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

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Abstract

In this paper we study the exchange rate predictability across a range of investment horizons by proposing a term structure model to capture exchange rate dynamics with a broad set of predictors meanwhile handle both parameter and model uncertainties. We demonstrate the time-varying term-structural and model disagreement effects of exchange rate determinants as well as the projections of predictive information over the term structure. We further utilize the time-variation in the probability weighting from dynamic model averaging to identify the scapegoat drivers of customer order flows, which are also informative about the term structure of carry trade risk premia. 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. 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. We further comprehensively evaluate both statistical and economic significance of the model allowing for a full spectrum of currency investment management, and find that the model generates substantial performance fees of 6.5% per annum.

Keywords: Exchange Rate Forecasting, Carry Trade Risk Premia, Term Structure Factors, Dynamic (Bayesian) Model Averaging, Model Disagreement, Scapegoat Variables, Customer Order Flows.

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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 paper is organized as follows: In Section 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 3 contains information about the data sets used in this paper, and describes the empirical methodologies, i.e. dynamic Nelson-Siegel model, time-varying parameter estimations, dynamic (Bayesian) model averaging and disagreement. Section 4 introduces both economic and statistical evaluations of the our model. Section 5 presents detailed discussions on the results, respectively. We draw a conclusion in Section 6. The main findings of this paper are delegated to Appendix A while Appendix B is (complementary) technical appendix.

2 Models of Exchange Rate Determination

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

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

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:

$$s_t = \mathbb{E}_t[z_t] + \frac{\eta}{1-\eta}\mathbb{E}_t[\Delta s_{t+1}] \tag{2}$$

which can be rearranged to give:

$$\Delta s_{t+1} = \frac{1-\eta}{\eta}(s_t - \mathbb{E}_t[z_t]) + \varepsilon_{t+1} \tag{3}$$

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).

Ample empirical evidence finds a weak relationship between nominal exchange rate and macroeconomic fundamentals (see Appendix A for the macro-based models). Bacchetta and Van Wincoop (2004) broach 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).

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.

3 Data and Methodology

Our financial data set is obtained from Datastream and Bloomberg, including spot rates, forward rates and risk-free interest rates[1] of weekly (1-week, 2-week, and 3-week), 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)[2]. All Option data are used to construct volatility

[1]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 Lando, 2008).

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

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)[3].

Our macroeconomic data set is collected from several sources. To measure money supply, we use non-seasonally adjusted M1[4] 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[5]. The price level is captured by Consumption Price Index (CPI) from OECD's *Main Economic Indicators* (*MEI*)[6]. The output gap is defined as the 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[7] 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.

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[8]:

[3]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).

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

[5]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.

[6]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 of CPI.

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

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

$$\Delta s_{t+\tau}^{(\tau)} = \underbrace{s_{t+\tau} - f_t^{(\tau)}}_{c_{t+\tau}^{(\tau)}} + \underbrace{f_t^{(\tau)} - s_t}_{r_t^{(\tau),*} - r_t^{(\tau)}} \tag{4}$$

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 premia 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.

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). 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:

$$c_t^{(\tau)} = L_t^{NS} + \frac{1-\exp(-\lambda\tau)}{\lambda\tau} S_t^{NS} + \left[\frac{1-\exp(-\lambda\tau)}{\lambda\tau} - \exp(-\lambda\tau)\right] C_t^{NS} + \zeta_t^{(\tau)} \tag{5}$$

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[9]. 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.

[9] 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.

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

Given that forecasting carry trade risk premia 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):

$$z_t = \beta_{0,t} + \beta_{1,t} z_{t-1} + \cdots + \beta_{n,t} z_{t-n} + u_t \tag{6}$$

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.

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 (5) by x_{t-n}[10] as we focus on the information commonality in the term structure of exchange rate

[10] 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 $\text{cov}[x_{t-n}, \zeta_t^{(\tau)}] \neq 0$, 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

predictability in this paper.

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)[11]. More sophisticated and efficient shrinkage techniques, e.g. ridge (Hoerl and Kennard, 1970), LASSO[12] (Tibshirani, 1996), bagging (Breiman, 1996) and bumping (?) 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. Please refer to Appendix B for estimation procedures.

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

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.

[11]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.

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

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.

$$MD_t = \sqrt{\frac{1}{l}\sum_{j=1}^{l}\left[\Pr(L_t = j \mid z_t) - \frac{1}{l}\right]^2} \tag{7}$$

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.

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[13] 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)[14]. We then extend the macro-based model to incorporate signals generated from two types of technical trading rules, from which most of other popular indicators[15] derive, as follows in Appendix C.

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,

[13]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.

[14]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-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).

[15]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.

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[16] 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:

$$CTD_t = \lim_{q \to 0^+} \frac{\Pr\left(FX \leq F_{FX,t}^{-1}(q), MKT \leq F_{MKT,t}^{-1}(q)\right)}{\Pr\left(MKT \leq F_{MKT,t}^{-1}(q)\right)} = \lim_{q \to 0^+} \frac{C_t(q,q)}{q} \tag{8}$$

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.

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[17]:

$$HPF_t = \frac{HPF_t^S - HPF_t^L}{HPF_{t-1}^S + HPF_{t-1}^L} \tag{9}$$

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.

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

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

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

and the effect becomes stronger and permanent when market liquidity is low (Brandt and Kavajecz, 2004). From a 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.

$$TSF_t = \varpi_0^{TS} + \varpi_1^{TS} \cdot o_t + \varpi_2^{TS} \cdot o_{t-1} + \nu_t^{TS} \tag{10}$$

$$o_t = \varpi_0^{SG} + \sum_{j=1}^{k} \varpi_j^{SG} \cdot \Pr(L_t = j \mid z_t) \cdot x_{j,t} + \nu_t^{SG} \tag{11}$$

$$o_t = \varpi_0^{MD} + \varpi_1^{MD} \cdot \Delta MD_t + \varpi_2^{MD} \cdot \Delta MD_{t-1} + \nu_t^{MD} \tag{12}$$

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 (10) 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 (11) 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 (12) 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 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[18], as a parsimonious benchmark.

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

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

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, $\Delta\hat{s}^{(\tau)}_{t+\tau|t}$:

$$R^2_{OOS} = 1 - \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2} \tag{13}$$

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):

$$\Delta RMSE = \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} - \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} \tag{14}$$

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[19] with mean quadratic loss differential:

$$\bar{d}_t = \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2 - \sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau} \left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F} \tag{15}$$

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

$$DMW = \frac{\bar{d}_t}{\hat{\sigma}_{\bar{d}_t}} \xrightarrow{d} \mathcal{N}(0,1) \tag{16}$$

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.

[19] 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.

4.2 Economic Value

We assess the economic value of our model in a mean-variance dynamic asset allocation framework[20] 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 $\bar{\sigma}_p$:

$$\begin{aligned} &\max_{\omega_t} \left\{ \mu_{p,t+\tau} = \underbrace{\omega_t^\top (\mathbb{E}_t[\Delta s_{t+\tau}^{(\tau)}] + r_t^{(\tau),*})}_{Foreign\ Investment} + \underbrace{(1 - \omega_t^\top \iota)\, r_t^{(\tau)}}_{Domestic\ Investment} - \underbrace{r_t^{(\tau)}}_{Benchmark} \right\} \\ &\text{s.t. } \bar{\sigma}_p^2 = \omega_t^\top \Sigma_{t+\tau|t}\, \omega_t \end{aligned} \tag{17}$$

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[21]. 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):

$$\omega_t = \frac{\bar{\sigma}_p}{\sqrt{\varrho}} \cdot \Sigma_{t+\tau|t}^{-1}\, \mathbb{E}_t[c_{t+\tau}^{(\tau)}] \tag{18}$$

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)

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

[21]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.

in evaluating portfolio management. More accurate forecasts result in better portfolio rebalance decisions, and therefore better asset 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:

$$\begin{aligned}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})^2\right] \\ =\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{RW})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{RW})^2\right]\end{aligned} \tag{19}$$

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

$$\begin{aligned}\mathcal{P}=\frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{TS}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right] \\ -\frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{RW}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right]\end{aligned} \tag{20}$$

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 $\mathcal{SR}_{\mathcal{DR}}$[22]. 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 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 $c_{t+\tau|t}^{(\tau)}$ 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:

$$\begin{aligned}\Delta\tilde{s}_{t+\tau|t}^{(1)} &= \underbrace{\left(\hat{c}_{t+\tau|t}^{(\tau)}+f_t^{(\tau)}-s_t\right)}_{\Delta\hat{s}_{t+\tau|t}^{(\tau)}}-\underbrace{\left(\hat{c}_{t+\tau-1|t}^{(\tau-1)}+f_t^{(\tau-1)}-s_t\right)}_{\Delta\hat{s}_{t+\tau-1|t}^{(\tau-1)}} \\ &= \left(\hat{c}_{t+\tau|t}^{(\tau)}-\hat{c}_{t+\tau-1|t}^{(\tau-1)}\right)+\left(f_t^{(\tau)}-f_t^{(\tau-1)}\right)\end{aligned} \tag{21}$$

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

5 Empirical Results and Discussion

5.1 Preliminary Analysis

Figure 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 premia 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.

[Insert Figure 1. about here]

The descriptive statistics of the term structure of carry trade risk premia are shown in Figure 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.

[Insert Figure 2. about here]

We extract the Nelson-Siegel factors from the term structure of the carry component. As shown in Figure 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.

[Insert Figure 3. about here]

Figure 4. provides the time-series and cross-sectional goodness of fit of the term structure of carry components with contemporaneous Nelson-Siegel factors and 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%.

[Insert Figure 4. about here]

5.2 Probability Weighting and Model Disagreement

Table 1 below reports the descriptive statistics of the probability weighting of each empirical model or "scapegoat" variable for all currencies[23]. 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.

[Insert Table 1 about here]

Figure 5. 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 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).

[Insert Figure 5. about here]

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 6. shows the DMA-implied 1-month horizon model disagreements (MD) of individual currencies. The corresponding index in foreign exchange market as the average

[23]Figure E.1., Figure E.2., Figure E.3., Figure E.4., Figure E.5., Figure E.6., and Figure E.7. 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 paper, 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 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.

across all currencies is closely associated with volatility (VIX) and liquidity (TED) risks (see Figure 7.).

[Insert Figure 6. about here]

[Insert Figure 7. about here]

Table 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 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.

[Insert Table 2 about here]

5.3 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 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.

[Insert Table 3 about here]

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 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[24], and (ii) the predictive information set that is common to both short-run and long-run forecasting.

[Insert Table 4 about here]

To assess the information commonality in the term structure of exchange rate predictability, we run pooled-OLS[25] regressions of the absolute forecasting errors (AFE) 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, overall, hedging pressure in futures market (HPF) and liquidity risk (TED) contain the common information that possesses

[24]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.

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

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 also confirm the existence of "scapegoat" effects of exchange rate predictors.

[Insert Table 5 about here]

Table 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 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[26] (target at 10%) in the existing literature of exchange rate forecasting.

5.4 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 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

[26]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.

of customer order flows. Table 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.

[**Insert Table 6 about here**]

[**Insert Table 7 about here**]

Moreover, we identify the "scapegoat" drivers by running regressions of Equation (11) 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.

[**Insert Figure 8. about here**]

As shown in Figure 8., we find that almost all of the exchange rate predictors play a role of "scapegoat" variable to different types of clients across currencies. In 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[27]. 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.

[27]See Table F.1., Table F.2., Table F.3., Table F.4., Table F.5., Table F.6., Table F.7. in Appendix B.

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 premia 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 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.

Our term structure model of the carry component can be extended to other asset classes using return decomposition into carry and expected price appreciation/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 the 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[28] 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). 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 currency market as well.

[28] 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).

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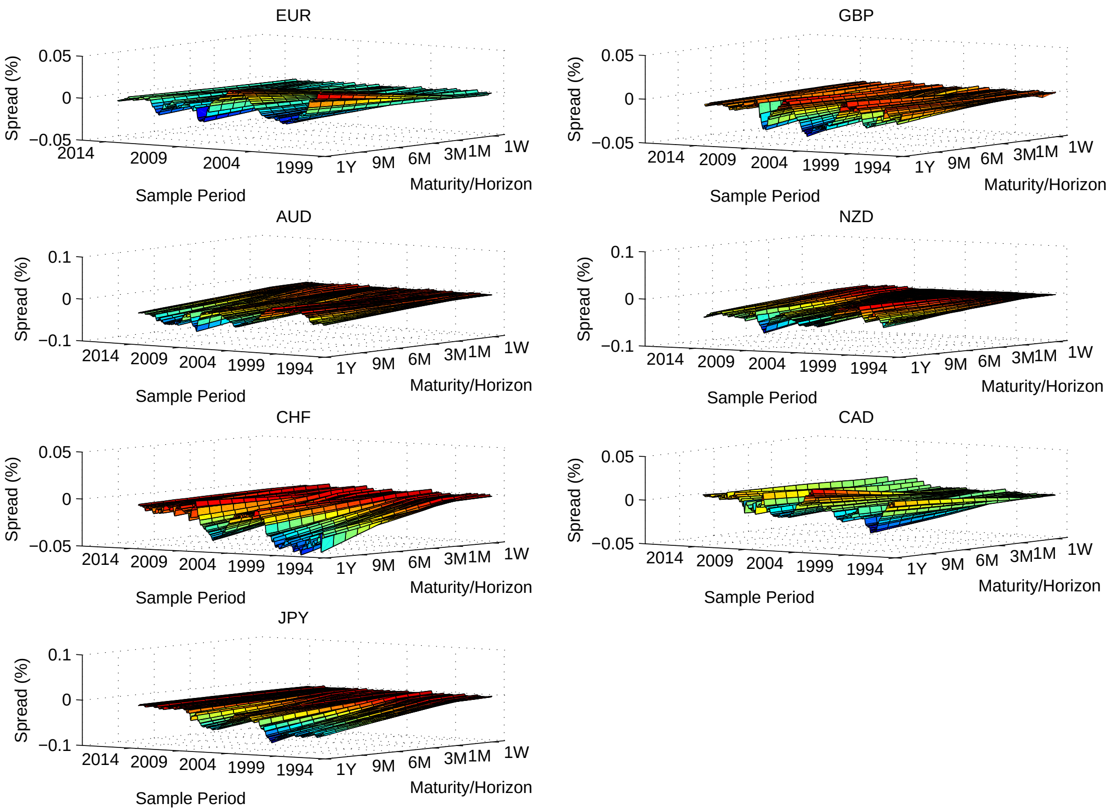
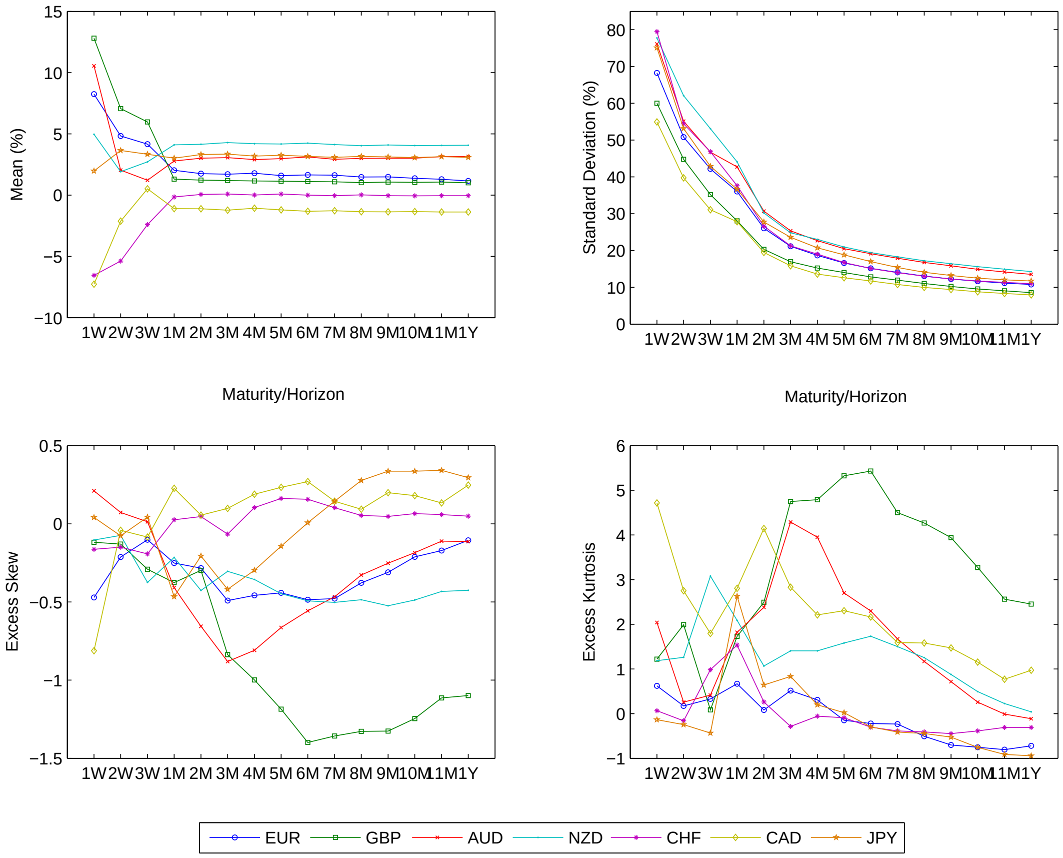
Figure 1: The Term Structure of Forward Risk Premia



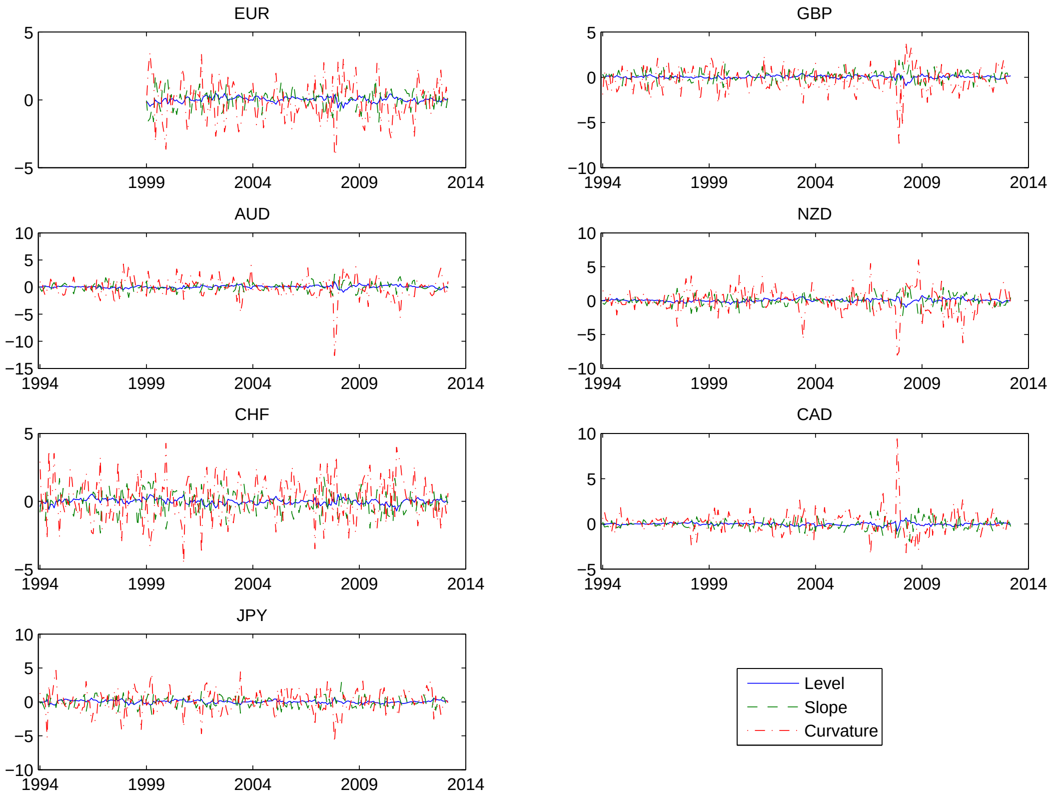
This figure shows the term structure of forward risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-week to 1-year (raw data). For the extraction of term structure factors, the data are annualized. The sample is from January 1994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

Figure 2: The Term Structure of Carry Trade Risk Premia: Descriptive Statistics



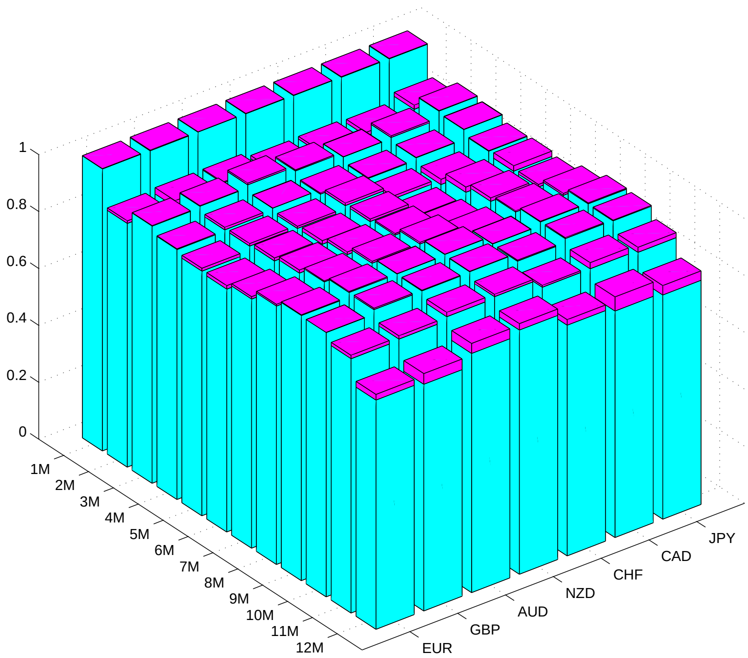
This figure shows the descriptive statistics for the term structure of carry trade risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-week to 1-year (annualized data). The sample is from January 1994 (except for EURUSD which is available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

Figure 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.

Figure 4: The Time-Series & Cross-Sectional (Contemporaneous) Goodness of Fit with Nelson-Siegel Factors & Scapegoats



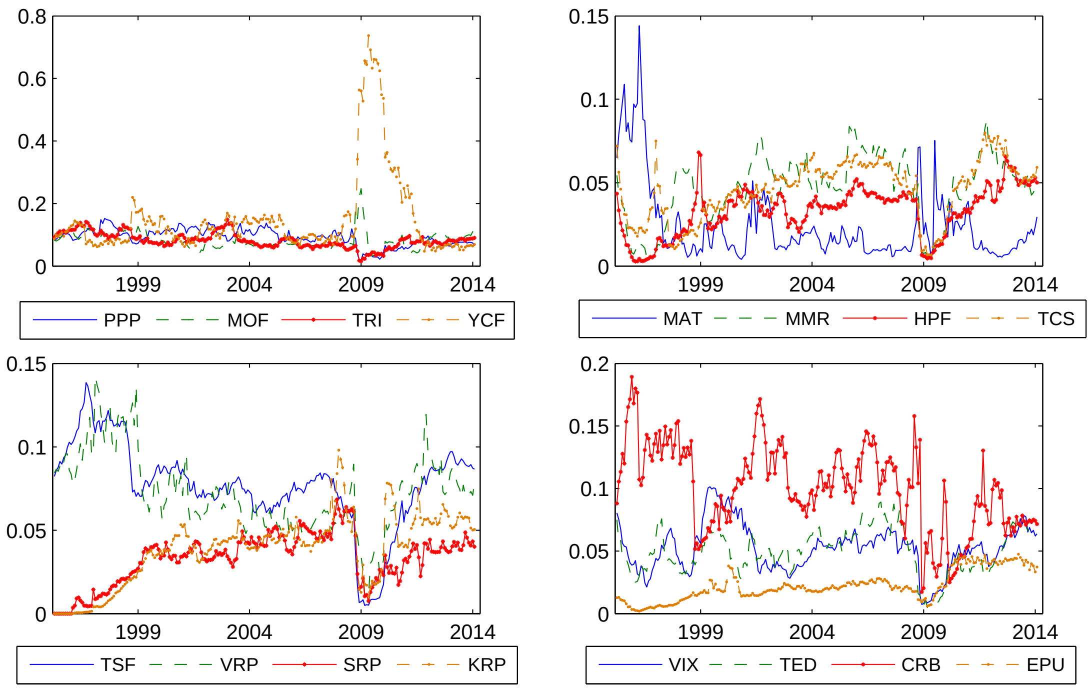
This figure shows the time-series and cross-sectional variations in the term structure of carry trade risk premia of G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from 1-month to 12-month (annualized data) explained by contemporaneous Nelson-Siegel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

Table 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
	$\mu_m(\%)$	**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**
EUR	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
GBP	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
AUD	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
NZD	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
CHF	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
CAD	$\sigma_m(\%)$	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
	$\mu_m(\%)$	**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**
JPY	$\sigma_m(\%)$	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

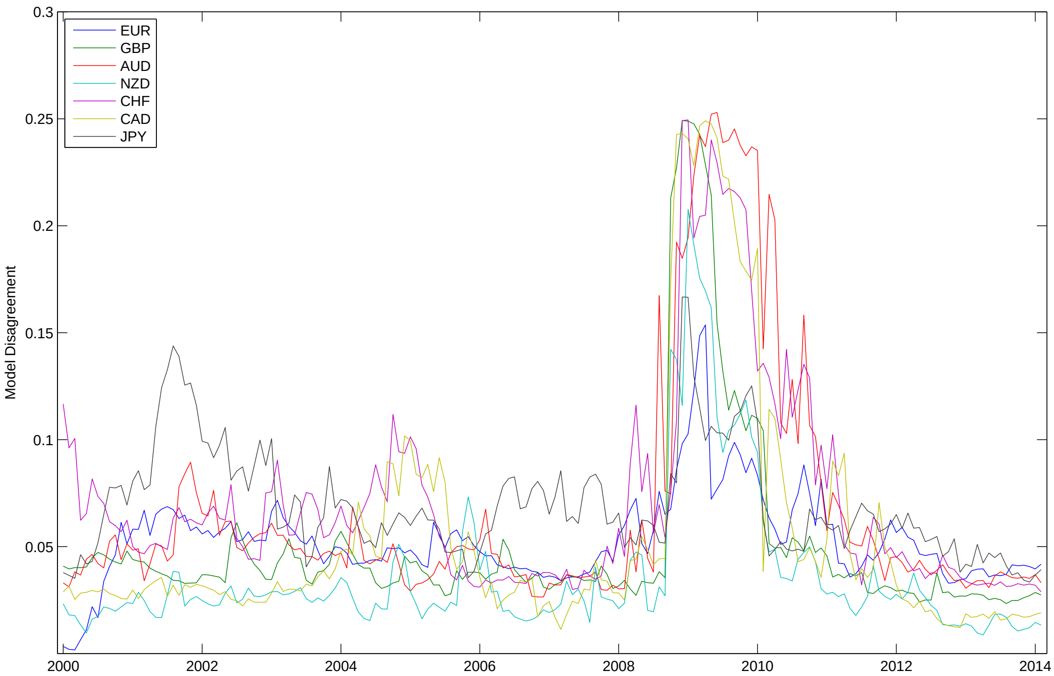
This table reports descriptive statistics (mean - μ_m in percentage; standard deviation - σ_m in percentage; stability ratio - $\mathcal{SR}_{\mathcal{PW}}$, which measures instability-adjusted average probability weighting) of the probability weighting of each empirical exchange rate model or "scapegoat" 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 5: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: Average across Currencies



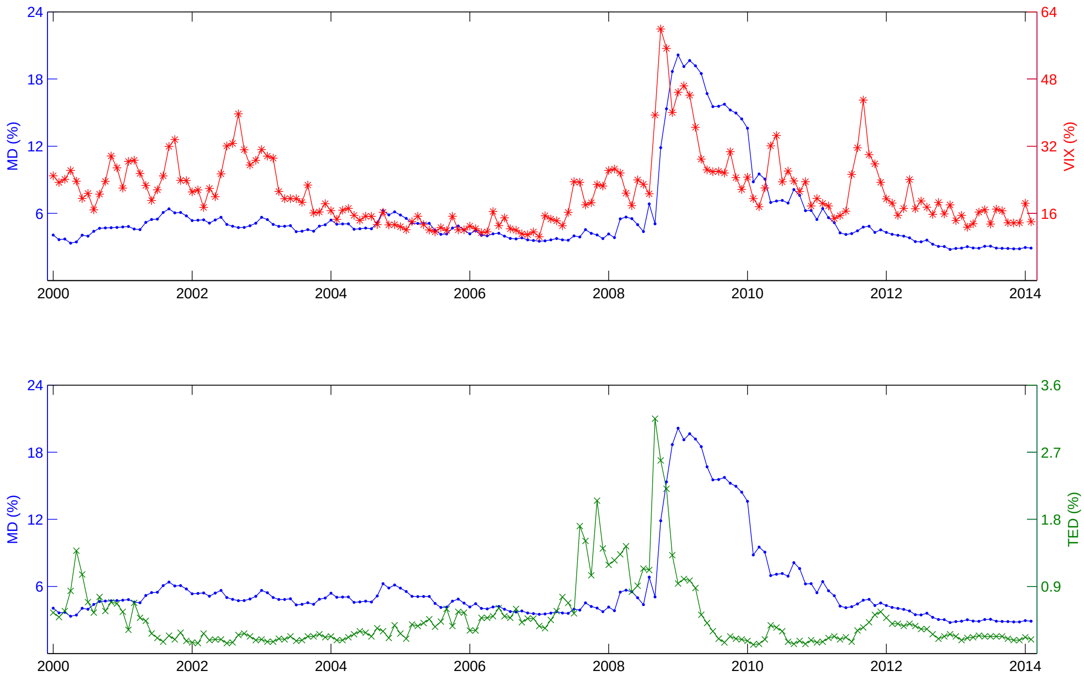
This figure shows the average probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (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.

Figure 6: 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.

Figure 7: 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.

Table 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.

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

Table 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.

Table 5: Economic Value of the Term Structure Model: Out-of-Sample Predictability of Carry Trade Risk Premia / Exchange Rate Returns

EV	Investment Management				
	Active	Tactic		Strategic	Passive
	(1M)	(3M)	(6M)	(Dynamic)	(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

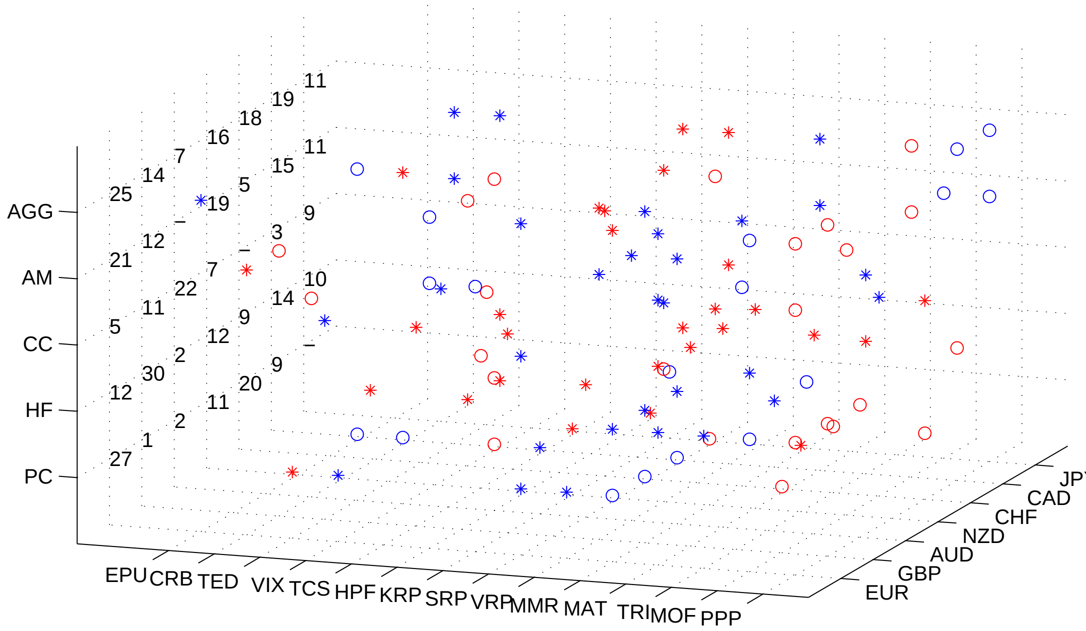
This table reports the economic value of the term structure of carry trade risk premium / exchange rate predictability for G10 currencies (EURUSD, GBPUSD, AUDUSD, NZDUSD, USDCHF, USDCAD, USDJPY, excluding USDSEK and USDNOK) from active (monthly rebalance), strategic (semi-annual or quarterly rebalance), 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.

Table 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***	9.92***		12.46**	3.09*			108.93***		12.37*		31.46**		12.70**
	s.e.	(0.44)	(3.22)		(5.44)	(1.79)			(31.02)		(6.38)		(13.06)		(5.84)
AGG	ϖ_{-1}	1.09***	13.49***		20.49***		34.87**		175.49***		12.93*		44.54***	-1.80***	26.14***
	s.e.	(0.41)	(4.10)		(4.45)		(6.38)		(29.83)		(6.79)		(14.11)	(0.67)	(5.82)
	$Adj-R^2$	**0.13**	**0.07**		0.05	0.01	0.05		**0.10**		0.01		0.04	0.03	**0.06**
	ϖ	2.96***	27.57***	2.58***	24.65***	8.96***	72.21***	19.24**	127.49***		47.37***	4.51**	63.68***		22.21**
	s.e.	(0.66)	(4.86)	(0.91)	(8.66)	(3.24)	(23.98)	(8.57)	(44.39)		(10.40)	(2.04)	(21.13)		(8.64)
AM	ϖ_{-1}	0.77*	30.82***		41.98***		92.76***		201.18***		48.47***		56.37***	-3.64***	39.44
	s.e.	(0.40)	(6.83)		(9.96)		(28.38)		(45.17)		(10.78)		(19.18)	(0.65)	(9.24)
	$Adj-R^2$	0.02	**0.17**	0.01	**0.09**	0.05	**0.12**	0.02	**0.08**		**0.09**	0.02	**0.06**	**0.08**	**0.08**
	ϖ	-4.06**	-28.36**	-45.82**			-100.58**			-8.20***	-70.76***				-89.77***
	s.e.	(1.78)	(11.87)	(19.02)			(42.98)			(2.24)	(24.16)				(30.99)
CC	ϖ_{-1}			-48.38**							-81.33***				-77.56**
	s.e.			(19.39)							(29.57)				(33.46)
	$Adj-R^2$	0.03	0.02	0.01			0.01			**0.08**	**0.10**				0.02
	ϖ	3.43***			25.80***	6.35**	52.08***		169.78***		36.53***	52.09**	59.77***		24.44**
	s.e.	(0.84)			(9.75)	(2.88)	(16.37)		(47.43)		(10.55)	(21.35)	(18.55)		(9.77)
HF	ϖ_{-1}	2.91***	24.14***		40.49***		58.97***		221.07***	-18.93*	53.29***	57.93**	112.33***		46.14***
	s.e.	(0.84)	(6.02)		(12.48)		(21.47)		(56.88)	(9.77)	(12.29)	(22.92)	(20.68)		(8.16)
	$Adj-R^2$	**0.12**	0.05		0.04	0.01	**0.06**		**0.07**	0.01	**0.07**	0.03	**0.07**		**0.09**
	ϖ		18.53**		96.50***	17.30***	218.34***	45.43*	497.87***		-78.79***	21.82***	297.61***		-154.47***
	s.e.		(8.57)		(20.73)	(3.48)	(31.79)	(26.13)	(129.70)		(27.74)	(7.00)	(34.56)		(25.71)
PC	ϖ_{-1}	18.13*	64.26***		136.39***		178.53***		377.64***		-130.18***		292.80***		-201.42***
	s.e.		(9.66)		(23.46)		(40.63)		(126.85)		(34.05)		(51.09)		(22.64)
	$Adj-R^2$	0.01	**0.11**		**0.17**	**0.08**	**0.27**	0.01	**0.07**		**0.10**	**0.06**	**0.23**		**0.27**

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.

Figure 8: 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.

Table 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.

Appendix

to

"The Term Structure of Exchange Rate Predictability"

A Appendix: Empirical Exchange Rate Models

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

Covered Interest Rate Parity (CIP):

$$f_t^{(\tau)} - s_t = r_t^{(\tau),*} - r_t^{(\tau)} \tag{22}$$

Uncovered Interest Rate Parity (UIP):

$$\mathbb{E}_t[s_{t+\tau}] = f_t^{(\tau)} \tag{23}$$

Purchasing Power Parity (PPP):

$$p_t^* = s_t + p_t \tag{24}$$

Monetary Fundamentals[29] (MOF):

$$\begin{aligned} m_t^* - p_t^* &= y_t^* - \phi\, r_t^{(\tau),*} \\ m_t - p_t &= y_t - \phi\, r_t^{(\tau)} \end{aligned} \tag{25}$$

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

$$\begin{aligned} r_t^{(\tau),*} &= \theta_0 + \theta_1 \pi_t^{(\tau),*} + \theta_2 \tilde{y}_t^{(\tau),*} \\ r_t^{(\tau)} &= \theta_0 + \theta_1 \pi_t^{(\tau)} + \theta_2 \tilde{y}_t^{(\tau)} \end{aligned} \tag{26}$$

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[30]. $\tau = 1$ for monthly observations.

[29] 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.

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

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 (23). We substitute Equations (22), (24) (25) into Equation (23) to yield the reduced form:

$$s_t = \frac{1}{1+\phi}\left[(m_t^* - m_t) - (y_t^* - y_t) - \phi\,\xi_t\right] + \frac{\phi}{1+\phi}\mathbb{E}_t[\Delta s_{t+1}] \tag{27}$$

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 (26) to formulate an augmented (relative) Taylor rule, we get:

$$\begin{aligned} s_t = & -\frac{1}{1+\theta_3}\left\{\theta_1[\pi_t^{(1),*} - \pi_t^{(1)}] + \theta_2[\tilde{y}_t^{(1),*} - \tilde{y}_t^{(1)}] + \theta_3(p_t^* - p_t)\right\} \\ & -\frac{1}{1+\theta_3}\left\{\theta_4[r_{t-1}^{(1),*} - r_{t-1}^{(1)}] + \xi_t\right\} + \frac{1}{1+\theta_3}\mathbb{E}_t[\Delta s_{t+1}] \end{aligned} \tag{28}$$

B Appendix: Dynamic Model Averaging Estimation Procedure

The Bayesian method to update a vector of coefficients β_t takes the form as below:

$$\begin{aligned} p(\beta_t|\Omega_t) &\propto \mathbf{L}(z_t;\beta_t, z_{t-1},\cdots, z_{t-n},\Omega_{1:t-1})\, p(\beta_t|\Omega_{t-1}) \\ p(\beta_t|\Omega_{t-1}) &= \int_{\wp} p(\beta_t|\Omega_{1:t-1},\beta_{t-1})\, p(\beta_{t-1}|\Omega_{t-1})\,\mathrm{d}\beta_t \end{aligned} \tag{29}$$

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[31] (see **?**, for details).

The posterior probabilities of the coefficients is given by:

$$p(\beta_{t-1}|z_{t-1}) = \sum_{j=1}^{l} p(\beta_{j,t-1} \mid L_{t-1} = j, z_{t-1})\,\Pr(L_{t-1} = j \mid z_{t-1}) \tag{30}$$

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 $t-1$.

$$\Pr(L_t = j \mid z_{t-1}) = \frac{[\Pr(L_{t-1} = j \mid z_{t-1})]^\alpha}{\sum_{j=1}^{l}[\Pr(L_{t-1} = j \mid z_{t-1})]^\alpha} \tag{31}$$

where $\alpha \in (0,1]$ is the forgetting factor[32] and set to 0.99. The model is then updated by:

$$\Pr(L_t = j \mid z_t) = \frac{\Pr(L_t = j \mid z_{t-1})p_j(z_t|z_{t-1})}{\sum_{j=1}^{l}\Pr(L_t = j \mid z_{t-1})p_j(z_t|z_{t-1})} \tag{32}$$

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

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

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):

$$\Sigma_{i,0} = \begin{cases} \psi/i^2 & \text{for coefficients on lag } i \text{ where } i = 1, \cdots, n; \\ 1 & \text{for the intercept, } i = 0. \end{cases} \tag{33}$$

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.

C Appendix: Technical Indicators

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

$$\begin{aligned} DIF_t &= \frac{EMA_t[s_t, T_1] - EMA_t[s_t, T_2]}{EMA_t[s_t, T_2]} \cdot 100\% \\ DEA_t &= EMA_t[DIF_t, T_3] \\ HTG_t &= DIF_t - DEA_t \end{aligned} \tag{34}$$

KDJ Stochastic Oscillator as a momentum and mean reversion indicator:

$$\begin{aligned} K_t &= EMA_t[RSV_t, T_4] \\ D_t &= EMA_t[K_t, T_5] \\ J_t &= 3D_t - 2K_t \end{aligned} \tag{35}$$

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, $T_1 = 12$, $T_2 = 26$, $T_3 = T_7 = 9$, and $T_4 = T_5 = 3$ trading days[33]. Shorter or faster MA

[33]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.

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[34] 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 $J_t < 0$)[35]. 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:

$$MMR_t = [\varphi_{MMT}(K_t - D_t) + \varphi_{MRV}(100 - J_t)\iota_{OB} + \varphi_{MRV}(0 - J_t)\iota_{OS}] \cdot 100\% \tag{36}$$

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

D Appendix: Term-Structural Effects of Exchange Rate Predictors

Figure D.1. demonstrates the time-varying effects of exchange rate predictors on the term structure of carry trade risk premia 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 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.

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

[35] 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.

[Insert Figure E.1. about here]

[Insert Figure D.1. about here]

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 D.2.). After the crisis, CRB rises remarkably as a key predictor with a negative effect on the level of risk premia.

[Insert Figure E.2. about here]

[Insert Figure D.2. about here]

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 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 D.3.).

[Insert Figure E.3. about here]

[Insert Figure D.3. about here]

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 D.4.) as they are both characterized by commodity currencies.

[Insert Figure E.4. about here]

[Insert Figure D.4. about here]

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 D.5.).

[Insert Figure E.5. about here]

[Insert Figure D.5. about here]

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 D.6.).

[Insert Figure E.6. about here]

[Insert Figure D.6. about here]

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 D.7.).

[Insert Figure E.7. about here]

[Insert Figure D.7. about here]

Figure D.8. shows the impulse response of the term structure of carry trade risk premia to the relative yield curve[36], 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[37]. 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 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[38]) adjustment which implies a flattened term structure. The opposite reactions

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

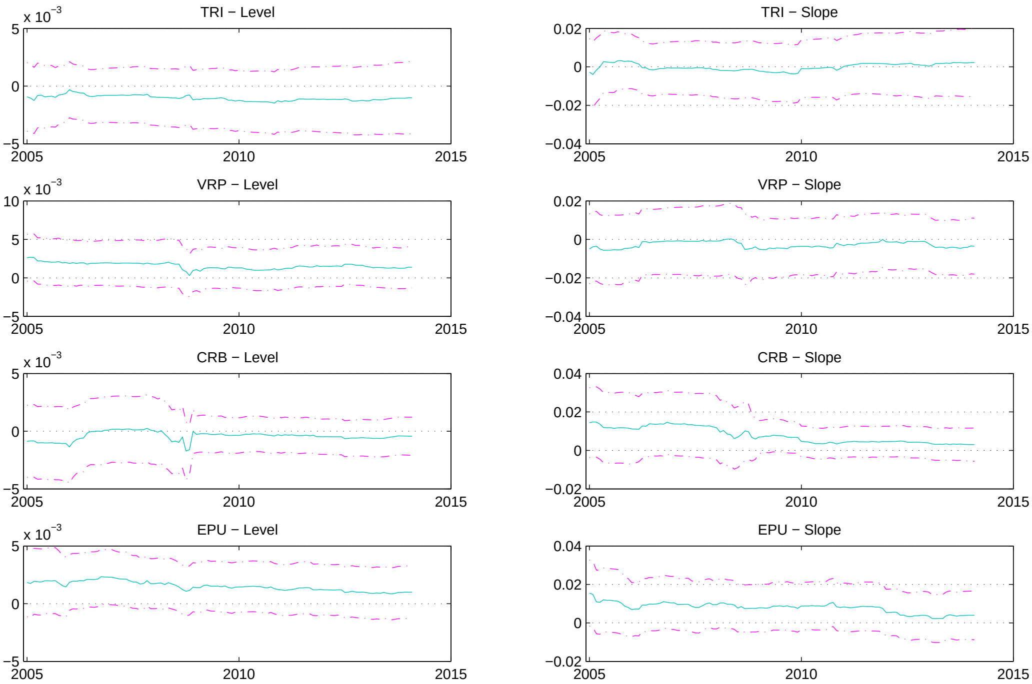
[37]Ferreira Filipe and Suominen (2013) reveal that funding liquidity risk (see also Brunnermeier and Pedersen, 2009) explains a large proportion of AUD versus JPY speculative positions in currency futures market.

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

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.

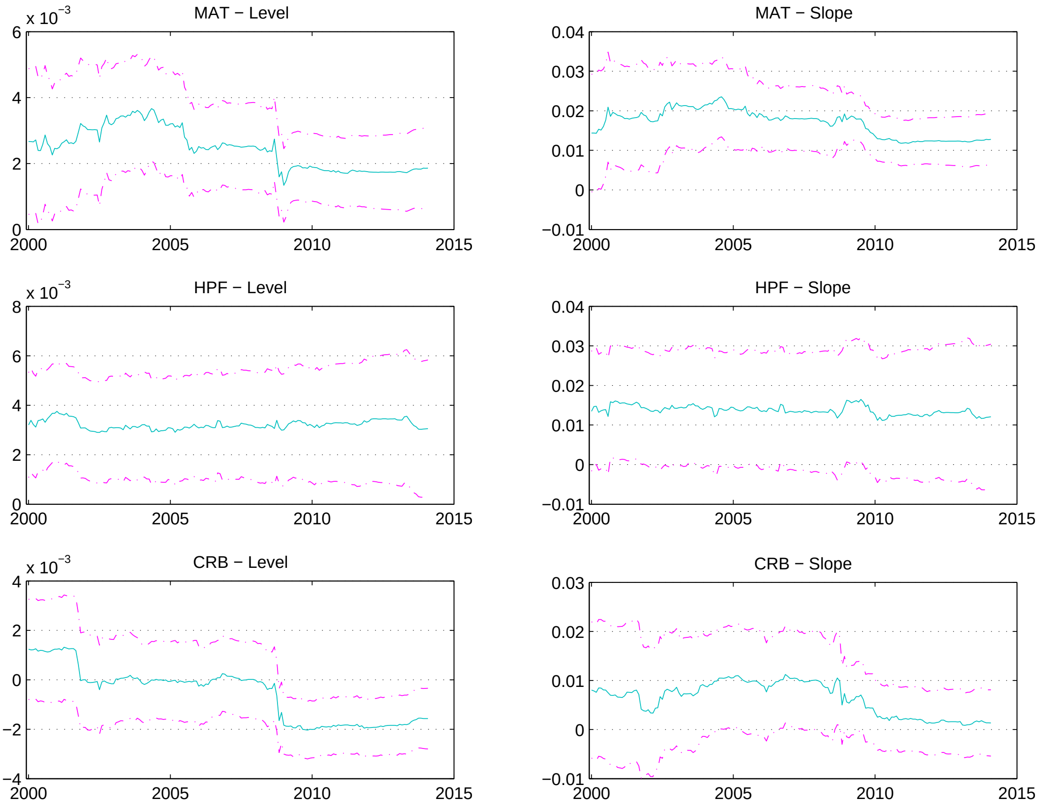
[Insert Figure D.8. about here]

Figure D.1: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): EUR



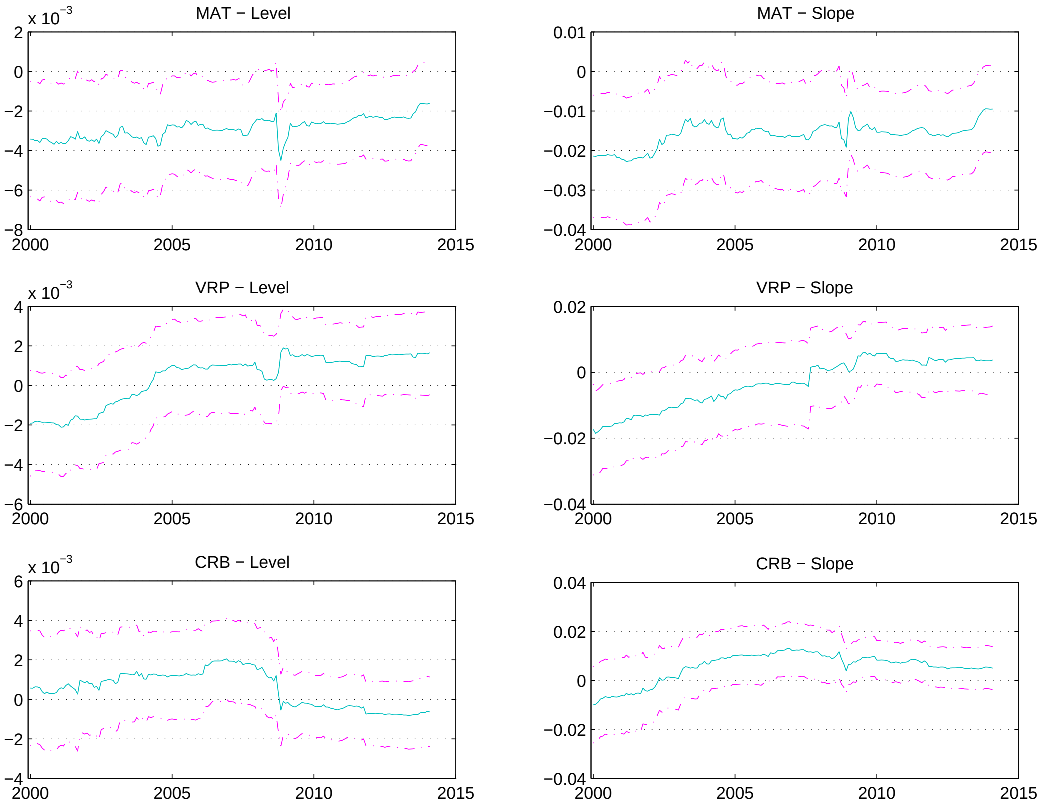
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.2: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): GBP



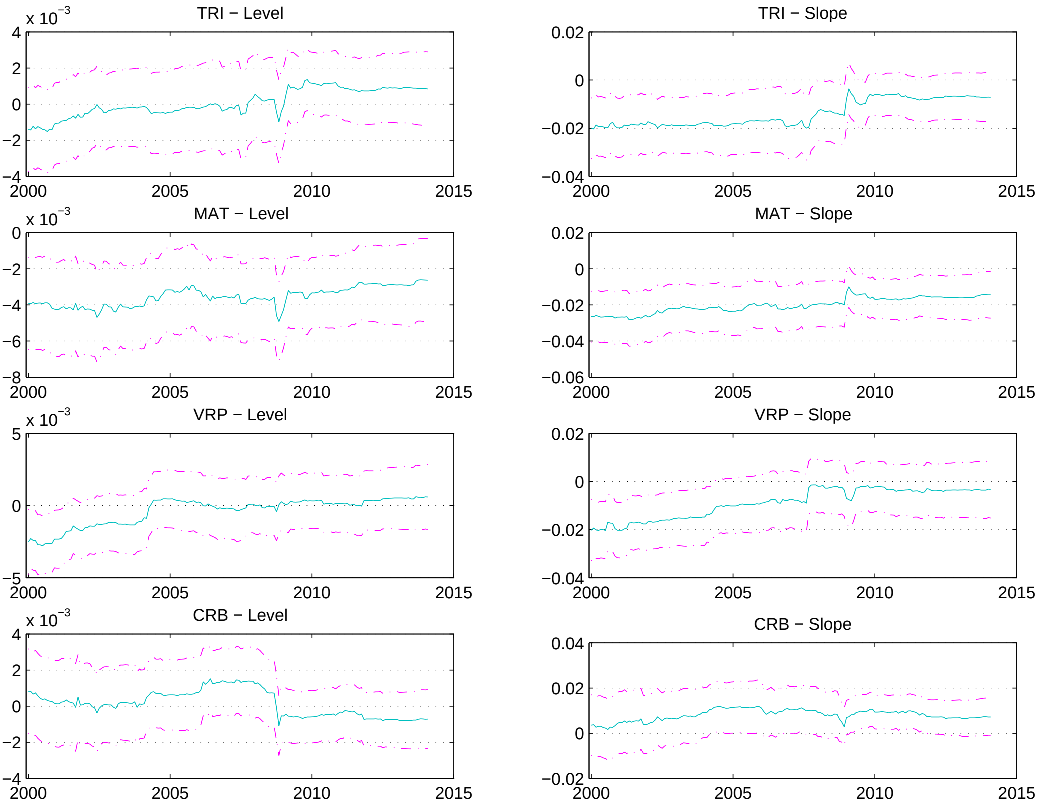
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.3: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): AUD



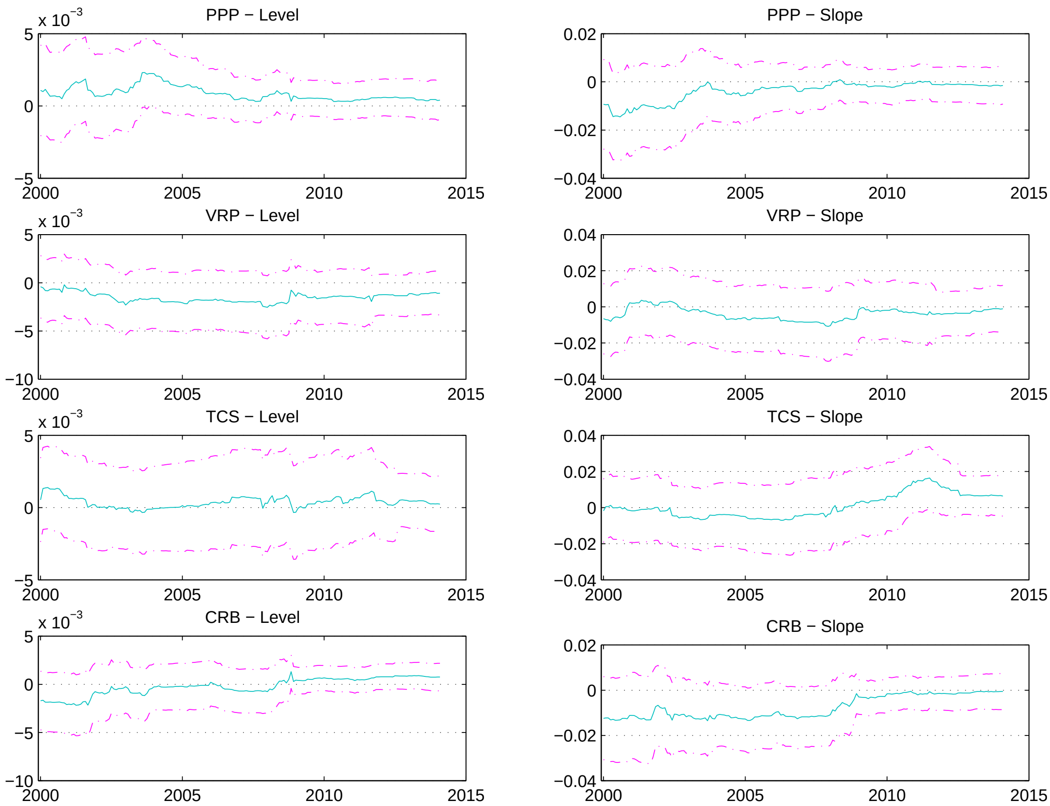
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.4: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): NZD



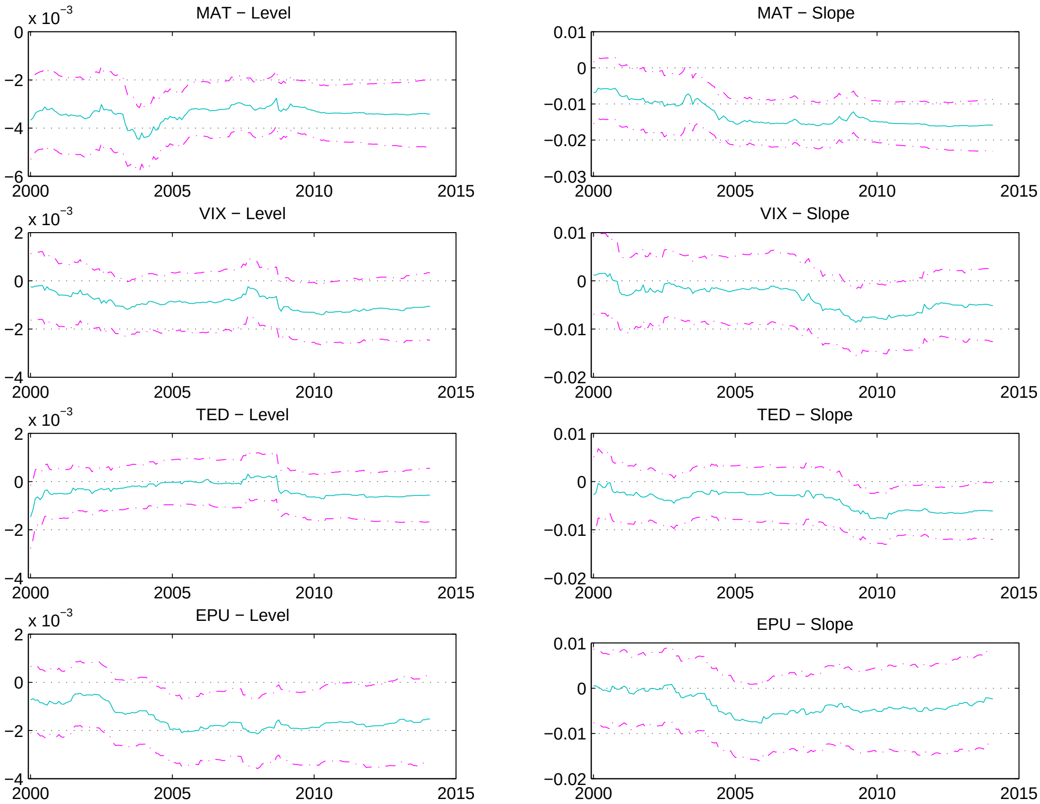
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.5: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): CHF



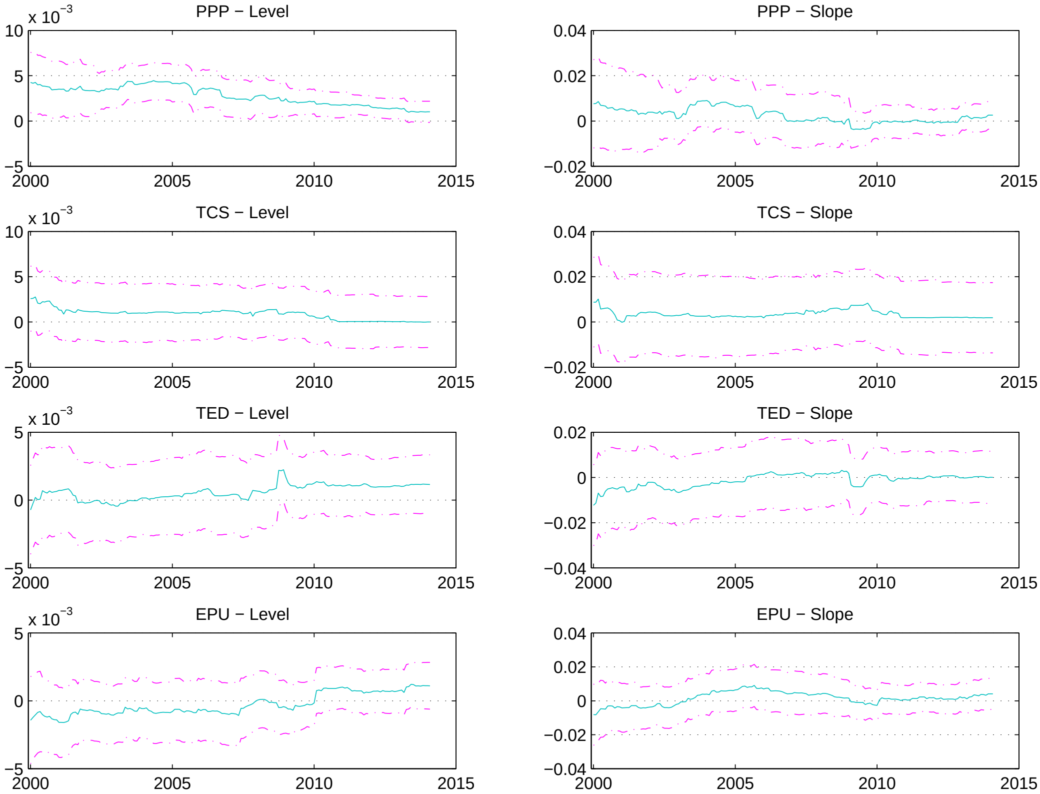
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.6: Time-Varying Effects of Exchange Rate Predictors on the Term Structure of Carry Trade Risk Premia (Out-of Sample): CAD



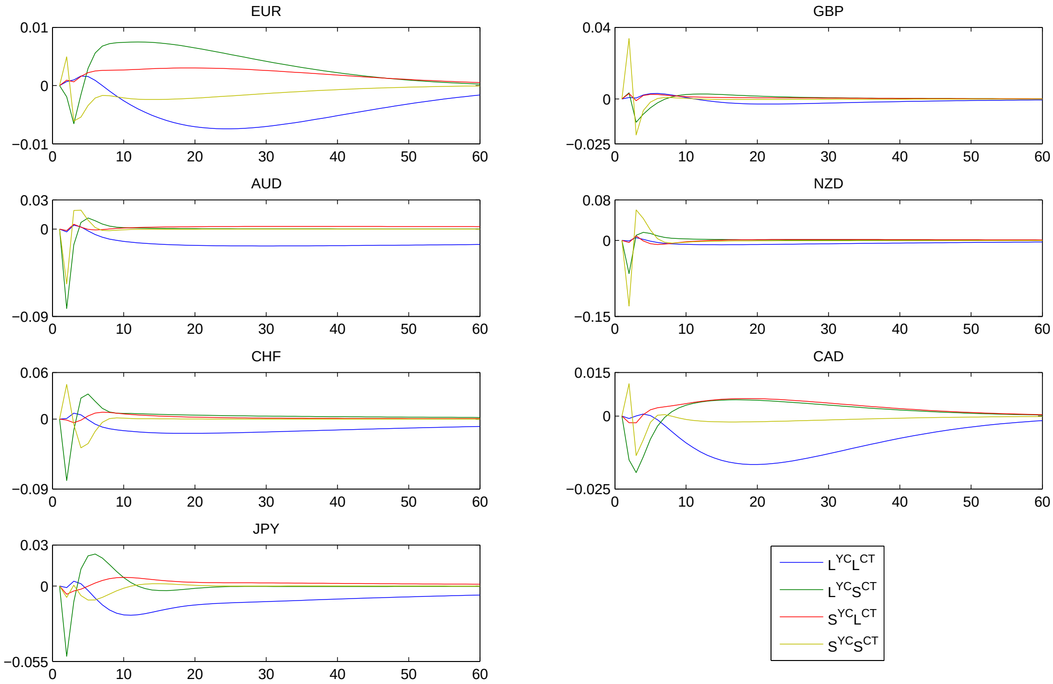
This figure shows the Bayesian time-varying parameters (measuring the effects on the Nelson-Siegel level & slope factors) to the most influential (selected based on the significance and stability of the corresponding probability weighting) exchange rate predictors, including Macroeconomic Fundamentals: 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% credible intervals.

Figure D.7: 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% credible intervals.

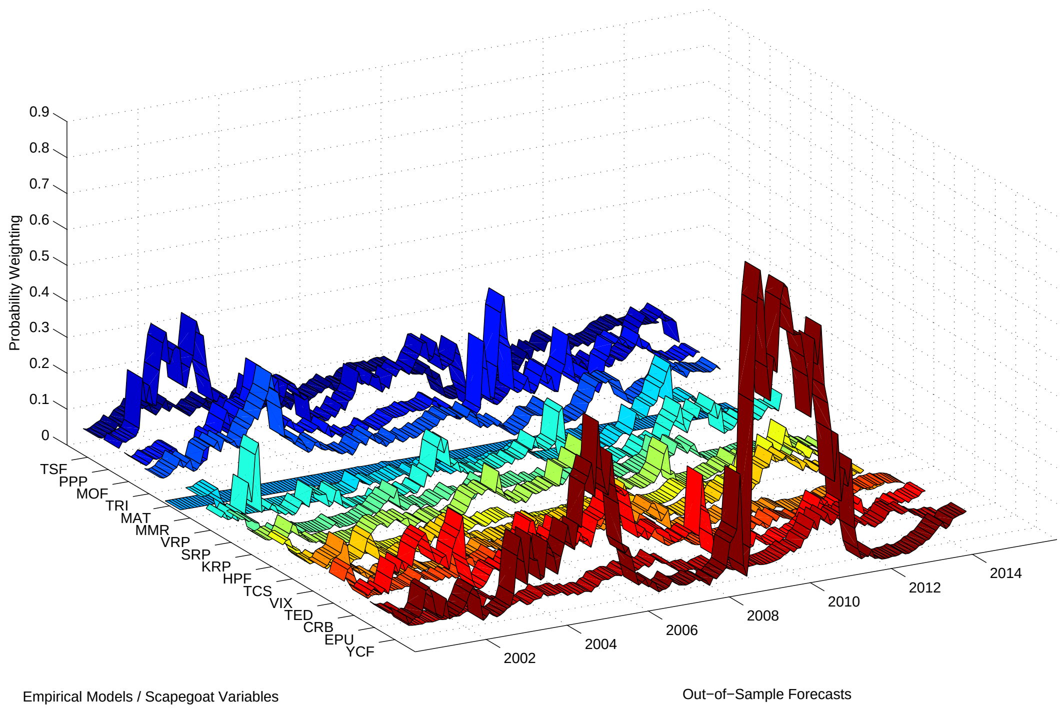
Figure D.8: Impulse Response of the Term Structure of Carry Trade Risk Premia to the Yield Curve



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.

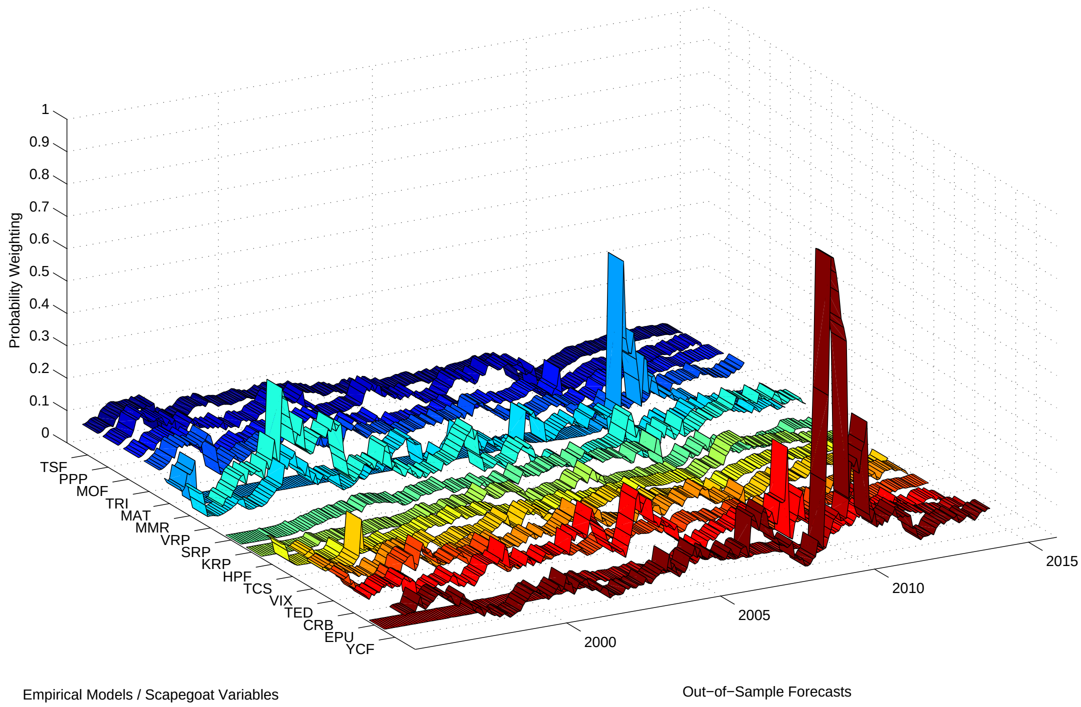
E Appendix: DMA Probability Weighting of TVP-FAVAR Models: Sample Countries

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



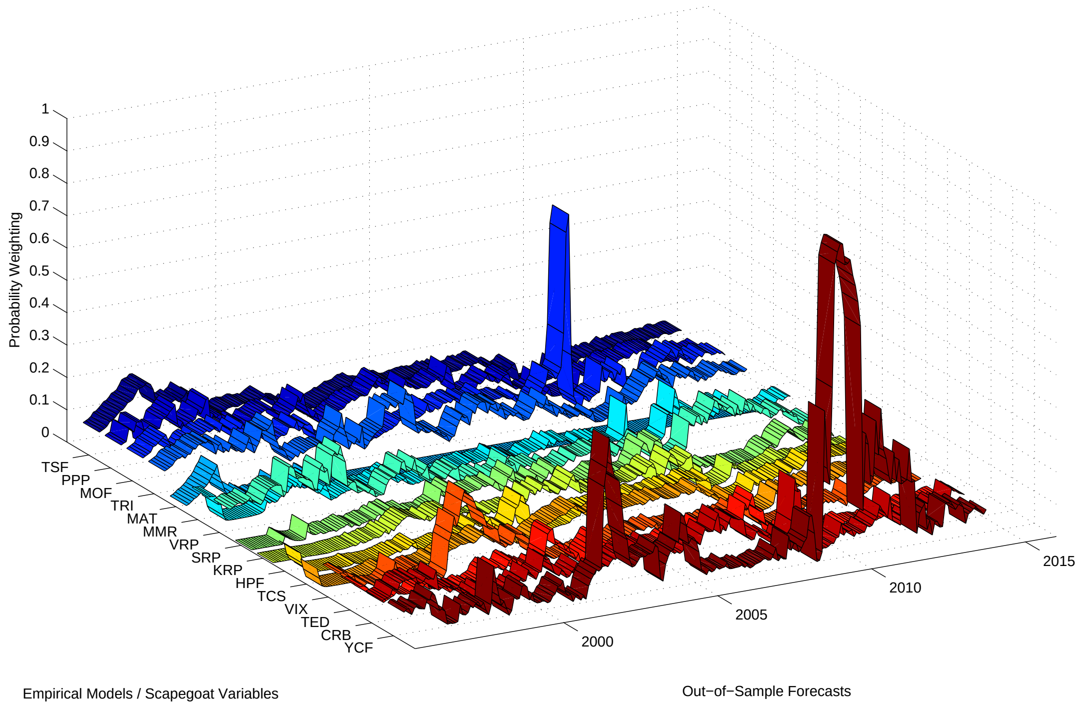
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor 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 E.2: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: GBP



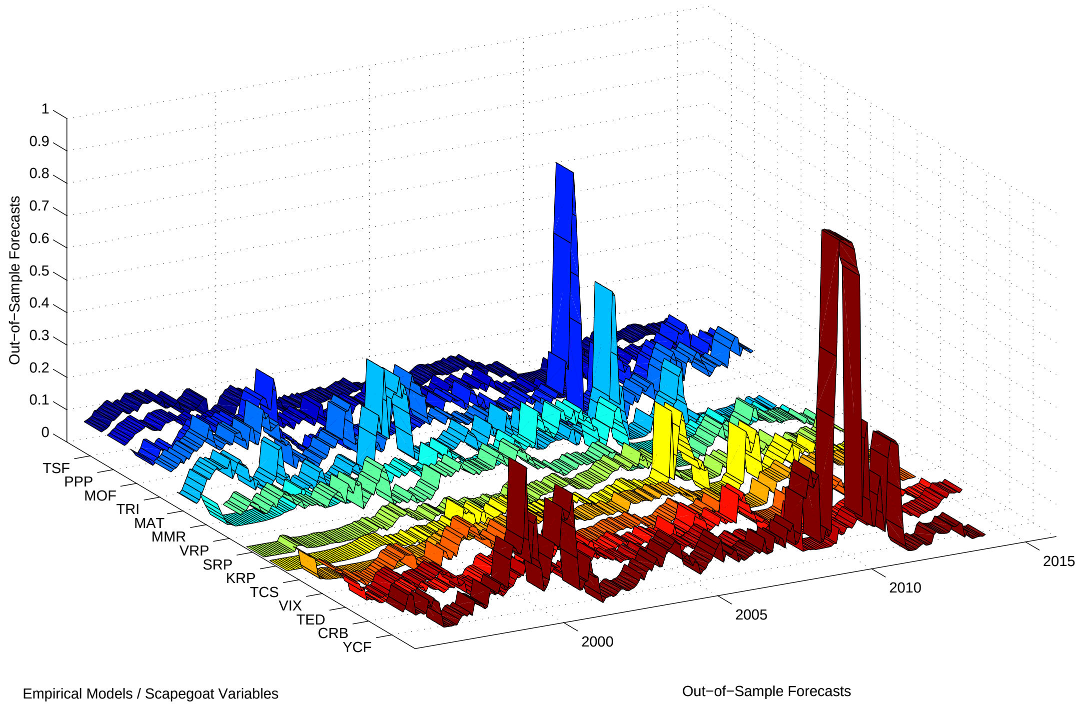
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor 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 E.3: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: AUD



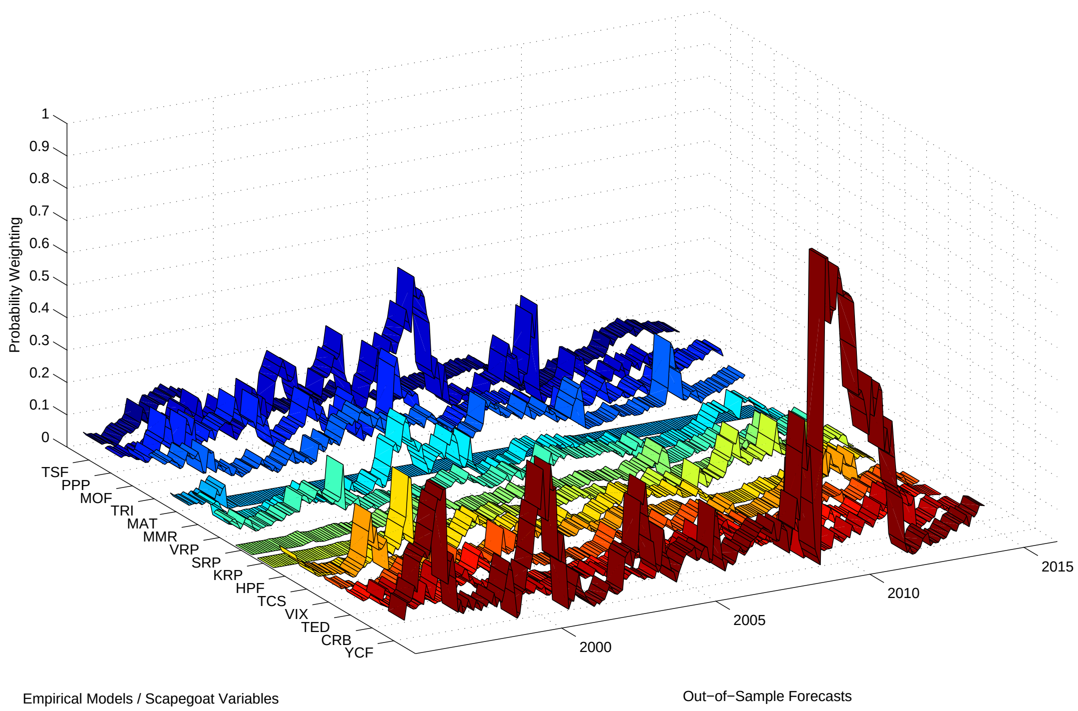
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor 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 E.4: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: NZD



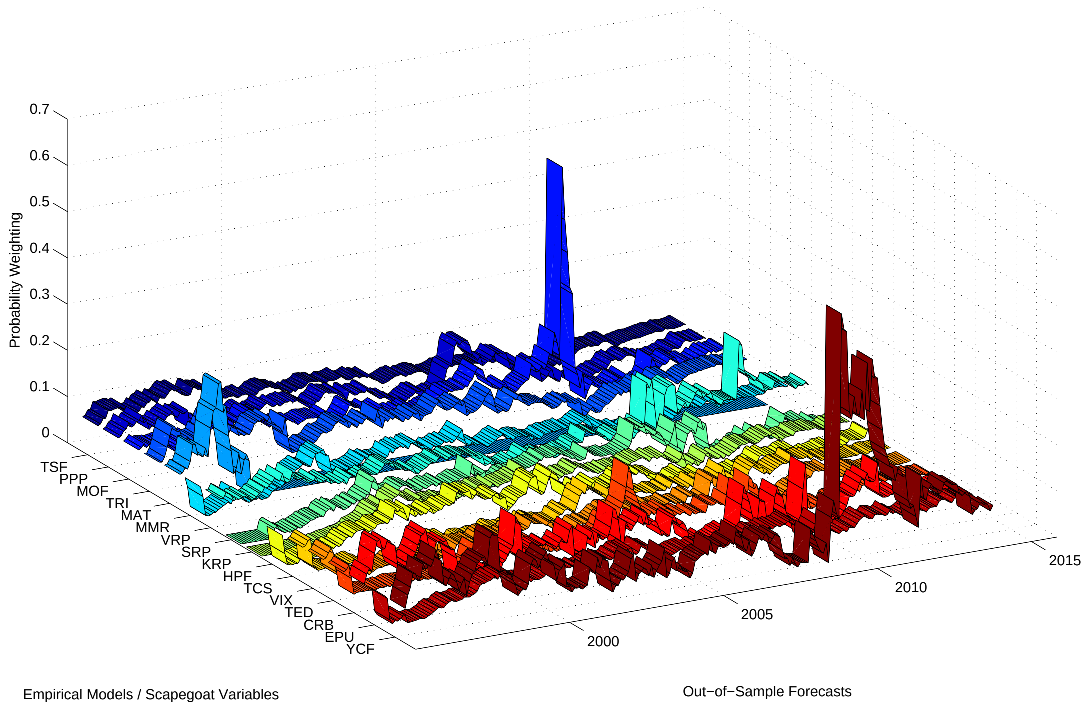
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor 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 E.5: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: CHF



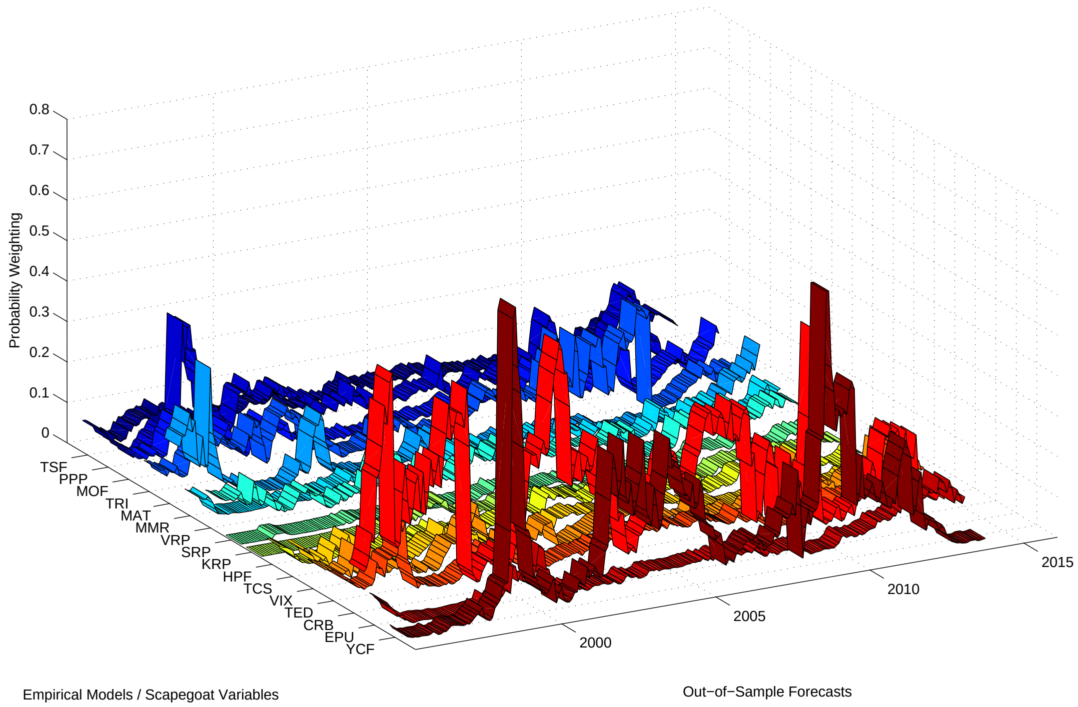
This figure shows the probability weighting of each empirical exchange rate model or "scapegoat" variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other "scapegoat" variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF), Taylor 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 E.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 E.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.

F Appendix: Scapegoat Drivers of Customer Order Flows: Sample Countries

Table F.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 F.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 F.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*		-0.20E-2**	0.21E-2***
		(0.08E-2)		(0.10E-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*** **			**0.12E-2** **	**0.06E-2** **
	(0.08E-2)			(0.05E-2)	(0.03E-2)
TCS					
VIX	**-1.33E-2** **				0.70E-2**
	(0.61E-2)				(0.30E-2)
TED	0.02**				0.46E-2*
	(0.01)				(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 F.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 F.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 F.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 F.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.