Global Currency Hedging with Common Risk Factors*

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Abstract

We propose a novel method for dynamically hedging foreign exchange exposure in international equity and bond portfolios. The method exploits time-series predictability in currency returns that we find emerges from a forecastable component in currency *factor* returns. The hedging strategy outperforms leading alternative approaches out-of-sample across a large set of performance metrics. Moreover, we find that exploiting the predictability of currency returns via an independent currency portfolio delivers a high risk-adjusted return and provides superior diversification gains to global equity and bond investors relative to currency carry, value, and momentum investment strategies.

Keywords: global currency hedging, currency risk factors, currency returns, international portfolio diversification.

JEL Classification: F31, G11, G15.

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1 Introduction

How should global investors manage their foreign exchange (FX) exposure? The question represents one of the most important and largely unresolved issues in international finance. It is also critical to address given the vast and growing allocation of wealth towards international securities denominated in foreign currencies: in the U.S., for example, the level of domestic-held foreign debt and equity has risen to over 50% of GDP, a ten-fold increase in just 25 years (see Figure 1).[1] The classical approach to currency hedging via mean-variance optimization is theoretically appealing and encompasses both risk management and speculative hedging demands (Glen and Jorion, 1993; Campbell, Serfaty-De Medeiros, and Viceira, 2010). However, this approach, when applied out of sample, suffers from acute estimation error in currency return forecasts, which leads to poor hedging performance (Gardner and Stone, 1995; Larsen Jr. and Resnick, 2000).[2]

In this paper we devise a novel method for dynamically hedging FX exposure using mean-variance optimization, in which we predict currency returns using common currency risk factors. Recent breakthroughs in international macro-finance have documented that the cross-section of currency returns can be explained as compensation for risk, in a linear two-factor model that includes *dollar* and *carry* currency factors. The *dollar* factor corresponds to the average return of a portfolio of currencies against the U.S. dollar, while the *carry* factor corresponds to the returns on the currency carry trade (Lustig, Roussanov, and Verdelhan, 2011; Verdelhan, 2018). We show that the cross-sectional currency return predictability also extends to the *time-series*, once we account for predictable time-variation in the currency factor returns.

We take the perspective of a mean-variance U.S. investor who can invest in a portfolio of 'G10' developed economies.[3] We adopt the standard assumption that the investor has a predetermined long position in either foreign equities or bonds and desires to optimally manage the FX exposure using forward contracts.[4] We form estimates of currency returns using a conditional version of the two-factor model where both factor returns and factor betas are time-varying. Lustig, Roussanov, and

[1]Allocating a large fraction of wealth to foreign assets is a natural outcome of applying mean-variance portfolio optimization (Markowitz, 1952; Solnik, 1974a,b). Since asset return correlations are lower *across* countries than they are *within* countries (Eun and Resnick, 1984; Eun, Huang, and Lai, 2008), systematic risk can be reduced, and risk-return profiles improved, through the inclusion of foreign assets in an otherwise well-diversified domestic portfolio (Eun, Wang, and Xiao, 2015; Eun et al., 2017).

[2]Mean-variance optimization is known, in general, to be hampered by estimation error in input parameters that results in weak out-of-sample performance (Jorion, 1985; DeMiguel, Garlappi, and Uppal, 2009).

[3]In currency markets, the 'G10' refers to 10 developed market currencies that include the Australian dollar, Canadian dollar, euro, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, Swiss franc, British pound sterling and the U.S. dollar. We refer to the issuing countries of the G10 currencies as the G10 economies, with Germany representing the euro zone.

[4]The process is also known as "currency overlay", which is the common practice within the investments industry and is the principal focus of academic enquiry into optimal global currency hedging (see, *inter alia*, Jorion, 1994; Campbell, Serfaty-De Medeiros, and Viceira, 2010).

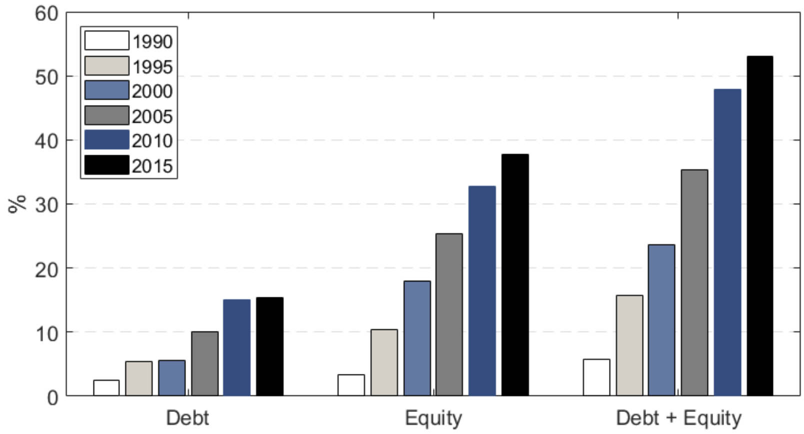

Figure 1: U.S.-Resident Holdings of Foreign Debt and Equity (% GDP)
The figure presents year-end U.S.-resident holdings of foreign debt and equity as a percentage of Gross Domestic Product (GDP). Data is collected from Philip Lane's website (see Lane and Milesi-Ferretti (2001, 2007) for further details).

Verdelhan (2011) demonstrate that exposure to *dollar* and *carry* factors (i.e. factor betas) accounts for a large proportion of the cross-sectional variation in currency portfolio returns, while Verdelhan (2018) highlights that a large proportion of currency return variation can be explained *contemporaneously* with the factors, and thus if the factor returns contain a forecastable component it implies currency returns can also be predicted in the time series.

A related literature provides strong empirical evidence, with underpinning theoretical support, that the *dollar* and *carry* factor returns *are* partly predictable. Variables including the average forward discount (Lustig, Roussanov, and Verdelhan, 2014), FX volatility (Bakshi and Panayotov, 2013; Cenedese, Sarno, and Tsiakas, 2014), the TED spread (Brunnermeier, Nagel, and Pedersen, 2009), and commodity returns (Ready, Roussanov, and Ward, 2017), have all been shown to have predictive power in explaining future *dollar* or *carry* factor returns. We exploit this predictability to forecast currency returns. Specifically, we estimate factor betas and 1-month ahead *dollar* and *carry* factor returns in the time series, and then form expected bilateral currency returns using these estimates. This vector of expected currency returns enters the mean-variance optimizer to produce optimal, currency-specific, hedge positions. We update the positions monthly and refer to the approach as Dynamic Currency Factor (*DCF*) hedging.

We evaluate the performance of *DCF* hedging, over a 20-year out-of-sample period, against nine leading alternative approaches ranging from naive solutions in which FX exposure is either fully hedged or never hedged, through to the most sophisticated techniques that also adopt mean-variance optimization. We find *DCF* hedging generates systematically superior out-of-sample performance compared to all alternative approaches across a range of statistical and economic performance measures for both international equity and bond portfolios. As a preview, in Figure 2 we show the cumulative

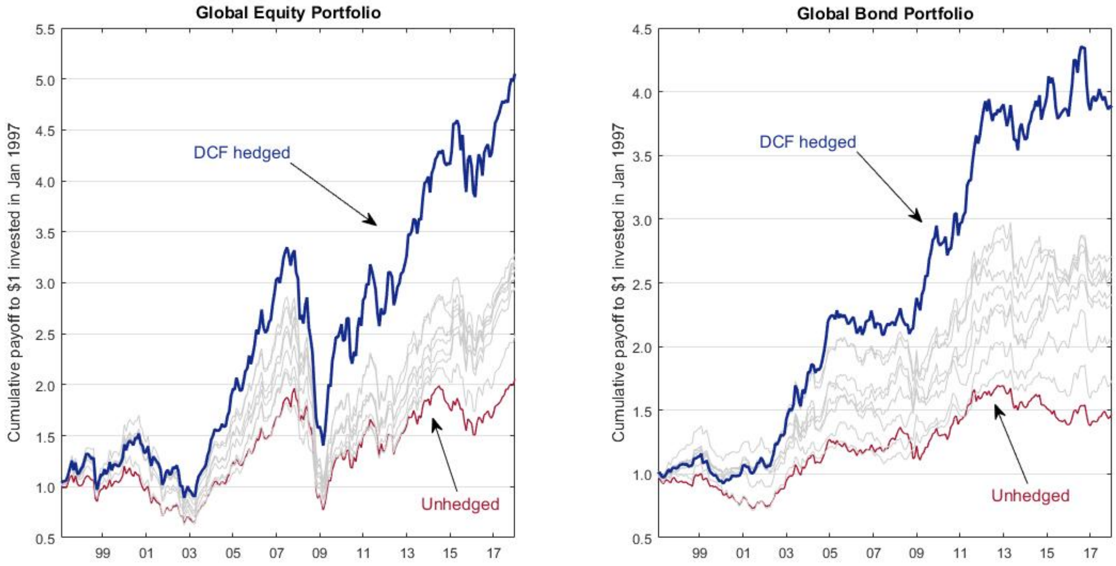

Figure 2: Cumulative Payoff to Investing in Global Equity and Bond Portfolios
The figure presents the cumulative payoff to \$1 invested in equal-weighted global equity and bond portfolios in January 1997, under different currency hedging frameworks from the perspective of a U.S. investor. The payoffs to the *DCF* hedge portfolio and the unhedged portfolio are highlighted, all other approaches are presented in grey. Full details of the *DCF* strategy and the alternative hedging frameworks are described in Section 3.

payoff to a \$1 investment in international equity and bond portfolios in January 1997. When adopting *DCF* hedging, the \$1 investment grows to over \$5 by July 2017 for the global equity portfolio, and to almost \$4 for the global bond portfolio. These values contrast with \$2 and \$1.5, which a U.S. investor would have obtained, if the FX exposure in the equity or bond portfolios was left unhedged.

While we evaluate the performance of *DCF* hedging across a large set of performance measures, we pay special attention to the out-of-sample Sharpe ratio and Certainty Equivalent (*CEQ*) return that capture the utility preferences of a mean-variance investor. We find an equal-weighted global equity portfolio has a statistically higher Sharpe ratio under *DCF* hedging relative to all nine alternative frameworks. The improvement is over 90% relative to an unhedged portfolio and over 40% relative to a portfolio that fully hedges FX exposure. We also evaluate *DCF* hedging using an equal-weighted global bond portfolio, and find the Sharpe ratio is higher than all nine alternative approaches and statistically significantly higher than seven. These findings are particularly surprising given the difficulty in generating *statistically* superior Sharpe ratios relative to unhedged or passively hedged strategies (Glen and Jorion, 1993). Moreover, eliminating FX exposure is often viewed as the optimal approach to managing currency risk in global bond portfolios (Campbell, Serfaty-De Medeiros, and Viceira, 2010), yet we show that *DCF* hedging delivers a Sharpe ratio that is over 40% higher than the fully-hedged bond portfolio. The relative performance of the strategy is also impressive once evaluated using the *CEQ* return that accounts for investor risk aversion. In each comparison, the *CEQ* return is found to be statistically significantly higher under *DCF* hedging and thus a mean-variance global investor would always choose to adopt the approach relative to each alternative. We perform the same exercise using GDP-weighted equity and bond portfolios and find qualitatively identical results. In particular, the Sharpe ratio and CEQ return are consistently the highest under *DCF* hedging relative to each alternative framework.

We confirm our core results using a battery of alternative statistical and economic performance metrics. The average return to the international equity and bond portfolios increases substantially under *DCF* hedging but without negatively impacting portfolio variance or skewness. In fact, the *DCF* hedged equity portfolio has the least negative skewness and one of the lowest maximum drawdowns, indicating that the superior performance of *DCF* hedging is not due to an increase in crash risk. The strategy thus generates the strongest performance across measures designed to penalize negatively-skewed return distributions, including the Sortino ratio (Sortino and van der Meer, 1991) and the manipulation-proof 'theta' measure (Ingersoll et al., 2007). We also show that *DCF* hedging provides the largest information ratio relative to the unhedged and fully hedged equity and bond portfolios, highlighting the persistence of the outperformance over time. Moreover, we compute the performance fee a mean-variance investor would pay to switch to *DCF* hedging from each alternative and show it is large in every case. A mean-variance investor is found willing to pay a fee of 3% per annum, for example, to switch to *DCF* hedging from portfolios that are unhedged against FX exposure, which is economically large considering the unhedged portfolio excess returns are only 4.9% for global equities and 2.3% for global bonds.

We extend our analysis by: (i) exploring if refinements to the measurement of covariance terms can further enhance *DCF* hedging, but find that even perfect foresight of the following month's returns – and hence employing the *actual* realized covariance structure – has little effect on the overall investment performance; (ii) taking the perspective of investors situated in all other G10 economies and show that *DCF* hedging has broad applicability, delivering either the highest or second highest Sharpe ratio and *CEQ* return in 95% of tests we perform; and (iii) exploring the source of the gains arising from *DCF* hedging and find it stems almost entirely from capturing the predictable component of factor *returns*, rather than from incorporating time-varying factor *betas*.

Finally, an alternative approach to managing FX exposure involves the construction of an *independent* currency portfolio to generate speculative returns. The portfolio is subsequently combined with fully hedged global equity and bond portfolios to generate diversification gains. This 'separate' currency investment approach is often unavailable to fund managers, who are usually mandated to hedge only *existing* FX exposure. But for managers with broader mandates, the option has the advantage of placing less constraint on currency positions and has been found to deliver strong investment gains (Asness, Moskowitz, and Pedersen, 2013; Kroencke, Schindler, and Schrimpf, 2014; Barroso and Santa-Clara, 2015). We explore this possibility via a *DCF* currency trading strategy using the same currency return estimates adopted in the baseline *DCF* hedging approach. The *DCF* trading strategy goes long in currencies with positive expected returns and short in currencies with negative expected returns. We find the strategy delivers a high Sharpe ratio of 0.78, which is higher than that of the currency carry trade. Moreover, the *DCF* strategy generates returns largely uncorrelated with existing currency strategies, and offers diversification benefits to international investors exceeding those provided by currency carry, value, and momentum investment strategies.

In sum, we contribute by developing a novel method for hedging FX exposure in a mean-variance framework. In contrast to previous evidence showing mean-variance currency hedging fails out-of-sample because of estimation error, we illustrate that exploiting predictable time-variation in common currency factors provides a means for successfully hedging international asset portfolios within a mean-variance framework. Our method provides a high benchmark when assessing the performance of candidate currency hedging approaches and raises the tantalizing prospect that further breakthroughs in our understanding of the factors driving currency returns could generate even larger investment gains from currency management. In addition, for managers with a broad mandate to invest in a separate currency portfolio, we propose a new multi-currency investment strategy. The strategy generates high risk-adjusted returns and offers substantial diversification benefits to global equity and bond investors.

The remainder of the paper is organized as follows: In Section 2 we outline the related literature. In Section 3 we explain *DCF* hedging and the alternative currency hedging frameworks. In Section 4 we describe the data. In Section 5 we present the core results on the performance of *DCF* hedging for international equity and bond portfolios. In Section 6 we show results on various extensions to *DCF* hedging. In Section 7 we construct an independent *DCF* trading strategy. Section 8 concludes.

2 Related Literature

Our paper is closely related to the literature studying global currency hedging. Managing FX exposure is known to potentially benefit investment performance (Adler and Dumas, 1983; Eun and Resnick, 1988; Black, 1990; Glen and Jorion, 1993; Gagnon, Lypny, and McCurdy, 1998; Ang and Bekaert, 2002; Campbell, Serfaty-De Medeiros, and Viceira, 2010; Brusa, Ramadorai, and Verdelhan, 2014). The debate in the literature principally centers on *which* hedging strategy is optimal, with early solutions including the extremes of 'full hedge' to completely eliminate FX exposure (Perold and Schulman, 1988; Eun and Resnick, 1988) and to never hedge if the investment horizon is sufficiently long (Froot, 1993).[5] The most sophisticated techniques consider the joint distribution of foreign exchange rates and underlying asset returns within a mean-variance framework. Campbell, Serfaty-De Medeiros, and Viceira (2010), for example, provide strong evidence that global equity investors can minimize portfolio variance by holding positions in currencies, such as the U.S. dollar and euro, that have a negative correlation with international stock market returns. The investor is therefore recommended to leave sizeable exposure in "safe haven" currencies that offer a natural source of insurance.[6] De Roon et al. (2012) argue, however, that the insurance is not free and comes at the cost of lower portfolio returns and Sharpe ratios because "safe haven" currencies typically offer the lowest expected currency returns. Exploiting currency return predictability is thus critical for maximizing overall investment performance. Indeed, in the seminal study of Glen and Jorion (1993), the authors form expectations of currency returns by conditioning on interest rates, and find large investment performance gains are available when exploiting currency return predictability stemming from forward premiums.

We relate to this literature by proposing a novel approach to dynamically estimating currency hedge positions that exploits currency return predictability. Our approach is quite different, however, from previous studies because we are the first to bridge to the recent and burgeoning literature in international macro-finance exploring currency returns.[7] The core finding from the literature is that the *cross-section* of currency returns can be explained as compensation for risk in a linear two-factor model using *dollar* and *carry* factors (Lustig, Roussanov, and Verdelhan, 2011; Verdelhan, 2018).[8] We show that this currency return predictability also extends to the *time-series* once we incorporate economically motivated variables that can predict time-variation in factor returns, including FX volatility (Menkhoff et al., 2012a; Cenedese, Sarno, and Tsiakas, 2014), commodity returns (Bakshi and Panayotov, 2013; Ready, Roussanov, and Ward, 2017) and the average forward discount against the U.S dollar (Lustig, Roussanov, and Verdelhan, 2014).

Finally, our study relates to the literature studying optimal currency portfolios (see, *inter alia*,

[5] Schmittmann (2010) finds that even over long horizons, currency hedging still offers benefits through risk reduction and meaningfully higher expected returns.

[6] Ranaldo and Söderlind (2010) define a safe haven currency as a currency that provides hedging benefits on average and/or in times of stress, while Habib and Stracca (2012) explore the determinants of becoming a "safe haven" currency.

[7] See, *inter alia*, Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012a), Lettau, Maggiori, and Weber (2014), and Verdelhan (2018).

[8] Burnside et al. (2006) provide details on the construction and properties of the currency carry trade. Other studies replace the *carry* factor with alternative risk factors including, *inter alia*, volatility risk (Menkhoff et al., 2012a), liquidity risk (Mancini, Ranaldo, and Wrampelmeyer, 2013), global imbalance risk (Della Corte, Riddiough, and Sarno, 2016) and international correlation risk (Mueller, Stathopoulos, and Vedolin, 2017). A recent literature has also sought to regalvanize the international asset pricing literature on equities by incorporating the *dollar* and *carry* factors within an asset pricing model. Brusa, Ramadorai, and Verdelhan (2014), for example, find that common currency risk factors are important for understanding international equity returns, although Karolyi and Wu (2017) find less supportive evidence (see, among others, Solnik (1974a), Adler and Dumas (1983), Jorion (1991) and Ferson and Harvey (1993) for seminal studies within the earlier International CAPM literature).

Della Corte, Sarno, and Tsiakas, 2009; Asness, Moskowitz, and Pedersen, 2013; Barroso and Santa-Clara, 2015; Ackermann, Pohl, and Schmedders, 2018). If global investors are not constrained to hedge only *existing* FX exposure and can allocate capital to a separate currency portfolio – in addition to a global equity or bond portfolio – it may enhance overall investment performance. Kroencke, Schindler, and Schrimpf (2014), for example, find evidence to this effect when combining international equity and bond portfolios with a currency "style" portfolio, comprising of carry, value and momentum strategies. We find strong evidence that superior diversification benefits arise from a currency strategy that exploits the time-series predictability of currency returns. Moreover, the returns to the strategy are largely uncorrelated with the returns to other popular currency strategies and are thus indicative of an economically distinct source of investment returns.

3 Dynamic Currency Factor Hedging

In this section we explain the Dynamic Currency Factor (DCF) approach to currency hedging. We first summarize the general framework for generating optimal currency hedge positions and then describe the estimation of expected currency returns – the key innovation in DCF hedging. Finally, we outline the alternative hedging frameworks that we evaluate DCF hedging against.

3.1 General Framework for Deriving Optimal Currency Hedge Positions

Our principal objective is to dynamically formulate optimal currency hedge positions from the perspective of a U.S investor. To hedge foreign exchange exposure we add FX forward contracts to a pre-existing portfolio of foreign equities or bonds. To determine hedge positions, each month we select the currency hedges that maximize a mean-variance investor's utility, according to the objective function:

$$\mu_{p,t} - \frac{\gamma}{2}\sigma^2_{p,t} \tag{1}$$

where $\mu_{p,t} = w_t'\mu_t$ represents the expected portfolio return over the following month, $\sigma^2_{p,t} = w_t'\Sigma_t w_t$ is the portfolio risk, μ_t is the vector of expected excess returns with associated covariance matrix Σ_t, the portfolio weights are given by w_t, and γ is the investor's level of risk aversion that we set equal to three.[9]

In an unconstrained optimization, portfolio weights are given by $w_t^* = \frac{1}{\gamma}\Sigma_t^{-1}\mu_t$ (with the remainder of wealth allocated to the risk-free security). In a currency hedging framework, however, it is

[9] We adopt other reasonable parameters for risk aversion including two and four, but find the results remain qualitatively unchanged. These results are available upon request.

appropriate to assume the underlying asset weights are pre-determined by the portfolio manager, and hence the ultimate aim is to determine the weights assigned to FX forward contracts (i.e. the optimal currency hedge positions).The optimization problem can be restated by first partitioning the expected return vector and associated covariance matrix between the underlying assets (equity or bond) and FX forward components (see, e.g. Anderson and Danthine, 1981; Jorion, 1994),

$$\mu_t = \begin{pmatrix} \mu_{x,t} \\ \mu_{f,t} \end{pmatrix}, \quad \Sigma_t = \begin{pmatrix} \Sigma_{xx,t} & \Sigma_{xf,t} \\ \Sigma_{fx,t} & \Sigma_{ff,t} \end{pmatrix} \tag{2}$$

in which the underlying assets and FX forwards are represented by x and f, respectively. The optimal weights in FX forwards are then given by:

$$w^*_{f,t}(f|x) = \frac{1}{\gamma}\left(\Sigma^{-1}_{ff,t}\mu_{f,t}\right) - \delta_t w_{x,t} \tag{3}$$

where $w_{x,t}$ is the vector of pre-determined underlying security weights and δ_t is the regression coefficient obtained from projecting underlying asset returns on the returns to long FX forward contracts, i.e, $\delta_t = \Sigma^{-1}_{ff,t}\Sigma_{fx,t}$. In our core analysis, we constrain each element of $w^*_{f,t}$ to be between $-w_{x,t}$ (fully hedged) and zero (unhedged).[10] We estimate δ_t and Σ_t each month using rolling 60-month windows and set the weights in the underlying securities ($w_{x,t}$) to either be the same across countries (equal-weighted) or a function of the previous year's Gross Domestic Product (GDP-weighted).[11]

3.2 Expected Currency Returns and Common Risk Factors

The key input in Equation (3), from the perspective of *DCF* hedging, is the expected currency return vector $\mu_{f,t}$. We define the return at time t+1, to a U.S. investor who enters a long forward contract (i.e. the currency return) on foreign currency i at time t, as:

$$R_{i,t+1} = \frac{S_{i,t+1} - F_{i,t}}{S_{i,t}}, \tag{4}$$

where $S_{i,t}$ is the time-t spot exchange rate, defined as the U.S. dollar price of foreign currency i, and $F_{i,t}$ is the one-period-ahead forward exchange rate at time t.

Common Risk Factors. Lustig, Roussanov, and Verdelhan (2011) and Verdelhan (2018) show that the cross-section of expected currency returns are determined as a linear function of two common

[10] This constraint reflects the practice in currency overlay management that restricts managers from entering speculative FX forward positions beyond the underlying security position, i.e. it is not possible to *over* hedge a position, nor is it possible to leverage the foreign asset position via FX forwards.

[11] We find that estimating Σ_t using a rolling 120-month window provides qualitatively identical results. Results available upon request.

risk factors, *dollar* and *carry*:

$$\mathbb{E}R_i = \beta_{i,dol}\lambda_{dol} + \beta_{i,car}\lambda_{car} \tag{5}$$

where $\mathbb{E}$ is the expectations operator, $\beta_{i,dol}$ and $\beta_{i,car}$ are currency i's exposure to the *dollar* and *carry* factors, and λ_{dol} and λ_{car} are the unconditional factor prices of risk. The *dollar* factor is constructed as the average currency return of a basket of currencies against the U.S. dollar. The systematic component of the *dollar* factor appears to correlate with low frequency global business cycle conditions and can therefore be interpreted as capturing the *level* of global macroeconomic risk (Verdelhan, 2018). The *carry* factor is a zero-cost portfolio, constructed by investing in high-yielding currencies while funding the position in low-yielding currencies. It thus equals the return on a currency carry trade. The factor exploits the well-documented deviations from uncovered interest rate parity (Hansen and Hodrick, 1980; Fama, 1984) and is closely related to measures of global volatility, liquidity and uncertainty (Menkhoff et al., 2012a; Mancini, Ranaldo, and Wrampelmeyer, 2013; Verdelhan, 2018).

3.3 Currency Return Predictability and Dynamic Currency Factor Hedging

We forecast currency returns each month using a conditional version of the two-factor model. Doing so takes account of two empirically observed features of common currency factors: factor betas are time-varying and factor returns are partially predictable in the time series. Verdelhan (2018) finds bilateral *dollar* betas fluctuate over time and across currencies, and that capturing these changes helps to generate a large cross-sectional spread in returns on portfolios sorted by dollar betas.[12] Lustig, Roussanov, and Verdelhan (2011) evaluate their asset pricing model on *portfolios* sorted by interest rates, and thus indirectly capture time-varying bilateral factor betas since, while the *dollar* and *carry* betas remain constant, the currency *composition* of each underlying portfolio changes.

We capture time-varying factor betas each month by regressing currency returns on a constant and the *dollar* and *carry* factor premia (λ_t^{dol} and λ_t^{car}) using a 60-month rolling window,

$$R_{i,t} = \alpha_i + \beta_{i,t}^{dol}\lambda_t^{dol} + \beta_{i,t}^{car}\lambda_t^{car} + \varepsilon_{i,t}, \tag{6}$$

and collect the month-t factor exposure estimates, $\hat{\beta}_{i,t}^{dol}$ and $\hat{\beta}_{i,t}^{car}$. Next, we account for factor return predictability by running predictive regressions of monthly factor returns on a constant and a set of time t-1 predictor variables X_{t-1},[13]

[12] Differences in bilateral *dollar* betas may be accounted for by changing capital flows (Verdelhan, 2018) or through a trade-based gravity model that relates betas to the physical distance between countries (Lustig and Richmond, 2018).

[13] We initially use the first ten years of data to estimate the first out-of-sample regression and then continue over an expanding window. We also condition the model using the first five and 15 years of data and find qualitatively identical

$$\lambda_t^j = \varsigma_{j,t} + \psi_{j,t} X_{t-1} + \eta_{j,t};\ j = \{dol, car\}, \tag{7}$$

to form one-month-ahead conditional expected factor returns $\mathbb{E}_t \lambda_{t+1}^j = \hat{\varsigma}_{j,t} + \hat{\psi}_{j,t} X_t$. We consider four theoretically justified and empirically supported predictor variables in our analysis:

Average forward discount. Lustig, Roussanov, and Verdelhan (2014) find that *dollar* factor returns can be predicted using the average forward discount of currencies against the U.S. dollar. When U.S. short-term interest rates are relatively high, the U.S. dollar tends to appreciate against a broad basket of currencies and vice-versa when U.S. short-term interest rates are comparatively low. The predictability is driven by time-variation in the U.S.-specific exposure to global risk. We construct the one-month forward discount on currency i against the U.S. dollar by extracting month-end data on spot and one-month forward rates, $fd_{i,t} = s_{i,t} - f_{i,t}$, where $f_{i,t} = log(F_{i,t})$ and $s_{i,t} = log(S_{i,t})$. A positive $fd_{i,t}$ indicates that short-rates in the United States are lower than those in country i. The predictor variable is constructed as the average forward discount across all N currencies against the U.S. dollar at time t,

$$\overline{fd_t} = \frac{1}{N} \sum_{i=1}^{N} fd_{i,t}.$$

Foreign exchange volatility. *Carry* factor returns are known to exhibit a strong negative relationship with FX volatility (Bhansali, 2007; Clarida, Davis, and Pedersen, 2009; Menkhoff et al., 2012a; Cenedese, Sarno, and Tsiakas, 2014), since currency carry trades typically exhibit large drawdowns around periods of heightened uncertainty (Melvin and Taylor, 2009). Cenedese, Sarno, and Tsiakas (2014) motivate their empirical examination of the relationship between volatility and currency returns via the ICAPM, and find the relationship is negative and particularly strong when volatility is high. Indeed, the authors find FX volatility is particularly good at predicting carry trade returns prior to the *largest* carry trade losses. We measure monthly aggregate foreign exchange market volatility as the average daily squared returns across G10 currency pairs against the U.S. dollar,

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau=1}^{T_t} \left(\sum_{i=1}^{K_\tau} \frac{R_{i,\tau+1}^2}{K_\tau} \right),$$

where T_t is the number of trading days in month t, and K_τ is the number of currency pairs with available return data on day τ. We follow Bakshi and Panayotov (2013), who document that a strong relationship exists between carry trade returns and momentum in various predictor variables. We

results. Results are available upon request.

therefore use the 3-month average (log) growth in FX volatility:

$$\Delta\sigma_t^{FX} = \frac{1}{3} log\left(\frac{\sigma_t^{FX}}{\sigma_{t-3}^{FX}}\right).$$

TED Spread. Brunnermeier, Nagel, and Pedersen (2009) find that tighter funding liquidity, as proxied by increases in the TED spread can also forecast short-term (one-week ahead) carry returns, likely due to a "flight-to-safety" or "flight-to-quality" effect, in which funding constraints reduce market liquidity. This effect builds on the theoretical predictions on the relationship between asset prices and funding liquidity in the model of Brunnermeier and Pedersen (2009). We sample end-of-month values of 3-month LIBOR and 3-month Treasury bills from *Datastream* and construct the TED spread as the difference between the two rates, $TED_t = LIBOR_t^{3M} - Tbills_t^{3M}$. We calculate the quarterly growth in the TED spread as,

$$\Delta TED_t = \frac{1}{3} log\left(\frac{TED_t}{TED_{t-3}}\right).$$

Commodity returns. Higher commodity prices predict higher carry trade returns (Bakshi and Panayotov, 2013; Ready, Roussanov, and Ward, 2017). The positive relationship is intuitive because carry trade investment currencies are also typically *commodity* currencies, such as the Australian dollar, New Zealand dollar, and Norwegian krone, and thus higher commodity prices are associated with improved 'terms-of-trade' for the group of high yielding currencies. Ready, Roussanov, and Ward (2017) provide a theoretical foundation for the relationship and show that the time-series predictability can be understood as a function of changes in the level of global shipping costs.[14] We proxy for commodity prices using daily values of the Commodity Research Bureau's raw industrials index collected via *Datastream*. We sample end-of-month values and construct the variable as the quarterly growth in the commodity price index (CRB),

$$\Delta CRB_t = \frac{1}{3} log\left(\frac{CRB_t}{CRB_{t-3}}\right).$$

Dynamic Currency Factor Hedging. Equipped with the estimated factor betas from Equation (6) and expected factor returns (i.e. factor premia) from Equation (7), we form conditional expected currency return over the following month for each bilateral currency pair i,

$$\mathbb{E}_t R_{i,t+1} = \hat{\beta}_{i,t}^{dol} \mathbb{E}_t \lambda_{t+1}^{dol} + \hat{\beta}_{i,t}^{car} \mathbb{E}_t \lambda_{t+1}^{car}. \tag{8}$$

[14] Other studies on the relationship between commodity prices and exchange rate returns include Chen and Rogoff (2003) and Chen, Rossi, and Rogoff (2010).

The expected currency returns form the column vector $\mu_{f,t}$ that enters the calculation of optimal currency hedge positions defined in Equation (3). Combining $\mu_{f,t}$ with an historical variance-covariance matrix Σ_t, estimated over a rolling 60-month window, enables us to formulate the vector of optimal currency hedges, $w^*_{f,t}$.

3.4 Alternative Currency Hedging Frameworks

We evaluate *DCF* hedging against a set of leading alternative currency hedging frameworks. Specifically, we consider nine alternative approaches that build in complexity from naive strategies that apply a blanket rule across currencies, to the most complex schemes, that combine expected currency returns and cross-asset variance-covariance matrices within a mean-variance framework.

Naive hedging. We consider two 'naive' approaches to currency hedging. The first naive approach is to ignore currency risk and maintain a portfolio that is entirely *unhedged* against FX exposure. Froot (1993) shows that over longer investment horizons in which Purchasing Power Parity (PPP) holds and real exchange rates display mean reversion, an unhedged portfolio is optimal. On the other hand, if exchange rates correlate positively with the underlying asset price and currency returns average zero over the long run, the volatility of an international portfolio increases as a result of FX exposure but without sufficient compensation in return. It has been common, therefore, to argue that entirely eliminating FX exposure provides the best approach to managing currency risk, especially within global bond portfolios (Perold and Schulman, 1988; Eun and Resnick, 1988; Campbell, Serfaty-De Medeiros, and Viceira, 2010). The second naive approach is thus to *fully hedge* all FX exposure.[15]

Characteristic hedging. Fully hedging FX exposure can reduce portfolio volatility but can also limit any upside return potential. If a currency is expected to earn positive returns, the extra volatility from not hedging may be acceptable if the return benefit is sufficient. In a seminal paper, Glen and Jorion (1993) document that dynamically conditioning hedge ratios on interest rate differentials can yield sizeable portfolio gains, since high-interest rate currencies typically earn higher currency returns (Hansen and Hodrick, 1980; Fama, 1984). Hedging only currencies with lower short-term interest rates exploits this predictability in currency returns. We follow this general approach and construct three 'characteristic' hedging strategies based on three different sources of cross-sectional currency return predictability. First, we follow Glen and Jorion (1993) and condition on interest rates, which

[15] A common industry practice is to apply a 50/50 hedged/unhedged policy, in which 50% of all foreign exchange exposure is hedged at all times. Michenaud and Solnik (2008) show that this type of rule can be optimal if investors are averse to 'regret' risk. In the interest of space we do not report results on the 50/50 naive hedge because of the similarity with the results on the fully hedged and unhedged positions. Results are available upon request.

can also be viewed as exploiting the returns generated by the currency carry trade (Burnside et al., 2006; Lustig, Roussanov, and Verdelhan, 2011). We denote this the '*Carry* hedge'. The strategy hedges all currencies with lower short-term interest rates than the U.S. short-term rate and leaves FX exposure unhedged in currencies with higher short-term rates. Second, we condition on currency value, since undervalued currencies typically earn higher returns than their overvalued counterparts (see, e.g. Asness, Moskowitz, and Pedersen, 2013; Menkhoff et al., 2017). Following Asness, Moskowitz, and Pedersen (2013) we construct a measure of currency value using the real exchange rate against the domestic currency over the previous five years and leave FX exposure unhedged in undervalued currencies, while fully hedging overvalued currencies.[16] We denote this the '*Value* hedge'. Third, we condition on currency momentum since recently appreciated currencies typically continue appreciating in subsequent months (see, e.g. Asness, Moskowitz, and Pedersen, 2013; Menkhoff et al., 2012b). The strategy hedges FX exposure in currencies that depreciated against the U.S. dollar over the previous three months and leaves FX exposure unhedged in currencies that appreciated over the same period. We denote this the '*Momentum* hedge'.

Mean-variance hedging. Characteristic hedging focuses entirely on expected currency returns and fails to capture, therefore, any potential benefits arising from exploiting the covariance structure across assets and currencies. Some currencies typically exhibit low or negative correlation with global equity markets and thus provide a useful natural hedging mechanism (Campbell, Serfaty-De Medeiros, and Viceira, 2010). During the global financial crisis, for example, the U.S. dollar and Japanese yen generated large positive returns, providing a beneficial source of diversification. We therefore construct four alternative currency hedging strategies that attempt to optimally combine information in *both* expected currency returns and the cross-asset covariance matrix. As with *DCF* hedging, this approach generates optimal hedge positions according to Equation (3). Indeed, while expected currency returns are formed differently across each strategy, we set the values for γ, $w_{x,t}$ and Σ_t to be the same as under *DCF* hedging.

The first strategy assumes Uncovered Interest Parity (UIP) holds and thus expected currency returns equal zero. The strategy thus shuts down the expected return input and instead seeks to maximize investment performance by minimizing portfolio variance. By focussing on variance minimization the approach is similar to the methodology applied in Campbell, Serfaty-De Medeiros, and Viceira (2010). We denote the approach the '*UIP* hedge'.

The second approach exploits the stylized fact in international economics that foreign exchange

[16] The value measure is the negative of the 5-year return on the exchange rate from 4.5 to 5.5 years ago divided by the spot exchange rate today minus the log difference in the change in CPI in the foreign country relative to the U.S. over the same period.

rates are difficult to predict over short horizons (Meese and Rogoff, 1983; Rossi, 2013). Indeed, the commonly employed benchmark in international economics, when assessing predictability, is a random-walk model without drift. If exchange rates are expected to follow a random walk, the expected return in Equation (4) simplifies to $R_{i,t+1} = 1 - F_{i,t}/S_{i,t}$.[17] We denote the approach the '*Random Walk* hedge'.

The third strategy provides a hybrid of the first two. *UIP* hedging assumes exchange rates are perfectly predictable while *Random Walk* hedging implies no predictability. In the third approach we allow for *some* predictability following Glen and Jorion (1993). Specifically, we regress time-t currency returns on time-t-1 interest rate differentials using a 60-month rolling window. We then extract the parameter estimates to form a conditional estimate of currency returns at time-t+1. We denote the approach the '*Interest Rate* hedge'.

The fourth mean-variance strategy extends the *Interest Rates* hedge via a 'model combination'. Combined model forecasts provide better forecasts, on average, than individual models, principally by reducing the level of forecast volatility (Rapach, Strauss, and Zhou, 2010). We combine models by first estimating bivariate ordinary least square regressions of exchange rate returns on a set of predictor variables, to form model-specific forecasts. We then average the model forecasts to construct the model combined estimate. We use nine predictor variables: the three 'characteristic' variables described above (carry, value and momentum); the four factor return predictors (average forward premia, FX volatility, TED spread, and commodity returns), which we define in Section 3.3; global equity volatility that we proxy using MSCI country stock index returns following Lustig, Roussanov, and Verdelhan (2011); and the output-gap differential, which has been found to have some of the best properties for predicting exchange rate returns (Molodtsova and Papell, 2009; Rossi, 2013).[18] The regression for currency i using predictor variable j takes the form,

$$R_{i,t} = \iota_{i,t} + \pi_{i,t} x_{j,t-1} + \epsilon_{i,t}. \tag{9}$$

We estimate the regressions over rolling 5-year windows. Combining $x_{j,t}$ with the estimates $\hat{\iota}_{i,t}$ and $\hat{\pi}_{i,t}$ we form an expectation of the currency return over the following period.[19] We denote the approach the '*Model Combo* hedge'. The approach provides a particularly difficult benchmark since it includes all the predictor variables employed within *DCF* hedging when forecasting currency factor returns.

[17] Ackermann, Pohl, and Schmedders (2018) show that a currency portfolio constructed on this basis generates large returns within a mean-variance framework – particularly relative to an equally weighted currency portfolio.

[18] We construct the output gap for each country by fitting a Hodrick-Prescott (1980) filter through (log) industrial production data, collected from the *OECD*, and extract the cyclical component to proxy for the output gap.

[19] Rapach, Strauss, and Zhou (2010) also estimate a "kitchen-sink" model, which includes all predictor variables in the same regression and find weaker results than when using the simple model average. We also implement the "kitchen-sink" approach and find, consistent with Rapach, Strauss, and Zhou (2010), generally weaker performance relative to the average model combination. We use the mean as our measure of average, although find almost identical results when using the median. Results available upon request.

Doing so, however, provides a sharp test to assess if the predictability of currency returns via *currency factors* is particularly important for generating an incremental source of investment gains, or whether the same performance could have been achieved by using the predictor variables directly.

4 Data

We collect foreign exchange rate data from two sources. First, we obtain daily bid, mid, and ask spot and forward exchange rate data from Barclays via *Datastream*. Second, we collect daily bid and ask spot exchange rates from *Olsen Financial Technologies*, a provider of inter-dealer wholesale quotes. The sample period is from January 1987 to July 2017, which corresponds with the broad availability of U.S. dollar foreign exchange rate data across the two datasets, and with a period in which FX market liquidity was sufficient to implement currency hedges. The exchange rate data includes quotes against the U.S. dollar for nine developed market economies: Australia, Canada, Germany, Japan, New Zealand, Norway, Sweden, Switzerland and the United Kingdom. We refer to the nine countries plus the United States as the 'G10'. The Barclays exchange rate data is used to construct the monthly currency returns associated with entering a long forward contract. We calculate currency returns according to Equation (4) by first extracting the end-of-month spot and forward exchange rates. After 1999, the German deutschmark is replaced in our sample by the euro.

In the core analysis we estimate *monthly* variances and covariances of underlying securities and foreign exchange rate returns. We later extend the analysis to estimate *realized* variances and covariances using daily return data for both underlying assets and foreign exchange rates. However, using daily data exacerbates the asynchronous trading problem arising from differences in market closing times. We mitigate the problem using the exchange rate data from *Olsen Financial Technologies*, which is collected at 4.10pm EST to correspond with the closing time of the Canadian equity market – the final market to close each day in our sample. The data allows us to construct estimates of the cross-asset covariance structure via the synchronization procedure in Burns, Engle, and Mezrich (1998). We provide further details of the procedure in Section 6. We also collect monthly currency factor returns, constructed using developed market currencies, from the website of Adrien Verdelhan. The data matches that used in the study of Lustig, Roussanov, and Verdelhan (2011) and ends in June 2015. We update the series following the procedure of Lustig, Roussanov, and Verdelhan (2011) to coincide with the end of our sample period.

We incorporate transaction costs arising from currency hedging following Darvas (2009). The method accounts for both newly opened and rolled-over forward contracts associated with currency hedging; currency hedge positions fluctuate over time and include both pre-existing hedges that are rolled-over to the subsequent month and newly opened contracts. The procedure requires the full bid-ask spread to be absorbed in the month a contract is first entered, with smaller transaction costs being charged in subsequent months as, consistent with practice, banks roll over forward contracts at lower cost. If at time t, for example, a U.S. investor employs a 50% FX hedge on a Japanese yen denominated security but increases the hedge to 60% at time $t+1$, the full bid-ask spread is charged on the original 50% hedge at $t+1$ but only on the newly entered 10% hedge at time $t+2$. Instead, the rolled-over 50% hedge is charged a lower 'roll-over cost' at time $t+2$.[20]

We collect daily data on MSCI country equity indexes (the net return with dividends reinvested after witholding tax) for all G10 economies and sample the end-of-month index values to calculate discrete monthly returns in local currency. We also collect monthly G10 data on 10-year government bond yields from *Global Financial Data* and construct returns following the approximation in Campbell, Lo, and MacKinlay (1997).[21] We convert equity and bond returns into U.S. dollars using the spot exchange rate return over the month, which equates to the returns a U.S. investor would receive if the asset positions were unhedged against FX exposure. Equity and bond market portfolios are constructed using equal-weights and GDP-weights. GDP data is sampled yearly from the *OECD*, with GDP-weights constructed using the previous year's values. Finally, to construct *excess* equity and bond returns we collect one-month money market rates from the IMF's *International Financial Statistics* dataset to proxy for the local risk-free rate.

Summary statistics. Table 1 reports summary statistics for the returns across FX, equity, bond and money markets over the sample. Risk-free rates have varied substantially across countries with some currencies, such as the Australian dollar (6.26%), New Zealand dollar (6.84%) and Norwegian krone (5.69%) offering comparatively high interest rates relative, in particular, to the Japanese yen (1.37%) and Swiss franc (2.09%).[22] Larger cross-sectional variation emerges when comparing equity premiums. The Swedish stock market generated the highest return over the period, which may in part reflect its higher level of total risk. The U.S. stock market was the best performer on a risk-adjusted

[20]Specifically, the after cost total return on a long forward position is given by the realized return on the new and rolled over positions, $R_t = R_t^{new} + R_t^{roll}$. The returns on the new and rolled over positions are given by,

$$R_t^{new} = A_{t-1}^{new}\left(S_t^b - F_{t-1}^a\right) \tag{10}$$

$$R_t^{roll} = A_{t-1}^{roll}\left(S_t^b - \left[S_{t-1}^b + (F_{t-1}^a - S_{t-1}^a)\right]\right). \tag{11}$$

where A_{t-1}^{new} and A_{t-1}^{roll} are the notional amounts of the new or rolled over contracts, and the superscripts b and a reflect the bid and ask prices of either the spot or one-month forward exchange rates.

[21]See Chapter 11 (pp. 406-408) for further details.

[22]Differences in risk-free rates have been explained theoretically, *inter alia*, as relating to a country's size (Hassan, 2013), its position in the global trade network (Richmond, 2016), and its trade specialization (Ready, Roussanov, and Ward, 2017).

basis, generating a Sharpe ratio of almost 0.50 over the sample, followed closely by the Swiss stock market. Consistent with prior evidence, high interest-rate economies, such as Australia and New Zealand were associated with the lowest overall risk-adjusted equity returns (see e.g. Verdelhan, 2010, for an external-habit perspective). A narrower spread exists across 10-year sovereign bond returns. The sample consists of developed market countries with low sovereign default probabilities. Perhaps unsurprising, therefore, the spread over the risk-free rate is similar across countries, ranging from 2.10% in Switzerland to 3.34% in Sweden, while the Sharpe ratios are also in a tight range from a low of 0.36 in the U.S. to 0.45 in Germany, Sweden and Norway. Exchange rate returns are known to be difficult to predict out-of-sample (Meese and Rogoff, 1983; Rossi, 2013), which we see reflected in the near zero average FX returns. There are, however, some interesting cross-sectional features. According to Uncovered Interest Parity (UIP), the bedrock theory in international finance, the exchange rate return should perfectly offset the risk-free rate differential. A long-standing literature has documented the failure of UIP and the tendency of high-interest rate currencies to appreciate against their low-interest rate counterparts (Hansen and Hodrick, 1980; Fama, 1984; Engel, 1996). The average returns in Table 1, however, paint a slightly different picture. The Japanese yen and Swiss franc for example – currencies with the lowest interest rates – have typically *appreciated* the most against the U.S. dollar, while the U.S. dollar has typically appreciated against currencies with higher interest rates.[23] These exchange rate returns were not sufficient, however, to offset the interest rate differentials, leading to the familiar pattern in currency returns, documented in the final row of Table 1, in which the New Zealand dollar and Australian dollar generate a persistently high total currency return.[24]

5 Empirical Evidence on Dynamic Currency Factor Hedging

In this section we present our empirical findings. We begin by assessing the predictability of currency factors before moving to the core results on the out-of-sample investment performance of *DCF* hedging for global equity and bond portfolios.

5.1 Forecasting Currency Factor Returns

Table 2 presents results for a series of ordinary least square (OLS) regressions, in which we forecast *dollar* and *carry* currency factor returns at time $t+1$ using time-t predictor variables (FX volatility, commodity returns, average forward discount and TED spread) described in Section 3.3. The exercise is in-sample and uses the full dataset from January 1987 to July 2017. The purpose is not, therefore,

[23]See Hassan and Mano (2017) for comparable evidence.

[24]See, e.g. Burnside et al. (2006, 2011) and Lustig, Roussanov, and Verdelhan (2011) for further details on the properties of the cross-section of currency returns.

to evaluate the economic value of predictability, but instead to assess the relevance of the predictor variables for understanding global currency factor returns.

The *dollar* currency factor is found to be negatively related to FX volatility, consistent with the U.S. dollar appreciating against foreign currencies when global risk aversion spikes. This may reflect the dollar's role as a 'safe-haven' currency (Ranaldo and Söderlind, 2010) and that investors enter 'flight-to-safety' trades when uncertainty spikes (Maggiori, 2013). The negative impact of FX volatility is, however, much larger for the *carry* factor. The finding is consistent with a large body of work that contends the *carry* factor provides a measure of global risk aversion, related to U.S. equity volatility (see, *inter alia*, Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a; Bakshi and Panayotov, 2013). We show that commodity returns have the most economically significant impact on the two factors. Higher commodity prices strongly predict larger *dollar* and *carry* factor returns. Surprisingly, the effect is strong across both factors, despite evidence in the literature only speaking to the positive relationship between commodity prices and *carry* factor returns (Bakshi and Panayotov, 2013; Ready, Roussanov, and Ward, 2017). The finding on *dollar* factor returns is likely driven by periods of strong world growth, which coincides with higher investment levels, elevated demand, and rising raw material prices – and thus to broad currency appreciations against the U.S. dollar.

We also find, consistent with Lustig, Roussanov, and Verdelhan (2014), that *dollar* factor returns are increasing in the average forward discount, i.e. when the U.S. economy is relatively strong *vis-a-vis* the rest-of-the-world, U.S. interest rates are high and the dollar appreciates against foreign currencies. We find no clear relationship, however, between the average forward discount and *carry* factor returns, which is likely caused by the *carry* factor being dollar-neutral and thus less exposed to U.S. business cycle shocks. Finally, we find the TED spread has no perceivable relationship with either *dollar* or *carry* factor returns – both coefficients are not statistically different from zero and the point estimates become particularly small when we also control for FX volatility.[25] We therefore adopt a parsimonious model in our out-of-sample analysis that includes FX volatility, commodity returns and the average forward discount.

5.2 Performance Measures

We evaluate the relative out-of-sample performance of *DCF* hedging using a mix of statistical and economic performance measures.

[25] The effect of the TED spread is difficult to separate from the relationship between carry trade returns and volatility because times of restricted funding liquidity tend to coincide with elevated levels of global uncertainty. Indeed, Brunnermeier, Nagel, and Pedersen (2009) also proxy for funding conditions using U.S. stock market volatility and thus interbank funding conditions may provide an *alternative* theoretical link between volatility and carry trade returns.

5.2.1 Statistical performance measures

Sharpe ratio. The out-of-sample Sharpe ratio is one of the most commonly employed measures to evaluate a portfolio's statistical performance (DeMiguel, Garlappi, and Uppal, 2009). The measure provides information on the excess return of an investment k per unit of risk. The measure is directly relevant to a mean-variance investor – who seeks to maximize the risk-adjusted return – since they derive utility solely from achieving a higher average return for a given standard deviation of returns. The out-of-sample Sharpe ratio is defined as:

$$\widehat{SR}_k = \frac{\hat{\mu}_k^e}{\hat{\sigma}_k},$$

where $\hat{\mu}_k^e$ is the out-of-sample average return of strategy k in excess of the domestic risk-free rate r_f, and $\hat{\sigma}_k$ is the out-of-sample standard deviation, i.e. the risk of the strategy.

Sortino ratio. The out-of-sample Sortino ratio (Sortino and van der Meer, 1991; Sortino and Price, 1994) is an alternative risk-adjusted measure to the Sharpe ratio. While a mean-variance investor targets a higher Sharpe ratio, it is possible that they do so at the expense of negative skewness (or 'downside risk'), which features in other investor's preferences (Kraus and Litzenberger, 1974; Harvey and Siddique, 2002). The Sortino ratio addresses the concern by penalizing negatively skewed return distributions, which could substantially change the relative performance of a strategy compared to the ranking implied by the Sharpe ratio. The out-of-sample Sortino ratio for strategy k is defined as:

$$\widehat{Sortino}_k = \frac{\hat{\mu}_k^e}{\hat{\sigma}_{d,k}},$$

where $\hat{\sigma}_{d,k}$ is the standard deviation of returns below the risk-free rate, i.e. the 'downside risk'.

Theta. Ingersoll et al. (2007) contend that many performance measures, including the Sharpe ratio and Sortino ratio, are subject to potential 'manipulation' that leads to differences between reported performance and the *true* economic performance. The authors thus develop an alternative 'manipulation-proof' performance measure to adjust returns by risk. This out-of-sample 'theta' measure is defined as:

$$\widehat{\Theta}_k = \frac{1}{(1-\rho)\Delta t} ln \left(\frac{1}{T} \sum_{t=1}^{T} [(1 + r_{k,t})/(1 + r_{f,t})]^{1-\rho} \right),$$

where $r_{k,t}$ reflects the per-period return for strategy k, $r_{f,t}$ is the time-t risk-free rate, while the risk aversion parameter ρ 'penalizes' risk, such that higher values of ρ result in lower values of $\hat{\Theta}_k$.[26] The statistic $\hat{\Theta}_k$ can be viewed as an estimate of the strategy's return premium after adjusting for risk and thus the strategy is equivalent to a risk-free asset that outperforms the interest rate by $\hat{\Theta}_k$.

Information ratio. The information ratio provides a performance measure for strategy k relative to a benchmark strategy b. We use the unhedged and fully hedged portfolios as our benchmark portfolios. A high information ratio provides a positive sign that the strategy *consistently* outperforms a given benchmark and thus adds a time-series element to our set of statistical performance measures. The out-of-sample information ratio is defined as:

$$\widehat{IR}_{k,b} = \frac{\hat{\mu}_k - \hat{\mu}_b}{\hat{\sigma}_{k-b}},$$

where μ_b is the out-of-sample average return of the benchmark portfolio, and $\hat{\sigma}_{k-b}$ is the standard deviation of the difference in the two strategies' returns.

5.2.2 Economic performance measures

Certainty Equivalent Return. The out-of-sample Certainty Equivalent (CEQ) return reflects the return an investor would accept, *with certainty*, rather than investing in strategy k. The measure can thus be viewed as reflecting the *opportunity cost* associated with risk. The measure takes into consideration both the variability of the strategy returns, as well as the investor's level of risk aversion γ. The out-of-sample CEQ return is defined as:

$$\widehat{CEQ}_k = \hat{\mu}_k^e - \frac{\gamma}{2}\hat{\sigma}_k^2,$$

The measure directly captures the mean-variance investor's utility function and therefore maximizing the utility function is equivalent to maximizing the CEQ return.

Performance fee. The performance fee represents the percentage return (ϕ), a mean-variance investor would be willing to sacrifice in order to switch from strategy j to an alternative strategy k. We calculate the fee following Fleming, Kirby and Ostdiek (2001). The method equates the utilities

[26] The parameter ρ can be calculated using the return and risk of a benchmark portfolio via the following equation:

$$\rho = \frac{ln[\mathbb{E}(1+\tilde{r}_b)] - (1+r_f)}{Var[ln(1+\tilde{r}_b)]}. \tag{12}$$

Historically, ρ is found to be between two and four for the CRSP value-weighted market portfolio. Following Ingersoll et al. (2007), we use a risk aversion of three, which is also consistent with the risk aversion parameter used in our mean-variance optimization.

arising from two investment strategies, one of which (k) requires the investor to pay a performance fee, ϕ:

$$\sum_{t=0}^{T-1}\left\{(R_{k,t+1}-\phi)-\frac{\delta}{2(1+\delta)}(R_{k,t+1}-\phi)^2\right\}=\sum_{t=0}^{T-1}\left\{R_{j,t+1}-\frac{\delta}{2(1+\delta)}R_{j,t+1}^2\right\}$$

The parameter δ is the investor's level of relative risk aversion, which we set equal to two or six.[27]

5.3 Dynamic Currency Factor Hedging for International Portfolios

5.3.1 Global equity portfolios

Table 3 presents the core results on the performance of *DCF* hedging in global equity portfolios from the perspective of a U.S. investor. The results in the table reflect the *out-of-sample* period beginning in January 1997 and ending in July 2017 (the first ten years of data, from January 1987 to December 1996, form the in-sample period in which we estimate the initial parameters). In Panel A, we report results based on an equal-weighted global equity portfolio (excluding the U.S. equity index). Each column reflects the performance of the equity portfolio with foreign exchange exposure hedged using an alternative currency hedging scheme. The underlying equity positions are the same in every case and hence any difference between the portfolios' investment performance is driven entirely by the impact of currency hedging. The results based on *DCF* hedging are reported in the first column. Comparing broadly across all nine alternative frameworks, we find that the *DCF* hedged equity portfolio generates the highest overall return of 7.93%, yet has similar portfolio volatility (15.3%) to other strategies, and hence it produces the strongest overall investment performance as measured by the Sharpe ratio (*Sharpe*, 0.52). Sharpe ratios can also be formally compared to assess whether one ratio is *statistically* higher than another (Ledoit and Wolf, 2008). In the row denoted Δ*Sharpe*, we report the difference in Sharpe ratios between the *DCF* hedged portfolio and each alternatively hedged equity portfolio. The superscripts ***,**,* represent statistically significant differences at the 1%, 5% and 10% significance levels. We find that compared to the alternative currency hedging strategies, the *DCF* hedged equity portfolio always generates a statistically higher Sharpe ratio, at least at the 10% level of statistical significance.

The higher expected returns and Sharpe ratios do not appear, however, to be achieved at the expense of larger 'downside' risk. The *DCF* hedged equity portfolio has less negative portfolio skewness (*skew*, -0.58), and one of the the lowest maximum drawdowns (*MDD*) compared to the alternative frameworks. In contrast, strategies that exploit interest rates, such as the *Random Walk* or *Interest*

[27] The choice of values for relative risk aversion are consistent with those in Della Corte, Sarno, and Tsiakas (2009).

Rate hedge, result in notably higher negative skewness (-1.02 and -1.00, respectively) and thus induce a higher likelihood of an investor realizing large negative payoffs. Consistent with these findings, we find the *DCF* hedged portfolio generates a Sortino ratio of 0.76, that is over 30% larger than the second best performer (*Momentum* hedge, 0.57), while the theta measure (4.28%) is around twice as large as all other strategies. Furthermore, the information ratio, when measured using either the unhedged or fully hedged portfolio as the benchmark, is higher than that of every other currency hedging strategy, emphasising the persistent outperformance of *DCF* hedging for international equity portfolios.

In the remainder of Panel A, we present results on *economic* performance measures. According to the *CEQ* return, the risk-free rate would need to equal 4.40% before the investor would prefer the guaranteed return rather than to invest in international equities using *DCF* hedging. The return is high and much larger than the average U.S. risk-free rate observed over the sample, and higher than all other *CEQ* returns across the alternative hedging strategies. In the row denoted $\Delta\,CEQ$ we report the differences between the *CEQ* return generated under *DCF* hedging and that obtained from hedging using the alternative strategies.[28] In every case, we find that *DCF* hedging generates a statistically higher *CEQ* equity return at either the 1% or 5% significance level, indicating substantial economic performance gains from employing *DCF* hedging within a global equity portfolio. In the final two rows of Panel A, we report the annualized performance fee a mean-variance investor would pay to switch to *DCF* hedging. The performance fee (ϕ) effectively captures the amount a mean-variance investor would be willing to pay to implement *DCF* hedging *over-and-above* the amount they would pay to a manager adopting one of the alternative hedging schemes. We find that investors would pay a substantial performance fee, of up to 3.38% per annum, to switch to *DCF* hedging, while even the *lowest* fee is a substantial 1.60% per annum.

In Panel B, we report the equivalent results for the GDP-weighted equity portfolio. GDP-weights place a larger fraction of wealth in the German, Japanese and British stock markets relative to the equal-weighted portfolio. The equal-weighted portfolio therefore provides a better gauge of the overall hedging performance because it requires the approach to work well *on average* across currency pairs. Nonetheless, we still find that *DCF* hedging generates the highest average annualized return of 6.16%, which is over 80% higher than the unhedged portfolio (3.36%) and over 35% higher than the fully hedged portfolio (4.51%).[29] Consistent with the results for the equal-weighted portfolio, the *DCF* hedged portfolio also generates the highest Sharpe ratio (0.40), which is statistically higher than five

[28] See Green (2002) and DeMiguel, Garlappi, and Uppal (2009) for further details on the calculation of p-values associated with the null hypothesis that the difference between two *CEQ* returns is zero.

[29] The lower overall returns for the GDP-weighted portfolios is consistent with the core result of DeMiguel, Garlappi, and Uppal (2009). Higher returns are achieved in a 1/N environment, in which more weight is placed in small and comparatively less liquid country indices compared to a value-weighted allocation.

of the alternative currency hedging strategies. Furthermore, *DCF* hedging always generates the highest Sortino ratio (0.57), theta performance measure (2.53%) and information ratio (relative to both the unhedged and fully hedged portfolios). The economic performance is also impressive. In particular, the *CEQ* return of 2.66% is the largest and is statistically higher than six of the alternative approaches. Only the *Momentum* hedge, *UIP* hedging and the *Model Combo* have statistically indistinguishable *CEQ* returns – yet even for these approaches, a mean-variance investor is found willing to pay a sizeable performance fee of up to 1.41% per annum to switch to *DCF* hedging. The unhedged investor is found most willing to switch – paying up to 3% per annum to adopt *DCF* hedging, which is economically large given the annualized unhedged equity return is only 3.36%.

5.3.2 Global bond portfolios

Table 4 presents our findings on *DCF* hedging for global bond portfolios. Fully hedging FX exposure is often viewed as the optimal strategy for managing currency risk in global bond portfolios because of the large reduction in portfolio volatility (Glen and Jorion, 1993; Campbell, Serfaty-De Medeiros, and Viceira, 2010). Indeed, relative to an unhedged portfolio, the fully hedged portfolio reduces volatility by 50% in both the equal-weighted (9.23% to 4.66%) and GDP-weighted portfolios (8.48% to 4.23%). Nonetheless, *DCF* hedging still delivers a higher Sharpe ratio (0.77) than the fully hedged bond portfolio (0.54), principally because it captures the higher returns available from FX exposure. Furthermore, the Sharpe ratio is statistically higher than seven of the alternative Sharpe ratios. The *CEQ* bond return (4.52%) is also statistically higher than all alternative strategies at the 1% or 5% significance level. We therefore find that a mean-variance investor is willing to pay a large performance fee, of up to 3.05% per annum, to switch to *DCF* hedging. We find comparable evidence that *DCF* hedging also delivers the highest Sharpe ratio and *CEQ* return for the GDP-weighted bond portfolio.

Turning to the other statistical performance measures, we find that *DCF* hedging does not produce negatively skewed returns and thus the Sortino ratio (1.32) and and theta measures (4.52%) are the highest across both the equal-weighted and GDP-weighted bond portfolios. Moreover, the *DCF* hedged bond portfolio has the largest information ratio (0.15), which is over twice the magnitude of any other currency hedging strategy. Overall, the findings for bond portfolios echo those observed for global equity portfolios: *DCF* hedging consistently delivers superior statistical and economic investment performance compared to every other alternative currency hedging strategy: the *DCF* hedged portfolio consistently delivers the highest overall return, Sharpe ratio, Sortino ratio, theta measure, information ratio, and *CEQ* return. In the majority of cases, the relative improvement in Sharpe ratio and *CEQ* return is statistically significant, while a mean-variance investor is found willing to pay a large performance fee to switch to the *DCF* hedged portfolio.

Overall, we conclude from this section that *DCF* hedging is consistently the strongest out-of-sample currency hedging strategy between 1997 and 2017, and that a mean-variance U.S. investor would have a strong preference to adopt *DCF* hedging as part of their global equity or bond investment strategy.

6 Extensions to Dynamic Currency Factor Hedging

We extend our analysis on *DCF* hedging in three directions. First, we evaluate the benefits fom estimating the variance-covariance matrix using higher frequency synchronized returns. Second, we investigate if investors outside the United States can also benefit from *DCF* hedging. Third, we explore the source of the performance gains from *DCF* hedging.

6.1 Alternative Covariance Matrices

DCF hedging focuses on predicting currency returns (i.e. the vector μ_f in Equation (3)), while the conditional covariance matrix Σ, which is also required to formulate hedge positions, is estimated using a simple rolling 60-month window with historical data. Therefore, while *DCF* hedging appears to offer substantial investment gains relative to alternative hedging schemes, it is natural to ask whether the performance of *DCF* hedging could be improved via more precise estimates of the conditional cross-asset variance-covariance matrix. We investigate this possibility by analyzing daily-level price data. A problem arises with cross-asset analysis at the daily level (particularly in international data) because returns are not synchronous due to differences in market closing times. To mitigate the problem, we estimate *synchronized* returns using a first-order Vector Moving Average (VMA(1)) following Burns, Engle, and Mezrich (1998).[30]

Table 5 presents our results on alternative covariance matrices, for global equities and bonds, across equal-weighted (Panel A) and GDP-weighted (Panel B) portfolios. The first column reports results for the historical 60-month rolling estimated covariance matrix (*Hist*) that serves as our benchmark and is equivalent to the values presented in Tables 3 and 4. In the second column (*Realized*), we present results when employing synchronized daily returns and a realized covariance matrix. Surprisingly, we find the use of daily-level data does not provide additional investment performance gains. For both equity

[30]The VMA(1) takes the form $R_t = \varepsilon_t + M\varepsilon_{t-1}$, where R is a vector of stock or bond returns, M is a moving average matrix with lower triangular elements constrained to be zero, and ε is a vector of the unexpected component of returns. The synchronized returns take the form

$$\hat{R}_t = \varepsilon_t + M\varepsilon_t.$$

We obtain data from *Olsen Financial Technologies* that is recorded at 4.10pm in Toronto to match with the Canadian market's closing time (consistent with the MSCI's approach in constructing the Canadian country-level index), which is the point at which we synchronize daily returns. Equipped with these returns, we calculate the realized covariance matrix using a 3-month rolling window as in Mueller, Stathopoulos, and Vedolin (2017).

and bond portfolios, the Sharpe ratio and *CEQ* return *deteriorate* relative to the benchmark portfolio – principally due to weaker overall returns. In the case of global equity returns, the deterioration is statistically significant, with a mean-variance investor found willing to pay a premium of over 0.7% per annum to *revert back* to the benchmark case. The weakness in investment performance suggests a problem of estimation error: higher-frequency data improves precision if the model is well specified, but may otherwise increase volatility and bias.[31] We attempt to mitigate any estimation error by implementing the covariance shrinkage approach of Ledoit and Wolf (2004) (column denoted *Realized w. Shrink*), but find the results remain virtually unchanged. In the next two columns we consider two strikingly opposed covariance matrices in terms of their information content. In the first (*Diag*) we set all covariance terms equal to zero (and thus only estimate the realized variance terms) and, in doing so, evaluate how important the covariance terms are to mean-variance currency hedging. In the second, denoted *Actual Covar*, we consider the realized covariance matrix estimated using the following month's returns, and thus incorporate forward looking information. By doing so we assess the potential gains from capturing precise variance-covariance information. Surprisingly, we find the performance of the simple diagonal covariance matrix is *superior* to the perfect foresight covariance matrix and not statistically worse than the benchmark approach.

This finding highlights that estimating realized variances and covariances can *detract* from the overall investment performance, but that the covariance terms, in general, have only a modest impact on the final investment performance. Indeed, when we estimate the realized covariance matrix using *future* return data, and allow for perfect foresight of the covariance structure, the investment performance continues to remain weak relative to the benchmark case, thus efforts to substantially improve currency hedging investment performance via refinements to the variance-covariance matrix appear to have limited upside potential. This finding is consistent with earlier evidence in the literature that suggests perfect knowledge of variances and covariances does little to improve the out-of-sample estimation of optimal hedge ratios (Gardner and Stone, 1995). In the final column (*Actual Rets*), we instead modify the μ_f vector, rather than the covariance matrix, to equal the *actual* returns over the following month and thus incorporate the perfect foresight of returns directly. Investment performance improves substantially, highlighting the potential gains that remain from a richer understanding of the factors driving currency returns. We conclude that further gains from currency hedging are most likely to emerge from insights into the nature and predictability of common currency factors.

[31] Martens and Poon (2001) investigate non-synchroneity adjustments and find large differences between the covariance matrix predicted by the adjustment procedures and an observable *synchronous* covariance matrix. The non-synchroneity adjustment we implement may therefore be subject to substantial estimation error.

6.2 Alternative Investors' Perspectives

The core analysis on *DCF* hedging was undertaken from the perspective of a U.S. investor. But the expected currency returns can be estimated from all other G10 investor's perspectives. It is natural therefore to ask if the investment gains available to a U.S. investor are broadly available. Table 6 presents our findings on *DCF* hedging from all other G10 investor perspectives. In Panel A (Panel B) we report results for equal-weighted (GDP-weighted) global equity and bond portfolios. In each panel we report the Sharpe ratio and *CEQ* return generated under *DCF* hedging, as well as the relative ranking (in square brackets) across all currency hedging frameworks. In the final two rows we report the performance fee a mean-variance investor would pay to switch to *DCF* hedging from either an unhedged or fully hedged portfolio.

The equal-weighted equity portfolios have a wide range of Sharpe ratios, from 0.39 for an Australian investor to 0.52 for a Japanese investor. Yet for eight of the nine investors, the *DCF* hedged portfolio generates the highest Sharpe ratio overall. This pattern is echoed exactly for the *CEQ* returns. Moreover, across all investors, the *DCF*-hedged portfolio commands a high performance fee relative to both an unhedged and fully hedged portfolio. For example, a mean-variance New Zealand investor is found willing to pay 3.97% to switch from the unhedged portfolio, while a Japanese investor is found willing to pay 3.56% to switch from the fully hedged portfolio. These results are closely paralleled when evaluating *DCF* hedging via GDP-weighted portfolios: the Sharpe ratio and *CEQ* return are typically highest under *DCF* hedging and, only for the Japanese and Swiss investors, does *DCF* hedging not deliver the strongest overall investment performance. We find comparable results for global bond portfolios, with the *DCF*-hedged portfolio having the highest or second highest Sharpe ratio or CEQ return in the majority of tests. Furthermore, in each case, a mean-variance investor would always pay to switch from a fully hedged global bond portfolio to a *DCF*-hedged bond portfolio, paying between 0.31% per annum in Australia to 3.56% in Japan. In sum, we view these results as confirming that *DCF* hedging has broad applicability for investors across the G10 economies. The approach consistently outperforms alternative currency hedging frameworks for global equity and bond portfolios and, only in rare instances, would investors not consider *DCF* hedging to be optimal.

6.3 The Source of Performance Gains

DCF hedging is centered around the prediction of currency returns. In this section, we investigate if the source of the investment gains from *DCF* hedging are principally driven by exploiting time variation in factor betas or from the forecastable component of currency factor returns.

We present our findings in Table 7 for global equity and bond portfolios, formed using both equal- and GDP-weights. In the first column, we present the benchmark results equivalent to those presented in Tables 3 and 4. In the second column (titled 'Factor Betas'), we shut-down factor return predictability by setting factor returns equal to their historical average (estimated using an expanding window). If the investment performance of equity and bond portfolios hedged using the *DCF* approach remain comparable to our core analysis, it indicates that exploiting time-variation in factor returns is not critical to the investment gains from *DCF* hedging. In each case, however, we find the investment performance deteriorates substantially from the benchmark, with the Sharpe ratio and *CEQ* return always statistically lower at either the 1% or 5% level of significance. A mean-variance investor would thus pay a high performance fee to incorporate the predictability stemming from *dollar* and *carry* factors. The weaker performance from capturing only time-variation in factor betas suggests that *DCF* hedging benefits principally from the forecastable component of currency factor returns.

The finding raises a natural question as to whether capturing time-variation in factor betas provides *any* overall enhancement to the portfolios' investment performance. We explore the question by reintroducing the predictability of factor returns, while setting factor betas equal to their unconditional averages. Results are reported in the column titled 'Factor Returns'. We find the investment performance using constant factor betas is always comparable to the baseline *DCF* hedging performance, indicating that the inclusion of time-varying betas only marginally affects the core results. Indeed, Sharpe ratios and *CEQ* returns are not statistically different from those generated in the baseline case.[32]

7 A Dynamic Currency Factor Trading Strategy

An alternative approach to including currency in an international portfolio involves the construction of a *separate* currency portfolio, which can then be combined with a fully-hedged underlying asset portfolio to aid diversification. This strategy is not always available since fund managers are usually mandated to hedge only *existing* FX exposure and not to take speculative FX positions. But with a less restrictive mandate, the strategy may provide additional investment performance gains because it relaxes the constraint on currency weights.. To explore the possibility, we construct an out-of-sample 'separate' currency portfolio based on *DCF* hedging that exploits the predictability of currency returns. To do so, we first form a vector of expected currency returns across the nine foreign currencies against the U.S. dollar based on Equation (8), and then implement a simple 'signal rule', in which a positive expected return at time t indicates the need to enter a long position in foreign currency over

[32]Ghysels (1998) shows that a constant beta model in equity markets produces smaller average pricing errors in cross-sectional test if betas are otherwise mismeasured.

the following month, while a negative expected return results in a short position being adopted. In essence, we form a 'time-series' portfolio based on expected currency return signals, which we denote DCF_{TS}.[33]

Table 8 presents summary statistics on the performance of the DCF_{TS} currency portfolios. In Panel A, we report findings for *bilateral* time-series 'portfolios' in which, for each bilateral pair, we enter a long position in foreign currency when the expected currency return is positive and a long position in the U.S. dollar when the expected currency return is negative. The portfolios display strong investment performance across currencies. For the Australian dollar portfolio, the strategy generates a return of 8.11% and a Sharpe ratio of 0.66, while the New Zealand dollar portfolio performs even better, generating a return and Sharpe ratio of 10.86% and 0.85, respectively. The weakest investment performance is associated with the Japanese yen and Swiss franc, although the signal rule still improves the returns by around 3%-4% relative to a simple buy-and-hold strategy documented in Table 1. The final column in Panel A reports the core result for the time-series portfolio. The portfolio generates a high return of 5.78% and a Sharpe ratio of 0.78, and hence stronger in performance than the currency carry trade (Lustig, Roussanov, and Verdelhan, 2011) and 'dollar carry' trade (Lustig, Roussanov, and Verdelhan, 2014).

Kroencke, Schindler, and Schrimpf (2014) document an impressive international diversification benefit from adding a currency portfolio, including currency carry, value and momentum, to a pre-existing international portfolio of stocks and bonds. In Panel B, we report findings on the diversification properties of the DCF_{TS} portfolio when combined with either an equal-weighted global equity or global bond portfolio.[34] In the first column, we employ the fully hedged global equity and bond portfolios, reported in Tables 3 and 4, as the benchmark portfolios. We then add one of five different currency portfolios that include: (i) carry; (ii) momentum; (iii) value (iv) an equal combination of carry, momentum, and value (the "style" portfolio) and (v) the newly constructed DCF_{TS} portfolio.[35] Consistent with Kroencke, Schindler, and Schrimpf (2014) we find that allocating capital to a

[33]The difference between this portfolio and a 'cross-sectional' portfolio, which takes an equal-weighted long position in the highest expected return currencies and equal-weighted short position in the lowest expected return currencies is the role of the U.S. dollar. The time-series portfolio is not necessarily neutral to the U.S. dollar, while the cross-sectional portfolio is. The time-series portfolio is more appropriate in this case because the signal is equal to the expected return, rather than being a characteristic (such as momentum) that proxies for the expected return. Hence the time-series portfolio should exploit the signal to greater effect. Moskowitz, Ooi, and Pedersen (2012) document the strong performance of a time-series momentum portfolio in equity markets, while Goyal and Jegadeesh (2018) provide an analytical discussion on the differences between cross-sectional and time-series portfolios.

[34]We also perform the analysis on GDP-weighted portfolios and find qualitatively identical results. These results are available upon request.

[35]Carry, value and momentum characteristics are constructed as described in Section 3. We form the portfolio using rank weights, given by

$$w_{i,t+1} = c_t \left\{ rank(x_{i,t}) - \sum_{i=1}^{N_t} rank(x_{i,t})/N_t \right\},$$

currency style portfolio offers investors with a statistically higher Sharpe ratio than investing in the global equity portfolio alone – the Sharpe ratio improves by over 40%, while the CEQ return is over 1.3% per annum higher. Yet the improvements fall below the investment gains arising from adding the DCF_{TS} portfolio. The addition of the portfolio almost doubles the equity portfolio Sharpe ratio, while a mean-variance investor in the fully-hedged equity portfolio is found willing to pay a performance fee of up to 5.63% to invest in the portfolio. We document equivalent results for the global bond portfolio: the inclusion of the DCF_{TS} portfolio increases the Sharpe ratio by 80%, and a mean-variance investor would pay a performance fee of up to 5.61% to add the portfolio to the existing global bond portfolio, which is over three-times the fee they would pay to add the currency style portfolio.

Overall, the results indicate that the predictability of currency returns can be adapted to a portfolio setting to provide an alternative approach to currency management when capital can be freely allocated to a pure currency portfolio; the investment performance gains are large and superior to those offered by leading currency strategies including carry, value and momentum.

8 Conclusions

We propose a novel approach to global currency hedging that builds on recent advances in international macro-finance. Specifically, we show that the cross-sectional predictability of currency returns arising from *dollar* and *carry* currency factors also extends to the time series, once we account for the predictability of factor returns. We refer to the approach as Dynamic Currency Factor (DCF) hedging. Over a 20-year out-of-sample period, we find that DCF hedging generates superior investment performance across a range of statistical and economic evaluation metrics relative to all alternative approaches we consider. A mean-variance investor is thus found willing to pay a large performance fee to switch to DCF hedging from the alternative strategies.

In contrast to previous evidence showing mean-variance currency hedging fails out-of-sample because of estimation error when forecasting currency returns, our findings indicate that the predictability of currency returns, stemming from common currency factors, provides a way to successfully hedge international portfolios in a mean-variance framework. We also show that a pure currency portfolio that exploits currency return predictability, generates high risk-adjusted returns and outperforms currency carry, value, and momentum as a source of diversification for global stock and bond investors.

Our findings have two primary implications for the future literature. First, DCF hedging sets a high benchmark when assessing the investment performance of alternative approaches to currency

where $x_{i,t}$ is the signal for currency i at time t, N_t is the number of currencies in the sample, which equals nine each month and c_t is a scaling factor such that the overall portfolio is scaled to one dollar long and one dollar short.

hedging; outperforming a full hedge, for example, is not sufficient to claim success of a proposed currency hedging strategy. Second, the study sheds light on the likely source of future gains from currency hedging: further advances in our understanding of the *factors* that drive currency returns could deliver performance gains beyond those documented in this study.

As the dollar value of international investments grows and currency increasingly becomes the dominant asset class under management, it is paramount for greater attention to be directed towards the optimal approach to managing FX exposure in global portfolios. Exploiting the insights from the burgeoning body of knowledge in international macro-finance, that sheds light on the factors driving currency returns, appears to be a fruitful direction forward.

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Table 1: Summary Statistics

The table presents summary statistics for the foreign exchange, equity, bond, and interest rate market data used in the study. We report the monthly average (*mean*) and standard deviation (*std*) for the risk-free interest rate, excess stock return in local currency, excess bond return in local currency, exchange rate return vis-à-vis the U.S. dollar and the currency excess return vis-à-vis the U.S. dollar for all ten countries in the sample. Excess returns are calculated as the realized return minus the local risk-free interest rate. All values are reported in percent per annum. Further details of the data and sources are described in Section 4. The data sample is from January 1987 to July 2017.

	United States	Germany	Japan	United Kingdom	Canada	Australia	Switzerland	Sweden	Norway	New Zealand
					Risk-free rate (%, annualized)					
mean	3.47	3.29	1.37	5.12	4.22	6.26	2.09	5.00	5.69	6.84
std	0.79	0.77	0.64	1.15	0.96	1.09	0.78	1.66	1.19	1.28
					Excess stock returns in local currency (%, annualized)					
mean	6.91	5.21	1.68	4.29	4.53	3.18	6.63	8.42	5.16	-2.11
std	14.9	21.1	19.5	15.2	14.9	15.9	16.1	23.2	22.7	19.7
					Excess bond returns in local currency (%, annualized)					
mean	2.69	2.62	2.37	2.78	2.65	2.86	2.10	3.34	2.86	2.83
std	7.38	5.81	5.82	7.19	6.82	7.37	5.17	7.39	6.29	6.77
					Exchange rate returns (%, annualized)					
mean	-	-0.05	0.56	-0.86	0.04	-0.05	1.06	-1.22	-0.80	0.44
std	-	10.5	11.0	9.86	7.59	11.4	11.1	11.3	10.8	11.8
					Excess currency returns (%, annualized)					
mean	-	-0.31	-1.79	0.72	0.75	2.72	-0.34	0.01	0.96	3.90
std	-	10.5	11.1	9.90	7.63	11.5	11.1	11.3	10.7	11.9

Table 2: Currency Factor Predictability

The table presents the output from estimating two ordinary least square (OLS) regressions across the full sample from January 1987 to July 2017. The dependent variables are the monthly returns at time *t+1* of the *dollar* and *carry* currency risk factors. We collect data on currency factors from Adrien Verdelhan's website. The independent variables are all recorded at time t and include the change in FX volatility, the change in the CRB's commodity price index, the change in the TED spread, defined as the difference between 3-month U.S. LIBOR and 3-month U.S. T-bills, and the average forward discount of currencies against the U.S. dollar. Both OLS regressions include a constant. We provide full details on the calculation of independent variables in Section 4. Newey and West (1987) standard errors for the coefficients are reported in parentheses. We also report the R^2 statistic and model F-statistic with associated p-value in brackets. A p-value below 0.05 indicates the model provides a better fit of the data than a constant return model. The final row documents the number of monthly observations (*Nobs*).

	Dependent variable: *dollar* factor returns (*t+1*)					Dependent variable: *carry* factor returns (*t+1*)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
					coefficient estimates					
Δ*fx volatility (t)*	-0.010*				-0.006	-0.019**				-0.013**
	(0.007)				(0.010)	(0.006)				(0.007)
Δ*commodity returns (t)*		0.181***			0.172***		0.253***			0.223***
		(0.056)			(0.058)		(0.107)			(0.093)
avg forward discount (t)			0.171**		0.179**			0.049		0.056
			(0.100)		(0.092)			(0.109)		(0.098)
Δ*TED spread (t)*				0.005	0.001				0.013	0.008
				(0.010)	(0.009)				(0.014)	(0.011)
constant	0.001	0.000	0.000	0.001	0.000	0.004***	0.004***	0.004**	0.004	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
					goodness-of-fit					
R^2	0.006	0.023	0.011	0.000	0.038	0.017	0.034	0.000	0.004	0.045
F-stat	2.31	8.95	3.94	0.31	3.56	6.38	12.85	0.23	1.56	4.28
	[0.13]	[0.00]	[0.05]	[0.58]	[0.01]	[0.02]	[0.00]	[0.63]	[0.21]	[0.00]
Nobs	367	367	367	367	367	367	367	367	367	367

Table 3: Global Equity Portfolio: A U.S. Investor's Perspective

The table presents statistical and economic performance measures for global equity portfolios when hedged using one of 10 alternative currency hedging frameworks. The results reflect the *out-of-sample* period from January 1997 to July 2017. In Panel A (Panel B), we report the results for an equal-weighted (GDP-weighted) equity portfolio. The first column presents results for Dynamic Currency Factor (DCF) hedging. The remaining nine approaches are described in Section 4. We report the portfolio mean, standard deviation (*std*), Sharpe ratio (*Sharpe*), the difference in Sharpe ratio relative to the DCF approach (Δ*Sharpe*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown (*MDD*), Sortino ratio (*Sortino*), theta measure (*theta*) and information ratios relative to unhedged ($IR_{unhedged}$) and fully hedged (IR_{hedged}) portfolios. We also report economic performance criteria, including the certainty-equivalent return (CEQ), difference in certainty-equivalent return relative to the DCF approach (ΔCEQ), and performance fee a risk averse investor would pay for a manager to switch from each hedging framework to the DCF approach, assuming the investor either has a risk aversion coefficient of two (ϕ_2) or six (ϕ_6). The superscripts *,**,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolio

		Naive Hedges		*Characteristic Hedges*			*Mean-Var Optimized Hedges*			
	DCF	No Hedge	Full Hedge	Carry	Value	Mom.	UIP	Rnd Walk	Int Rates	Model Combo
					Statistical performance evaluation					
mean (%)	7.93	4.92	5.10	6.46	4.95	6.21	5.10	5.62	5.83	6.11
std (%)	15.3	17.9	13.9	16.5	15.2	15.4	13.6	14.5	15.2	15.1
Sharpe	0.52	0.27	0.37	0.39	0.33	0.40	0.38	0.39	0.38	0.40
Δ*Sharpe*	-	-0.25***	-0.15*	-0.13**	-0.19***	-0.12**	-0.14**	-0.13**	-0.14*	-0.12*
skew	-0.58	-0.79	-0.88	-0.81	-0.70	-0.62	-0.84	-1.02	-1.00	-1.02
kurt	4.21	5.07	4.55	4.59	4.44	4.13	4.72	5.40	5.42	5.67
MDD (%)	52.2	60.8	49.7	58.3	50.3	50.1	48.7	55.8	56.6	57.03
Sortino	0.76	0.38	0.50	0.54	0.45	0.57	0.52	0.53	0.53	0.56
theta (%)	4.28	-0.20	2.04	2.16	1.33	2.52	2.20	2.27	2.16	2.47
$IR_{unhedged}$	0.15	-	0.01	0.11	0.00	0.07	0.01	0.03	0.05	0.06
IR_{hedged}	0.16	-0.01	-	0.07	-0.01	0.07	0.00	0.05	0.05	0.07
					Economic performance evaluation					
CEQ	4.40	0.12	2.19	2.39	1.48	2.66	2.33	2.45	2.38	2.69
ΔCEQ	-	-4.28***	-2.21**	-2.01**	-2.92***	-1.74**	-2.07**	-1.95**	-2.02**	-1.71**
ϕ_2	-	3.30	2.70	1.60	2.97	1.73	2.67	2.23	2.08	1.80
ϕ_6	-	3.38	2.66	1.63	2.97	1.73	2.62	2.21	2.08	1.79

Panel B: GDP-Weighted Portfolio

		Naive Hedges		*Characteristic Hedges*			*Mean-Var Optimized Hedges*			
	DCF	No Hedge	Full Hedge	Carry	Value	Mom.	UIP	Rnd Walk	Int Rates	Model Combo
					Statistical performance evaluation					
mean (%)	6.16	3.36	4.51	5.23	3.85	5.45	4.62	4.73	4.74	5.04
std (%)	15.3	16.8	14.7	15.8	15.3	15.4	13.9	14.6	15.4	14.9
Sharpe	0.40	0.20	0.31	0.33	0.25	0.36	0.33	0.32	0.31	0.34
Δ*Sharpe*	-	-0.20***	-0.09	-0.07**	-0.15**	-0.04	-0.07	-0.08*	-0.09*	-0.06
skew	-0.67	-0.69	-0.80	-0.75	-0.56	-0.67	-0.74	-0.84	-1.09	-0.91
kurt	4.03	4.36	4.06	4.04	3.65	3.90	4.03	4.42	5.68	4.70
MDD (%)	54.2	57.4	54.0	56.4	56.4	52.6	52.1	55.2	58.7	55.4
Sortino	0.57	0.27	0.42	0.45	0.35	0.49	0.46	0.44	0.41	0.46
theta (%)	2.53	-1.06	1.14	1.28	0.24	1.77	1.60	1.40	0.93	1.51
$IR_{unhedged}$	0.15	-	0.05	0.11	0.03	0.13	0.07	0.07	0.07	0.09
IR_{hedged}	0.12	-0.05	-	0.06	-0.04	0.06	0.01	0.02	0.02	0.04
					Economic performance evaluation					
CEQ	2.66	-0.84	1.29	1.47	0.35	1.92	1.72	1.55	1.18	1.69
ΔCEQ	-	-3.50***	-1.37*	-1.19*	-2.31**	-0.74	-0.94	-1.11*	-1.48*	-0.97
ϕ_2	-	2.95	1.59	0.99	2.31	0.72	1.41	1.36	1.43	1.08
ϕ_6	-	3.00	1.57	1.01	2.31	0.72	1.37	1.34	1.44	1.07

Table 4: Global Bond Portfolio: A U.S. Investor's Perspective

The table presents statistical and economic performance measures for global bond portfolios when hedged using one of 10 alternative currency hedging frameworks. The results reflect the *out-of-sample* period from January 1997 to July 2017. In Panel A (Panel B), we report the results for an equal-weighted (GDP-weighted) bond portfolio. The first column presents results for Dynamic Currency Factor (*DCF*) hedging. The remaining nine approaches are described in Section 4. We report the portfolio mean, standard deviation (*std*), Sharpe ratio (*Sharpe*), the difference in Sharpe ratio relative to the *DCF* approach (Δ*Sharpe*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown (*MDD*), Sortino ratio (*Sortino*), theta measure (*theta*) and information ratios relative to unhedged ($IR_{unhedged}$) and fully hedged (IR_{hedged}) portfolios. We also report economic performance criteria, including the certainty-equivalent return (*CEQ*), difference in certainty-equivalent return relative to the *DCF* approach (ΔCEQ), and performance fee a risk averse investor would pay for a manager to switch from each hedging framework to the *DCF* approach, assuming the investor either has a risk aversion coefficient of two (ϕ_2) or six (ϕ_6). The superscripts *,**,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolio

		Naive Hedges		*Characteristic Hedges*			*Mean-Var Optimized Hedges*			
	DCF	No Hedge	Full Hedge	Carry	Value	Mom.	UIP	Rnd Walk	Int Rates	Model Combo
					Statistical performance evaluation					
mean (%)	5.21	2.33	2.52	3.88	2.37	3.63	1.94	3.19	3.11	3.28
std (%)	6.81	9.23	4.66	6.84	6.92	6.70	4.61	5.99	6.39	6.53
Sharpe	0.77	0.25	0.54	0.57	0.34	0.54	0.42	0.53	0.49	0.50
Δ*Sharpe*	-	-0.52***	-0.23	-0.20	-0.43***	-0.23*	-0.35**	-0.24*	-0.28*	-0.27*
skew	0.22	-0.05	0.09	0.07	0.26	0.29	0.08	0.00	-0.03	0.02
kurt	3.61	3.69	2.96	4.15	4.11	3.72	3.74	4.26	5.13	4.30
MDD (%)	15.2	27.2	10.5	12.2	27.0	17.5	11.5	11.3	15.4	15.3
Sortino	1.32	0.38	0.87	0.92	0.54	0.90	0.65	0.83	0.76	0.78
theta (%)	4.52	1.06	2.19	3.17	1.66	2.96	1.62	2.65	2.50	2.64
$IR_{unhedged}$	0.15	-	0.01	0.11	0.00	0.07	-0.02	0.05	0.04	0.05
IR_{hedged}	0.15	-0.01	-	0.07	-0.01	0.07	-0.12	0.05	0.04	0.05
					Economic performance evaluation					
CEQ	4.52	1.06	2.19	3.18	1.65	2.96	1.62	2.65	2.50	2.64
ΔCEQ	-	-3.46***	-2.33**	-1.34*	-2.87***	-1.56**	-2.90***	-1.87**	-2.02**	-1.88**
ϕ_2	-	3.01	2.62	1.34	2.85	1.58	3.20	1.99	2.08	1.92
ϕ_6	-	3.05	2.59	1.34	2.85	1.58	3.17	1.98	2.08	1.91

Panel B: GDP-Weighted Portfolio

		Naive Hedges		*Characteristic Hedges*			*Mean-Var Optimized Hedges*			
	DCF	No Hedge	Full Hedge	Carry	Value	Mom.	UIP	Rnd Walk	Int Rates	Model Combo
					Statistical performance evaluation					
mean (%)	4.16	1.54	2.69	3.41	2.03	3.63	2.27	2.94	2.69	3.05
std (%)	5.53	8.48	4.23	5.56	6.80	6.33	4.20	4.96	5.87	5.87
Sharpe	0.75	0.18	0.64	0.61	0.30	0.57	0.54	0.59	0.46	0.52
Δ*Sharpe*	-	-0.57***	-0.11	-0.14	-0.45***	-0.18	-0.21	-0.16	-0.29*	-0.23*
skew	0.00	-0.01	0.11	0.08	0.04	-0.01	0.09	-0.02	-0.30	-0.17
kurt	3.46	3.33	2.95	4.51	4.05	4.05	3.87	4.34	5.01	4.43
MDD (%)	12.4	26.0	8.6	11.1	25.6	12.1	9.0	10.7	15.1	11.3
Sortino	1.25	0.27	1.06	1.00	0.45	0.92	0.86	0.94	0.68	0.79
theta (%)	3.69	0.47	2.42	2.94	1.34	3.03	2.00	2.56	2.17	2.53
$IR_{unhedged}$	0.14	-	0.05	0.11	0.03	0.13	0.03	0.07	0.06	0.08
IR_{hedged}	0.11	-0.05	-	0.06	-0.04	0.06	-0.10	0.03	0.00	0.03
					Economic performance evaluation					
CEQ	3.70	0.47	2.42	2.94	1.33	3.03	2.00	2.57	2.17	2.53
ΔCEQ	-	-3.23***	-1.28	-0.76	-2.37**	-0.67	-1.70**	-1.13*	-1.53**	-1.17*
ϕ_2	-	2.76	1.43	0.76	2.19	0.56	1.85	1.20	1.48	1.13
ϕ_6	-	2.80	1.41	0.76	2.20	0.57	1.84	1.20	1.49	1.13

Table 5: Global Equity Portfolio with Alternative Covariance Matrices

The table presents statistical and economic performance measures for global equity and bond portfolios when hedged using the Dynamic Currency Factor (*DCF*) approach. The results reflect the *out-of-sample* period from January 1997 to July 2017. Each column reflects an alternative method for estimating the cross-asset covariance matrix. We describe the alternative approaches in Section 5. In Panel A (Panel B), we report the results for equal-weighted (GDP-weighted) equity and bond portfolios. The first column presents results for the standard *DCF* approach calculated using an historical 60-month rolling estimate of the covariance matrix. We report the portfolio mean, standard deviation (*std*), Sharpe ratio (*Sharpe*), and the difference in Sharpe ratio relative to the standard *DCF* approach (Δ*Sharpe*). We also report economic performance criteria, including the certainty-equivalent return (*CEQ*), difference in certainty-equivalent return relative to the standard *DCF* approach (Δ*CEQ*), and performance fee a risk averse investor would pay for a manager to switch to the standard *DCF* approach, assuming the investor either has a risk aversion coefficient of two (ϕ_2) or six (ϕ_6). The superscripts *,**,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolios

	Global Equity Portfolios						*Global Bond Portfolios*					
	Hist.	Realized	Realized w. Shrink	Diag.	Actual Covar	Actual Rets	Hist.	Realized	Realized w. Shrink	Diag.	Actual Covar	Actual Rets
	Statistical performance evaluation											
mean (%)	7.93	7.20	7.21	7.78	7.20	19.00	5.21	5.17	5.16	5.20	4.96	16.48
std (%)	15.3	15.4	15.4	15.8	15.5	15.2	6.8	6.8	6.8	7.1	6.8	6.6
Sharpe	0.52	0.47	0.47	0.49	0.47	1.25	0.77	0.76	0.76	0.73	0.73	2.52
Δ*Sharpe*	-	-0.05**	-0.05**	-0.03	-0.05**	0.73***	-	-0.01	-0.01	-0.04	-0.04	1.75***
	Economic performance evaluation											
CEQ	4.40	3.62	3.65	4.01	3.62	15.52	4.52	4.48	4.47	4.44	4.27	15.84
Δ*CEQ*	-	-0.78**	-0.75**	-0.39	-0.78**	11.12***	-	-0.04	-0.05	-0.08	-0.25	11.32***
ϕ_2	-	0.74	0.73	0.21	0.74	-11.08	-	0.04	0.05	0.03	0.25	-11.28
ϕ_6	-	0.74	0.73	0.22	0.74	-11.08	-	0.04	0.05	0.03	0.25	-11.28

Panel B: GDP-Weighted Portfolios

	Global Equity Portfolios						*Global Bond Portfolios*					
	Hist.	Realized	Realized w. Shrink	Diag.	Actual Covar	Actual Rets	Hist.	Realized	Realized w. Shrink	Diag.	Actual Covar	Actual Rets
	Statistical performance evaluation											
mean (%)	6.16	5.37	5.43	6.01	5.63	17.20	4.16	4.03	4.02	4.21	3.89	15.44
std (%)	15.3	15.4	15.4	15.6	15.3	15.1	5.5	5.5	5.5	5.8	5.5	6.0
Sharpe	0.40	0.35	0.35	0.38	0.37	1.14	0.75	0.73	0.73	0.72	0.71	2.56
Δ*Sharpe*	-	-0.05**	-0.05**	-0.02	-0.03	0.74***	-	-0.02	-0.02	-0.03	-0.04	1.81***
	Economic performance evaluation											
CEQ	2.66	1.83	1.89	2.35	2.14	13.76	3.70	3.57	3.56	3.70	3.44	14.90
Δ*CEQ*	-	-0.83**	-0.77**	-0.31	-0.52	11.10***	-	-0.13	-0.14	0.00	-0.26*	11.20***
ϕ_2	-	0.80	0.73	0.19	0.52	-11.05	-	0.13	0.14	-0.03	0.27	-11.26
ϕ_6	-	0.80	0.74	0.20	0.52	-11.06	-	0.13	0.14	-0.03	0.27	-11.26

Table 6: Alternative Investors' Perspectives
The table presents statistical and economic performance measures for global equity and bond portfolios when hedged using the Dynamic Currency Factor (*DCF*) approach. The results reflect the *out-of-sample* period from January 1997 to July 2017. In Panel A (Panel B), we report the results for equal-weighted (GDP-weighted) equity and bond portfolios. Each column reflects the portfolio performance from the perspective of an investor in one of nine home countries. We report the portfolio Sharpe ratio (*Sharpe*), certainty-equivalent return (*CEQ*), and performance fee a risk averse investor would pay for a manager to switch to the *DCF* approach from either an unhedged (ϕ_2 *unhedged*) or fully-hedged portfolio (ϕ_2 *full hedge*), assuming a risk-aversion coefficient of two in both cases. Numbers in square brackets reflect the rank of either the Sharpe ratio or *CEQ* return relative to the nine alternative frameworks described in Section 3. A rank of 1/10 implies that the statistic was the highest among all ten frameworks evaluated in the study.

Panel A: Equal-Weighted Portfolio

	Investor's Home Country								
	Germany	Japan	UK	Canada	Australia	Switzerland	Sweden	Norway	N. Zealand
					Global Equity Portfolio				
Sharpe	0.44	0.52	0.47	0.42	0.39	0.41	0.47	0.47	0.47
	[1/10]	[2/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]
CEQ	3.26	4.49	3.64	2.90	2.48	2.71	3.65	3.62	3.67
	[1/10]	[2/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]	[1/10]
ϕ_2 *unhedged*	0.38	1.24	1.15	1.70	2.39	0.97	0.63	1.66	3.97
ϕ_2 *full hedge*	1.12	3.06	1.45	1.03	0.59	0.71	1.81	1.98	1.20
					Global Bond Portfolio				
Sharpe	0.71	0.70	0.71	0.58	0.56	0.69	0.73	0.64	0.61
	[1/10]	[2/10]	[1/10]	[2/10]	[4/10]	[1/10]	[1/10]	[1/10]	[4/10]
CEQ	3.56	4.99	3.98	3.09	2.76	3.59	3.80	3.37	3.19
	[1/10]	[1/10]	[1/10]	[1/10]	[2/10]	[1/10]	[2/10]	[1/10]	[1/10]
ϕ_2 *unhedged*	0.49	1.27	1.51	1.71	2.53	1.30	0.55	1.29	3.66
ϕ_2 *full hedge*	1.34	3.56	1.83	0.79	0.31	1.33	1.59	1.53	0.60

Panel B: GDP-Weighted Portfolio

	Investor's Home Country								
	Germany	Japan	UK	Canada	Australia	Switzerland	Sweden	Norway	N. Zealand
					Global Equity Portfolio				
Sharpe	0.51	0.48	0.52	0.45	0.47	0.41	0.55	0.52	0.50
	[1/10]	[2/10]	[1/10]	[1/10]	[1/10]	[3/10]	[1/10]	[1/10]	[1/10]
CEQ	4.21	3.83	4.28	3.35	3.60	2.80	4.64	4.30	4.02
	[2/10]	[2/10]	[1/10]	[1/10]	[1/10]	[3/10]	[1/10]	[1/10]	[1/10]
ϕ_2 *unhedged*	1.62	-0.01	1.91	2.12	3.64	1.07	1.84	2.66	4.61
ϕ_2 *full hedge*	2.18	1.97	2.08	1.38	1.73	0.68	2.71	2.74	1.88
					Global Bond Portfolio				
Sharpe	0.65	0.61	0.68	0.54	0.51	0.60	0.66	0.58	0.56
	[1/10]	[2/10]	[1/10]	[1/10]	[4/10]	[1/10]	[2/10]	[1/10]	[2/10]
CEQ	3.97	4.11	4.19	3.08	3.07	3.45	4.20	3.57	3.45
	[1/10]	[2/10]	[1/10]	[1/10]	[2/10]	[1/10]	[2/10]	[1/10]	[1/10]
ϕ_2 *unhedged*	1.46	0.19	2.06	1.95	3.41	1.52	1.55	2.08	4.35
ϕ_2 *full hedge*	1.91	2.48	2.05	0.74	0.89	1.21	2.08	1.89	1.13

Table 7: Dynamic Factor Exposures and Factor Prices of Risk

The table presents statistical and economic performance measures for global equity and bond portfolios when hedged using one of three approaches to Dynamic Currency Factor (*DCF*) hedging. The results reflect the *out-of-sample* period from January 1997 to July 2017. In Panel A (Panel B), we report the results for an equal-weighted (GDP-weighted) bond portfolio. The first column presents results for the standard Dynamic Currency Factor (*DCF*) hedging reported in Tables 3 and 4. We provide details of the second two approaches to *DCF* hedging in Section 6. We report the portfolio mean, standard deviation (*std*), Sharpe ratio (*Sharpe*), and the difference in Sharpe ratio relative to the standard *DCF* approach (Δ*Sharpe*). We also report economic performance criteria, including the certainty-equivalent return (*CEQ*), difference in certainty-equivalent return relative to the standard *DCF* approach (Δ*CEQ*), and performance fee a risk averse investor would pay for a manager to switch from each hedging framework to the standard *DCF* approach, assuming the investor either has a risk aversion coefficient of two (ϕ_2) or six (ϕ_6). The superscripts *,**,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolio

	Global Equity Portfolios			*Global Bond Portfolios*		
	DCF	Factor Betas	Factor Returns	DCF	Factor Betas	Factor Returns
			Statistical performance evaluation			
mean (%)	7.93	4.99	7.83	5.21	2.23	5.28
std (%)	15.3	16.1	15.4	6.81	7.78	6.82
Sharpe	0.52	0.31	0.51	0.77	0.29	0.77
Δ*Sharpe*	-	-0.21***	-0.01	-	-0.48***	0.00
			Economic performance evaluation			
CEQ	4.40	1.10	4.26	4.52	1.32	4.58
Δ*CEQ*	-	-3.30***	-0.14	-	-3.20***	0.06
ϕ_2	-	3.02	0.11	-	3.03	-0.06
ϕ_6	-	3.04	0.11	-	3.04	-0.06

Panel B: GDP-Weighted Portfolio

	Global Equity Portfolios			*Global Bond Portfolios*		
	DCF	Factor Betas	Factor Returns	DCF	Factor Betas	Factor Returns
			Statistical performance evaluation			
mean (%)	6.16	4.33	6.34	4.16	2.38	4.30
std (%)	15.3	15.6	15.4	5.53	6.33	5.52
Sharpe	0.40	0.28	0.41	0.75	0.38	0.78
Δ*Sharpe*	-	-0.12**	0.01	-	-0.37***	-0.03
			Economic performance evaluation			
CEQ	2.66	0.67	2.81	3.70	1.78	3.85
Δ*CEQ*	-	-1.99***	0.15	-	-1.92**	0.15
ϕ_2	-	1.86	-0.18	-	1.81	-0.14
ϕ_6	-	1.87	-0.18	-	1.82	-0.14

Table 8: International Diversification via an Independent Currency Portfolio

The table presents the out-of-sample performance of currency strategies constructed using expected currency returns (i.e, *DCF*-based portfolios). The results reflect the *out-of-sample* period from January 1997 to July 2017. In Panel A, we report statistics for time-series portfolios. The first nine columns reflect portfolios constructed using bilateral exchange rates against the U.S. dollar. If the foreign currency has a positive expected return at time t, it is purchased against the U.S. dollar and held until time t+1, while a negative expected return results in a short position. The final column, DCF Time Series, represents a broader portfolio that takes a long position in all currencies against the U.S. dollar with a positive expected return at time t and short position in all currencies with a negative expected return. In Panel B, we report statistical and economic performance measures for global equity and bond portfolios when combined in a 50-50 portfolio with currency portfolio strategies. The first column reflects the performance of a fully hedged portfolio consistent with the results presented in Tables 3 and 4. We combine the portfolio with currency carry, momentum (*Mom*), value, a style portfolio that combines currency carry, value and momentum in equal weights and the DCF Time Series portfolio. We report the portfolio mean, standard deviation (*std*), Sharpe ratio (*Sharpe*), the difference in Sharpe ratio relative to the fully hedged portfolio ($\Delta Sharpe$), skewness (*skew*) and information ratio relative to the fully hedged (IR_{hedged}) portfolio. We also report economic performance criteria, including the certainty-equivalent return (CEQ), difference in certainty-equivalent return relative to the fully hedged portfolio (ΔCEQ), and performance fee a risk averse investor would pay for a manager to switch from the fully hedged underlying portfolio, assuming the investor either has a risk aversion coefficient of two (ϕ_2) or six (ϕ_6). The superscripts *,**,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Currency Strategies by Currency Pair and as a Portfolio

	German DM/euro	Japanese yen	British pound	Canadian dollar	Australian dollar	Swiss franc	Swedish krona	Norwegian krone	New Zealand dollar	DCF Time Series
mean (%)	5.58	1.34	4.26	4.15	8.11	3.66	5.67	7.33	10.86	5.78
std (%)	9.87	10.71	8.53	8.72	12.33	10.33	10.95	10.97	12.76	7.38
Sharpe	0.57	0.13	0.50	0.48	0.66	0.35	0.52	0.67	0.85	0.78
skew	0.08	-0.22	-0.24	0.60	0.41	-0.08	0.14	0.07	0.41	0.20

Panel B: Allocating Capital to Currency Strategies

	Global Equity Portfolios						*Global Bond Portfolios*					
	Full Hedge	Carry	Mom	Value	Style Combo	DCF Time Series	Full Hedge	Carry	Mom	Value	Style Combo	DCF Time Series
					Statistical performance evaluation							
mean (%)	5.10	7.84	4.81	7.82	6.82	10.88	2.52	5.26	2.23	5.24	4.24	8.30
std (%)	13.9	18.9	15.1	14.8	14.9	15.4	4.66	8.56	8.98	8.71	5.46	8.60
Sharpe	0.37	0.41	0.32	0.53	0.46	0.70	0.54	0.61	0.25	0.60	0.78	0.97
$\Delta Sharpe$	-	0.04	-0.05	0.16	0.09*	0.33***	-	0.07	-0.29	0.06	0.24	0.43*
skew	-0.88	-0.95	-0.28	-0.57	-0.64	-0.52	0.09	-0.93	0.35	0.56	-0.08	0.32
IR_{hedged}	-	0.10	-0.01	0.11	0.14	0.23	-	0.10	-0.01	0.11	0.14	0.23
					Economic performance evaluation							
CEQ	2.19	2.46	1.38	4.54	3.50	7.30	2.19	4.16	1.02	4.10	3.79	7.19
ΔCEQ	-	0.07	-0.78	2.54	1.31*	5.11***	-	1.89	-1.20	1.91	1.57**	5.00***
ϕ_2	-	-2.19	0.40	-2.64	-1.63	-5.63	-	-2.57	0.48	-2.54	-1.70	-5.61
ϕ_6	-	-2.03	0.44	-2.62	-1.61	-5.59	-	-2.52	0.54	-2.49	-1.69	-5.56