Dynamic Allocations for Currency Investment Strategies

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Abstract

This study conducts out-of-sample tests for returns on individual currency investment strategies and the weights on the universe of these strategies. We focus upon five investment strategies: carry, momentum, value, dollar carry, and conditional FX correlation risk. The performances of our predictive models are evaluated using both statistical and economic measures. Within a dynamic asset allocation framework, an investor adjusts investment strategy weights based upon results of the prediction models. We find that our predictive model outperforms our benchmark, which uses historical average information in terms of statistical and economic measures. When the Sharpe ratio of the benchmark model is 0.52, our predictive model generates economic gain of approximately 1.16% per annum over the benchmark. These findings are robust to the changes in investors' risk aversion and target volatility for portfolio optimization.

Keywords: Currency portfolio, Out-of-sample predictability, Economic value, Portfolio optimization, Risk diversification

JEL codes: C32, F31, F37, G11

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1. Introduction

A currency investment strategy that exploits cross-sectional information across currencies is one of the important research themes in the foreign exchange (FX) market. Compared to exchange rate prediction models, currency investment strategies have been more successful in generating positive profits.[4] For instance, Lustig et al. (2011) use differentials of forward discounts, Menkhoff et al. (2012a) employ past currency excess returns, Asness et al. (2013) and Menkhoff et al. (2017) adopt deviation from real exchange rates. These currency investment strategies generally create positive average returns. Moreover, currency investment managers have generated returns that are closely related to investment strategies like carry, trend, and value (Pojarliev and Levich, 2010).

Among these currency investment strategies, currency carry trades have been widely investigated by the literature. Out-of-sample predictability for currency carry trades is explored by Bakshi and Panayotov (2013), Lu and Jacobson (2016), and Baek et al. (2020). They employ the out-of-sample testing framework proposed by Campbell and Thompson (2008), and Rapach et al. (2010) in the stock market context, and find that FX volatility, commodity prices, world stock markets and yield curve information are promising predictive variable candidates for carry trades. Currency carry trades, however,

[4] See, Messe and Rogoff (1983), Engel and West (2005), and Rossi (2013).

have a weak point that they have negative skewness and suffer large negative returns when stock markets plunge (e.g. Brunnermeier et al., 2009; Dobrynskaya, 2014). To avoid this drawback from investors' perspective, Kroencke et al. (2014), and Barroso and Santa-Clara (2015) demonstrate that diversifying currency investment strategies leads to a higher Sharpe ratio than investing in the carry portfolios only. The interest rates of commodity exporting countries declined after the global financial crisis, which resulted in lower profitability of the carry trade (Ready et al., 2017a). Therefore, seeking a new currency investment method is an important challenge for FX investors. We extend the studies of Kroencke et al. (2014) and Barroso and Santa-Clara (2015), and explore whether we can predict expected returns on these currency investment strategies and whether a change in the investment weight of each strategy provides a higher risk-return ratio in an out-of-sample context. Recently, Dupuy (2021) and Maurer et al. (2022) propose approaches that dynamically adjust weights on currencies in carry portfolios. Our study shares the motivation with these studies, whereas we adjust weights on currency investment strategies, which provide further risk diversification. Another strand of the literature, Campbell et al. (2003), Rapach and Wohar (2009), and Spierdijk and Umar (2014) focus on a multi-period portfolio choice problem with an infinite time horizon in stock and bond markets, but we explore one-month-ahead predictability in an out-of-sample context. Campbell et al.'s approach investigates both short- and long-run asset demands based on the Epstein-Zin utility and their motivation is related to the theoretical model. Our motivation is application of investment strategies and we consider the case that investors update information every month and conduct new prediction at a monthly frequency.[5]

The first contribution of this study is to extend the work of Bakshi and Panayotov (2013) to wider currency investment strategies. We consider the most widely used three strategies: carry (Lustig et al., 2011), momentum (Menkhoff et al., 2012a), value (Asness et al., 2013), while Bakshi and Panayotov (2013) explore only carry trades.[6] Furthermore, we investigate dollar carry trades (Lustig et al., 2014) and conditional FX correlation risk (Mueller et al., 2017). Carry trades are constructed based upon interest rate differentials between two countries, but dollar carry trades depend upon the differentials between the U.S. short-term interest rate and the average short-term interest rate across the other countries. Lustig et al. (2014) show that the correlation between carry trades and dollar carry trades is low. All portfolios are constructed based upon real-time financial market

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[5] Mutual funds are generally evaluated their performances at a monthly frequency (e.g. Ferson and Schadt, 1996; Fama and French, 2010).

[6] Filippou et al. (2018) and Grobsy et al. (2018) find that global market and political risks are linked to profits of currency momentum portfolios. Kremer et al. (2019) also investigate relationships between political risks and currency groups.

information, and hence they are applicable to investment strategies. In other words, we explore the predictability of the returns on five investment strategies. If predictability exists, we can improve the overall currency portfolio performance by dynamically adjusting the weights on the five strategies. It is because the five strategies use different information sets and diversification benefits are expected.

The second contribution of this study is that we evaluate our prediction performance based upon economic criteria. Della Corte et al. (2009) highlight that statistical evidence for exchange rate predictability does not imply that investors can obtain positive profits. Investors rebalance their portfolios if the new portfolio leads to significant economic gain. In order to reflect this point, Della Corte et al. employ a dynamic asset allocation framework and investigate a risk-averse invertor's willingness to pay for switching from a dynamic allocation portfolio based upon the random walk model to that based upon forecast models. This evaluation criteria is adopted in exchange rates, global bonds and equity markets (Della Corte et al., 2011; Rime et al., 2010; Thornton and Valente, 2012; Ahmed et al., 2016; Opie and Riddiough, 2020). We assess the predictability of the return on currency investment strategies and the important difference from the previous studies of Della Corte et al. (2009) and Rime et al. (2010), is that our framework determines their weights on investment strategies. In contrast to the previous studies, we construct the test portfolios using the following two steps. First, for each investment strategy, we explore which currencies are in a long (short) position based upon the currency portfolio literature. Second, we adopt the prediction models and determine the weights on investment strategies. Our framework significantly benefits to currency investors who employ multiple investment strategies in currency markets.

To preview our results, we find that predictive ability of all five currency investment strategies against the benchmark using historical average returns in the out-of-sample tests. In particular, combination forecasts significantly outperform the benchmark. The prediction model that exploits information of commodity prices, global stock markets, and FX volatility, provides an estimate of the economic value for a U.S. dollar based investor who switches from the benchmark to the predictive model. These findings are robust to the changes in investor's risk aversion and target volatility for the portfolio optimization.

We also uncover that FX volatility and commodity prices are important information for currency investment strategies, which is a complement to Bakshi and Panayotov (2013), who report that these predictors are associated with carry returns. We present empirical evidence that they are also linked to momentum, value, dollar carry, and correlation strategies. Our results are relevant to policy makers which affect commodity prices. The literature demonstrates that raising interest rates and large scale asset purchases by central banks cause declines in commodity prices (Frankel, 2008; Glick and Leduc, 2012; Hammoudeh et al., 2015). This indicates that a change in monetary policy drives a change in currency investment strategies for FX investors, and generates currency price fluctuations that influence both financial institutions and non-financial firms. For instance, Bruno and Shin (2017) report that many non-U.S. firms borrow in U.S. dollars, and Maggiori et al. (2020) uncover that non-U.S. investors prefer to hold U.S. dollar-denominated bonds after 2008.

The remainder of the paper is organized as follows. Section 2 provides literature review and Section 3 describes predictive regression models and currency investment strategies. Section 4 introduces statistical and economic measures in assessing forecast performances. Section 5 reports our data and main empirical results. Section 6 presents several robustness test results, and Section 7 concludes.

2. Literature Review

After introducing a currency portfolio approach proposed by Lustig and Verdelhan (2007), currency portfolios constructed by forward discounts (Lustig et al., 2011), past returns (Menkhoff et al., 2012a), and fundamental values (Asness et al., 2013; Menkhoff et al., 2017) are widely investigated in the literature. Many studies have sought risk factors that explain cross-sectional returns of currency portfolios. For example, Lustig et al. (2011) propose carry that is based on interest rate spreads, and Menkhoff et al. (2012b) and Ahmed and Valente (2015) focus on FX volatility. Stock market downside risk is also related to currency portfolio risk (Atanasov and Nitschka, 2014; Dobrynskaya, 2014; Byrne et al., 2018). Yin and Nie (2021) employ information from primary dealers. Some studies focus on macroeconomic information such as global imbalance (Della Corte et al., 2016), skewness of the unemployment gap (Berg and Mark, 2018), commodity price common factors (Byrne et al, 2019), combination of macroeconomic indicators at different frequencies (Dahlquist and Hasseltoft, 2020), relative output gap (Colacito et al., 2020), and credit default swap (Della Corte et al., 2021). Moreover, recent studies extract information from option markets. Fullwood et al. (2021) use implied volatility of currency options, Della Corte et al. (2021) employ term structures of implied volatility, and Fan et al. (2022) deploy equity tail risk from out-of-the-money put options on the stock market index.

In contrast to the burgeoning cross-sectional studies, a small number of studies focus on the out-of-sample predictability of currency investment strategies. Bakshi and Panayotov (2013) uncover that FX market volatility and commodity prices are important predictors, and Lu and Jacobson (2016) show that commodity prices are tied to a long position in carry trades. Baek et al. (2020) present that yield curve gaps are linked to carry trade predictability.

A carry strategy is the most popular investment strategy, and several studies enhance this strategy. Anatolyev et al. (2017) predict signs and absolute returns separately to improve the carry trade predictability. Bekaert and Panayotov (2020) propose a method for excluding a typical short currency (e.g. Japanese yen) and a long currency (e.g. Australian dollar). Dupuy et al. (2021) implement the carry strategy when transaction costs are relatively lower than expected returns. Dupuy (2021) and Maurer et al. (2022) introduce a volatility timing approach in carry portfolios. The former employs aggregate FX market volatility and the letter extracts information about correlations across currency returns.

The relationships between market conditions and carry trade profitability are also explored. Profitability is associated with FX market average variance (Cenedese et al., 2014), stock market implied volatility (Egbers and Swinkels, 2015), liquidity (Orlov, 2016), macroeconomic common factors (Filippou and Taylor, 2017), and order flows (Biswas et al., 2021). Kim (2015) and Sakemoto (2019) estimate time-varying relationships between carry trade profitability and market states, and Byrne and Sakemoto (2021) extend the time-varying relationships beyond carry trades.

This study fills a gap between out-of-sample prediction and currency investment strategies, because the previous out-of-sample prediction literature focuses on the carry strategy, whereas diversification of strategies is beneficial for FX investors. Kroencke et al. (2014) and Barroso and Santa-Clara (2015) also explore the diversification benefits, but the important deviation from our study is that we focus on out-of-sample predictions for each currency investment strategy.

We employ a dynamic asset allocation framework proposed by Della Corte et al. (2009), which focuses on a short-term predictability. This approach is adopted for currency (Della Corte et al., 2009; Rime et al., 2010; Ahmed et al., 2016), bond (Thornton and Valente, 2012; Opie and Riddiough, 2020), and equity (Opie and Riddiough, 2020) markets. Campbell et al. (2003) introduce a multi-period portfolio choice problem with an infinite time horizon, which provides both short- and long-term asset demands. This approach is employed for advanced (Rapach and Wohar, 2009), emerging (Spierdijk and Umar, 2014) and euro countries' stock and bond markets (Umar et al., 2019). Spierdijk and Umar (2015) also focus on short- and long-term asset prices and investigate inflation hedging abilities. Della Corte et al.'s (2009) approach is advantageous for investment application, because fund managers need to change portfolio weights at a shorter frequency using the new information. In contrast, Campbell et al.'s (2003) approach has strong theoretical backgrounds and is beneficial to consider long-term asset demands.

3. Predictive Models and Currency Investment Strategies

In this section, we begin with predictive models for currency investment strategies. We employ three candidate predictive variables and construct combined models. Then, we describe our five currency investment strategies: (i) carry, (ii) momentum, (iii) value, (iv) dollar carry, and (v) conditional FX correlation (ΔFXC).

3.1. Predictive models

We model the predictability of returns on each currency investment strategy based upon financial market variables. Following Bakshi and Panayotov (2013), and Lu and Jacobson (2016), an excess return r_{t+1} is driven by a vector of financial market variables x_t:

$$r_{t+1} = a + b'x_t + u_{t+1} \tag{1}$$

where a is a constant term, b is a vector of the estimated parameters and u_{t+1} is an error term. With respect to the financial variables used to predict the investment strategy excess return, we consider the following three variables (Bakshi and Panayotov, 2013; Lu and Jacobson, 2016).

1. *Change in global FX volatility* $\Delta\sigma_t^{FX}$: one-month change in global FX

volatility[7]

2. *Change in the CRB material index* ΔCRB_t: three-month change in the CRB material index

3. *Change in the world stock market* $\Delta MSCI_t$: two-month change in the MSCI world index

FX market volatility reflects short-term information, and hence we focus upon the one-month change. Bakshi and Panayotov (2013) propose to employ the three-month change in the CRB material index and Lu and Jacobson (2016) confirm that a longer term such as the three-month change contains more predictive power for carry returns. Furthermore, Lu and Jacobson (2016) report that the two-month change is the best interval for the MSCI world index. Other intervals for the returns are explored in Online Appendix. We focus upon one-month-ahead forecasts that have been widely investigated in the prediction literature (e.g. Campbell and Thompson, 2008). We follow Bakshi and Panayotov (2013) who report joint significance for these predictive variables and investigate the following four models: Model 1: $\Delta\sigma_t^{FX}$ and ΔCRB_t; Model 2: ΔCRB_t and $\Delta MSCI_t$; Model 3: $\Delta\sigma_t^{FX}$ and $\Delta MSCI_t$; and Model 4: $\Delta\sigma_t^{FX}$, ΔCRB_t and $\Delta MSCI_t$.

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[7] We calculate global FX volatility based upon Menkhoff et al. (2012b). See Online Appendix.

3.2. Currency investment strategies

We consider five investment strategies. We assume the perspective of a U.S. investor and the all positions are denominated in U.S. dollars. Following Bakshi and Panayotov (2013) and Kroencke et al. (2014), the currency excess return of a long position in currency *i* in month *t* is calculated as:

$$r_{i,t}^{long} = \frac{F_{i,t-1}^{bid} - S_{i,t}^{ask}}{S_{i,t}^{ask}} \tag{2}$$

where $F_{i,t-1}^{bid}$ is the bid price of one-month forward exchange rate per one U.S. dollar for delivery at the end of month *t* and $S_{i,t}^{ask}$ is the ask price of exchange rate per one U.S. dollar. Similarly, the currency excess return of a short position in currency *j* in month *t* is calculated as:

$$r_{j,t}^{short} = \frac{-F_{j,t-1}^{ask} + S_{j,t}^{bid}}{S_{j,t}^{bid}} \tag{3}$$

where $F_{j,t-1}^{ask}$ is the ask price of one-month forward exchange rate per one U.S. dollar for delivery at the end of month *t* and $S_{j,t}^{bid}$ is the bid price of exchange rate per one U.S. dollar. Then, the total excess return of this long-short position is calculated as:

$$er_{st,t}^{(k)} = r_{i,t}^{long} + r_{j,t}^{short} \tag{4}$$

where *k* is the number of currency pairs in the long-short position and *k*=1 indicates the highest (lowest) currency pair based upon a characteristic we will describe below.

The subscript *st* indicates investment strategies (carry, momentum, value, dollar carry and FX correlation). We calculate the average of total excess return over *k* currency positions $ter_{st,t}$ as:

$$ter_{st,t} = \frac{1}{K}\sum_{k=1}^{K} er_{st,t}^{(k)}. \quad (5)$$

3.2.1. Carry

We employ five currency investment strategies and begin with a currency carry trade which is constructed based upon forward discounts. This strategy exploits deviations from the uncovered interest rate parity and is explored in the literature (e.g. Lustig et al., 2011; Menkhoff et al., 2012b; Bakshi and Panayotov, 2013). A high interest rate currency generates a higher return than a low interest rate currency when the interest rate difference is not fully offset by the change in the spot exchange rate. Following Lustig et al. (2011), a forward discount $FD_{i,t}$ is computed as the difference between one-month forward and spot rates at time t:

$$FD_{i,t} = \frac{F_{i,t} - S_{i,t}}{S_{i,t}}. \quad (6)$$

When $FD_{i,t}$ is positive, this means that the interest rate in the foreign country i is higher than that in U.S., since we assume that the covered interest rate parity (CIP) condition is satisfied (e.g. Akram et al., 2008).[8] In carry portfolios, investors go long (short) in currencies when there are high (low) forward discounts. In other words, currency pairs in Equations (2) and (3) are determined by the forward discounts in Equation (6).

3.2.2. Momentum

In momentum portfolios, investors go long (short) in currencies that have had high (low) past excess returns. We employ a past three months cumulative currency excess return. Kroencke et al. (2014) and Barroso and Santa-Clara (2015) also adopt this definition, since Menkhoff et al. (2012a) report that momentum has persistence, but that including longer than the past three months does not provide a higher return. The past three months cumulative currency excess return, $PCUM_{i,t}$, is calculated as:

$$PCUM_{i,t} = \prod_{j=0}^{2}\left(1 + r_{i,t-j}^{long}\right) - 1. \tag{7}$$

A long position in Equation (2) and a short position (3) are determined by $PCUM_{i,t}$ in Equation (7).

[8] CIP may be violated after the global financial crisis (e.g. Du et al., 2018; Ibhagui, 2021). We use the only rank information of the forward discounts in order to construct the carry strategy, and therefore the impact of the systematic deviation of CIP is not large. Moreover, we investigate a portfolio that excludes the carry strategies in Section 6.4., and our conclusion does not change.

3.2.3. Value

A value strategy exploits information of a fundamental value: and if the price of currency *i* is undervalued compared with what is considered its fundamental value, then investors invest in the currency *i*. This strategy focuses upon deviation from purchasing-power parity (PPP), and a value of the exchange rate has a mean-reversion property in the long-run (e.g. Taylor, 2002; Boudoukh et al., 2016). The fundamental value is computed as the cumulative five-year change of the real exchange rate as in Kroencke et al. (2014) and Barroso and Santa-Clara (2015). The fundamental value $VA_{i,t}$ is computed as:

$$VA_{i,t} = \frac{S_{i,t-3} CPI_{i,t-60} CPI_{US,t-3}}{S_{i,t-60} CPI_{i,t-3} CPI_{US,t-60}} \tag{8}$$

where $CPI_{i,t-3}$ is the price level of consumer goods in country *i* at *t*-3, and $CPI_{US,t-3}$ is the price level in the U.S. We follow Kroencke et al. (2014) and employ a three-month lag to avoid overlaps between momentum and value strategies. Further, Barroso and Santa-Clara (2015) document that a lag value is appropriate since there is a time lag involved in the observation of price levels. In value portfolios, a long position in Equation (2) and a short position in Equation (3) are based on $VA_{i,t}$ in Equation (8).

3.2.4. Dollar carry trade

The dollar carry trade is based upon the average one-month forward discount (AFD) which is calculated as the average of forward discounts on foreign currency against the U.S. dollar (Lustig et al., 2014). AFD_t is calculated as:

$$AFD_t = \sum_{i=1}^{N} \frac{FD_{i,t}}{N} \tag{9}$$

where N is the number of all currency pairs and N=10 in this study. When AFD is above the U.S. short-term interest rate, 10 equally weighted foreign currencies are included in the long position in Equation (10), and when AFD is below the U.S. short-term interest rate, 10 equally weighted foreign currencies are included in the short position in Equation (11):

$$er_{dcarry,t} = \sum_{i=1}^{N} \frac{r_{i,t}^{long}}{N} \quad \text{if } AFD_t \geq 0 \tag{10}$$

$$er_{dcarry,t} = \sum_{i=1}^{N} \frac{r_{i,t}^{short}}{N} \quad \text{if } AFD_t < 0. \tag{11}$$

Note that $er_{AFD,t}$ does not have a superscript (k), since this strategy always employs 10 currency pairs. This strategy means that a U.S. dollar based investor buys foreign currencies against the U.S. dollar when the U.S. short-term rate is relatively low, and sells foreign currencies when the U.S. short-term rate is relatively high. This is a risky trade for the U.S. dollar based investor since she sells the U.S. dollar when demand of the U.S. dollar is high, and hence an average high return is compensation for this risk.

3.2.5. Conditional FX correlation risk

We employ a conditional FX correlation risk (ΔFXC) measure to formulate our final currency investment strategy. [9] This measure focuses upon increases of the correlation dispersion of exchange rate returns during bad market states (Mueller et al., 2017).[10] When financial market stress is high, high correlation FX pairs become more correlated than low correlation FX pairs. Currencies which work as hedges against the correlation risk yield average low returns, because they should be traded at premium prices due to the hedge function. We apply this property in the investment strategy by a beta sorting method (Lustig et al, 2011; Menkhoff et al, 2012b).

We follow Mueller et al. (2017) and employ the following four steps. First, a conditional correlation between FX spot rate changes is obtained, with a rolling window size of three months (66 days).[11] There are nine FX pairs of the U.S. dollar exchange rate, and therefore the total number of correlations is 36. Second, we sort 36 FX correlations into deciles based on the values of correlations, and take the difference between the correlation in the top decile and that in the bottom decile. This is called as the cross-

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[9] A conditional correlation means that the correlation varies over time based upon economic states (e.g. Lustig et al. 2011).

[10] Eriksen (2019) reports that return dispersion is related to profits of momentum portfolios.

[11] FX spot rate changes are calculated as: $s_{i,t+1} - s_{i,t}$, where s_i is the logarithm of the spot exchange rate i.

sectional dispersion in conditional FX correlation (FXC). Third, we select FXC at each end of month and take the innovation part of FXC (ΔFXC). Finally, we sort the currency pairs based upon factor betas on ΔFXC and we construct three portfolios. The low beta currency pairs are in the long position in Equation (2) and the high beta currency pairs in the short position in Equation (3). The high beta currency pairs function as hedges during market stress periods, and therefore the average returns are low in normal periods.

4. Forecast Evaluation

In this section, we first describe the statistical evaluation criteria used to evaluate each investment strategy return. Second, we describe the construction of a portfolio based upon the predictive models and the selection of weights on five investment strategies. Third, we turn to the performance evaluation based upon the portfolios constructed using the five investment strategies.

4.1. Statistical measures

This section describes the measures used to evaluate the out-of-sample predictive power of the investment strategy return. Our first measure is the out-of-sample R_{os}^2 to compare the mean squared errors (MSE) of the forecast and those of benchmark models (Campbell and Thompson, 2008; Rapach et al., 2013; Bakshi and Panayotov, 2013; Risse, 2019). Let $\widehat{ter}_{st,t+1}$ be the individual forecast of one-month ahead return based upon the predictive regression model and $\overline{ter}_{st,t+1}$ be the benchmark return that is calculated as the historical average of realized returns (e.g. Campbell and Thompson, 2008), then R_{os}^2 statistic is defined as follows:

$$R_{os}^2 = \left[1 - \frac{\sum_{t=0}^{T-1}\left(ter_{st,t+1} - \widehat{ter}_{st,t+1}\right)^2}{\sum_{t=0}^{T-1}\left(ter_{st,t+1} - \overline{ter}_{st,t+1}\right)^2}\right] \tag{12}$$

where $ter_{st,t+1}$ is the realized return. When $R_{os}^2 > 0$, the forecast return $\widehat{ter}_{st,t+1}$ outperforms the historical average forecast return $\overline{ter}_{st,t+1}$ in terms of MSE. We employ the adjusted mean squared prediction error statistic (*MSPE-adjusted*) proposed by Clark and West (2007) to assess the significance of the improvement (Rapach et al., 2010; Bakshi and Panayotov, 2013; Risse, 2019). This test statistic extends the Diebold and Mariano (1995), and West (1996) statistic given its nonstandard distribution when comparing forecasts from nested models. Following Rapach et al. (2010), a *p*-value for a one-sided (upper-tail) test is adopted. Our predictive regression models are nested models when we use the historical average as the benchmark.

The second measure for the out-of-sample predictions is the McCracken (2007) *F*-test (Welch and Goyal, 2008; Maio, 2014). The null hypothesis of this test is that the MSE of the predictive regression model MSE_A is less than or equal to that of the benchmark model MSE_N. The test statistic $MSE - F$ is given as:

$$MSE - F = T\frac{MSE_N - MSE_A}{MSE_N} \tag{13}$$

where $MSE_N = \sum_{t=0}^{T-1}\left(ter_{st,t+1} - \overline{ter}_{st,t+1}\right)^2$ and $MSE_A = \sum_{t=0}^{T-1}\left(ter_{st,t+1} - \widehat{ter}_{st,t+1}\right)^2$. The asymptotic null distribution of this statistic is nonstandard, which is written as a function of stochastic integrals of Brownian motion. We adopt the critical values provided by McCracken (2007).

4.2. Asset allocation framework

We consider that an investor adopts a dynamic asset allocation strategy in order to maximize the conditional expected return subjected to target conditional volatility (Della Corte et al., 2009, 2011; Rime et al., 2010; Thornton and Valente, 2012; Ahmed et al., 2016). We consider the following two steps. First, each investment strategy's one-month-ahead return forecast is generated by the predictive models described in the previous section. Second, the currency portfolios' optimal weights are determined on the mean-variance efficient frontier.

Let TER_{t+1} be the 5×1 vector of investment strategy returns at time $t+1$ and include carry ($ter_{carry,t+1}$), momentum ($ter_{mom,t+1}$), value ($ter_{value,t+1}$), dollar carry ($er_{dcarry,t+1}$) and conditional FX correlation risk ($ter_{FXC,t+1}$). It is written as $TER_{t+1} = \left(ter_{carry,t+1}, ter_{mom,t+1}, ter_{value,t+1}, er_{dcarry,t+1}, ter_{FXC,t+1}\right)$. Note that the excess return of the dollar carry trade is independent of the number of currency pairs

k, and hence we use $er_{dcarry,t+1}$, instead of $ter_{dcarry,t+1}$. The conditional expectation of TER_{t+1} is denoted as $\mu_{t+1|t} = E_t[TER_{t+1}]$ and the conditional variance-covariance matrix of TER_{t+1} is denoted as $\Sigma_{t+1|t} = E_t\left[(TER_{t+1} - \mu_{t+1|t})(TER_{t+1} - \mu_{t+1|t})'\right]$. An investor determines the weights on investment strategies w_t at each time based upon the following optimization problem:

$$\max_{w_t}\{(\mu_{p,t+1|t} = w_t'\mu_{t+1|t} + (1 - w_t'\iota)r_{f,t})\} \tag{14}$$

$$s.t. \qquad (\sigma_P^*)^2 = w_t'\Sigma_{t+1|t}w_t$$

where $\mu_{p,t+1|t}$ is the conditional expectation of the portfolio return vector constructed by currency investment strategies and the risk-free asset $r_{f,t}$, ι is a 5×1 vector of one, and σ_P^* is the target conditional volatility of the portfolio returns. The optimal weights are obtained as the solution to Equation (14) and written as:

$$w_t = \frac{\sigma_P^*}{\sqrt{C_t}}\Sigma_{t+1|t}^{-1}(\mu_{t+1|t} - \iota\, r_{f,t}) \tag{15}$$

where $C_t = (\mu_{t+1|t} - \iota\, r_{f,t})'\Sigma_{t+1|t}^{-1}(\mu_{t+1|t} - \iota\, r_{f,t})$. Following Ahmed et al. (2016), we impose a restriction for the optimal weights to avoid extreme values as: $-\iota \leq w_t \leq 2\,\iota$. Assuming that our base currency is the U.S. dollar, as in the standard of the literature,[12] a one-month Treasury bill rate is used as the risk-free rate (e.g. Fama and French, 1993). Then the gross return of an investor's optimal portfolio is calculated as follows:

[12] See Lustig et al. (2011) and Menkhoff et al. (2012a, 2012b).

$$R_{p,t+1} = 1 + r_{p,t+1} = 1 + (1 - w_t'\iota)\, r_{f,t} + w_t' TER_t \tag{16}$$

where $1 - w_t'\iota$ is the weight of the risk-free asset. After obtaining the portfolio return $R_{p,t+1}$, we assess performance of the predictive models using the following four measures.

4.3. Performance measures

The first performance measure is the Sharpe ratio, which is widely used in evaluating portfolio performances (e.g. Campbell and Thompson, 2008; Barroso and Santa-Clara, 2015). The Sharpe ratio is interpreted as a risk-adjusted return measure and calculated as a realized average excess return over realized standard deviation on a portfolio return.

The second measure is the Sortino ratio, which is related to the Sharpe ratio while focusing upon downside risk (Sortino and van der Meer, 1991; Sortino and Price, 1994). This measure employs downside risk rather than realized standard deviation in the Sharpe ratio, and is calculated as:

$$\frac{\overline{r_p - r_f}}{\sigma_P^-} \tag{17}$$

where $\overline{r_p - r_f}$ is the realized average excess return and $\sigma_P^- = \sigma_P\left(r_p < 0\right)$ is the downside risk on the portfolio.

The third measure is the performance fee measure which is based upon mean-variance analysis with quadratic utility and used in exchange rate and bond market studies (West et al.,1993; Della Corte et al., 2009, 2011; Rime et al., 2010; Thornton and Valente, 2012; Opie and Riddiough, 2020). The average realized utility $\bar{U}(\cdot)$ for an investor with initial wealth W_0 is constructed by the quadratic utility written as follows:

$$\bar{U}(\cdot) = \frac{W_0}{T}\sum_{t=0}^{T-1}\left(R_{p,t+1} - \frac{\gamma}{2(1+\gamma)}R_{p,t+1}^2\right) \tag{18}$$

where $R_{p,t+1}$ is the gross return on the investor's portfolio and γ is the investor's relative risk aversion (RRA). Following Fleming et al. (2001), we consider that a benchmark portfolio generates the same average utility to an alternative portfolio that is subjected to monthly expenses Φ expressed as a fraction of wealth invested in the portfolio. Monthly expenses Φ are considered as the maximum performance fee that an investor is willing to pay to switch from the alternative portfolio to a benchmark portfolio. The performance fee Φ is obtained by the following equation:

$$\sum_{t=0}^{T-1}\left\{\left(R_{p,t+1}^{*} - \Phi\right) - \frac{\gamma}{2(1+\gamma)}\left(R_{p,t+1}^{*} - \Phi\right)^2\right\} \tag{19}$$
$$= \sum_{t=0}^{T-1}\left\{\left(R_{p,t+1}^{BM}\right) - \frac{\gamma}{2(1+\gamma)}\left(R_{p,t+1}^{BM}\right)^2\right\}$$

where $R_{p,t+1}^{*}$ is the gross portfolio return constructed by a predictive model and $R_{p,t+1}^{BM}$ is the gross benchmark portfolio return. Note that $\Phi \leq 0$ means that the model has no predictive power.

The fourth measure is also a performance fee measure, however it is based upon a mean-variance utility function (Ahmed et al., 2016). We consider the following average realized utility of an investor:

$$\bar{U}_{MV}(\cdot) = \bar{R}_P - \frac{\gamma}{2T}\sum_{t=0}^{T-1}\left(R_{p,t+1} - \bar{R}_P\right)^2 \tag{20}$$

where $\bar{R}_P = \frac{1}{T}\sum_{t=0}^{T-1} R_{p,t+1}$. Then, performance fee Ψ is obtained as:

$$\Psi = \bar{U}_{MV}\left(R^*_{p,t+1}\right) - \bar{U}_{MV}\left(R^{BM}_{p,t+1}\right). \tag{21}$$

We obtain combined currency portfolios based upon the procedures described in Section 4.2., then we employ these four measures in order to compare the performance of the combined portfolio by the predictive models with that of the benchmark portfolio.

5. Empirical results

This section describes our data and empirical results. First, we introduce our data and present summary statistics of currency investment strategies. Second, we report out-of-sample investment strategy return forecasts based upon statistical measures. Finally, we present out-of-sample portfolio return forecasts based upon economic valuation measures.

5.1. Data and summary statistics of currency investment strategies

The data set employed in this study is daily spot and one-month forward exchange rates against the U.S. dollar, which are obtained from Datastream. Following Lustig et al. (2011) and Menkhoff et al. (2012b), we utilize bid and ask quotes to account for transaction costs. Our portfolio is monthly and calculated at the end of month values (e.g. Lustig et al., 2011). We focus upon G10 currencies which are most liquid currencies, and are widely traded by investors such as investment banks and hedge funds (Bakshi and Panayotov, 2013; Lu and Jacobsen, 2016; Aloosh and Bekaert, 2021).[13] G10 currencies are constructed by the Australian dollar, Canadian dollar, Danish krone, Swiss franc, British pound, Japanese yen, Norwegian krone, New Zealand dollar, Swedish krona, and euro.[14] The data cover from December 1983 to April 2017 (402 observations).[15] We also employ the consumer price index obtained from OECD/Main Economic Indicators to construct value portfolios.

We begin with the summary statistics of currency investment strategies and we consider three cases for each strategy except for the dollar carry (DC). For instance, Carry 1 means that one currency is in the long (short) position, and Carry 2 does two currency in the long (short) position, and so on.[16] In other words, Carry 1 is K=1 in Equation (5). All strategies in Table 1 provide positive excess returns, which is consistent with the

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[13] Lyons (2001) reports that these bid and ask quotes are larger than the actual quotes traded in the market, and hence our proposed portfolios may create higher returns in the actual market. Aloosh and Bekaert (2021) point out a problem to include emerging currencies in test portfolios.

[14] We replace the Deutsche mark with the euro prior to 1999.

[15] We extend the sample period and include the recent pandemic period in Section 6 and Table A11.

[16] $\Delta FXC1$ means that one currency that has the lowest (highest) factor beta on ΔFXC is in the long (short) position.

literature (e.g. Kroencke et al., 2014; Lustig et al., 2014; Barro and Santa-Clara, 2015; Mueller et al., 2017). When an investor holds one currency pair in the long (short) position, both average returns and standard deviation increase except for Δ FXC. This concentration on the investment currency pair leads to a higher Sharpe ratio for Mom, while the other strategies do not have the same pattern. DC provides the highest Sharpe ratio, 0.55 and Mom 3 does the worst, 0.09.

5.2. Results of statistical measures

We move on to the out-of-sample performances of our predictive models based upon the rolling window scheme, and the window size is 10 years (e.g. Rapach et al., 2010; Thorton and Valente, 2012). Table 2 reports the results for the out-of-sample R_{os}^2 and the $MSE-F$ statistic. We notice that most models have predictive power for returns of the carry strategy in Panel A. It is because all results for R_{os}^2 are statistically significant at least at the 5% level according to the *MSPE-adjusted* statistics, and those for $MSE-F$ are statistically significant at the 1% level. This finding is consistent with that reported by Bakshi and Panayotov (2013) and Lu and Jacobsen (2016) who present that the commodity prices, world stock markets, and FX volatility contain future information for carry trades. More importantly, we observe that these variables can forecast other investment strategy returns from Panels B to E of Table 2, except Model 3 in Panel D. These findings provide new insights since the previous literature focuses upon carry strategy returns, whereas our results show that the predictive variables are also linked to other investment strategy returns. Moreover, the momentum and value investment strategy results confirm that including several predictive variables leads to better performance as reported by Rapach et al. (2010) in the stock market context. We also observe that forecasting investment strategies of *K*=1 is more difficult because currency-specific components significantly impact returns of investment strategies. For instance, the results of Mom 1 in Panel B show that two out of the four models are statistically significant only at the 10% level. In contrast, the results of Mom 3 demonstrate that all four models are statistically significant at the 5% level. Therefore, we focus on *K*=2 or 3 in the later analysis.

Next, we follow Ahmed et al. (2016) and repeat the same analysis using the recursive scheme that increases the window size. Table 3 indicates that performances of the recursive scheme are inferior to those of the rolling window scheme. For instance, Panel C in Table 3 reveals that eight of the 12 models have a statistically significant R_{os}^2, but all models reduce the values of R_{os}^2 in comparison with the rolling window scheme. The results of Tables 2 and 3 suggest that the predictive models reflecting changes in economic states provide more accurate forecasts (Thornton and Valente, 2012).

Overall, the combination of commodity prices, world stock markets and FX volatility contain forward looking information that improves all five currency investment strategies.

5.3. Results of economic measures

Given the promising statistical measure results, we move on to the economic evaluations for the out-of-sample forecast models. We focus upon one-month-ahead forecasts. Each currency investment strategy is predicted by Models 1 to 4 in Table 2, and the currency portfolio is optimized based upon Equation (14). The optimized portfolio is dynamically rebalanced at a monthly frequency using the predictive models in Equation (1). We focus upon the rolling scheme that achieves a better performance than the recursive scheme in Tables 2 and 3. We set the target conditional volatility σ_P^* to 10% and the investor's relative risk aversion (RRA) γ to 6 as in Della Corte et al. (2009) and Ahmed et al. (2016).[17] The historical average of realized returns is employed as the benchmark (e.g. Campbell and Thompson, 2008).

[17] Grandelman and Hernandez-Murillo (2015) report smaller values of the risk aversion. We set a smaller risk aversion value in Section 6.

We start with rows (1) to (5) in Table 4, which reports results of Portfolio 2.[18] Models 1, 3, and 4 outperform the benchmark model (BM) based upon the performance fee measures Φ and Ψ, and the economic value ranges from 0.33% to 3.36%. These values are in the same levels compared with forecasting spot exchange rate returns (Della Corte et al., 2009). Only model 2 does not outperform the BM, which suggests that FX volatility contains useful information for prediction since the other models include the change in FX volatility as the predictive variable. The combined portfolios provide higher Sharpe ratios than individual investment strategies do, since each strategy has a different risk exposure. It is well-known that the carry strategy entails crash risk, and investors suffer negative profits when market liquidity dries up or stock prices plunge (Brunnermeier et al., 2009; Dobrynskaya, 2014). In contrast, the value strategy creates a higher profit during financial crises (Byrne and Sakemoto, 2021), which is related to mean reversion to the fundamental values of exchange rates (Jorda and Taylor, 2012). When a financial crisis occurs, then investors unwind the carry trades and demand for safe haven currencies which are generally low interest rate currencies. This opposite effect protects the value of the combined currency portfolios. Moreover, the dollar carry trade strategy

[18] We employ the same portfolio for the dollar carry since the definition of dollar carry does not allow us to change the number of investing currencies.

focuses on U.S. business cycles, while the conventional carry trade is more linked to commodity prices. Commodity exporting countries tend to keep higher interest rates compared with commodity importing countries due to weaker demand for precautionary saving (Ready et al., 2017b).

Next, we turn to Portfolio 3 and rows (6) to (10) in Table 4 present the empirical evidence that only model 4 has positive performance fees ranging from 0.35% to 0.39%. Model 4 includes three variables, which implies that combining information is useful as described in the previous section. Moreover, the predictive ability is unstable and depends upon economic states, which is similar to spot exchange rate forecasts (Sarno and Valente, 2009). We also conduct the same analysis using the recursive scheme in Table A6. We observe that three out of the eight models have the positive economic value ranging between 0.04% and 5.62%. In particular, Model 3 shows the highest economic value for Portfolios 2 and 3.

In summary, Model 4 outperforms the BM based upon the performance fee measures for both Portfolios 2 and 3. Moreover, most forecast models improve the prediction of BM for Portfolio 2.

5.4. Comparison with the previous studies

We compare our results with those of past studies that focus on currency prediction. Table 5 presents the results of the best model for each study. We employ Model 1 for Portfolio 2 in Table 4, which demonstrates that the economic value is 3.36%. Della Corte et al. (2009) adopt forward discounts as predictors and their economic value is 2.67%, which is relatively lower than ours. This is explained by the higher Sharpe ratio of the BM, which indicates 0.76, whereas ours shows 0.52. This strong BM suggests that the diversification of investment currencies provides high profitability during this period. However, the Sharpe ratios of the BM reported by Ahmed et al. (2016) and this study demonstrate that the diversification of investment currencies reduces effectiveness in the recent period. This is associated with a strong demand for U.S. dollars after the global financial crisis (Bruno and Shin, 2017; Maggiori et al., 2020). The decline in the risk diversification merits in the currency market highlights the advantage of our approach, which diversifies investment strategies, not investment currencies.

In addition, Rime et al. (2010) provide empirical evidence that adopting order flows leads to higher economic gain. Their strong results stem from the difference in investment time horizons and they focus on daily prediction, but the other studies, including us, conduct monthly predictions. In terms of the investment perspective, investors need to take into account high transaction costs for daily prediction, but our predictive models have already included transaction costs in Equations (2) and (3).

6. Robustness

Having found the positive performance fee for model 4, we investigate robustness of the findings. More specifically, we conduct (i) change in the target conditional volatility; (ii) change in the relative risk aversion parameter; (iii) estimating confidence intervals; (iv) excluding the carry strategy; (v) split sample periods; and (vi) change in conditional FX correlation parameters.

6.1. Change in the target target conditional volatility

First, we set different target conditional volatility when we optimize portfolios. Following Della Corte et al. (2009), we repeat the same calculations at σ_P^* = 8% and 12%, respectively. Panel A in Table 6 displays the results at σ_P^* = 8%. We note that models 1, 3 and 4 beat the BM based upon the performance fee measures for Portfolio 2 in rows (2), (4), and (5) of Table 6. These findings are consistent with those of Table 4. We find the same pattern at σ_P^* = 12% in Panel B of Table 6. The economic value for the investor at σ_P^* = 12% is higher than those at σ_P^* = 8%, which suggests that the predictive models are more useful when we set higher target volatility. Della Corte et al. (2009) report the same pattern in the spot exchange rate context; therefore, the pattern holds when we extend to the currency investment portfolios.

6.2. Change in the risk aversion parameter

Second, we follow Della Corte et al. (2009) and set RRA γ to 2, which indicates a less risk-averse investor. Table 7 reports that the change in RRA does not affect our conclusions qualitatively, whereas the magnitudes are smaller than those in Tables 4 and 6. These results imply that the performance fee measures increase with a higher RRA, unlike the bond market results reported by Thornton and Valente (2012). Our results suggest that when investors are risk-averse, the forecast models present better performances. This pattern does not change when we set different target conditional volatility.

6.3. Calculating confidence intervals

There may be concern of data mining when we select the best predictor in the out-of-sample context (e.g. Welch and Goyal, 2008). For this reason, we focus upon model 4, which includes all predictive variables. We calculate the median economic gains for the model with changing RRA from 2 to 6, and target volatility from 8% to 12%. Table 8 presents the median economic gain generated by model 4 and the 95% confidence interval.[19] We find that the economic gain (Φ) for Portfolio 2 is about 0.89% and that for Portfolio 3 is about 0.27%. Importantly, the confidence intervals for both portfolios are above zero. Note that our BM portfolios have high Sharpe ratios since they diversify investment strategies. (e.g. Kroencke et al., 2014). For instance, the Sharpe ratio of the BM for Portfolio 2 is 0.52 and the ratio for Portfolio 3 is 0.63, using the setting of Table 4. Our results suggest that our predictive model employing all three variables generates economic gains over the strong benchmarks.

6.4. Excluding carry trades

Covered interest rate parity may be violated after the global financial crisis and it may affect the performance of the carry strategy (Du et al., 2018). Moreover, Ready et al. (2017a) and Bussiere et al. (2019) point out that carry trades do not make profits after the crisis. Because of these results, we exclude the carry strategy and construct a portfolio using our four other strategies. Then, we repeat the same evaluation that we conducted in

[19] Our bootstrapped-based distributions are based on 10,000 draws with replacement from the respective sample.

Table 4. We report the results in Table A7, and find that our main prediction models generate positive economic gains.

6.5. Subsample predictions

We also evaluate the predictive model performances in different subsample periods, since relations between exchange rates and predictive variables are unstable (Sarno and Valente, 2009). Moreover, we explore effects of market turmoil trigged by the COVID19 outbreak. We investigate the following four subsamples; 1993:11-1999:12; 2000:1-2009:12; 2010:1-2019:12; 2020:1-2021:12, which indicates 90s, 00s, 10s and the pandemic period. The rolling estimation scheme is adopted for each period and the window size is 120 months as in Table 4. The target conditional volatility is 10% and RRA is 6, which also corresponds to the estimations in Table 4.

The best subsample period is 2010-2019, as shown in Panel C of Table 9. Most models outperform the BM for Portfolios 2 and 3 in terms of performance fee measures. The BM demonstrates a much lower Sharpe ratio during this period; hence, the predictive variables have incremental information. Table A12 shows that most strategies do not generate a high Sharpe ratio in this period. The weak performance of the BM is associated with low interest rates for commodity exporting countries, which leads to a low return for the carry strategy. Ready et al. (2017a) explain this situation using a theoretical model that illustrates slow adjustment in the shipping sector, which expanded its capacity before the global financial crisis. Tables 1 and A12 present that the carry strategies in this period provide lower profitability compared with those in other periods. Moreover, the momentum strategy shows the worst return during 2010-2019, which is consistent with the recent work of Byrne et al. (2022). The weak performance of the momentum strategy is also linked to structural changes in the currency market. Maggiori et al. (2020) point out that demand for U.S. dollars strengthened and that for the euro weakened after the global financial crisis and the debt crisis in the euro area.

Finally, Panel D of Table 9 indicates that both BM and predictive portfolios create higher Sharpe ratios in this period. This is related to an increase in expected inflation generated by the ceasing monetary policy and the disruption of supply chain during the pandemic. This raises a return of the carry strategy, and Table A13 provides empirical evidence that the carry strategy is a main driving force for higher Sharpe ratios in portfolios.

6.6. Change in conditional FX correlation parameters

We explore whether a choice of the conditional FX correlation strategy parameters impacts our results. There are four parameters in this strategy; window size of daily correlations; the number of portfolios to calculate average correlation spread; window size of beta estimation; and the number of investment currencies.

Table A8 presents the summary statistics for different parameter combinations. We note that our base parameters do not cause extreme results. We evaluate predictability based upon the statistical measures in Table A9. We observe that the predictive model that includes FX volatility, commodity and world stock market returns is successful in improving the BM results. Finally, we repeat the evaluation by the performance measures. In addition to the conditional FX correlation strategy with different parameter combinations, we employ the other four strategies used in Table 4. Table A10 presents that five out of the six results are positive economic gains in Panel A. More importantly, median values are positive for both Panels A and B. Note that our BM is strong compared with that of the traditional currency forecast literature, since it diversifies investment strategies (Kroencke et al., 2014 and Barroso and Santa-Clara, 2015). Therefore, the incremental power of the predictive model is important.

7. Conclusion

Exchange rate prediction has been regarded as difficult to outperform the random walk ever since Messe and Rogoff (1983). Recent studies present more promising results by adopting cross-sectional differentials of currency characteristics and currency investment strategies (Lustig et al., 2011 and Menkhoff et al., 2012a). In particular, currency carry trades have been widely investigated by the literature and adopted by investors (e.g. Menkhoff et al., 2012b). Furthermore, Bakshi and Panayotov (2013) find that the predictive models for the currency carry strategy outperform the historical average prediction in the out-of-sample context.

This study extends out-of-sample forecasts of currency portfolios in the two aspects. First, we consider five different types of currency investment strategies hoping to gain from diversification of currency investment styles to produce a higher Sharpe ratio and mitigate negative skewness of carry trades (Kroencke et al., 2014; Barroso and Santa-Clara, 2015). We focus upon the following five strategies widely implemented by investors, namely, carry (Lustig et al., 2011), momentum (Menkhoff et al., 2012a), value (Asness et al., 2013), dollar carry trade (Lustig et al., 2014) and conditional FX correlation risk (Mueller et al., 2017). Second, we assess the out-of-sample forecast performances based upon economic measures, since investors adjust their portfolio weights when economic gain from the predictive models is sufficiently large (Della Corte et al., 2009). In contrast to the previous studies, we construct a combined portfolio from currency investment strategies.

Our empirical evidence shows that the predictive models outperform the BM in terms of statistical measures. This finding is observed not only for carry, but also for the other four investment strategies. More importantly, our analysis demonstrates that prediction models have the positive economic value. When the Sharpe ratio of the BM model is 0.52, our predictive model generates the economic gain about 1.16% per annum over the BM. This is robust to changes in target volatility and investor's risk-aversion. The predictive power increases with higher target volatility is set. Our results demonstrate that diversified currency investment strategies and a change in the allocation of the strategies generate economic gain for FX investors. We also uncover that FX volatility and commodity price information contain predictive power for these strategies. Policy makers should be careful when they change monetary policy, which impacts not only commodity prices but also FX investors' currency allocation. This may cause an unexpected fluctuation in exchange rates.

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Table 1. Summary statistics of currency investment strategies

	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
Carry 1	3.93	12.95	-0.61	6.62	15.89	-19.05	0.30
Carry 2	2.99	8.90	-0.40	4.82	10.84	-10.57	0.34
Carry 3	2.80	7.37	-0.48	4.89	8.18	-8.64	0.38
Mom 1	2.90	12.65	0.83	8.72	26.01	-10.13	0.23
Mom 2	1.67	9.43	0.44	4.96	12.52	-6.90	0.18
Mom 3	0.71	7.77	0.41	5.23	10.58	-6.60	0.09
Value 1	4.17	12.97	0.65	6.76	20.84	-12.30	0.32
Value 2	3.40	9.09	0.08	4.75	11.19	-10.34	0.37
Value 3	2.00	7.27	0.02	4.14	8.67	-8.19	0.28
DC	4.52	8.26	0.02	3.81	10.32	-7.29	0.55
ΔFXC 1	1.87	13.52	-0.96	7.91	10.15	-26.01	0.14
ΔFXC 2	2.30	10.20	-0.47	4.64	8.49	-12.52	0.23
ΔFXC 3	2.91	8.32	-0.21	3.83	7.41	-9.64	0.35

Notes: This table reports annualized mean, annualized standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of currency portfolio excess returns. We employ five currency portfolios: carry, momentum, value, dollar carry (DC, Lustig et al., 2014), and conditional FX correlation risk (ΔFXC, Mueller et al., 2017). We consider three portfolios for each strategy except DC. For instance, Carry *j* indicates that *j* currencies are in the long and short positions. The sample period is December 1983 to April 2017.

Table 2. Out-of-sample forecasting results based upon the rolling scheme

Panel A: Carry		R^2_{os}		MSE-F		Panel B: Momentum		R^2_{os}		MSE-F	
(1) Model 1	Carry 1	6.22	**	18.71	***	(1) Model 1	Mom 1	4.51	*	13.33	***
(2) Model 2	Carry 1	6.54	**	19.72	***	(2) Model 2	Mom 1	4.04	**	11.86	***
(3) Model 3	Carry 1	3.79	**	11.12	***	(3) Model 3	Mom 1	3.87	*	11.37	***
(4) Model 4	Carry 1	7.67	**	23.43	***	(4) Model 4	Mom 1	6.25	**	18.80	***
(5) Model 1	Carry 2	5.88	***	17.62	***	(5) Model 1	Mom 2	2.14	*	6.17	***
(6) Model 2	Carry 2	6.48	***	19.53	***	(6) Model 2	Mom 2	2.19	**	6.30	***
(7) Model 3	Carry 2	3.58	***	10.47	***	(7) Model 3	Mom 2	1.67	**	4.80	***
(8) Model 4	Carry 2	7.42	***	22.59	***	(8) Model 4	Mom 2	3.00	**	8.73	***
(9) Model 1	Carry 3	4.62	**	13.66	***	(9) Model 1	Mom 3	3.13	**	9.11	***
(10) Model 2	Carry 3	5.07	**	15.07	***	(10) Model 2	Mom 3	2.91	**	8.45	***
(11) Model 3	Carry 3	2.42	**	6.99	***	(11) Model 3	Mom 3	1.77	**	5.08	***
(12) Model 4	Carry 3	5.97	***	17.89	***	(12) Model 4	Mom 3	3.94	**	11.55	***

Panel C: Value		R^2_{os}		MSE-F		Panel D: ΔFXC		R^2_{os}		MSE-F	
(1) Model 1	Value 1	4.07	*	11.97	***	(1) Model 1	ΔFXC 1	6.52	**	19.66	***
(2) Model 2	Value 1	6.28	**	18.90	***	(2) Model 2	ΔFXC 1	5.85	**	17.51	***
(3) Model 3	Value 1	5.59	**	16.70	***	(3) Model 3	ΔFXC 1	3.14		9.15	***
(4) Model 4	Value 1	7.72	**	23.58	***	(4) Model 4	ΔFXC 1	7.90	**	24.20	***
(5) Model 1	Value 2	2.30	**	6.65	***	(5) Model 1	ΔFXC 2	7.60	**	23.20	***
(6) Model 2	Value 2	4.27	***	12.57	***	(6) Model 2	ΔFXC 2	7.54	***	23.00	***
(7) Model 3	Value 2	3.45	***	10.08	***	(7) Model 3	ΔFXC 2	1.94		5.58	***
(8) Model 4	Value 2	5.24	***	15.60	***	(8) Model 4	ΔFXC 2	8.72	***	26.94	***
(9) Model 1	Value 3	2.30	**	6.65	***	(9) Model 1	ΔFXC 3	6.64	***	20.06	***
(10) Model 2	Value 3	4.27	**	12.57	***	(10) Model 2	ΔFXC 3	6.60	***	19.94	***
(11) Model 3	Value 3	3.45	**	10.08	***	(11) Model 3	ΔFXC 3	2.68	*	7.78	***
(12) Model 4	Value 3	5.24	***	15.60	***	(12) Model 4	ΔFXC 3	8.56	***	26.40	***

Panel E: Dollar Carry		R^2_{os}		MSE-F	
(1) Model 1	DC	4.55	***	13.45	***
(2) Model 2	DC	3.31	***	9.64	***
(3) Model 3	DC	3.11	**	9.06	***
(4) Model 4	DC	5.28	***	15.71	***

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The predictive variables are $\Delta\sigma_t^{FX}$, ΔCRB_t, and $\Delta MSCI_t$. The second column indicates an investment strategy that is predicted. For instance, Carry *j* indicates that *j* currencies are in the long and short positions. We consider four combination forecasts : Model 1 includes $\Delta\sigma_t^{FX}$ and ΔCRB_t; Model 2 does ΔCRB_t and $\Delta MSCI_t$; Model 3 does $\Delta\sigma_t^{FX}$ and $\Delta MSCI_t$; Model 4 does $\Delta\sigma_t^{FX}$, ΔCRB_t and $\Delta MSCI_t$. The Campbell and Thompson (2008) out-of-sample R_{os}^2 statistic is reported, and the *p*-value based upon the Clark and West (2007) *MSPE-adjusted* statistic is employed. The McCracken (2007) *F*-test statistic (*MSE-F*) is reported and the critical value is based upon McCracken (2007). *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The out-of-sample forecasts are November 1993 to April 2017.

Table 3. Out-of-sample forecasting results based upon the recursive scheme

Panel A: Carry		R^2_{os}		MSE-F		Panel B: Momentum		R^2_{os}		MSE-F	
(1) Model 1	Carry 1	4.35	**	12.81	***	(1) Model 1	Mom 1	2.15		6.19	***
(2) Model 2	Carry 1	5.35	**	15.95	***	(2) Model 2	Mom 1	1.28		3.66	**
(3) Model 3	Carry 1	2.95	**	8.57	***	(3) Model 3	Mom 1	1.21		3.44	**
(4) Model 4	Carry 1	5.81	**	17.38	***	(4) Model 4	Mom 1	2.21		6.36	***
(5) Model 1	Carry 2	4.79	***	14.19	***	(5) Model 1	Mom 2	4.79	*	14.19	***
(6) Model 2	Carry 2	5.69	***	17.02	***	(6) Model 2	Mom 2	1.26	*	3.60	**
(7) Model 3	Carry 2	2.47	***	7.13	***	(7) Model 3	Mom 2	0.85	**	2.41	**
(8) Model 4	Carry 2	5.92	***	17.75	***	(8) Model 4	Mom 2	1.63	**	4.69	***
(9) Model 1	Carry 3	3.56	**	10.42	***	(9) Model 1	Mom 3	1.79	*	5.13	***
(10) Model 2	Carry 3	3.90	**	11.44	***	(10) Model 2	Mom 3	1.99	*	5.73	***
(11) Model 3	Carry 3	1.03	**	2.94	**	(11) Model 3	Mom 3	0.99	**	2.83	**
(12) Model 4	Carry 3	4.11	**	12.08	***	(12) Model 4	Mom 3	2.30	*	6.64	***

Panel C: Value		R^2_{os}		MSE-F		Panel D: ΔFXC		R^2_{os}		MSE-F	
(1) Model 1	Value 1	1.44		4.13	**	(1) Model 1	ΔFXC 1	0.63	*	1.80	**
(2) Model 2	Value 1	3.67	*	10.75	***	(2) Model 2	ΔFXC 1	0.38		1.07	*
(3) Model 3	Value 1	2.70	*	7.84	***	(3) Model 3	ΔFXC 1	0.67		1.91	**
(4) Model 4	Value 1	4.07	*	11.96	***	(4) Model 4	ΔFXC 1	0.68	*	1.93	**
(5) Model 1	Value 2	0.94	*	2.68	**	(5) Model 1	ΔFXC 2	1.50	*	4.29	***
(6) Model 2	Value 2	0.90	*	2.55	**	(6) Model 2	ΔFXC 2	1.63	**	4.67	***
(7) Model 3	Value 2	0.59		1.68	*	(7) Model 3	ΔFXC 2	-0.04		-0.10	
(8) Model 4	Value 2	1.21	*	3.45	**	(8) Model 4	ΔFXC 2	1.38	**	3.94	**
(9) Model 1	Value 3	1.34	**	3.82	**	(9) Model 1	ΔFXC 3	1.51	**	4.34	***
(10) Model 2	Value 3	0.48		1.36		(10) Model 2	ΔFXC 3	1.55	**	4.43	***
(11) Model 3	Value 3	0.64		1.80	**	(11) Model 3	ΔFXC 3	0.81	*	2.30	**
(12) Model 4	Value 3	1.21	*	3.45	**	(12) Model 4	ΔFXC 3	1.93	**	5.54	***

Panel E: Dollar Carry		R^2_{os}		MSE-F	
(1) Model 1	DC	2.57	**	7.43	***
(2) Model 2	DC	2.11	***	6.09	***
(3) Model 3	DC	1.41		4.03	**
(4) Model 4	DC	3.10	***	9.03	***

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of currency investment strategies from recursive scheme with a 120 month initial expanding window. See notes of Table 2.

Table 4. Economic value of portfolio return predictability

	Portfolio	SR	SOR	Φ	Ψ
(1) BM	2	0.52	1.20		
(2) Model 1	2	0.52	1.20	3.36	3.28
(3) Model 2	2	0.50	1.19	-0.17	-0.26
(4) Model 3	2	0.52	1.22	0.39	0.33
(5) Model 4	2	0.54	1.31	1.16	1.09
(6) BM	3	0.63	1.47		
(7) Model 1	3	0.53	1.25	-2.61	-2.66
(8) Model 2	3	0.55	1.31	-2.34	-2.35
(9) Model 3	3	0.46	1.08	-4.84	-4.86
(10) Model 4	3	0.64	1.54	0.39	0.35

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). The one-month-ahead return forecasts of investment strategies from rolling regressions with a 120 month window. The first column contains the predictive models, the second column indicates the number of currencies in the long and short positions. The third and the fourth columns indicate Sharpe ratio (SR) and Sortino ratio (SOR). The fifth column presents performance fees (Φ) for predictive models against the benchmark model. The portfolio target volatility (σ_P^*) is 10% and a risk-averse investor has a quadratic utility function as in Fleming et al. (2001) and the relative risk aversion parameter γ is 6 (Della Corte et al., 2009). The last column presents performance fees (Ψ) for predictive models against the benchmark model, which is calculated based upon a mean-variance function form for utility (Ahmed, 2016). The SR and SOR are annualized, while Φ and Ψ are reported in % per annum.

Table 5. Comparisons with past studies

	Predictive variables	Periods	SR_BM	SR	Φ	γ	TV
Model 1	commodity, FX volatility, world stock return	198311-201704	0.52	0.52	3.36	6	10
Della Corte et al. (2009)	forward bias	197601-200412	0.76	1.12	2.67	6	10
Rime et al. (2010)	order flow, forward bias	2004/Jun/15-2005/Feb/14	-1.35	1.45	24.83	5	10
Ahmed et al. (2016)	currency factors	198311-201311	0.47	0.38	-1.00	6	10

Notes: This table presents comparisons with previous studies. Model 1 indicates that it is Model 1 for Portfolio 2 in Table 4. We report the Sharpe ratio of the benchmark model (Sharpe ratio (SR), Sharpe ratio (SR), performance fees (Φ), the relative risk aversion parameter (γ), and target volatility (TV). We present the model with highest performance fee for Della Corte et al. (2009) Table 8, Rime et al. (2010) Table 5, and Ahmed et al. (2016) Table 8, respectively.

Table 6. Economic value of portfolio return predictability: (σ_P^*) = 8 or 12%

	Portfolio	SR	SOR	Φ	Ψ
Panel A: σ_P=8					
(1) BM	2	0.58	1.36		
(2) Model 1	2	0.67	1.61	2.65	2.59
(3) Model 2	2	0.53	1.31	-0.61	-0.67
(4) Model 3	2	0.58	1.40	0.35	0.32
(5) Model 4	2	0.58	1.44	0.57	0.52
(6) BM	3	0.67	1.61		
(7) Model 1	3	0.56	1.36	-2.57	-2.60
(8) Model 2	3	0.58	1.42	-2.15	-2.16
(9) Model 3	3	0.50	1.21	-4.20	-4.20
(10) Model 4	3	0.67	1.66	0.09	0.07
Panel B: σ_P=12					
(1) BM	2	0.50	1.12		
(2) Model 1	2	0.60	1.39	4.29	4.18
(3) Model 2	2	0.48	1.13	0.36	0.25
(4) Model 3	2	0.51	1.16	0.97	0.89
(5) Model 4	2	0.53	1.26	2.07	1.96
(6) BM	3	0.61	1.38		
(7) Model 1	3	0.52	1.22	-2.11	-2.20
(8) Model 2	3	0.54	1.26	-2.24	-2.25
(9) Model 3	3	0.43	0.99	-5.31	-5.35
(10) Model 4	3	0.63	1.50	1.00	0.95

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). The one-month-ahead return forecasts of investment strategies from rolling regressions with a 120 month window. The first column contains the predictive models, the second column indicates the number of currencies in the long and short positions. The third and the fourth columns indicate Sharpe ratio (SR) and Sortino ratio (SOR). The fifth column presents performance fees (Φ) for predictive models against the benchmark model. The portfolio target volatility (σ_P^*) is 8 or 12%. and a risk-averse investor has a quadratic utility function as in Fleming et al. (2001) and the relative risk aversion parameter γ is 6 (Della Corte et al., 2009). The last column presents performance fees (Ψ) for predictive models against the benchmark model, which is calculated based upon a mean-variance function form for utility (Ahmed, 2016). The SR and SOR are annualized, while Φ and Ψ are reported in % per annum.

Table 7. Economic value of portfolio return predictability: γ=2

	Portfolio	Φ	Ψ
Panel A: σ_P=8, γ=2			
(1) Model 1	2	2.23	2.23
(2) Model 2	2	-1.13	-1.13
(3) Model 3	2	0.07	0.07
(4) Model 4	2	0.18	0.18
(5) Model 1	3	-2.79	-2.79
(6) Model 2	3	-2.24	-2.24
(7) Model 3	3	-4.25	-4.25
(8) Model 4	3	-0.05	-0.06
Panel B: σ_P=10, γ=2			
(1) Model 1	2	2.81	2.80
(2) Model 2	2	-0.82	-0.83
(3) Model 3	2	-0.01	-0.02
(4) Model 4	2	0.62	0.62
(5) Model 1	3	-2.98	-2.99
(6) Model 2	3	-2.44	-2.44
(7) Model 3	3	-4.94	-4.94
(8) Model 4	3	0.15	0.14
Panel C: σ_P=12, γ=2			
(1) Model 1	2	3.52	3.51
(2) Model 2	2	-0.42	-0.44
(3) Model 3	2	0.38	0.37
(4) Model 4	2	1.33	1.32
(5) Model 1	3	-2.73	-2.73
(6) Model 2	3	-2.29	-2.29
(7) Model 3	3	-5.56	-5.56
(8) Model 4	3	0.67	0.67

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns. The first column contains the predictive models, the second column indicates the number of currencies in the long and short positions. The third column presents performance fees (Φ) for predictive models against the benchmark model. The last column presents performance fees (Ψ) for predictive models against the benchmark model, which is calculated based upon a mean-variance function form for utility. Φ and Ψ are reported in % per annum.

Table 8. Median values for Model 4

Model	Portfolio		Φ	Ψ
Model 4	2	Median	0.89	0.86
		95% CI	(0.18, 1.34)	(0.35, 1.32)
Model 4	3	Median	0.27	0.25
		95% CI	(0.02, 0.67)	(0.01, 0.67)

Notes: This table presents the median values of performance fees (Φ, Ψ) for predictive models against the benchmark. We calculate the median values with changing RRA from 2 to 6, and target volatility from 8% to 12%. The predictive model is Model 4 that includes all three variables: a one-month change in global FX volatility ($\Delta\sigma_t^{FX}$), a three-month change in the CRB material index (ΔCRB_t) and a two-month change in the world stock market index ($\Delta MSCI_t$). 95% bootstrap confidence intervals are reported in parentheses. The bootstrapped-based distributions are based on 10,000 draws with replacement from the respective sample.

Table 9. Subsample analysis

	Portfolio	SR	SOR	Φ	Ψ
Panel A: 1993:11-1999:12					
(1) BM	2	0.16	0.33		
(2) Model 1	2	0.02	0.04	-3.91	-3.91
(3) Model 2	2	0.15	0.34	-0.41	-0.39
(4) Model 3	2	0.03	0.07	-2.81	-2.83
(5) Model 4	2	0.06	0.13	-2.84	-2.83
(6) BM	3	0.00	-0.01		
(7) Model 1	3	-0.28	-0.63	-6.89	-6.89
(8) Model 2	3	-0.28	-0.62	-6.96	-6.96
(9) Model 3	3	0.36	0.82	8.93	8.95
(10) Model 4	3	-0.05	-0.11	-1.43	-1.42
Panel B: 2000:01-2009:12					
(1) BM	2	0.90	2.13		
(2) Model 1	2	1.03	2.45	4.71	4.52
(3) Model 2	2	0.89	2.20	0.52	0.34
(4) Model 3	2	0.89	2.13	-0.04	-0.10
(5) Model 4	2	0.91	2.24	0.59	0.50
(6) BM	3	1.34	3.23		
(7) Model 1	3	0.95	2.30	-12.17	-11.86
(8) Model 2	3	1.02	2.51	-10.37	-9.91
(9) Model 3	3	0.96	2.33	-12.38	-11.94
(10) Model 4	3	1.01	2.49	-10.77	-10.26

Notes: See the next page.

Table 9. Continued

	Portfolio	SR	SOR	Φ	Ψ
Panel C: 2010:1-2019:12					
(1) BM	2	0.19	0.42		
(2) Model 1	2	0.42	0.97	8.62	8.57
(3) Model 2	2	0.16	0.37	1.29	1.35
(4) Model 3	2	0.38	0.85	7.15	7.10
(5) Model 4	2	0.16	0.37	1.28	1.34
(6) BM	3	0.05	0.12		
(7) Model 1	3	0.50	1.14	11.59	11.60
(8) Model 2	3	0.10	0.21	0.76	0.76
(9) Model 3	3	-0.29	-0.61	-8.73	-8.73
(10) Model 4	3	0.32	0.73	6.79	6.80
Panel D: 2020:1-2021:12					
(1) BM	2	1.21	2.86		
(2) Model 1	2	1.12	2.84	-3.61	-3.18
(3) Model 2	2	0.49	1.18	-21.47	-21.15
(4) Model 3	2	0.60	1.48	-19.78	-19.08
(5) Model 4	2	0.83	2.08	-12.33	-11.78
(6) BM	3	1.44	3.79		
(7) Model 1	3	1.99	6.09	14.50	14.49
(8) Model 2	3	1.03	2.52	-11.84	-11.37
(9) Model 3	3	1.46	3.71	0.29	0.60
(10) Model 4	3	1.23	3.22	-6.74	-5.97

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). We explore the following four periods: (i) November 1993 to December 1999; (ii) January 2000 to December 2009; (iii) January 2010 to December 2019; and (vi) January 2020 to December 2021. See notes of Table 4.

Dynamic Allocations for Currency Investment Strategies

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A1. Global FX volatility

We calculate global FX volatility as in Menkhoff et al. (2012b). Let $r_{j,d}$ be an excess return of currency *j* in day *d*, and global FX volatility $\sigma_{FX,d}$ is obtained as:

$$\sigma_{FX,d} = \sum_{j=1}^{K_d} \left(\frac{|r_{j,d}|}{K_d} \right) \tag{A1}$$

where $|r_{j,d}|$ is the absolute value of $r_{j,d}$, and K_d is the number of currencies in day *d*. Next, monthly global FX volatility in month *t*, $\sigma_{FX,t}$, is calculated as:

$$\sigma_{FX,t} = \frac{1}{T_t} \sum_{d=1}^{T_t} \sigma_{FX,d} \tag{A2}$$

where T_t is the total number of trading days in month *t*. The monthly global FX volatility $\sigma_{FX,t}$ is employed in the later analysis.

Table A1. Out-of-sample forecasting results: Carry strategies

Panel A: Carry 1	R^2_{os}		MSE-F	
(1) ΔCRB1L	3.27	*	9.53	***
(2) ΔCRB2L	4.16	**	12.24	***
(3) ΔCRB3L	5.73	**	17.15	***
(4) $\Delta\sigma_{FX}$1L	1.60		4.59	***
(5) $\Delta\sigma_{FX}$2L	5.28	**	15.71	***
(6) $\Delta\sigma_{FX}$3L	3.61	***	10.55	***
(7) ΔMSCI1L	1.87		5.36	***
(8) ΔMSCI2L	2.62	**	7.59	***
(9) ΔMSCI3L	2.56	*	7.40	***
Panel B: Carry 2	R^2_{os}		MSE-F	
(1) ΔCRB1L	2.60	**	7.52	***
(2) ΔCRB2L	4.90	**	14.53	***
(3) ΔCRB3L	6.24	***	18.77	***
(4) $\Delta\sigma_{FX}$1L	0.38		1.09	*
(5) $\Delta\sigma_{FX}$2L	4.89	***	14.49	***
(6) $\Delta\sigma_{FX}$3L	2.93	***	8.51	***
(7) ΔMSCI1L	5.84	***	17.49	***
(8) ΔMSCI2L	4.96	***	14.73	***
(9) ΔMSCI3L	6.14	***	18.44	***
Panel C: Carry 3	R^2_{os}		MSE-F	
(1) ΔCRB1L	3.10	*	9.01	***
(2) ΔCRB2L	5.40	**	16.11	***
(3) ΔCRB3L	5.33	**	15.88	***
(4) $\Delta\sigma_{FX}$1L	0.84		2.38	**
(5) $\Delta\sigma_{FX}$2L	5.68	***	17.00	***
(6) $\Delta\sigma_{FX}$3L	3.22	***	9.38	***
(7) ΔMSCI1L	8.88	***	27.49	***
(8) ΔMSCI2L	4.46	***	13.16	***
(9) ΔMSCI3L	7.39	***	22.50	***

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of carry strategy from rolling regressions with a 120 month window. See notes in Table 2.

Table A2. Out-of-sample forecasting results: Momentum strategies

Panel A: Mom 1	R^2_{os}		MSE-F	
(1) ΔCRB1L	5.69		17.02	***
(2) ΔCRB2L	7.55		23.04	***
(3) ΔCRB3L	6.02		18.07	***
(4) $\Delta\sigma_{FX}$1L	2.46		7.12	***
(5) $\Delta\sigma_{FX}$2L	2.79		8.10	***
(6) $\Delta\sigma_{FX}$3L	1.85		5.32	***
(7) ΔMSCI1L	4.45		13.13	***
(8) ΔMSCI2L	3.24		9.44	***
(9) ΔMSCI3L	2.20		6.34	***
Panel B: Mom 2	**R^2_{os}**		**MSE-F**	
(1) ΔCRB1L	0.83		2.35	**
(2) ΔCRB2L	3.07		8.92	***
(3) ΔCRB3L	3.06	*	8.91	***
(4) $\Delta\sigma_{FX}$1L	3.19		9.29	***
(5) $\Delta\sigma_{FX}$2L	0.12		0.35	*
(6) $\Delta\sigma_{FX}$3L	0.55		1.56	**
(7) ΔMSCI1L	0.73		2.07	**
(8) ΔMSCI2L	1.62	*	4.66	***
(9) ΔMSCI3L	-0.35		-0.99	
Panel C: Mom 3	**R^2_{os}**		**MSE-F**	
(1) ΔCRB1L	1.25		3.57	**
(2) ΔCRB2L	2.64		7.64	***
(3) ΔCRB3L	3.64	*	10.64	***
(4) $\Delta\sigma_{FX}$1L	1.53		4.39	***
(5) $\Delta\sigma_{FX}$2L	-0.45		-1.27	
(6) $\Delta\sigma_{FX}$3L	0.47		1.34	**
(7) ΔMSCI1L	-0.13		-0.36	
(8) ΔMSCI2L	1.49	**	4.28	***
(9) ΔMSCI3L	-0.10		-0.27	

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of momentum strategy from rolling regressions with a 120 month window. See notes of Table 2.

Table A3. Out-of-sample forecasting results: Value strategies

Panel A: Value 1	R^2_{os}		MSE-F	
(1) ΔCRB1L	2.39		6.89	***
(2) ΔCRB2L	4.50	*	13.28	***
(3) ΔCRB3L	5.28	*	15.73	***
(4) $\Delta\sigma_{FX}$1L	-1.45		-4.02	
(5) $\Delta\sigma_{FX}$2L	-1.64		-4.56	
(6) $\Delta\sigma_{FX}$3L	-3.25		-8.87	
(7) ΔMSCI1L	-0.50		-1.40	
(8) ΔMSCI2L	4.66	*	13.78	***
(9) ΔMSCI3L	2.52		7.30	***
Panel B: Value 2	R^2_{os}		MSE-F	
(1) ΔCRB1L	2.03	*	5.84	***
(2) ΔCRB2L	3.01	**	8.74	***
(3) ΔCRB3L	3.00	**	8.71	***
(4) $\Delta\sigma_{FX}$1L	-2.45		-6.75	
(5) $\Delta\sigma_{FX}$2L	-1.16		-3.23	
(6) $\Delta\sigma_{FX}$3L	-4.86		-13.07	
(7) ΔMSCI1L	-0.72		-2.01	
(8) ΔMSCI2L	2.18	**	6.30	***
(9) ΔMSCI3L	0.07		0.21	
Panel C: Value 3	R^2_{os}		MSE-F	
(1) ΔCRB1L	2.53	***	7.32	***
(2) ΔCRB2L	3.47	***	10.13	***
(3) ΔCRB3L	3.22	***	9.38	***
(4) $\Delta\sigma_{FX}$1L	-2.80		-7.68	
(5) $\Delta\sigma_{FX}$2L	-1.88		-5.22	
(6) $\Delta\sigma_{FX}$3L	-3.02		-8.26	
(7) ΔMSCI1L	-0.20		-0.57	
(8) ΔMSCI2L	2.02	**	5.83	***
(9) ΔMSCI3L	0.21		0.60	

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of value strategy from rolling regressions with a 120 month window. See notes of Table 2.

Table A4. Out-of-sample forecasting results: Dollar carry strategies

Dollar Carry	R^2_{os}		MSE-F	
(1) ΔCRB1L	-0.41		-1.15	
(2) ΔCRB2L	-1.83		-5.07	
(3) ΔCRB3L	-0.23		-0.66	
(4) $\Delta\sigma_{FX}$1L	-0.34		-0.96	
(5) $\Delta\sigma_{FX}$2L	-0.18		-0.51	
(6) $\Delta\sigma_{FX}$3L	2.04	*	5.86	***
(7) ΔMSCI1L	-2.30		-6.35	
(8) ΔMSCI2L	0.22		0.62	*
(9) ΔMSCI3L	-0.16		-0.45	

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of dollar carry strategy from rolling regressions with a 120 month window. See notes of Table 2.

Table A5. Out-of-sample forecasting results: ΔFXC strategies

Panel A: FXC 1	R^2_{os}		MSE-F	
(1) ΔCRB1L	10.85	*	34.32	***
(2) ΔCRB2L	9.07	*	28.12	***
(3) ΔCRB3L	8.76	**	27.07	***
(4) $\Delta\sigma_{FX}$1L	12.05	**	38.62	***
(5) $\Delta\sigma_{FX}$2L	10.73	**	33.90	***
(6) $\Delta\sigma_{FX}$3L	5.33	*	15.89	***
(7) ΔMSCI1L	10.97	***	34.75	***
(8) ΔMSCI2L	5.83	**	17.47	***
(9) ΔMSCI3L	7.86	**	24.07	***
Panel B: FXC 2	R^2_{os}		MSE-F	
(1) ΔCRB1L	5.05	*	15.00	***
(2) ΔCRB2L	6.07	**	18.23	***
(3) ΔCRB3L	6.10	***	18.33	***
(4) $\Delta\sigma_{FX}$1L	6.23	*	18.73	***
(5) $\Delta\sigma_{FX}$2L	6.47	**	19.49	***
(6) $\Delta\sigma_{FX}$3L	1.79		5.15	***
(7) ΔMSCI1L	8.66	***	26.73	***
(8) ΔMSCI2L	6.00	***	18.00	***
(9) ΔMSCI3L	6.61	***	19.96	***
Panel C: FXC 3	R^2_{os}		MSE-F	
(1) ΔCRB1L	6.72	**	20.30	***
(2) ΔCRB2L	5.93	**	17.79	***
(3) ΔCRB3L	6.10	**	18.31	***
(4) $\Delta\sigma_{FX}$1L	4.40	*	12.97	***
(5) $\Delta\sigma_{FX}$2L	5.16	**	15.34	***
(6) $\Delta\sigma_{FX}$3L	1.71		4.90	***
(7) ΔMSCI1L	8.52	***	26.27	***
(8) ΔMSCI2L	4.68	**	13.84	***
(9) ΔMSCI3L	4.96	**	14.73	***

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. The one-month-ahead return forecasts of ΔFXC strategy from rolling regressions with a 120 month window. See notes of Table 2.

Table A6. Economic value of portfolio return predictability: Recursive scheme

	Portfolio	SR	SOR	Φ	Ψ
(1) BM	2	0.42	0.96		
(2) Model 1	2	0.36	0.84	-1.37	-1.39
(3) Model 2	2	0.40	0.95	0.09	0.04
(4) Model 3	2	0.53	1.23	3.34	3.34
(5) Model 4	2	0.23	0.55	-5.05	-5.10
(6) BM	3	0.30	0.70		
(7) Model 1	3	0.19	0.43	-2.79	-2.83
(8) Model 2	3	0.06	0.13	-6.21	-6.26
(9) Model 3	3	0.50	1.15	5.62	5.62
(10) Model 4	3	0.14	0.33	-3.97	-4.01

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). The one-month-ahead return forecasts of investment strategies from rolling regressions with a 120 month initial expanding window. See notes of Table 4.

Table A7. Economic value of portfolio return predictability: Excluding carry

	Portfolio	SR	SOR	Φ	Ψ
(1) BM	2	0.42	0.95		
(2) Model 1	2	0.52	1.24	3.25	3.23
(3) Model 2	2	0.41	0.97	0.31	0.27
(4) Model 3	2	0.44	1.03	1.37	1.31
(5) Model 4	2	0.43	1.03	0.82	0.78
(6) BM	3	0.56	1.27		
(7) Model 1	3	0.52	1.24	-2.70	-2.47
(8) Model 2	3	0.53	1.22	-0.52	-0.54
(9) Model 3	3	0.59	1.38	1.35	1.29
(10) Model 4	3	0.72	1.73	4.76	4.71

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). The portfolio is constructed by four strategies and we exclude the carry strategy. The one-month-ahead return forecasts of investment strategies from rolling regressions with a 120 month window. See notes of Table 4.

Table A8. Summary statistics of Δ*FXC* strategies

Panel A: ΔFXC 2										
	Correlation	Spread	Factor betas	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
(1) Base result	66 days	P10-P1	36 months	2.30	10.20	-0.47	4.64	8.49	-12.52	0.23
(2)	22 days	P10-P1	36 months	2.88	10.26	-0.75	6.92	10.04	-17.56	0.28
(3)	132 days	P10-P1	36 months	1.18	9.59	-0.15	5.46	9.98	-15.51	0.12
(4)	66 days	P4-P1	36 months	2.10	9.81	-0.52	5.68	8.49	-15.51	0.21
(5)	66 days	P10-P1	12 months	2.20	9.54	-0.28	4.36	9.35	-13.38	0.23
(6)	66 days	P10-P1	60 months	3.06	9.62	-0.58	4.16	7.04	-12.52	0.32
Panel B: ΔFXC 3										
	Correlation	Spread	Factor betas	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
(1) Base result	66 days	P10-P1	36 months	2.91	8.32	-0.21	3.83	7.41	-9.64	0.35
(2)	22 days	P10-P1	36 months	2.97	8.28	-0.52	5.68	7.93	-12.43	0.36
(3)	132 days	P10-P1	36 months	1.33	7.72	-0.20	5.62	7.41	-12.81	0.17
(4)	66 days	P4-P1	36 months	3.07	8.22	-0.51	5.33	7.41	-12.81	0.37
(5)	66 days	P10-P1	12 months	1.76	7.84	-0.31	4.87	7.84	-11.39	0.22
(6)	66 days	P10-P1	60 months	3.14	8.04	-0.46	4.74	6.08	-11.39	0.39

Notes: This table reports annualized mean, annualized standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of the conditional FX correlation strategy (Δ*FXC*, Mueller et al., 2017). Each row has a different combination of the parameters. The second column "Correlation" indicates the window size of daily correlations. The third column, "Spread", indicates the number of portfolios to calculate average correlation spread. P10-P1 (P4-P1) means that the correlation spread between top and bottom deciles (quartiles). "Factor betas" means the window size of beta estimation. Two (three) currencies are in the long and short positions in Panel A(B). The base result is employed in Table 4.

Table A9. Out-of-sample forecasting results: different parameters of ΔFXC strategies

Panel A: ΔFXC 2	Correlation	Spread	Factor betas	R^2os		MSE-F	
(1) Base result	66 days	P10-P1	36 months	7.60	**	23.20	***
(2)	22 days	P10-P1	36 months	9.36	***	29.13	***
(3)	132 days	P10-P1	36 months	8.14	***	25.00	***
(4)	66 days	P4-P1	36 months	11.16	***	35.43	***
(5)	66 days	P10-P1	12 months	7.30	***	22.22	***
(6)	66 days	P10-P1	60 months	8.21	***	25.21	***

Panel B: ΔFXC 3	Correlation	Spread	Factor betas	R^2os		MSE-F	
(1) Base result	66 days	P10-P1	36 months	8.56	***	26.40	***
(2)	22 days	P10-P1	36 months	7.30	***	22.21	***
(3)	132 days	P10-P1	36 months	6.71	***	20.29	***
(4)	66 days	P4-P1	36 months	10.49	***	33.05	***
(5)	66 days	P10-P1	12 months	5.76	***	17.24	***
(6)	66 days	P10-P1	60 months	8.56	***	26.40	***

Notes: This table shows statistical measures of the out-of-sample forecast of predictive models. We employ Model 4 that includes a change in global FX volatility ($\Delta\sigma_t^{FX}$), a change in the CRB material index (ΔCRB_t), a change in the world stock market index ($\Delta MSCI_t$). The one-month-ahead return forecasts of ΔFXC strategy from rolling regressions with a 120 month window. Each row has a different combination of the parameters. The second column "Correlation" indicates the window size of daily correlations. The third column, "Spread", indicates the number of portfolios to calculate average correlation spread. P10-P1 (P4-P1) means that the correlation spread between top and bottom deciles (quartiles). The fourth column "Factor betas" means the window size of beta estimation. Two (three) currencies are in the long and short positions in Panel A(B). The base result is employed in Table 3. See notes of Table A1.

Table A10. Economic value of portfolio return predictability: different parameters of ΔFXC strategies

Panel A: ΔFXC 2								
	Portfolio	Correlation	Spread	Factor betas	SR	SOR	Φ	Ψ
(1) Base result	2	66 days	P10-P1	36 months	0.54	1.31	1.16	1.09
(2)	2	22 days	P10-P1	36 months	0.46	1.06	2.53	2.47
(3)	2	132 days	P10-P1	36 months	0.50	1.15	0.52	0.47
(4)	2	66 days	P4-P1	36 months	0.48	1.15	0.03	-0.03
(5)	2	66 days	P10-P1	12 months	0.21	0.47	-4.88	-4.97
(6)	2	66 days	P10-P1	60 months	0.50	1.15	0.52	0.47
Median							0.83	0.78
95% CI							(-4.88, 1.81)	(-4.97, 1.75)
Panel B: ΔFXC 3								
	Portfolio	Correlation	Spread	Factor betas				
(1) Base result	3	66 days	P10-P1	36 months	0.64	1.54	0.39	0.35
(2)	3	22 days	P10-P1	36 months	0.53	1.21	2.52	2.48
(3)	3	132 days	P10-P1	36 months	0.46	1.04	2.12	2.09
(4)	3	66 days	P4-P1	36 months	0.31	0.72	-5.97	-5.95
(5)	3	66 days	P10-P1	12 months	0.65	1.54	1.97	1.94
(6)	3	66 days	P10-P1	60 months	0.58	1.37	-1.57	-1.59
Median							1.18	1.14
95% CI							(-5.97, 2.12)	(-5.95, 2.10)

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns. The portfolio is constructed by five strategies. Each row has a different combination of the parameters for the ΔFXC strategy. We employ Model 4 that includes a change in global FX volatility ($\Delta\sigma_t^{FX}$), a change in the CRB material index (ΔCRB_t), a change in the world stock market index ($\Delta MSCI_t$). We calculate the median values of six parameter combinations and 95% bootstrap confidence intervals are reported in parentheses. The bootstrapped-based distributions are based on 10,000 draws with replacement from the respective sample. See notes of Tables 4 and A9.

Table A11. Economic value of portfolio return predictability: different time period

	Portfolio	SR	SOR	Φ	Ψ
(1) BM	2	0.45	1.01		
(2) Model 1	2	0.52	1.21	3.02	2.93
(3) Model 2	2	0.43	1.01	0.38	0.28
(4) Model 3	2	0.52	1.22	3.05	2.97
(5) Model 4	2	0.34	0.82	-1.98	-2.07
(6) BM	3	0.56	1.29		
(7) Model 1	3	0.61	1.44	1.21	1.22
(8) Model 2	3	0.43	0.99	-4.11	-4.06
(9) Model 3	3	0.39	0.89	-5.17	-5.14
(10) Model 4	3	0.46	1.09	-3.05	-3.03

Notes: This table presents the out-of-sample economic value of the predictive models for currency portfolio returns, including the historical average benchmark model (BM). The portfolio is constructed by five strategies and the out-of-sample forecasts are November 1993 to December 2021. The one-month-ahead return forecasts of investment strategies from rolling regressions with a 120 month window. See notes of Table 4.

Table A12. Summary statistics: January 2010-December 2019

	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
Carry 2	0.44	7.81	-0.20	3.14	5.48	-5.92	0.06
Carry 3	0.46	6.44	-0.18	2.98	4.33	-4.59	0.07
Mom 2	-4.02	7.90	-0.13	3.22	5.62	-6.53	-0.51
Mom 3	-3.88	6.38	-0.34	3.70	4.53	-6.60	-0.61
Value 2	0.25	6.81	-0.19	3.11	4.83	-5.68	0.04
Value 3	-0.41	5.70	-0.09	2.58	3.33	-4.27	-0.07
DC	-2.84	7.76	-0.37	3.47	5.69	-7.29	-0.37
∆FXC 2	0.56	8.51	-0.07	3.70	6.28	-7.61	0.07
∆FXC 3	0.00	6.59	-0.62	5.29	5.80	-7.09	0.00

Notes: This table reports annualized mean, annualized standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of currency portfolio excess returns. We employ five currency portfolios: carry, momentum, value, dollar carry (DC, Lustig et al., 2014), and conditional FX correlation risk (ΔFXC, Mueller et al., 2017). We consider three portfolios for each strategy except DC. For instance, Carry j indicates that j currencies are in the long and short positions. The sample period is January 2010-December 2019.

Table A13. Summary statistics: January 2020-December 2021

	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
Carry 2	12.40	10.84	0.93	4.25	9.98	-5.21	1.14
Carry 3	8.78	10.19	0.12	3.83	8.07	-6.68	0.86
Mom 2	-0.35	8.11	-0.12	2.59	5.23	-4.53	-0.04
Mom 3	-1.01	8.55	1.17	5.58	8.01	-4.12	-0.12
Value 2	-3.79	10.78	-0.58	2.58	4.81	-7.04	-0.35
Value 3	-1.96	8.63	-0.81	2.75	3.29	-5.83	-0.23
DC	-3.40	7.85	0.02	1.72	3.25	-4.27	-0.43
ΔFXC 2	-1.10	9.45	-0.10	2.52	5.70	-5.35	-0.12
ΔFXC 3	-1.33	7.14	-0.11	2.36	3.85	-3.85	-0.19

Notes: This table reports annualized mean, annualized standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of currency portfolio excess returns. We employ five currency portfolios: carry, momentum, value, dollar carry (DC, Lustig et al., 2014), and conditional FX correlation risk (ΔFXC, Mueller et al., 2017). We consider three portfolios for each strategy except DC. For instance, Carry j indicates that j currencies are in the long and short positions. The sample period is January 2020-December 2021.