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 generalized (term structure) model to capture the dynamics between the risk premium component of exchange rates and a broad set of variables meanwhile handle both parameter and model uncertainty. We also demonstrate the projections of common predictable information over the term structure, and existence of time-varying term-structural effect and model disagreement effect of exchange rate predictors in FX trading, which in turn validates the practical use of our model. We then utilize the time-variation in the probability weighting to identify the scapegoat drivers of customer order flows. 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, Disconnect Puzzle, Carry Trade Risk Premia, Term Structure Factors, Scapegoat Variables, Model Disagreement, Customer Order Flows.

JEL classification: C52, E43, F31, F37, G11.

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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 first evidenced by Meese and Rogoff (1983) that the macro-based structural models can hardly beat a naive random walk (RW). The macroeconomic fundamentals are not volatile enough to explain the fluctuations in exchange rates (Flood and Rose, 1995). Are exchange rates really predictable? Rossi (2013) provides a comprehensive study to answer this question: It depends on the choice of predictors, sample period, data transformation, forecasting horizon, model specification, and evaluation method of forecasts. In this paper, we propose a generalized model to forecast exchange rates over a range of horizons meanwhile addressing the above issues on variable selection, parameter and model uncertainty.

Scholars attribute the feeble relationship between exchange rates and the corresponding determinants to either the I(1) property (high persistency) of macroeconomic fundamental used by monetary models and the near unity Stochastic Discount Factor (SDF) (Rossi, 2005; Engel and West, 2005; Engel, Mark, and West, 2007; Sarno and Sojli, 2009), or the time-varying "scapegoat" effect of exchange rate predictors (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 speculation, manipulation, and the 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 premium components. Lustig, Stathopoulos, and Verdelhan (2017) theoretically derive that the term structure of carry trade risk premia (excess return) 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 excess return component, from which the predictability origins and by which an exchange rate model is generalized. In other words, exchange rates over a range of horizons are driven by common latent factors in our model. More specifically, we extract term structure factors from the cross section of risk premium component, 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 — any observed variable can possibly be a scapegoat, see Section 2 for details. This term structure effect is first studied in the literature. We then employ a dynamic (Bayesian) model averaging (DMA) method to handle model uncertainty and forecast the term structure of risk premium 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. We then turn on the microscope to investigate the sources of predictability. The outperformance of our model is attributable to (i) the generalization of exchange rate modeling in terms of relaxing the restrictions imposed on the structural parameters (similarly to the argument of Chen and Tsang (2013), and the term structure effect in our model may contribute to the rise of the observed "exchange rate disconnect puzzle" in the literature if the aggregate effect of a certain variable on level, slope, and curvature factors is close to zero but each individual effect is statistically significant); (ii) the exploration of the factor structure for the extraction of useful common predictable information over a range of horizons from data with high dimensionality, thereby filtering out noisy information in the data and reducing the estimation errors; and (iii) the employment of dynamic model averaging procedure that attaches time-varying probability weights to a broad set of scapegoat variables in their interactions with the term structure factors and thus boosts the model flexibility. 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. Another substantial contribution of our research is bridging our exchange rate forecasting model with FX trading that in turn validates the practical use of our proposed term structure model: (vi) from the perspective of foreign exchange market microstructure, we demonstrate that customer order flows are informative about the term structure of currency carry trade risk premia, which extends the analysis of Menkhoff, Sarno, Schmeling, and Schrimpf (2016) to a cross-horizon and factor-based perspective; (v) we introduce probability weighting into the identification of scapegoat drivers of customer order flows which is explained in details in the following section of this paper — we find that up to a quarter of the variation in aggregate and disaggregate customer order flows are driven by the scapegoat variables considered in the paper, which is not observed without attaching the time-varying probability weights (generated by our term structure model) to the scapegoat variables; and (vi) we apply these weights of probabilities to capture model disagreement[1] and analyze how this regression-based (vis-à-vis survey-based (see Carlin, Longstaff, and Matoba, 2014)) model uncertainty measure is dynamically related to term structure of currency risk premia, volatility, and customer order flows. Andrei, Carlin, and Hasler (2014) recently propose a relevant theoretical model on model disagreement.

The rest of this paper is organized as follows: In Section 2, we provide advances in models of exchange rate determination wherein heterogenous agents learn to predictability of exchange rate models and switch trading rules of scapegoat variables. Section 3 contains information about the data sets used in this paper, and describes the 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 complementary findings and technical details of this paper are delegated to Online Appendix.

2 Exchange Rate Determination

Ample empirical evidence finds a weak relationship between nominal exchange rate and macroeconomic fundamentals. 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 fluctuations to some observable variables, which are typically taken as "scapegoats" that coincidentally move with exchange rates at a time, when there are other unobserved variables affecting the exchange rates, such as order flows. As a result, the weights attached to these variables, i.e., the scapegoat 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. The recent literature generally holds the point of view that agents with heterogeneous beliefs or skills learn the predictability of each predictor or forecasting model and assign time-varying weights to the variables/models, and then relevant information is partially impounded into prices via the switching process of FX trading rules in the trading activities. 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. Their model gives rise to the fundamental disconnect puzzle. 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). 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. This is consistent with the scapegoat theory in the sense that market participants only focus on a sub-set of variables out of a much broader set of variables at a time according to the corresponding performance of their forecasting models on which they trade exchange rates. Hence, from the

[1] We construct a time-varying indicator of model disagreement to measure the dispersion in exchange rate forecasts that are generated by different empirical models considered in this paper, see Section 3.4 for further discussion.

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. If the DMA estimation procedure is able to mimick the trading activities in FX market, we expect that the DMA probability weights of variables/models correspond to the probability weights hidden behind the order flows. The market participants who do not observe order flows give higher weights to variables/models with high contemporaneous predictive power and discount the importance of those with low contemporaneous forecasting competency, and then make decisions to trade exchange rates according to the weighted average of all available variables/models. As a result, by regressing the unobservable customer order flows on a set of observed variables, we may not be able to identify the drivers of customer order flows, even though they are truly initiated by observable variables on the ground of the predictability of corresponding models. The observable variables interacted with the corresponding probability weights therefore potentially provide a measure to identify the scapegoat driver of customer order flows. We present the two-step identification procedure in Section 2.2.

2.1 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[2] 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)[3]. Please refer to Appendix A for details. 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). We then extend the macro-based model to incorporate signals generated from two types of technical trading rules, trend indicator MAT and momentum-and-mean-reverting indicator MMR from which most of other popular indicators derive, as in Appendix B. They are shown to predict future returns across asset classes (Moskowitz, Ooi, and Pedersen, 2012), and known as trend-following strategies in practice. We find that the lagged exchange rate returns (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012) are well captured by MAT and MMR.

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. 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

[2]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.

[3]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.

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). Following the above 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. Specifically, the volatility risk premium (VRP) as a measure of hedging demand imbalances (Garleanu, Pedersen, and Poteshman, 2009), and hence can be interpreted as a proxy for (relative) downside insurance cost (Della Corte, Ramadorai, and Sarno, 2016). According to Huang and MacDonald (2013), the skew risk premium (SRP) measures the expected change in the probability of UIP to hold, and therefore can be interpreted as a proxy for speculative risk premia of investment currencies relative to funding currencies, and the kurtosis risk premium (KRP) 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[4] subtracted by model-free option-implied moment (see Carr and Wu, 2009; Kozhan, Neuberger, and Schneider, 2013, for details). The model-free option-implied moments, the copula (lower) tail dependence CTD between individual currency and the global FX market as a measure of the crash sensitivity[5] (see Huang and MacDonald, 2013), and the aggregate hedging pressure in currency futures market measured by the sum of commercial and speculative long-short position imbalances HPF as in Acharya, Lochstoer, and Ramadorai (2013) are delegated to Appendix C. Other scapegoat variables we consider are: the past 3-month average changes (see also Bakshi and Panayotov, 2013) in commodity ΔCRB, volatility ΔVIX, and liquidity ΔTED indices. As for country-specific economic policy uncertainty indicators ΔEPU, we adopt 1-month changes in the indices.

2.2 Customer Order Flows

Customer order flows contain predictive information about future exchange rate movements (Evans and Lyons, 2002, 2005b). 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), the yield curve, and other scapegoat drivers. A direct solution is to test the relationship between customer order flows[6] and the term structure factors, and dynamically weighted (by forecast performance-driven probability) scapegoat variables or empirical exchange rate models. We first examine the predictive power of customer order flows on the term structure of currency carry trade excess returns. In the investigation of the scapegoat drivers of customer order flows, we do not include lags of the publicly observable variables and customer order flows are driven by both public and private information. Risk-averse market participants may reduce their exposures to high model-risk asset and shift their inventories to assets with low model risk when facing high market uncertainty. Thus, it is reasonable to expect negative coefficients in regressions, indicating that model uncertainty drives and/or predicts trading activities and asset returns.

When a scapegoat variable is spotted, the market participants who do not observe the order

[4]Skewness is not integrable (see Neuberger, 2012), and thus, we use monthly skew of daily returns as the proxy for realized skew.

[5]We adopt the changes in copula-based crash sensitivity, denoted by TCS, as one of the scapegoat variables in the model.

[6]The data set consists of order flows from asset managers, corporate (commercial) clients, hedge funds, and private clients. Asset managers and hedge funds are typical financial clients.

flows raise the weight of the predictability attached to it, and then possibly switch their rules from trading exchange rates on previous scapegoat to trading on current scapegoat. As discussed before, by regressing the unobservable customer order flows on a set of observed variables, we may not be able to identify the drivers of customer order flows, even though they are truly initiated by observable variables on the ground of the predictability of corresponding models — because market participants update the predictive variable/model probability weighting and accordingly adjust their trading initiatives over time. The observable variables interacted with the corresponding probability weights therefore potentially provide a measure to identify the scapegoat driver of customer order flows.

$$o_t = \varpi_{1,0} + \sum_{j=1}^{k} \varpi_{1,j} \cdot x_{j,t} + \nu_{1,t} \tag{1}$$

$$o_t = \varpi_{2,0} + \sum_{j=1}^{k} \varpi_{2,j} \cdot \Pr(L_t = j \mid z_t) \cdot x_{j,t} + \nu_{2,t} \tag{2}$$

where $\Pr(L_t = j \mid z_t)$ is the probability weights of each variable/model j, $x_{j,t}$ is a potential scapegoat variable, and o_t is the customer order flows (COF). The above two-step regressions are used for the identification of scapegoat driver of COF. The selection procedure is as follows: (i) We search for the stable drivers of COF — those with statistically significant correlations with COF within the basket of exchange rate predictors — market participants routinely trade foreign exchanges on these predictors as in Equation (1); (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 as in Equation (2); (iii) We refine the pool of scapegoat variables by excluding drivers that are statistically dominated by others.

3 Data and Methodology

Our financial data set is obtained from Datastream and Bloomberg, including spot rates, forward rates and risk-free interest rates 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)[7]. All Option data are used to construct volatility risk premia (see Della Corte, Ramadorai, and Sarno, 2016), skew and kurtosis risk premia (see Huang and MacDonald, 2013), 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 Chicago Board Options Exchange (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 (2013). we acquire data on the positions of currency

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

futures traders (both commercial and non-commercial) from the Commitment of Traders (COT) published by the Commodity Futures Trading Commission (CFTC).

Our macroeconomic data set is collected from several sources. To measure money supply, we use non-seasonally adjusted M1[8] 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[9]. The price level is captured by Consumption Price Index (CPI) from OECD's *Main Economic Indicators* (*MEI*)[10]. 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[11] 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:

$$\Delta s_{t+\tau}^{(\tau)} = \underbrace{s_{t+\tau} - f_t^{(\tau)}}_{c_{t+\tau}^{(\tau)}} + \underbrace{f_t^{(\tau)} - s_t}_{r_t^{(\tau),*} - r_t^{(\tau)}} \tag{3}$$

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 (2017) reveal that the term structure of carry trade risk premia is downward sloping because investment currencies tend to have low local sovereign term premia relative to funding currencies. Given that the forward premium component is already known at time t, exchange rate predictability originates from the carry trade risk premium 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 (3). For instance, in the circumstance that CIP holds (see Akram, Rime, and Sarno, 2008), the forward (interest rate differential) component can be expressed in a form of (relative)

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

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

[10] 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.

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

level (L_t^{NS}), slope (S_t^{NS}), and curvature (C_t^{NS}) factors (see Chen and Tsang, 2013). Latent factors of the excess return component are extracted in a similar way:

$$c_t^{(\tau)} = L_t^{NS} + \frac{1-\exp(-\lambda\tau)}{\lambda\tau} S_t^{NS} + \left[\frac{1-\exp(-\lambda\tau)}{\lambda\tau} - \exp(-\lambda\tau)\right] C_t^{NS} + \zeta_t^{(\tau)} \tag{4}$$

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. We employ Principal Component Analysis (PCA) to determine that three factors are required to explain the cross-sectional variation of two exchange rate return components — consistent with the NS approach as shown in Equation (4), which easily extracts latent factors with a given loading coefficient λ without the requirement to re-estimate the loadings that changes when more observations are added. λ controls the shape of the factor loadings that generate comparable results to the PCA approach. Thereby, we advocate the NS approach for forecasting purpose. 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 premium 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.

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

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

$$z_t = \beta_{0,t} + \beta_{1,t} z_{t-1} + \cdots + \beta_{n,t} z_{t-n} + u_t \tag{5}$$

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. Each empirical exchange rate model or variable is specified in Appendix A, B, and C. $\beta_{0,t}$ 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. Our results are robust to the choice of decay rate, "forgetting factor", grid, etc..

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 (macroeconomic and finance) risks and the feedback effects between factors and predictors (using impulse response analysis). It is worth accentuating that we assume, beyond the factors, there is no other sources of predictability — $\zeta_t^{(\tau)}$ in Equation (4) by x_{t-n} as we focus on the information commonality in the term structure of exchange rate predictability in this paper. Our model is flexible because it nests the model with latent factors only, and those with interactions in between the term structure factors and observable macroeconomic fundamentals and financial variables.

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).

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 D 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, e.g. Survey of Professional Forecasters, in previous literature to measure the model disagreement on expectations on asset prices, we resort to the DMA probability weighting generated via a Bayesian forecasting error optimization procedure to compute the regression-based model disagreement MD, which captures the model-implied dispersion of forecasts and is given by:

$$MD_t = \sqrt{\frac{1}{l}\sum_{j=1}^{l}\left[\Pr(L_t = j \mid z_t) - \frac{1}{l}\right]^2} \tag{6}$$

It is essentially the standard deviation of the DMA probability weights across the variables/models. 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, as Kozhan and Salmon (2009) find notable uncertainty aversion in FX market.

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

$$R^2_{OOS} = 1 - \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2} \tag{7}$$

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):

$$\Delta RMSE = \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} - \sqrt{\frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F}} \tag{8}$$

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 with mean quadratic loss differential:

$$\bar{d}_t = \frac{\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\bar{s}^{(\tau)}_{t+\tau|t}\right)^2 - \sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\Delta s^{(\tau)}_{t+\tau} - \Delta\hat{s}^{(\tau)}_{t+\tau|t}\right)^2}{T_F} \tag{9}$$

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 $\text{cov}[d_t, d_{t-\tau}] = \vartheta(\tau), \forall t$:

$$DMW = \frac{\bar{d}_t}{\hat{\sigma}_{\bar{d}_t}} \xrightarrow{d} \mathcal{N}(0,1) \tag{10}$$

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

4.2 Economic Value

We assess the economic value of our model in a mean-variance dynamic asset allocation framework[12] 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 structure of information projection 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 $\bar{\sigma}_p$:

$$\begin{aligned} &\max_{\omega_t} \left\{ \mu_{p,t+\tau} = \underbrace{\omega_t^\top (\mathbb{E}_t[\Delta s_{t+\tau}^{(\tau)}] + r_t^{(\tau),*})}_{Foreign\ Investment} + \underbrace{(1 - \omega_t^\top \iota)\, r_t^{(\tau)}}_{Domestic\ Investment} - \underbrace{r_t^{(\tau)}}_{Benchmark} \right\} \\ &\text{s.t. } \bar{\sigma}_p^2 = \omega_t^\top \Sigma_{t+\tau|t}\, \omega_t \end{aligned} \tag{11}$$

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. 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):

$$\omega_t = \frac{\bar{\sigma}_p}{\sqrt{\varrho}} \cdot \Sigma_{t+\tau|t}^{-1}\, \mathbb{E}_t[c_{t+\tau}^{(\tau)}] \tag{12}$$

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

[12] See also Abhyankar, Sarno, and Valente (2005); Thornton and Valente (2012); Sarno, Schneider, and Wagner (2016); Gargano, Pettenuzzo, and Timmermann (2014).

carry trade risk premia so that measuring the economic value of the carry trade risk premium component predictability is equivalent to measuring that of the exchange rate predictability. This leads to an optimal portfolio on the efficient frontier. The performance fee is a measure of economic values to investors introduced by Fleming, Kirby, and Ostdiek (2001, 2003) in evaluating portfolio management. More accurate forecasts result in better portfolio rebalance decisions, and therefore better asset allocation performance under mean-variance scheme.

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

$$\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{TS}-\mathcal{F})^2\right] = \sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left[(1+\mu_{p,t+\tau}^{RW})-\frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+\tau}^{RW})^2\right] \quad (13)$$

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

$$\mathcal{P} = \frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{TS}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right] - \frac{1}{1-\gamma}\ln\left[\frac{1}{T_F}\sum_{t=T_{IS}+\tau}^{T_{OOS}-\tau}\left(\frac{1+\mu_{p,t+\tau}^{RW}}{1+r_t^{(\tau)}}\right)^{1-\gamma}\right] \quad (14)$$

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 $\mathcal{SR}_{\mathcal{DR}}$[13]. Transaction cost is adjusted by time-varying bid-ask spread.

Moreover, besides active trading (monthly portfolio-rebalancing) in currency market to acquire absolute returns as discussed above, our framework embraces the strategic (annual portfolio-rebalancing), tactical (semi-annual and quarterly portfolio-rebalancing), and dynamic (rebalancing in presence of large deviation) asset allocation concepts in currency investment management in practice that portfolio decisions are made at different frequencies. 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 as follows:

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

$$
\begin{aligned}
\Delta\tilde{s}^{(1)}_{t+\tau|t} &= \underbrace{\left(\hat{c}^{(\tau)}_{t+\tau|t} + f^{(\tau)}_t - s_t\right)}_{\Delta\hat{s}^{(\tau)}_{t+\tau|t}} - \underbrace{\left(\hat{c}^{(\tau-1)}_{t+\tau-1|t} + f^{(\tau-1)}_t - s_t\right)}_{\Delta\hat{s}^{(\tau-1)}_{t+\tau-1|t}} \\
&= \left(\hat{c}^{(\tau)}_{t+\tau|t} - \hat{c}^{(\tau-1)}_{t+\tau-1|t}\right) + \left(f^{(\tau)}_t - f^{(\tau-1)}_t\right) \qquad (15)
\end{aligned}
$$

Specifically, dynamic portfolio decision is implemented every month to examine the 9-month portfolio-rebalancing target. If there is a large deviation, such as 5%, of the forecast made τ period ago from the updated forecast calculated using the above implied forecast in Equation (15), we adjust the position towards the updated target.

5 Empirical Results and Discussion

In this section, we perform preliminary analysis on the term structure of currency risk premia, and present the empirical results from the model statistical and economic evaluation. We then focus on the sources of predictability arising from our generalized predictive model for exchange rates. Finally, we bridge the model with the real-world FX trading via customer order flows. The findings, in turn, demonstrate the validity of our proposed model in terms of common predictable factors, term structure effects of predictive variables, more modeling flexibility that is subject to less estimation error, dynamic model averaging procedure that corresponds to scapegoat drivers and implied probability weighting of trades, and the influence of model disagreement on the term structure of currency risk premia.

5.1 Preliminary Analysis

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

[Insert Figure 2. about here]

Figure 2. provides the time-series and cross-sectional goodness of fit of the term structure of carry trade risk premium component 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 incremental adjusted R^2 lower than 1% across all 7 currencies on average). However, they seem to play a role in the long end (12-month horizon) of the curve in terms of an incremental adjusted R^2 over 3%.

5.2 Model Evaluation

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 1, 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 considered 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, or namely overfitting in the short end of the term structure of currency risk premia, seems to be achieved at the cost of medium and long end predictive accuracy, whereas CHF and JPY are the best predicted currencies at the 12-month horizon. This implies that the control of fitting (choice of λ) on the shape of the curve is important.

[Insert Table 1 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, and (ii) the predictive information set that is common to both short-run and long-run forecasting. These can be further investigated in future study.

[Insert Table 2 about here]

Table 2 reports the economic values of our term structure model for a full spectrum of currency investment management from 1-month to 12-month investment horizons.[14] 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 currency trading. The economic significance of strategic (12-month portfolio-rebalancing) asset allocation 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 asset allocation 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-rebalancing style, respectively. In dynamic portfolio decision, we rebalance the portfolio every 9-month with dynamic scrutiny

[14] As discussed in Section 4.2, the main differences of various investment strategies are differences in investment horizons.

and adjustment every 3-month if the deviation of the initial forecast from the updated forecast is over 5%, 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[15] (target at 10%) in the existing literature of exchange rate forecasting. This verifies the performance robustness of our term structure model in currency investment across horizons.

5.3 Sources of Predictability

We now turn on the microscope to investigate the sources of FX predictability. The outperformance of our model over random walk can be mainly attributed to the model generalization process that (i) differentiates the effect of predictive information according to the term structure in order to relax the restrictions imposed on the structural parameters; (ii) focuses on the common predictable information which drives the exchange rates over a range of horizons and therefore taking the advantage of a well-established factor structure to extract more useful information from the noisy data; and (iii) our model becomes more realistic when estimated by the dynamic model averaging procedure — it incorporates the time-varying probability weighting attached to scapegoat variables into forecasting exercise.

5.3.1 Model Generalization and Term Structure Effect

Given that the higher yield currencies tend to have lower local sovereign term premia than the lower yield currencies (Lustig, Stathopoulos, and Verdelhan, 2017), we are able to employ a term structure model to fit the the risk premium component of exchange rate returns via decomposition, which generalizes exchange rate models for different forecasting horizons. This generalization process differentiate the loadings on the latent factors that drive the exchange rate over a range of modeling horizons. Our model demonstrates that there should exist (time-varying) term structure effects of exchange rate predictors in terms of different loadings on the level, slope, and curvature factors of the term structure of carry trade risk premium component which relax the restrictions imposed on the structural parameters — a similar concept and logic to Chen and Tsang (2013) who advocate the use of yield curve factors rather than interest rate directly in the Fama regression. We also find similar empirical support against the parameter constraints imposed when the model is estimated without decomposition (or equivalently without accounting for the term structure effect). This term structure effect is also associated with the exchange rate disconnect puzzle that exchange rate fluctuations are found unrelated to the changes in relevant macro fundamentals. However, in our findings, a currency can be, overall, seemingly unaffected by a certain variable, but the variable drives up the level of risk premia over a investment horizon (positive effect) meanwhile flattens the slope of risk premia (negative effect), and two effects actually cancel out so that we cannot observe any linkage between the exchange rates and relevant variables, similarly to the unspanned macro risk issue in yield curve modeling (see Ludvigson and Ng, 2009).

[15] The volatility of the portfolio is found to increase with the forecasting horizon except for the dynamic asset allocation that achieves volatility slightly lower than the target, which possibly benefits from the dynamic portfolio-rebalancing nature on forecasting deviations.

5.3.2 Extraction of Common Predictive Information via Factor Structure

The outperformance of our model also replies on a well-established factor structure to extract common predictable information from a large set of noisy data, and to focus on the common dynamics. Exploring this latent structure of the data reduces the estimation errors. It is also worth noting that $\text{cov}[x_{t-n}, \zeta_t^{(\tau)}] = 0$ may not be realistic enough, and violation of this assumption can generate economically meaningful horizon-dependent probability weighting, which only varies with the predictive power of x_{t-n} on $\zeta_t^{(\tau)}$. In other words, the forecasting power of the scapegoat variables on factors are the same across horizons. Implementing forecasts beyond the short-end horizon requires recursive forecasts of the term structure factors so that the DMA probability weighting is optimized throughout to the long-end horizon.

[Insert Table 3 about here]

To assess the information commonality in the term structure of exchange rate predictability, we run pooled-OLS 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): $|\Delta s_{i,t+\tau}^{(\tau)} - \Delta \hat{s}_{i,t+\tau|t}^{(\tau)}| = a_i + b \cdot \Pr(L_{i,t} = j | z_{i,t}) + \epsilon_{i,t}$. 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 — their DMA probability weights are unstable in terms of volatility; and (ii) the coefficients are statistically significant across forecasting horizons. As shown in Table 3, overall, hedging pressure in futures market (HPF) and liquidity risk (TED) contain the common information that possesses stable predictive power on exchange rate returns over a range of horizons. Policy-related predictors, such as monetary fundamentals (MOF), Taylor rule (TRI) and economic policy uncertainty (EPU), provide important information for short-run forecasting up to 3 months, while crash risk indicators, such as tail risk premia (KRP) and crash sensitivity (TCS), matter for long-run forecasting from 9 months to 12 months. The empirical results in Table 3 implies that our model can be further improved by introducing horizon-dependent probability weighting.

5.3.3 Dynamic Probability Weighting

Table 4 below reports the descriptive statistics of the probability weighting of each empirical model or scapegoat variable for all currencies[16]. 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 (TSF), 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

[16]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 trade risk premium 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.

tail risk premia (SRP and KRP), hedging pressure in futures market (HPF), copula-based tail dependence measure for crash sensitivity (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 4 about here]

Figure 3. 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 TSF — the term structure factor-only model. It is as important as VRP and HPF, which are shown to be non-trivial predictors of exchange rates (Della Corte, Ramadorai, and Sarno, 2016), and also has low negative correlations with most of other predictors. This implies that during crisis periods the relative yield curve factors provide superior complementary information about expected future economic dynamics, as suggested in Chen and Tsang (2013). So do MOF, MAT, CRB, and EPU but to a lesser extent.

[Insert Figure 3. about here]

It is worth mentioning that the dramatic rise in the probability weighting of the yield curve model in forecasting the term structure of risk premium component in exchange rates during the periods of global financial crisis is possibly due to the fact that the UIP is found to only and broadly hold in the regime of high volatility (Clarida, Sarno, Taylor, and Valente, 2003), and hence the yield curve factors act as a predominant and unbiased predictor then.

To summarize, the outperformance is mainly due to (i) the relaxing of restrictions imposed on structural parameters via model generalization; (ii) the use of factor structure to extract common useful information from noisy data and reduce estimation errors; and (iii) the dynamic model averaging procedure that takes the time-varying predictability of variables in their interactions with term structure factors into consideration.

5.4 From Modeling to Trading

In this section, we reveal the existence of term structure effect of customer order flows in FX market, and show that model uncertainty/disagreement generated via the dynamic parameter and model probability weighting updating process is highly related to the real trading activities, such as the future currency returns and the term structure of currency risk premia, market volatility, and customer order flows. It also helps to identify the scapegoat drivers of customer order flows in FX trading, which in turns justifies the practical use of our model and method.

5.4.1 Term Structure Effect of FX Trading

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, suggesting that the utilization of factor structure over the term structure by decomposition is not only statistically significant but also economically meaningful in exchange rate forecasting and currency trading. As shown in Table 5, 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 (Chen and Tsang, 2013) has significant predictive implications on currency carry trade risk premia as well, it is of interest to study the yield curve driver 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. In sum, our analysis shares similar empirical findings to Menkhoff, Sarno, Schmeling, and Schrimpf (2016) but differs in the sense that we investigate the term structural effect of customer order flows on exchange rate predictability across different investment horizons via exchange rate return decomposition and emphasize that its slope impact is generally more prominent than the level impact.

[Insert Table 5 about here]

5.4.2 Model Disagreement Effect in FX Trading

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 as described in Equation (6). Figure 4. shows the DMA-implied model disagreements (MD) of individual currencies. The corresponding index in foreign exchange market as the equally weighted average across all currencies is closely associated with but clearly a different source of risk from volatility (VIX) and liquidity (TED) risks (see Figure 5.).

[Insert Figure 4. about here]

[Insert Figure 5. about here]

Table 6 reveals that the series of AR(1) innovations to DMA-implied model disagreement (ΔMD) has both predictive and contemporaneous relations with 1-month carry trade excess returns and the term structure of currency risk premia (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 and shift their 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 generated by our term structure model.

[Insert Table 6 about here]

The above results suggest that incorporating the model uncertainty/disagreement into the forecasting exercise is important for modeling the dynamics between the latent factors driving exchange rates and scapegoat variables over a range of investment horizons faced by the both currency speculators and hedgers in the real world business. In sum, the model disagreement based on DMA probability weighting is found to be also related to the term structure of currency risk premia and FX trading. We further investigate the usefulness of the DMA probability weighting in the identification of scapegoat drivers in FX trading.

5.4.3 Scapegoat Drivers of Order Flows

Moreover, we identify the scapegoat drivers by running two-step regressions on each currency. We restate the the selection procedure 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 as in Equation (1); (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 as in Equation (2); (iii) We refine the pool of scapegoat variables by excluding drivers that are statistically dominated by others.

[Insert Table 7 about here]

As shown in Figure 6., 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 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) drivers come into the spotlights and the signs of the coefficients are consistently reasonable. 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, implying that the use of the estimation methods makes very good economic sense. Using the above identification procedure, we find that up to a quarter of the variation in aggregate and disaggregate customer order flows are driven by the scapegoat variables considered in the paper, which is not observed without attaching the time-varying probability weights (generated by our term structure model) to the scapegoat variables.

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

To summarize, our findings suggest that the term structure effect indeed exist in real-world FX trading — customer order flows predict both the level and slope factors extracted from the term structure of currency risk premia, which verifies the practical use of our proposed generalized term structure model for exchange rate forecasting. The empirical results also suggest 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 macroeconomic and financial risks. 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.

6 Conclusion

We investigate the origins and the term structure of exchange rate predictability from 1-month to 12-month horizons by the decomposition of exchange rate returns into carry trade risk premia and forward risk premium components that allows us to forecast exchange rate indirectly via its risk premium component, for which we propose a generalized (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 then turn on the microscope to examine the sources of predictability. The outperformance of our model is attributable to (i) the generalization of exchange rate modeling in terms of relaxing the restrictions imposed on the structural parameters via term structure decomposition (a possible solution to exchange rate disconnect puzzle); (ii) the exploration of the factor structure for the extraction of useful common predictable information over a range of horizons from noisy data and thereby reducing the estimation errors; and (iii) the employment of dynamic model averaging procedure that attaches time-varying probability weights to a broad set of scapegoat variables in their interactions with the term structure factors and thus boosts the model flexibility. We further link our exchange rate forecasting model to FX trading. From the perspective of foreign exchange market microstructure, we find that customer order flows are also informative about the term structure of carry trade risk premia, which in turn validates the practical use of our proposed model. We 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. Moreover, we apply the DMA probability weighting to examine the scapegoat drivers of customer order flows, and we find that up to a quarter of the variation in aggregate and disaggregate customer order flows are driven by the scapegoat variables considered in the paper, which is not observed without attaching the time-varying probability weights (generated by our term structure model) to the scapegoat variables. To summarize, our findings confirm the existence of term structure effect in FX market and 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 macroeconomic and financial risks along the term structure. These empirical results suggest the affinity of our proposed model with the FX trading activities in reality.

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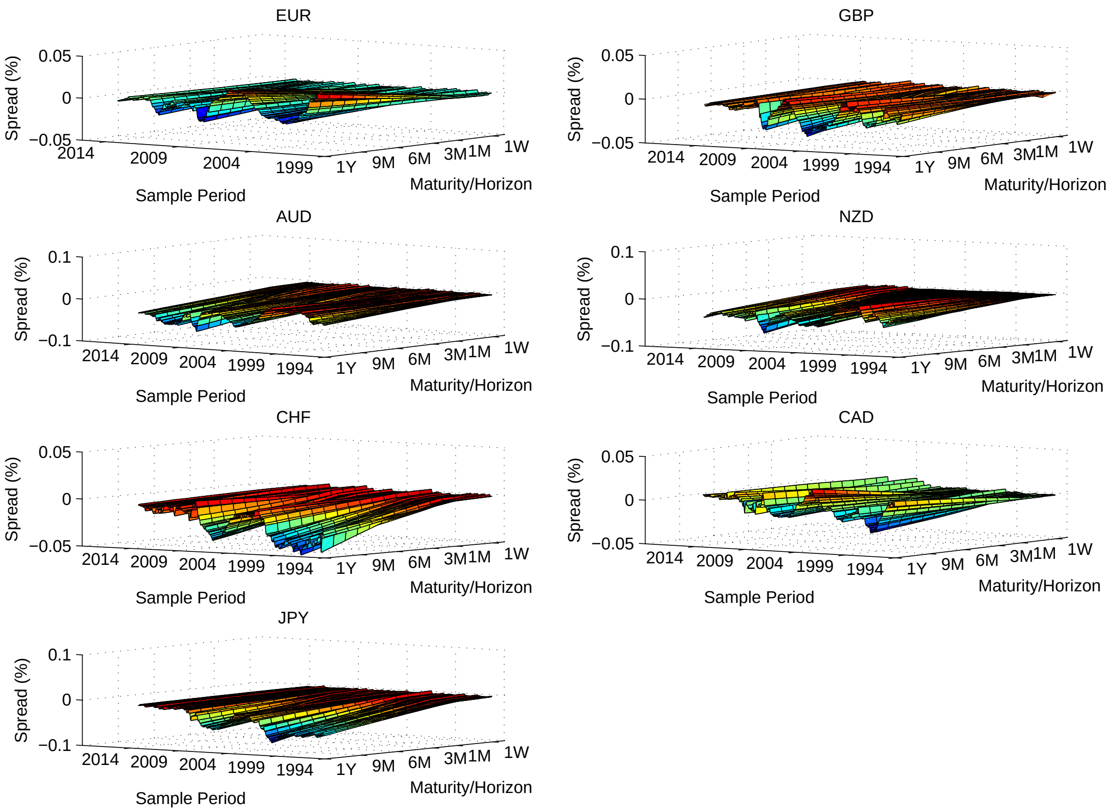
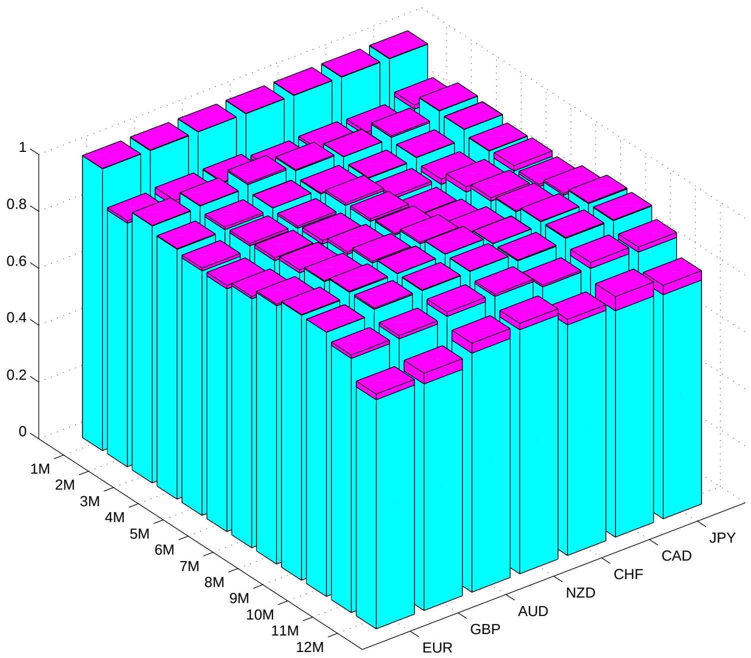
Figure 1: The Term Structure of Forward Risk Premia



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

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

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

Table 2: Economic Value of the Term Structure Model: Out-of-Sample Predictability of Carry Trade Risk Premia / Exchange Rate Returns

EV	Currency Investment Management				
	Active	Tactic		Dynamic	Strategic
	(1M)	(3M)	(6M)	(9M)	(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 portfolio-rebalancing), strategic (annual portfolio-rebalancing), tactic (semi-annual and quarterly portfolio-rebalancing), to dynamic (rebalancing in presence of a 5% deviation of the forecast made τ-period ago from the current updated forecast that is calculated using the implied τ-period forecast of the term structure model) portfolio decisions: 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 calculated 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 3: Information Commonality in the Term Structure of Exchange Rate Predictability

FX	IC	Empirical Models / Scapegoat Variables							
		TSF	PPP	MOF	TRI	MAT	MMR	VRP	SRP
1M	b	-3.14***	-2.51***	-1.68***	-1.84***	46.38***	-0.31	-1.15**	-1.06
	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
3M	b	-1.13***	-0.91***	-0.26	-0.97***	-4.67	0.44***	-0.16	-0.71**
	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
6M	b	-0.06	-0.33*	-0.36***	0.22*	-2.33	0.16*	-0.08	0.62***
	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
9M	b	-0.40***	-0.68***	-0.73***	0.18*	-1.21	0.00	-0.35***	1.13***
	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**
12M	b	0.01	-0.12	-0.58***	0.29***	-3.24***	0.04	-0.04	0.98***
	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
1M	b	1.60**	-1.49***	-0.59	-2.30	-2.02**	-0.84*	-2.48***	0.33***
	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**
3M	b	0.34	-0.77***	-0.25	-2.53**	-1.95***	0.05	-1.29***	0.14***
	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**
6M	b	-0.01	-0.41***	-0.29**	1.14*	-0.86***	0.29**	-0.09	0.02
	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
9M	b	-0.76***	-0.78***	-0.64***	0.19	-1.15***	-0.25**	0.05	0.10***
	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**
12M	b	-0.49***	-0.75***	-0.49***	0.90**	-1.13***	-0.09	0.26	0.05
	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

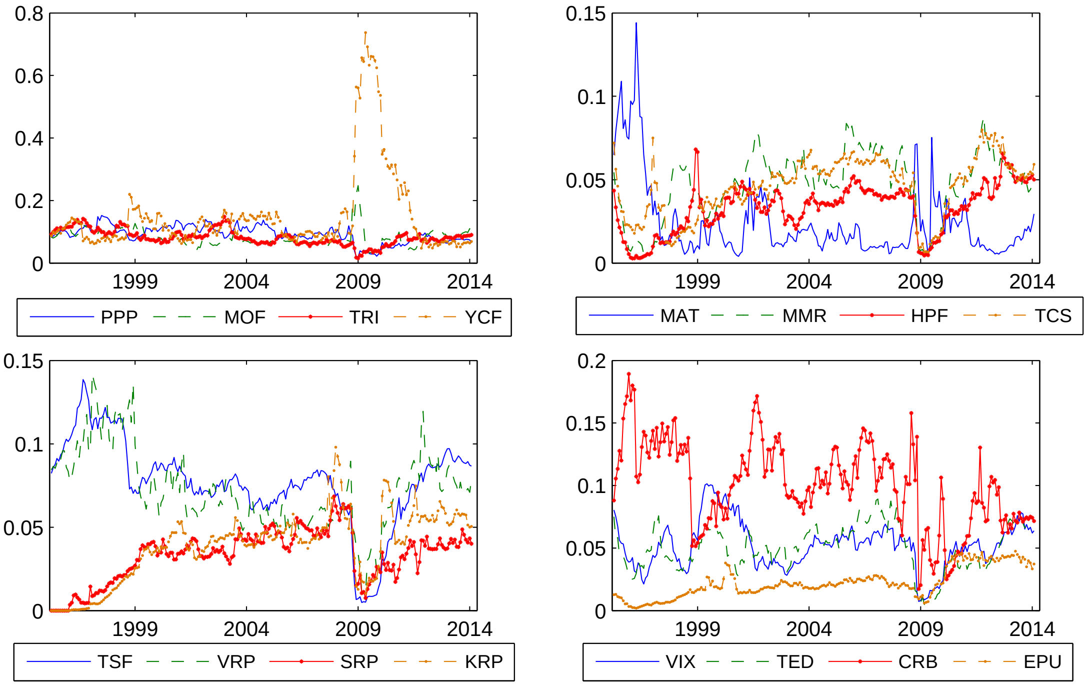
This table reports information commonality in the term structure of exchange rate predictability using pooled-OLS regressions. The dependent variable is Absolute Forecasting Error (AFE) in the forecasts of the term structure of carry trade risk premia / exchange rate returns for G10 currencies (EURUSD, 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 4: 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 3: Probability Weighting of Empirical Exchange Rate Models / Scapegoat Variables: Average across Currencies



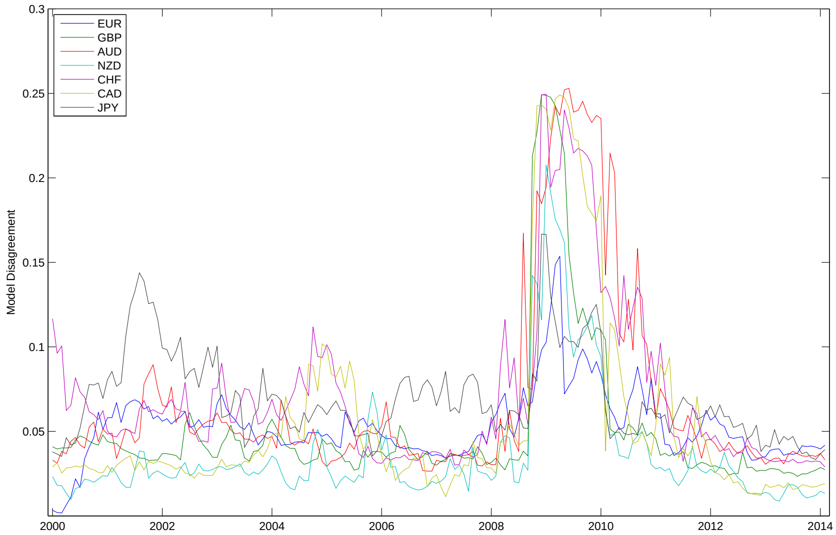
This figure shows the average probability weighting of each empirical exchange rate model or scapegoat variable, including Term Structure Factors of Carry Trade Risk Premia (TSF) only (no other scapegoat variables); Macroeconomic Fundamentals: Purchasing Power Parity (PPP), Monetary Fundamentals (MOF),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

Table 5: 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**

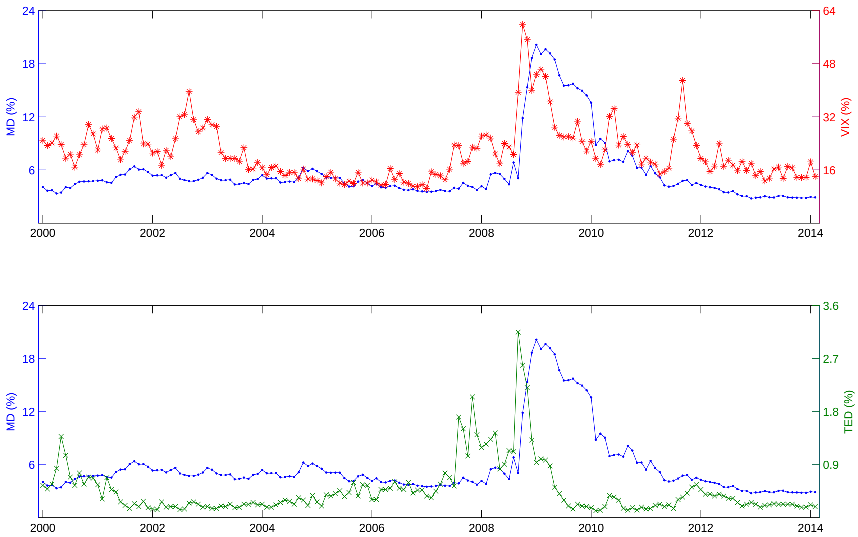
This table reports the predictive power of customer order flows, both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate clients (CC), hedge funds (HF), and private clients (PC), on the term structure of currency carry trade risk premia — Nelson-Siegel level (L^{CT}) and 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 4: 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 5: 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 6: 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

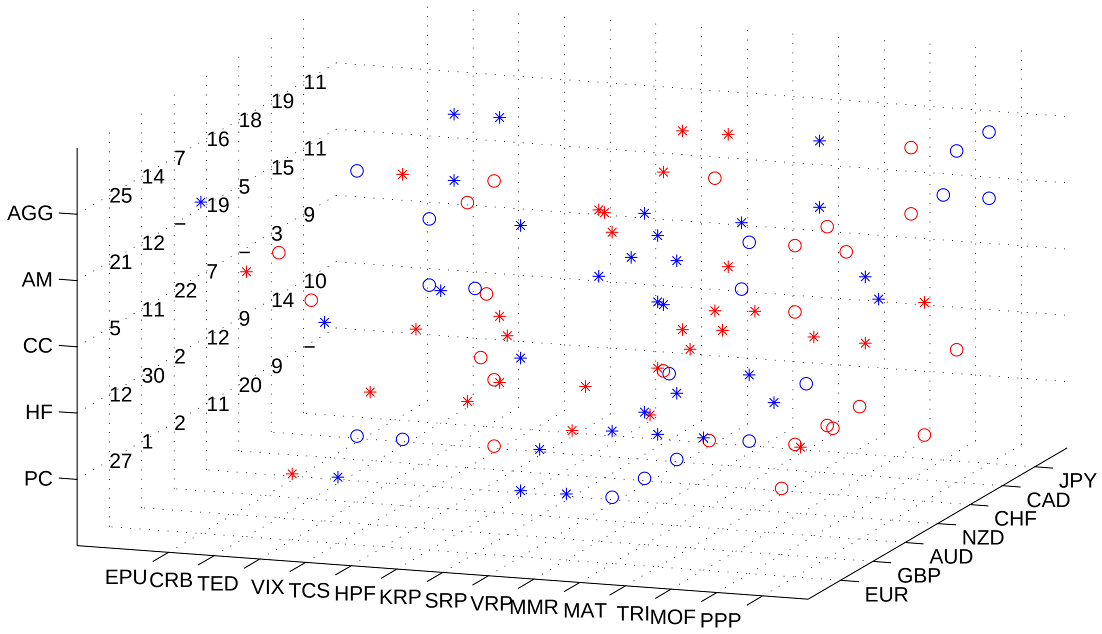
This table reports the effects of model disagreement on carry trade excess returns (xr), AR(1) innovations to FX volatility (Δvol), Nelson-Siegel level (L^{CT}) and slope (S^{CT}) factors, and customer order flows (both aggregate (AGG) and disaggregate order flows from asset managers (AM), corporate 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 7: Yield Curve Driver of Customer Order Flows

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

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

Figure 6: 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.

Online Appendix

to

"The Term Structure of Exchange Rate Predictability"

(Not for Publication)

A Fundamental-Based Empirical Exchange Rate Models

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:

$$s_t = (1-\eta)\sum_{\tau=0}^{\infty}\eta^{\tau}\mathbb{E}_t[z_{t+\tau}] \tag{16}$$

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:

$$s_t = \mathbb{E}_t[z_t] + \frac{\eta}{1-\eta}\mathbb{E}_t[\Delta s_{t+1}] \tag{17}$$

which can be rearranged to give:

$$\Delta s_{t+1} = \frac{1-\eta}{\eta}(s_t - \mathbb{E}_t[z_t]) + \varepsilon_{t+1} \tag{18}$$

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).

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

Covered Interest Rate Parity (CIP):

$$f_t^{(\tau)} - s_t = r_t^{(\tau),*} - r_t^{(\tau)} \tag{19}$$

Uncovered Interest Rate Parity (UIP):

$$\mathbb{E}_t[s_{t+\tau}] = f_t^{(\tau)} \tag{20}$$

Purchasing Power Parity (PPP):

$$p_t^* = s_t + p_t \tag{21}$$

Monetary Fundamentals[17] (MOF):

$$\begin{aligned} m_t^* - p_t^* &= y_t^* - \phi\, r_t^{(\tau),*} \\ m_t - p_t &= y_t - \phi\, r_t^{(\tau)} \end{aligned} \tag{22}$$

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

$$\begin{aligned} r_t^{(\tau),*} &= \theta_0 + \theta_1 \pi_t^{(\tau),*} + \theta_2 \tilde{y}_t^{(\tau),*} \\ r_t^{(\tau)} &= \theta_0 + \theta_1 \pi_t^{(\tau)} + \theta_2 \tilde{y}_t^{(\tau)} \end{aligned} \tag{23}$$

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

To allow for deviations from UIP based on rational expectations and risk neutrality, we introduce ξ_t as an expectation error and/or risk premium into Equation (20). We substitute Equations (19), (21) (22) into Equation (20) to yield the reduced form:

$$s_t = \frac{1}{1+\phi}\left[(m_t^* - m_t) - (y_t^* - y_t) - \phi\, \xi_t\right] + \frac{\phi}{1+\phi}\mathbb{E}_t[\Delta s_{t+1}] \tag{24}$$

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

$$\begin{aligned} s_t = &-\frac{1}{1+\theta_3}\left\{\theta_1[\pi_t^{(1),*} - \pi_t^{(1)}] + \theta_2[\tilde{y}_t^{(1),*} - \tilde{y}_t^{(1)}] + \theta_3(p_t^* - p_t)\right\} \\ &-\frac{1}{1+\theta_3}\left\{\theta_4[r_{t-1}^{(1),*} - r_{t-1}^{(1)}] + \xi_t\right\} + \frac{1}{1+\theta_3}\mathbb{E}_t[\Delta s_{t+1}] \end{aligned} \tag{25}$$

B Chartism-Based Indicators from Technical Analysis

We introduce two important types of technical analysis here: (i) medium-long-term trend indicator, and (ii) short-medium-term momentum and mean-reversion indicator. Moving

[17] 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.

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

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

$$
\begin{aligned}
DIF_t &= \frac{EMA_t[s_t, T_1] - EMA_t[s_t, T_2]}{EMA_t[s_t, T_2]} \cdot 100\% \\
DEA_t &= EMA_t[DIF_t, T_3] \\
HTG_t &= DIF_t - DEA_t
\end{aligned} \tag{26}
$$

KDJ Stochastic Oscillator as a momentum and mean reversion indicator:

$$
\begin{aligned}
K_t &= EMA_t[RSV_t, T_4] \\
D_t &= EMA_t[K_t, T_5] \\
J_t &= 3D_t - 2K_t
\end{aligned} \tag{27}
$$

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

We go long (short) the home currency against the foreign currency if the MACD line crosses its signal lines from below (above), and the signal is stronger when accompanied with a large swing below (above) zero. A positive (negative) MACD indicator means an increasing upward (downward) momentum. Price reversal can be confirmed by the bullish (bearish) divergence, particularly a crossover at the resistance (support) breakout. We simply adopt the trend-strength indicator HTG_t[20] 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 $J_t < 0$)[21]. 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:

$$
MMR_t = [\varphi_{MMT}(K_t - D_t) + \varphi_{MRV}(100 - J_t)\iota_{OB} + \varphi_{MRV}(0 - J_t)\iota_{OS}] \cdot 100\% \tag{28}
$$

[19]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.

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

[21]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.

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.

C Measures for Crash Risk, Speculative Activities and Hedging Pressure in FX Market

The second, third, fourth risk-neutral moments are respectively given by (see Huang and MacDonald, 2013; Della Corte, Ramadorai, and Sarno, 2016):

$$\mathbb{E}_t^{\mathbb{Q}}[RV_{t,T}] = \frac{2B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{1}{K^2} C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}} \frac{1}{K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{29}$$

$$\mathbb{E}_t^{\mathbb{Q}}[RS_{t,T}] = \frac{6B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{K - F_{t,T}}{F_{t,T}K^2} C_{t,T}(K)\mathrm{d}K - \int_0^{F_{t,T}} \frac{F_{t,T} - K}{F_{t,T}K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{30}$$

$$\mathbb{E}_t^{\mathbb{Q}}[RK_{t,T}] = \frac{12B_{t,T}}{T}\left[\int_{F_{t,T}}^{\infty} \frac{(K - F_{t,T})^2}{F_{t,T}^2K^2} C_{t,T}(K)\mathrm{d}K + \int_0^{F_{t,T}} \frac{(K - F_{t,T})^2}{F_{t,T}^2K^2} P_{t,T}(K)\mathrm{d}K\right] \tag{31}$$

where $B_{t,T} = \exp\left[-(r_t - r_t^*)T\right]$, representing the present value of a zero-coupon bond with a risk-free rate as the interest differential between T-period domestic risk-free rate r_t and foreign risk-free rate r_t^*. $P_{t,T}$, $C_{t,T}$ is the put and call prices at time t with a strike price of K and a maturity of T, respectively. The option prices are recovered from the at-the-money implied volatility, 10-delta and 25-delta risk reversal and butterfly quotes in currency option market. $F_{t,T}$ denotes the forward rate that matches the dates of the options.

Copula (lower) tail dependence CTD_t between individual currency and the global FX market as a measure of the crash sensitivity is given by:

$$CTD_t = \lim_{q\to 0^+} \frac{\Pr\left(FX \leq F_{FX,t}^{-1}(q), MKT \leq F_{MKT,t}^{-1}(q)\right)}{\Pr\left(MKT \leq F_{MKT,t}^{-1}(q)\right)} = \lim_{q\to 0^+} \frac{C_t(q,q)}{q} \tag{32}$$

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, 2013). 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[22]:

$$HPF_t = \frac{HPF_t^S - HPF_t^L}{HPF_{t-1}^S + HPF_{t-1}^L} \tag{33}$$

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).

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

D Dynamic Model Averaging Estimation Procedure

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

$$
\begin{aligned}
p(\beta_t|\Omega_t) &\propto \mathbf{L}(z_t; \beta_t, z_{t-1}, \cdots, z_{t-n}, \Omega_{1:t-1})\, p(\beta_t|\Omega_{t-1}) \\
p(\beta_t|\Omega_{t-1}) &= \int_{\wp} p(\beta_t|\Omega_{1:t-1}, \beta_{t-1})\, p(\beta_{t-1}|\Omega_{t-1})\, \mathrm{d}\beta_t
\end{aligned}
\tag{34}
$$

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[23] (see Koop, Poirier, and Tobias, 2007, for details).

The posterior probabilities of the coefficients is given by:

$$
p(\beta_{t-1}|z_{t-1}) = \sum_{j=1}^{l} p(\beta_{j,t-1} \mid L_{t-1} = j, z_{t-1})\, \Pr(L_{t-1} = j \mid z_{t-1}) \tag{35}
$$

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 $t-1$.

$$
\Pr(L_t = j \mid z_{t-1}) = \frac{[\Pr(L_{t-1} = j \mid z_{t-1})]^{\alpha}}{\sum_{j=1}^{l}[\Pr(L_{t-1} = j \mid z_{t-1})]^{\alpha}} \tag{36}
$$

where $\alpha \in (0, 1]$ is the forgetting factor[24] and set to 0.99. The model is then updated by:

$$
\Pr(L_t = j \mid z_t) = \frac{\Pr(L_t = j \mid z_{t-1}) p_j(z_t|z_{t-1})}{\sum_{j=1}^{l} \Pr(L_t = j \mid z_{t-1}) p_j(z_t|z_{t-1})} \tag{37}
$$

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):

$$
\Sigma_{i,0} = \begin{cases} \psi/i^2 & \text{for coefficients on lag } i \text{ where } i = 1, \cdots, n; \\ 1 & \text{for the intercept, } i = 0. \end{cases} \tag{38}
$$

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.

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

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

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