International Economics 54*(2), 293–308.

Vassalou, M. and Y. Xing (2004). Default risk in equity returns. *Journal of Finance 59*(2), 831–868.

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

Verdelhan, A. (2010). A habit-based explanation of the exchange rate risk premium. *Journal of Finance 65*(1), 123–146.

Wachter, J. (2006). A consumption-based model of the term structure of interest rates. *Journal of Financial Economics 79*(2), 365–399.

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

Welch, I. and A. Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies 21*(4), 1455–1508.

West, K. (1996). Asymptotic inference about predictive ability. *Econometrica 64*(5), 1067–1084.

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

Wright, J. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics 146*(2), 329–341.

Wright, J. (2011). Term premia and inflation uncertainty: Empirical evidence from an international panel dataset. *American Economic Review 101*(4), 1514–1534.

Xia, Y. (2001). Learning about predictability: The effects of parameter uncertainty on dynamic asset allocation. *Journal of Finance 56*(1), 205–246.

Yogo, M. (2006). A consumption-based explanation of expected stock returns. *Journal of Finance 61*(2), 539–580.

Zou, H. and T. Hastie (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology) 67*(2), 301–320.