An Integrated Approach to Currency Factor Timing

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Abstract

Using the G10 universe of currencies, we find evidence in favor of parametric portfolio policies to guide an optimal currency tilting strategy using cross-sectional factor characteristics, but less so an optimal currency timing strategy using time series predictors. While currency carry serves as the main return generator, the two characteristics momentum and value are implicit diversifiers to potentially balance the downside of the FX carry investing in flight-to-quality shifts of FX investors. In particular, we seek to expand the parametric portfolio policy's ability to mitigate the downside of the carry trade by incorporating an explicit currency factor timing element. Our proposed integrated approach not only outperforms a naive equally weighted benchmark, but also univariate and multivariate parametric portfolio policies.

JEL classification: G11, D81, D85

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1 Introduction

Investors are attracted to global investment portfolios due to the diversification benefits associated with investing in lowly correlated international markets. Usually these portfolios engage in international bonds and equities, and as such are directly exposed to and affected by foreign (FX) exchange rate fluctuations. Hence, there is a need to efficiently manage currency exposures.

In the literature, currency factor models have garnered attention over the last decade with carry, value and momentum being the salient currency factors. Factor investing per se has gained a lot of popularity among academics and practitioners in the last few decades. Factor investing can be understood as investing in a group of securities that share similar characteristics, such as value or momentum stocks, but are hardly correlated. [1]

Currency factor models aim to measure the exposure of each currency to different factors, so that currency portfolios may be created dynamically or exchange rates may be predicted. Engel *et al.* (2015) find promising results on bilateral exchange rate prediction for a sample from 1997 to 2007, when extracting factors from the cross-section of exchange rates using principal component analysis. Nevertheless, in a portfolio set-up, the choice of currency factors plays a crucial role, since an uninformed choices of currency factors can heavily impact portfolio performances. Nevertheless, finding the optimal combinations of factors is "unchartered territory" Brière and Szafarz (2016). Verdelhan (2018) suggests a two-factor model using dollar exchange rate return and carry exchange rate return as common factors. These two factors are chosen based on the argument that the dollar factor represents global macro-level risk and the carry factor represents risk arising due to uncertainty. Greenaway-McGrevy *et al.* (2018) also propose a two-factor model for predicting exchange rates. They conclude that the dollar factor and euro factor drive exchange rates whereas the prominent carry factor does not.

An investor's optimal portfolio choice is usually based on a range of criteria such as return expectations, risk appetite, macroeconomic environment, etc. Whereas the static portfolio optimization approach of Markowitz (1952) seems to be the go-to choice for practitioners due to its computational simplicity, dynamic portfolio selection strategies have been developed which rely on exploiting the predictability of the first and second moments of asset returns. Brandt *et al.* (2009) use a similar procedure for a large cross-sectional choice problem. Their objective function chooses portfolio weights to maximise the expected utility of

[1]Initial works on equity factors can be traced back to the 1970s when the focus was mainly on the sensitivity of stocks' return to the market hence called as market factor in the Capital Asset Pricing Model (CAPM). Ross (1976)'s Arbitrage Pricing Theory (APT) was the first to document the interplay between factors in a first multi-factor model combining various macro-economic factors. Since then, Rosenberg *et al.* (1976) multi-factor risk model, Fama and French (1992, 1993) three-factor model, and Carhart (1997) four-factor model have dominated the finance literature.

the portfolio return. This naturally implies that Markowitz mean-variance optimization can be applied without the need of estimating the full covariance matrix. This low-dimensional approach could also be easily modified or extended to include constraints on portfolio weights, shrinkage of the estimates, etc. Barroso and Santa-Clara (2015) confirm that FX momentum proxies exploit the persistence of currency in the short term. They find that currency portfolios constructed through carry, momentum and value strategies outperform equally weighted portfolios.

In this paper, we design an integrated currency allocation approach in which predictive information based on time-series variables and cross-sectional currency characteristics are used in order to 1) time currencies more efficiently, 2) tilt currencies according to cross-sectional factors and 3) integrate the notion of currency factor timing in order to time the chosen cross-sectional characteristics. We use the parametric portfolio policy (PPP) of Brandt and Santa-Clara (2006) and Brandt *et al.* (2009) to assess the joint relevance of various potential predictors. We focus on currency-only portfolios to forecast single currency levels using PPP that exploits complementary information to maximize the investors utility. In optimal currency factor tilting, we pick three FX style variables to proxy for currency expected returns in the PPP framework of Brandt *et al.* (2009). For the optimal currency factor timing, we examine whether a risk-averse investor may profit from timing currency factors with respect to fundamental and technical predictors using the PPP framework of Brandt and Santa-Clara (2006).

Our empirical analysis is based on the universe of the G10 currencies collected between February 1989 and December 2017. Our findings show that the optimal currency tilting strategy is more compelling and robust compared to the timing alternative. This finding is mainly due to the increasing evidence of predictability in the cross-section of currency excess returns compared to our choice of underlying fundamental variables and technical predictors. Unsurprisingly, the carry characteristic is the main driver of the PPP's performance. Still, including momentum and value characteristics helps alleviating major carry draw-down in volatile FX markets. Navigating the carry trade in the extant literature(Menkhoff *et al.* (2012a),Brunnermeier *et al.* (2008)) has investigated explicit timing the profitability of the carry trade. We investigate an extension of the tilting PPP to integrate the management of FX characteristics in light of meaningful conditioning information. This integrated currency factor management not only offers highest risk-adjusted performance but also allows us to conclude that such forecast-free options can be effectively adopted to overcome some drawbacks of models requiring forecasted expected returns.

The remainder of the paper is structured as follows: Section 2 gives a overview of the literature and the common choice of factors used for currency tilting and currency timing. Section 3 describes the optimal currency tilting based on the parametric portfolio policy framework of Brandt and Santa-Clara (2006). Section 4 expands on optimal currency timing and currency factor timing. Section 5 presents the integrated approach to currency factor timing. Section 6 concludes.

2 The notion of currency tilting and timing

2.1 Currency Tilting

The idea behind factor tilting is simple and straightforward. If we assume that CAPM is the true market model, then tilting towards any other factor, say for example size or value in equities, should not yield superior returns. In other words, the Sharpe ratio measured as the return per unit of risk must always remain constant so that tilting towards any other factors would only translate to an increase in risk. Yet, follow-up studies (Fama and French (1992, 1993), Carhart (1997), Ang *et al.* (2006)) have repeatedly found strong counter-evidence for a variety of factors such as size, momentum, value or low-volatility.

Several factor models have hogged the limelight since the foundation of CAPM. While the efficacy of style-based portfolio allocation has been extensively studied in equity markets, style investing is likewise popular in several other asset classes such as bonds, commodities and FX. In fact, extending such strategies to FX markets is straightforward and common factor strategies account for a large fraction of trading volumes in FX markets. For instance, Burnside *et al.* (2011) examine the profitability of the two famous style-based strategies, FX carry and FX momentum, and confirm existing evidence that payoffs to currency strategies are skewed with fat tails and that conventional risk factors cannot account for the return to these FX strategies. The authors provide possible theoretical, micro-structure and behavioral explanations for the continued profitability of such strategies and acknowledge the uncorrelated payoff to carry and momentum strategies. Such an uncorrelatedness offers a lot of scope for investors to use multiple currency strategies simultaneously.

An optimal currency factor tilting strategy would exploit informative currency characteristics and the extant literature offers a handful of proxies that have shown evidence of predictability in the cross-section of currency excess returns. We seek to integrate this information jointly in a portfolio utility context by adopting the methodology of Brandt *et al.* (2009). Their parametric portfolio policy tackles the issue of cross-sectional portfolio optimization by modeling the portfolio weights as a function of the related state variables. In this study, we examine three highly popular FX styles, namely FX Carry, FX Value and FX Momentum, that are unanimously favoured by practitioners and academics. We will also build on these same characteristics to construct naive currency portfolios to compare between both the naive and optimized methods.

2.1.1 FX Carry

The FX carry trade has received a great deal of attention not only for generating high returns but also for its robustness to several other traditional risk factors, like market, value, size, momentum to quote a few. In a nutshell, the carry trade compensates for systemic risk by exploiting interest rate differentials. The carry trade portfolio is simply constructed by buying the highest-yielding currencies and selling the lowest-yielding currencies. Researchers have provided various explanations for the performance of the carry trade. For example, Farhi *et al.* (2009) find evidence for crash risk being responsible for 25% of carry trade returns in developed countries whereas Caballero and Doyle (2012) point that carry trade returns are highly correlated to their "VIX rolldown strategy", that is shorting VIX futures and rolling down its term structure.

The FX carry trade strategy was first documented in the triennial survey of Galati and Melvin (2004). Their survey attributes the surge in FX trading to the sudden rise in attractiveness of FX carry and momentum strategies. While the FX carry trade strategy has performed extremely well, it remains hard to rationalize. Researchers have yet identified certain cases when the carry strategy might under-perform, for example, FX carry does not perform when there are liquidity squeezes (Brunnermeier, Nagel and Pedersen, 2008) and when there is an increase in FX volatility (Menkhoff, Sarno, Schmeling and Schrimpf, 2012a).

To proxy for the carry trade, we take the forward discount (or premium) of a given currency. Given the fact that covered interest rate parity empirically holds at a monthly frequency (Akram, Rime and Sarno, 2008) the forward premium is then equivalent to interest rate differentials. The forward discount is computed as:

$$fd_{i,t} = \frac{F^i_{t,t+1}}{S^i_{t+1}} - 1, \tag{1}$$

where $F^i_{t,t+1}$ is the price of one USD expressed in foreign currency units at time $t+1$ in a forward contract settled at time t and S_{t+1} is the spot price of one USD in foreign currency units at t.

2.1.2 FX Momentum

Momentum investing has been quite popular among asset managers and has been a subject of intense academic study since 1993 starting from the work of Jegadeesh and Titman (1993). In the realm of currencies, FX momentum strategies are also of relevance. A significant number of works on FX momentum suggest that it is not subsumed by any other traditional risk factor. The rationale behind FX Momentum is to exploit short-term price momentum effects in FX markets. FX momentum effects can be detected for formation periods between 1 and 12 months; 3 months is a common choice of formation period as it strikes a good balance between the goodness of signal and strategy turnover.[2] Hence, for capturing cross-sectional FX momentum, we consider the cumulative currency return over the previous three months between the quoted and the base currency to capture the persistence of currency returns in the short term. Therefore, we compute the momentum signal accordingly,

$$Mom_{i,t} = \frac{S_t^i}{S_{t-3}^i}, \tag{2}$$

where S_t^i is the price of one USD expressed in foreign currency units at time t and S_{t-3}^i is the spot price of one USD in foreign currency units at $t-3$ (months).

FX momentum persists in FX markets because of impediments constricting the deployment of arbitrage capital to exploit this phenomenon. Moreover, equity markets have a predictive role in explaining the variations in currency momentum payoffs. Okunev and White (2003) capture momentum in a cross-section of currencies and find positive evidence for existence of profits from a cross-sectional momentum based strategy. Since then, it has been widely accepted that momentum could be safely considered as a proxy for predicting currency returns.

There does not seem to be a systematic risk factor, which would explain (net) momentum returns. On the other hand, Menkhoff *et al.* (2012b) find that FX momentum returns are sensitive to transaction costs but less related to business cycle risk. Also, FX momentum returns are much higher in currencies with high lagged idiosyncratic volatility and high country risk rating and hence are more related to currency characteristics.

2.1.3 FX Value

The value strategy exploits long-term reversal effects in FX markets. The aim is to identify "undervalued" and "overvalued" currencies. However, there is no universally accepted rule to classify a currency into either of these groups and hence, one needs to proxy the fundamental value of a currency. Comparing the latter with the current trading price/deviation of the exchange rate would indicate whether a currency is "undervalued" or "overvalued".

In our study, we use purchasing power parity as measure of fundamental value relying on the assumption that goods should cost the same across countries. Currencies whose real exchange rate (RER) deviates significantly from 1 may be viewed as undervalued or overvalued. The FX value strategy would then exploit the reversal of currencies that have overshot their purchasing power parity values. When it comes to determining which measure of purchasing power parity to use, Asness *et al.* (2013) use the 60 month deviation from uncovered interest

[2] The choice of the three month formation period is consistent with Kroencke *et al.* (2013), Barroso and Santa-Clara (2015). Considering a lag longer than 3 months does not offer any additional gain, according to Menkhoff *et al.* (2012a).

rate parity. Based on their approach, we thus compute the cumulative real depreciation of currency i as:

$$Q_{i,h,t} = \frac{S_{i,t} CPI_{i,h} CPI_{US,t}}{S_{i,h} CPI_{i,t} CPI_{US,h}}, \tag{3}$$

where $h = t - 60$, CPI is the Consumer Price Index representing the price of a broad basket of goods at time period t or h in the US or the other country, and $S_{i,t}$, resp. $S_{i,h}$ is the spot price of one USD in foreign currency units at t, resp. h.

2.2 Currency Timing

We now turn to time-series information that could inform an optimal currency timing strategy to estimate optimal currency portfolio weights. Our choice of predictive variables stems from the literature of equity premium predictability. Whether macroeconomic and financial variables can forecast FX returns is still widely debated. Nevertheless, there is substantial evidence supporting the relevance of fundamental variables, interest-rate related variables (Cornell and Dietrich, 1978) and technical indicators (Cotter, Eyiah-Donkor and Potì, 2017).

2.2.1 Fundamental Variables

We consider 14 predictor variables as suggested by Welch and Goyal (2008) publicly available from July 1926 to December 2017 on Amit Goyal's web page[3]: Dividend Price Ratio (dp), Dividend Yield (dy), Earnings Price Ratio (ep), Dividend Payout Ratio (de), Stock Variance ($svar$), Book to Market Ratio (bm), Net Equity Expansion ($ntis$), Treasury Bills (tbl), Long Term Yield (lty), Long Term Rate of Return (ltr), Term Spread (tms), Default Yield Spread (dfy), Default Return Spread (dfr) and Inflation ($infl$).

It is important to ensure that the predictor variables are not correlated because such lagged variables could exhibit very high first order-autocorrelations. Ferson *et al.* (2003) suggest stochastic detrending of the lagged variable to avoid the bias emerging from spurious regressions. We thus standardize any predictor variable at time t by subtracting its arithmetic mean and dividing by its standard deviation. For the calculation of the mean and standard deviation we use a rolling window covering the 12 months preceding (and thus excluding) t. The choice of 12 months is advocated by Campbell (1990). Furthermore, as few standardized fundamental variables might attain extreme values, we truncate the variables at ± 5.

[3]The dataset is available on `http://www.hec.unil.ch/agoyal/`. For a more detailed description of the variables please refer to Welch and Goyal (2008).

2.2.2 Technical Indicators

Technical indicators are known to have the ability to time trades by recognizing the drivers of international financial markets from a behavioural perspective. Similar to Hammerschmid and Lohre (2018), we include 16 technical indicators based on three sets of trading rules related to the general concepts of momentum (MOM_k), moving averages (MA_{s-l}) and stochastic oscillator (KDS_m).

1. *Momentum (MOM_k)*: The momentum indicator gives a buy signal if the end of month closing spot exchange rate indicates an upward trend, i.e., when S_t is higher than S_{t-k}, then

$$MOM_k = \begin{cases} 1 & \text{if} \quad S_t > S_{t-k} \\ 0 & \text{if} \quad S_t \leq S_{t-k} \end{cases} \tag{4}$$

   S_t is the end of month closing spot exchange rate. We compute five momentum indicators for different look-back periods with $k = 1,\ 3,\ 6,\ 9,$ and 12 months.

2. *Moving Average (MA_{s-l})*: Trading rules based on moving averages detect trends and potential breaks in such trends. The moving average of an exchange rate i over j months is given by

$$\mathrm{MA}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} S_{t-i} \quad \text{for} \quad j \ = \ s,\ l, \tag{5}$$

   where S_t is the end of month closing spot exchange rate of the currency; $s = 1, 2, 3$ is used for short-term moving averages and $l = 9, 12$ for the long-term. The resulting indicator would give a buy signal when the short-term moving average crosses the long-term moving average from below and a sell signal vice-versa:

$$\mathrm{MA}_{s-l} = \begin{cases} 1 & \text{if} \quad MA_{s,t} > MA_{l,t} \\ 0 & \text{if} \quad MA_{s,t} \leq MA_{l,t} \end{cases} \tag{6}$$

   Hence, depending on the different long and short-term combinations, we would have six moving average indicators for analysis.

3. *Stochastic Oscillator (KDS_m)*: Introduced by George C. Lane in the 1950s, the stochastic oscillator records the momentum or speed of price fluctuations (and not of the price itself). It hence indicates, over a certain period of time, where the price is located within a high-to-low range. To compute the indicator, we first define K_t^{fast} as

$$K_t^{fast} = 100 * \frac{S_t - \min(S_{i=t-m}^t)}{\max(S_{i=t-m}^t) - \min(S_{i=t-m}^t)}, \tag{7}$$

   where $\max(S_{i=t-m}^t)$ and $\min(S_{i=t-m}^t)$ represent the high-to-low range within the last m months. We create a slower five stochastic oscillators based on five look-back periods by fixing $m = 12,\ 24,\ 36,\ 48,\ 60$ months. For better control of the onset of signal changes, we consider smoother versions based on a 3-months moving average of (7) called K_t^{slow} or D_t^{fast} as follows:

$$D_t^{fast} = K_t^{slow} = \mathrm{MA}_{3,t}\left(K_t^{fast}\right). \tag{8}$$

An even slower indicator is,

$$D_t^{slow} = \mathrm{MA}_{3,t}\left(D_t^{fast}\right). \tag{9}$$

Hence, the final stochastic oscillator gives a buy signal if the faster moving average D_t^{fast} is greater than the slower moving average D_t^{slow}:

$$KDS_m = \begin{cases} 1 & \text{if} \quad D_t^{fast} > D_t^{slow} \\ 0 & \text{if} \quad D_t^{fast} \leq D_t^{slow} \end{cases} \tag{10}$$

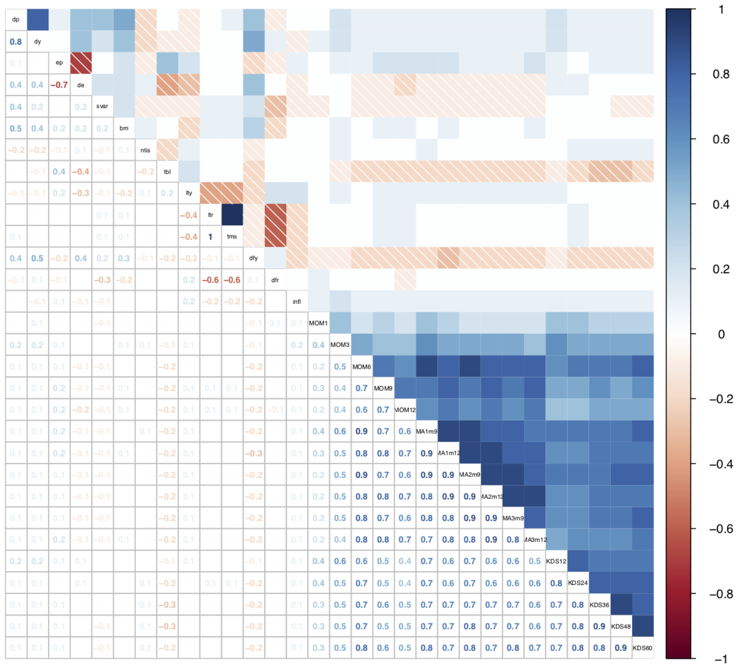
This means that if D_t^{fast} is larger than D_t^{slow}, the currency‘s excess return increased strongly, compared to its trading range and gained momentum, compared to the realization of the longer term average. Thus, this indicator depicts an upward trend in the currency return and a downward trend otherwise.

2.2.3 Predictors Variable Selection

Now that we have carefully chosen 14 fundamental variables and 16 technical predictors, it is quintessential to check for multicollinearity. Figure 1 shows the correlation structure (using the most liquid currency pair USD/EUR[4]) for the fundamental variables and technical indicators for our entire sample from February 1990 to December 2017. As expected, the technical indicators are highly correlated as seen in the bottom right of the chart, whereas the fundamental variables display a heterogenous correlation structure. While the valuation ratios *dp* and *dy* show the maximum positive correlation of 0.8, their peers *ep* and *de* have the highest negative correlation, which amounts to -0.7. Notably, fundamental and technical variables are fairly uncorrelated suggesting complementary predictive ability and suitability for our analysis.

[4]We will use the USD as our benchmark currency and we will only refer to each currency pair with the currency it is matched with. Meaning in the rest of the paper we will denote USD/EUR, only by EUR.

Figure 1: Correlation matrix of predictor variables: the case of EUR The figure shows the correlation structure between the standardized fundamental variables and the technical indicators (for the EUR currency pair). In the top left corner, the correlation between fundamental variables is displayed. The bottom right corner shows the correlation structure of the technical indicators for EUR. The sample period is from 02/1990 to 12/2017.



To reduce the number of predictors, we follow Neely *et al.* (2014) and Hammerschmid and Lohre (2018) and apply the principal component analysis (PCA) to the fundamental and technical indicators separately. This procedure not only gets rid of the noise within the predictors but also gives orthogonal predictors which helps avoid multicollinearity issues. Table 1 shows the PCA results on our in-sample data set from February 1990 till December 2017. The results confirm our findings from the correlation map in that the first three principal components of fundamental variables jointly explain what just the first principal component technical indicators could explain (around 56% of variance). [5]

[5] Please note that these results hold for all currencies, and due to space limitation we refrain to present them here. Nevertheless, they are available upon request.

Hence, for our analysis we use the first 3 principal components of the fundamental variables (denoted as F_t^{Fun1}, F_t^{Fun2} and F_t^{Fun3}) and the first principal component for technical indicator (denoted as F_t^{Tech}). Both capture a significant proportion of variation in the underlying variables and indicators (56% and 67%, respectively).

Table 1: PCA: portion of explained variance The table shows the proportion of variance that is explained by the factors. The period used is the IS (in sample) period between 02/1990 and 12/2017. EUR is used as an example for the technical indicators

	PC1	PC2	PC3	PC4	PC5	PC6
Fundemental PCA factors						
Proportion of variance	25.82%	18.05%	12.97%	10.17%	6.69%	5.70%
Cumulative proportion	25.82%	43.87%	56.84%	67.01%	73.70%	79.40%
Technical PCA factors						
Proportion of variance	66.48%	8.90%	5.76%	3.84%	2.86%	2.64%
Cumulative proportion	66.48%	75.38%	81.14%	84.98%	87.84%	90.48%

3 Optimal Currency Tilting

Modeling optimal portfolio weights is highly sophisticated due to a range of considerations and constraints. In their novel approach, Brandt *et al.* (2009) exploit the cross-sectional characteristics of equity returns to obtain optimal portfolio weights. The simple ingredient of their approach is the linear portfolio policy that models optimal portfolio weights as the sum of a benchmark weight plus a deviation term depending on chosen characteristics

3.1 Parametric Portfolio Policy framework

Having acknowledged the benefits of factor tilting and chosen potential candidates for factor tilting, we couch the above characteristics into the parametric portfolio policy (PPP) framework of Brandt *et al.* (2009). Their parametric portfolio policy framework seems an ideal setup to digest salient currency characteristics for generating a currency allocation that allows to harness the associated premia according to a given investors risk aversion.

The PPP framework specifically allows to model the weight of an asset as a function of its characteristics for which the coefficients are estimated by maximizing investor utility. Brandt, Santa-Clara and Valkanov (2009) consider an investor seeking to maximize her conditional expected utility of her portfolio return $r_{p,t+1}$:

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u(r_{p,t+1})\right] = E_t\left[u\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}\right)\right], \tag{11}$$

where $w_{i,t}$ denotes the portfolio weight for asset i among the total number of assets N_t at time t. The authors propose to model the portfolio weight as a linear function of its characteristics

$x_{i,t}$ as follows:

$$w_{i,t} = w(x_{i,t}; \phi) = \overline{w_{i,t}} + \frac{1}{N_t}\phi' \hat{x}_{i,t}, \tag{12}$$

where $\overline{w_{i,t}}$ is the weight of asset i in the benchmark portfolio, ϕ is the weight of the characteristic in the parametric portfolio that needs to be estimated as part of the utility maximization. $\hat{x}_{i,t}$ is the vector of cross-sectionally standardized characteristics of asset i at date t. Parametrization (12) implicitly assumes that the chosen characteristics fully capture the joint distribution of asset returns that are relevant for portfolio optimization. The portfolio policy is embedded in the idea of estimating the weights as a function of characteristics, that applies to all assets over time, rather than estimating one weight for each asset.

Naturally, the cross-sectional distribution of the standardized characteristics is stationary through time and the cross-sectional mean for each standardized characteristic is zero such that deviations from the benchmark are equivalent to a zero-investment portfolio. Hence, the weights of the resulting portfolio always add up to 100%. We rewrite the optimization problem in terms of ϕ-coefficients:

$$\max_{\phi} E\left[u(r_{p,t+1})\right] = E\left[u\left(\sum_{i=1}^{N_t} f(x_{i,t};\phi) r_{i,t+1}\right)\right]. \tag{13}$$

The first order condition of the maximisation problem is given by:

$$\frac{1}{T}\sum_{t=0}^{T-1} h(r_{t+1}, x_t; \phi) \equiv \frac{1}{T}\sum_{t=0}^{T-1} u'(r_{p,t+1})\left(\frac{1}{N_t}\hat{x}_t' r_{t+1}\right) = 0, \tag{14}$$

where $u'(r_{p,t+1})$ denotes the first derivative of the utility function. Thus, the optimization problem can be interpreted as a method of moments estimator. Based on Hansen (1982), the asymptotic covariance matrix estimator is

$$\Sigma_{\phi} \equiv AsyVar[\hat{\phi}] = \frac{1}{T}[G'V^{-1}G]^{-1}, \tag{15}$$

where

$$G \equiv \frac{1}{T}\sum_{t=0}^{T-1} \frac{\delta h(r_{t+1}, x_t; \phi)}{\delta \phi} = \frac{1}{T}\sum_{t=0}^{T-1} u''(r_{p,t+1})\left(\frac{1}{N_t}\hat{x}_t' r_{t+1}\right)\left(\frac{1}{N_t}\hat{x}_t' r_{t+1},\right)' \tag{16}$$

and V is a consistent estimator of the covariance matrix of $h(r, x; \phi)$.

3.2 Naive Currency Portfolio Construction

As a benchmark for the PPPs, we construct "*naïve*" currency portfolios for each of these currency characteristics. DeMiguel *et al.* (2009) show that portfolio optimization technique can be error prone and naive portfolio construction is a robust alternative. The naive or standard currency portfolio construction applies an equal weighting scheme in the investment and financing leg. The long-short allocation in the currencies rely on signals of a currency characteristic available one period before.

For constructing the naive currency portfolio, we rank the currencies in the G10 universe according to each of the conditional characteristic. The top 2 currencies and the bottom 2 currencies form the long and short leg of the portfolio respectively based on an equal weighting scheme. We construct the naive portfolio like Kroencke *et al.* (2013). As conditioning variables z_t we will use the characteristics defined in the previous section. The long ($\mathcal{L}_t^j$) and short ($\mathcal{S}_t^j$) with $N = 9$ set of currency are defined as follows

$$\mathcal{L}_t^j = \begin{cases} 1 & \text{if} \quad z_t^j \geq q(z_t)_{1-p} \\ 0 & \text{if} \quad z_t^j < q(z_t)_{1-p}, \end{cases} \tag{17}$$

and

$$\mathcal{S}_t^j = \begin{cases} 1 & \text{if} \quad z_t^j \leq q(z_t)_{p} \\ 0 & \text{if} \quad z_t^j > q(z_t)_{p}, \end{cases} \tag{18}$$

where $q(z_t)$is the p-quantile of z_t and $p = \frac{2}{9}$.

3.3 Empirical Results

Our currency investment universe comprises the G10 currencies with USD, as a base currency. This FX sample corresponds to the combination of the following countries: Australia (AUD), Canada (CAD), Germany (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF) and the United Kingdom (GBP). All the data has been collected from Bloomberg. The sample period spans between February 1989 and December 2017.

We defined the currency excess returns in USD for currency i from time t to $t+1$ as follows:

$$r_{t+1}^i = \frac{F_{t+1}^i}{S_{t+1}^i} - 1, \tag{19}$$

where F_{t+1}^i is the price of one USD expressed in foreign currency units and S_{t+1}^i spot price of one USD in foreign currency units.

Real exchange rate (RER) for our value characteristic is computed against the USD using the spot exchange rate and the consumer price index (CPI). Bloomberg provides monthly CPI data, with the exception of Australia and New Zealand, where only quarterly data are available. For these 2 countries/currencies, the most recent values were carried forward for the next months until new data are available for the new quarter. Since we are considering the Euro as the currency for Germany, we carried further with taking into account only the

CPI for Germany. To account for the deviation from the uncovered interest rate parity we lose 60 months of observations so that our sample for the value characteristic $Q_{i,h,t}$ spans between February 1994 and December 2017. In addition, we use an initial period of 5 years in the PPP optimization to determine the optimal coefficients. Together with the 60 months for the value characteristic, our backtest thus starts from February 1999. The portfolios are rebalanced monthly with an expanding window of 60 months.

Table 2 gives estimation results and performance statistics for our three univariate PPPs, multivariate PPP and naive models. In panel A, the carry and the value characteristics are significant at the 5% and 10% level respectively, while the momentum characteristic is not despite having a positive ϕ coefficient. This observation suggests that the FX momentum strategy was not profitable, while carry and value strategies were. [6]

The positive and significant value coefficient indicates that the currencies with the largest real depreciation vs. the USD are bought, and those with the smallest real depreciation are sold. The FX carry strategy offers the best risk-return trade-off in terms of Sharpe ratio followed by the FX value strategy, even though it is important to note that the FX carry strategy is vulnerable to crash risk as indicated by the 26% drawdown.

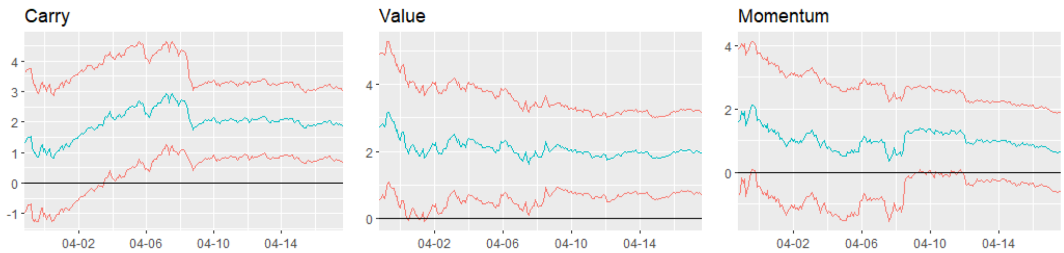
Table 2: Parametric Portfolio Policy: Performance Panel A gives the estimation results of the univariate parametric portfolio policies as well as the performance statistic of each investment style separately. Panel B gives the estimation results for the multivariate optimization with the performance statistic. Panel C gives the performance statistics for the naive portfolio construction of the three investment style as well as the equally weighted portfolio of the three styles. Return, volatility and maximum drawdown figures are measured in percentage terms. The sample period covers the period between 1994-02 and 2017-12.

		S.E	Return P.a	Vola P.a	Sharpe ratio	Max Draw-down ratio
Panel A : Univariate models						
Momentum	0.40	0.81	2.22	3.591	0.01	7.09
Value	1.72**	0.86	4.22	5.82	0.35	8.88
Carry	1.76**	0.79	5.94	7.48	0.50	26.58
Panel B : Multivariate model						
Optimal Portfolio			7.12	8.22	0.60	18.56
Momentum	0.71	0.63				
Value	1.96***	0.63				
Carry	1.90***	0.60				
Panel C : Naïve models						
Mom Naive			3.79	9.00	0.18	31.52
Val Naive			5.70	8.64	0.40	12.28
Carry Naive			7.31	10.92	0.47	35.58
Naive Portolio (1/N)			5.60	6.57	0.52	14.23

[6] This contradicts the findings of Barroso and Santa-Clara (2015) who observe a significant momentum coefficient (before transaction cost); yet, using a larger currency universe including emerging markets over a longer investment horizon.

Panel B shows the results of the combined strategy in a multivariate parametric portfolio policy aiming to capture the interactions of the three characteristics. Similar to the results in panel A, only the value and carry strategies are positive and significant at 1% level. The annualized return of the parametric portfolio policy is almost 2% higher than that for the Naive portfolio, and a more pronounced reduction in volatility by about 4%. Figure 3 shows the fluctuations of the ϕ-estimates of the PPP strategy over time. As expected, the loading of the carry characteristic drops during the financial crisis indicating that the portfolio is shifting towards more defensive currency allocations, whereas both momentum and value loadings increase during the same period. Moreover, the confidence bands of the momentum strategy are around zero, rendering the momentum characteristic surprisingly insignificant.

Figure 2: Parametric portfolio policy: ϕ coefficients. The figure shows parameters for the cross-sectional characteristics used in the parametric portfolio policy (blue line) over time. The red lines correspond to the 95% confidence interval. The sample period is between 1994-02 and 2017-12.



To foster intuition as to how the parametric portfolios work, we decompose each currency weight by the three characteristics. Figure 3 illustrates the optimal weights for two currencies, CHF and NZD, over time.[7] The weights in the CHF are almost always negative and mainly driven by the carry characteristic as expected. On the contrary, the weights in the NZD are neither too positive nor too negative, still driven by the carry characteristic. Figure 4 shows the overall currency allocation according to the parametric portfolio policy without any restrictions on the weights or the positions. We clearly note the pattern of a long-short portfolio, with perfect symmetry between the short and long leg, plus the weights adding up to zero.

Carry currencies such as AUD and NZD predominantly have long positions. Whereas currencies such as CHF, JPY and the EUR constitute almost the whole of the short leg. The Swedish Krona (SEK) modestly oscillates between positive and negative weights when compared with the other currencies. CHF, followed by the EUR and the JPY hold major short positions with average weights of -35.4%, -25.7% and -25.5% respectively. Major long positions are the NZD, the AUD and GBP with weights averaging 36.2%, 28.8% and 13.6%

[7] Results for all other currency pairs can be obtained upon request.

respectively.

Figure 3: Decomposition of the the optimal currency weights. The figure shows the currency weights decomposition in the parametric portfolio policy and the contribution of each conditioning variable. The right chart is for the CHF and the left one for the NZD currency. The sample period is between 1994-02 and 2017-12.

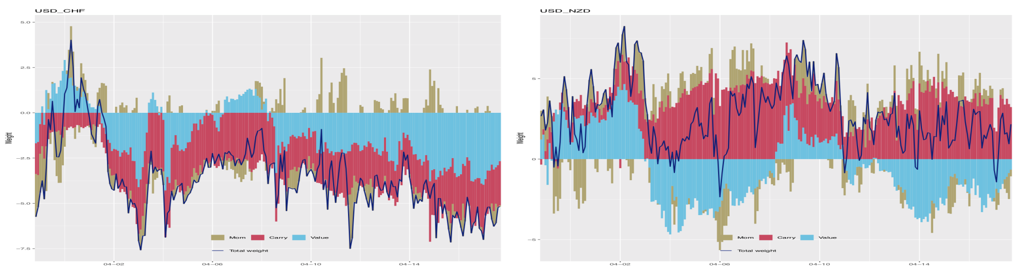
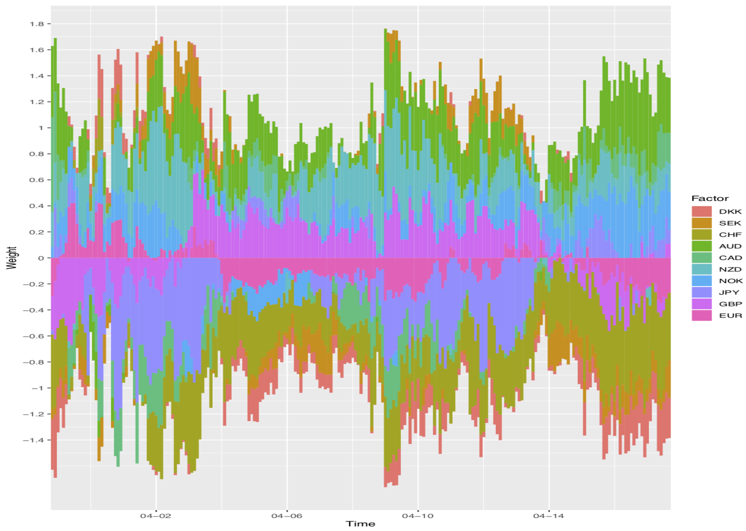


Figure 4: The aggregate optimal tilting currency allocation. The sample period is 1994-02 to 2017-12.



Overall, we can see that the chosen characteristics are relevant and useful to tilt currency factors. By couching the cross-sectional characteristics into the parametric portfolio policy of Brandt *et al.* (2009) we are able to construct a portfolio which not only improves risk-adjusted performance but also limits the maximum drawdown, in line with findings of Barroso and Santa-Clara (2015).

4 Optimal Currency Timing

Mounting evidence on the relevance of fundamental and technical variables in return predictability is hard to ignore. Though well-established in the equity market, there are a handful of studies that extend this to currency markets. Acknowledging the different undercurrents that might affect currency factor returns, we choose a wholesome set of fundamental and technical variables as shown in Section 2.2.3.

4.1.1 Methodology of Brandt and Santa-Clara (2006)

Brandt and Santa-Clara (2006) design a capital allocation model for a risk-averse investor who maximizes mean-variance utility function over next periods wealth. This corresponds to solving:

$$\max_{w_t} E\left[w_t' r_{t+1} - \frac{\gamma}{2} w_t' r_{t+1} r_{t+1}' w_t\right], \tag{20}$$

where γ is the risk-aversion parameter, w_t denotes the vector of currency factor portfolio weights and r_{t+1} is the vector of future excess return of the $N = 9$ currency pairs. The remainder is invested into the risk-free asset if the PPP is not fully invested. The Brandt and Santa-Clara (2006) methodology assumes optimal portfolio weights w_t to be linear in a vector z_t of K state variables, thereby capturing time variation in expected returns as follows:

$$w_t = \theta z_t, \tag{21}$$

where θ is an $(N \times K)$ matrix of parameters. Replacing the linear portfolio policy, w_t, in (20) yields:

$$\max_{\theta} E_t\left[(\theta z_t)' r_{t+1} - \frac{\gamma}{2} (\theta z_t)' r_{t+1} r_{t+1}' (\theta z_t)\right]. \tag{22}$$

with

$$(\theta z_t)' r_{t+1} = z_t' \theta' r_{t+1} = vec(\theta)'(z_t \otimes r_{t+1}), \tag{23}$$

where $vec(\theta)$ is a vectorization of the matrix θ into a column vector and $\otimes$ is the Kronecker product. If, $\tilde{w} = vec(\theta)$ and $\tilde{r}_{t+1} = z_t \otimes r_{t+1}$, then the objective function (22) can be rewritten as:

$$\max_{\tilde{w}} E_t\left[\tilde{w}' \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}' \tilde{r}_{t+1} \tilde{r}_{t+1}' \tilde{w}\right]. \tag{24}$$

Hence, the original dynamic optimization problem was transformed into a static one which can be applied to the augmented asset space represented by $\tilde{r}_{t+1}$, which is the return vector of "managed" portfolios that invest in a given currency proportional to the value of given state variables. As the same $\tilde{w}$ maximizes the conditional expected utility at all t, it also maximizes the unconditional expected utility, so (24) is equivalent to:

$$\max_{\tilde{w}} E\left[\tilde{w}' \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}' \tilde{r}_{t+1} \tilde{r}_{t+1}' \tilde{w}\right]. \tag{25}$$

To visualize the augmented asset space, $\tilde{r}_t$, consider the case of two assets ($N = 2$) and one conditioning variable ($K = 1$), while considering a time series of $T + 1$ observations. Let our investment universe be the two currencies EUR and GBP. Then, the matrix of excess returns for the two periods will be:

$$\begin{bmatrix} r_{t_1}^{EUR} & r_{t_1}^{GBP} \\ \\ r_{t_2}^{EUR} & r_{t_2}^{GBP} \\ \vdots & \vdots \\ r_{t_T}^{EUR} & r_{t_T}^{GBP} \end{bmatrix}.$$

If we consider one conditioning variable z solely influencing the conditional distribution of returns, we will get the following vector:

$$\begin{bmatrix} z_{t_0} \\ z_{t_1} \\ \vdots \\ z_{t_{T-1}} \end{bmatrix}.$$

This time series is lagged to enable the conditioning of each return period. Based on the information embedded in the state variable we can evaluate the portfolio policy depending on it. Hence, while the classical Markowitz approach would solve for portfolio weights, it here solves for the θ parameters in the augmented asset space format. The solution will then be equivalent to the optimal dynamic strategy and the weight invested in EUR for example is simply $w_t^{EUR} = \theta_{constant}^{EUR} + \theta_z^{EUR} z_t$ with the first and third element of $\tilde{w}$.

An additional benefit of this methodology is that PPP expresses the portfolio problem in an estimation setup which allows calculation of standard error of portfolio weights to asses the significance of a given conditioning variable in the portfolio policy. According to Brandt and Santa-Clara (2006), we use the covariance matrix of $\tilde{w}$ to compute the standard errors as:

$$\frac{1}{\gamma^2} \frac{1}{T \ - \ N \times K} (\iota_T - \tilde{r}\tilde{w})'(\iota - \tilde{r}\tilde{w})(\tilde{r}'\tilde{r})^{-1}, \tag{26}$$

where ι_T denotes a $T \times K$ vector of ones.

4.1.2 Empirical Results

The PCA analysis in Section 2.2.3 selected 3 fundamental principal factors and 1 technical principal factor, meaning we are considering $K = 4$ ($F_1^{Fun}, F_2^{Fun}, F_3^{Fun}, F^{Tech}$) conditioning variables for analysis. The portfolio optimization technique will be performed out-of-sample over an expanding window. We will first use an initial window of 9 years in order to compute the first optimal portfolio in February 1999 and rebalance on a monthly basis, thus aligning the dates for currency timing and tilting strategies. The risk parameter γ will be fixed at 10, a conservative value to represent high risk aversion. We implement a long-short strategy so that long positions cancel out short positions to mimic a zero-investment strategy. As further constraints, we do not allow single currency weights to exceed 100% in either direction.

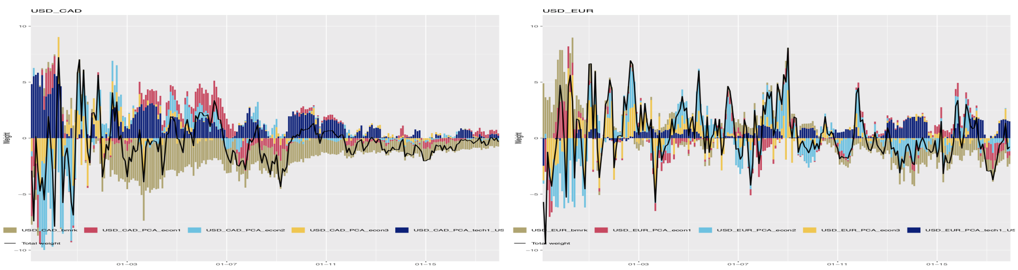
Panel A of Table 3 shows the θ estimates and their corresponding significance levels. Some of the coefficients are statistically significant such as the second fundamental PCA (F_2^{Fun}) factor for the EUR and GBP at the 5% significance level, and CHF at the 10% significance level. The third fundamental PCA (F_3^{Fun})factor is only significant at the 10% significance level for AUD, and the technical principal factor is significant at the 10% significance level for NZD and EUR. Panel B reports the performance of the PPP strategy. The weights of the PPP portfolio are constrained to 200% to make the results comparable to Panel B of table 2. The PPP strategy offers a meagre risk-adjusted return but with 14% draw-down.

Table 3: Parametric portfolio policy: θ coefficients and performance analysis Panel A presents the estimated θ coefficients from the parametric portfolio policy optimization using the IS period between February 1990 and December 2017. Panel B shows the performance analysis for the parametric portfolio policy. The performance analysis includes annualized returns and volatility, Sharpe and information ratio, and maximum drawdown.

Panel A	F_1^{Fun}	F_2^{Fun}	F_3^{Fun}	F^{Tech}
EUR	-0.18	0.56**	-0.25	-0.42*
GBP	0.09	-0.39**	0.23	0.07
JPY	0.01	0.15	-0.03	-0.18
NOK	-0.17	0.03	-0.13	0.22
NZD	-0.10	0.11	-0.05	-0.27*
CAD	0.09	0.09	0.01	-0.06
AUD	-0.02	0.06	0.32*	0.06
CHF	0.20	-0.34*	-0.05	0.19
SEK	0.10	-0.01	0.20	-0.23
Panel B	Return p.a.	Volatility ratio	Sharpe ratio	Max Draw down
PPP currency portfolio	3.02	6.24	0.13	14.44

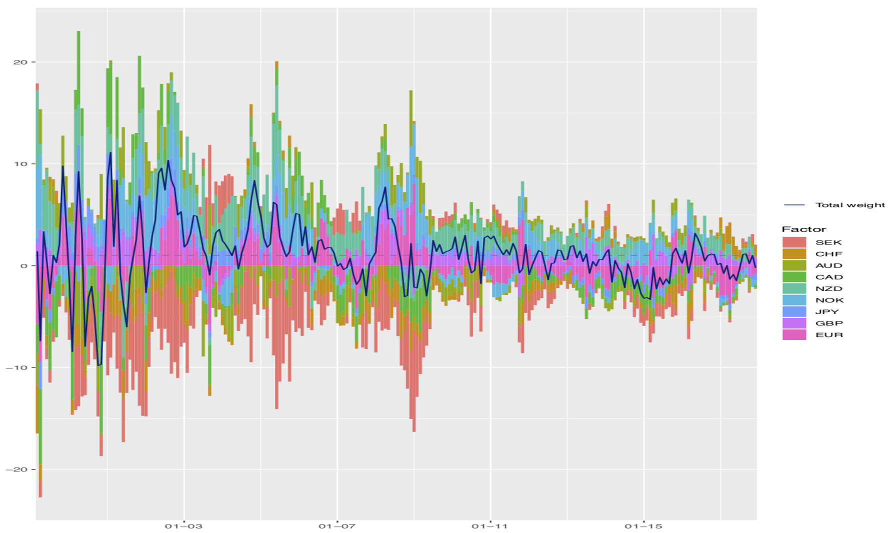
Figure 5 shows the impact of each of the conditioning variable on the resulting portfolio weights. As mentioned before, the total weight is simply the sum of the proportion invested in the currency plus the weights multiplied by the conditioning variables. Hence, these conditioning variables account for a large proportion of the aggregate weight. Especially for the CAD and EUR, we note an oscillating pattern of the conditioning variables, indicating the dynamic allocation in play. The beige colored area, which represents allocation in the currency itself, remains fairly stable in both the long and short legs for the entire period.

Figure 5: Decomposition of the the optimal currency weights. The figure shows the currency weights decomposition in the parametric portfolio policy and the contribution of each conditioning variable. The chart on the left is for the CAD and the one on the right for the EUR. The sample period is between 1999-02 and 2017-12.



The aggregate optimal portfolio policy with the shapes of the long and short portfolio are shown in figure 6. Given the fact that we did not constrain the portfolio optimization, we observe extreme positive weights for NOK. SEK was characterized by large short positions. EUR oscillates throughout the sample, taking large weights in both long or short legs.

Figure 6: The currency allocation following the parametric portfolio policy (Timing). The sample period is between 1999-02 and 2017-12.



To sum up, although the PPP timing strategy delivers higher returns, it is also associated with a high risk and leverage. Although, not many θ coefficients are significant, this exercise motivates us to investigate further by expanding currency tilting in such a way to operationalise factor timing.

5 Optimal Currency Factor Timing

While directly timing currencies through fundamental variables or technical indicators has proven difficult, the PPP for currency tilting was successfully exploiting the cross-sectional currency characteristics carry, value, and momentum. Notably, the carry trade is the chief return generator in the aggregate currency allocation. As it is prone to crash risk in flight-to-quality events it seems natural to diversify the carry signal by joining momentum and value signals. Yet, especially momentum can prove to be an expensive constant hedge and we wonder whether there are cheaper ways to navigate the downside risk of the carry trade. In particular, recent FX literature has seen a few works seeking to time carry strategies based on different indicators, such as FX volatility based exchange rate regimes, bid-ask spread, equity/bond returns, and VIX; see Christiansen *et al.* (2011), Clarida *et al.* (2009) which offer insights on the economic consequences of high vs low distress periods, business cycles, specific events, etc. Hence, this integrated approach would allow us to further appreciate the real-time choice of factors that we use in our model. For example, this model might partially capture the unwinding of carry trade positions during the 2008 financial crisis. Moreover, this integrated approach offers a deeper understanding of the variation in currency factor exposures.

Brandt *et al.* (2009) allow the coefficients that capture the joint distribution of returns to be time-variant by modifying the portfolio policy to include timing characteristics as follows:

$$w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T(z_t \otimes x_{i,t}), \tag{27}$$

where z_t is a vector of predictors known at time t. Hence, the effect of the characteristics on the portfolio weights will vary with the realization of the predictors z_t removing the assumption of a constant coefficient. To demonstrate this, Brandt *et al.* (2009) use an indicator based on the sign of the slope of the yield curve to obtain the coefficients of the portfolio policy.

5.1 Empirical results

The key to this approach is to identify relevant predictors for timing the chosen cross-sectional currency characteristic. We begin by choosing predictors for the carry characteristic, which univariately offers not only higher returns but also highest risk. Bekaert and Panayotov (2019) distinguish currency carry trades based on Sharpe ratio and highlight the relevance of equity market risk factors for the G10 currency universe between 1984 and 2014. Their results show that carry trades are driven by certain subsets of the G-10 currencies. On the flip side, Christiansen *et al.* (2011) use a currency volatility based regime-dependent pricing model to decode the time-varying systematic risk of carry trades. Clarida *et al.* (2009) also explore the volatility-regime based sensitivity of carry trades using an exponential GARCH model during crisis (1997-98) vs non-crisis period and establish volatility regime sensitivity of carry trade. Jordà and Taylor (2012) also resort to a regime -based model and conclude that regime based models better explain carry trades.

Carry trade returns and crash risk have been constantly criticized by numerous researchers. We know that carry trades are well-linked to market liquidity. Brunnermeier *et al.* (2008) relate the unfavorable movements in funding liquidity and crash risk of carry trades. They explain the unwinding of carry trades when funding liquidity falls. More evidence from the literature also supports liquidity based sensitivity of carry trades

Hence, we look for an indicators to capture liquidity and volatility. Unsurprisingly, TED spread seems to be the best proxy for money market liquidity. TED spread, which is the difference between 3-month LIBOR and 3-month T-bill, gauges the willingness of banks to lend money in the interbank market. The money market is said to be illiquid when the TED spread widens and vice versa. Hence, the TED spread is naturally shown to have positive correlation with currency crashes. We construct the FX volatility measure by using an Exponential Weighted Moving Average(EWMA) based realized volatility similar to Clarida *et al.* (2009). We use a λ of 0.95 and a 3 month window for constructing our volatility estimate. We also use the CBOE Volatility Index based regime for timing the carry trade. Since the VIX Index is forward-looking, we lag the series by a month to avoid any forward-looking bias.

We proceed by creating a liquidity regime-based model using TED spreads for our G10 currency universe. We construct this indicator function using the deviation of the TED spread from twice its average mean throughout the sample period. We construct a dummy variable from our predictor TED spread variable. These two regimes give us two carry characteristics instead of one. The first carry characteristic is identical to the original characteristic except for the illiquid months (defined by the TED spread), where the value is set to zero. Whereas, the second carry characteristic is identical to the original carry characteristic in illiquid months but in liquid months, its value is set to zero. For our FX volatility measure and VIX Index, we construct regimes based on whether the end of the month volatility exceeds the sample average.

Similar to our previous section, we use the first 5 years to initialise the optimization and re-estimate the parameters on a monthly basis using an expanding window. Panel A and B of Table 4 includes our univariate and multivariate results of carry trade from Table 2 for comparison. The estimated ϕ coefficient during low TED regimes is highly significant whereas it is insignificant for the high TED regime. This indicates the different impact of carry characteristic on the joint distribution of returns in periods of high and low market liquidity. The positive estimated ϕ coefficient of the low TED spread regime further indicates tilting of optimal currency portfolio towards carry currencies during liquid periods. On the flip side, the negative, although insignificant, coefficient hints the tilting of optimal portfolio towards low-interest-rate currencies during illiquid periods.

We also create a crystal-ball indicator for the carry trade in order to assess the accuracy of the model. We use the naive carry portfolio to construct a perfect foresight indicator for the carry trade. Intuitively, the regimes from this perfect foresight indicator should be able to exactly time carry trades. The univariate results in panel A and multivariate results in panel E confirm the correctness of the model. In panel A, not only are the coefficients in the high and low regime highly significant but the Sharpe ratios are 1.58 and 2.54 reassuring the timing ability of this model. A return of about 152% in panel F with a Sharpe ratio of 3.57 meets our expectations yet again.

With regards to other indicators, the Sharpe ratios in panel A speaks to the superiority of the integrated approach over the tilting strategy. Compared to the multivariate optimal tilting portfolio, the integrated strategy timed with the TED spread delivers a Sharpe ratio of 0.75. Moreover, the maximum drawdown is reduced from 26.58% to 15.80%, thus identifying and avoiding periods of higher crash risks. Such noticeable improvements across all performance metrics of the integrated strategy encourages us to pursue further in this direction.

For the multivariate model using TED spread, results are reported in Panel C of table 4 acknowledge the contribution of the carry timing element in improving performance and reducing risk. Not only do we observe an improvement in the Sharpe ratio when compared to panel B, but also we see a reduction in the drawdown suffered by the optimal portfolio. Overall, the results in this table offer a very positive outlook for our integrated portfolio policy approach. The multivariate results with FX volatility as an indicator also performs better than our tilting portfolio. Using equity based VIX as an indicator results in significant coefficients univariately during the high regime but offers better risk-adjusted performance when used multivariately.

We consider further the case of 2 carry currencies, the Swiss Franc and the New Zealand Dollar and analyse the decomposition of the optimal weights in order to get a better understanding of the contribution of each conditioning variable. The decomposition of the optimal currency weights is presented in Figure 7. The mostly red portions confirm that carry trades dominate the short and long positions of Swiss France and New Zealand Dollar respectively. This not only conforms with the results in Section 3 but also demonstrates similar movements during 2008 financial crisis. The time varying coefficient of the integrated parametric portfolio policy minimizes crash risk by varying with market liquidity conditions proxied by TED spread. This is also captured in 2001 when there was a stock market downturn which ends further credibility to this model. Hence the carry trade positions get automatically adjusted whenever there is a drop in liquidity during such periods of financial distress. Adding more support is the expected opposite weight distribution of the high carry currency (NZD) and low carry currency (CHF).

Table 4: Currency factor timing results. Panel A presents the estimation results of the univariate parametric portfolio policy as well as the performance statistic of the carry strategy using the tilting and the integrated method. Panel B gives the estimation result for the multivariate optimisation with the performance statistic for the tilting case. Panel C gives the estimation result for the multivariate optimisation with the performance statistic for the integrated case. The sample period covers the period between 1994-02 and 2017-12.

		S.E	Return p.a	Vola p.a	Sharpe ratio	Max Drawdown
Panel A: Univariate models						
Carry x TED			9.73	10.05	0.75	15.80
Carry x $I(low\ TED)$	2.94***	0.83				
Carry x $I(high\ TED)$	-1.83	1.37				
Carry x Vol			6.38	7.54	0.55	19.86
Carry x $I(low\ Vol)$	0.60	0.93				
Carry x $I(high\ Vol)$	2.24*	1.16				
Carry x FwdCarry			150.04	41.13	3.59	17.70
Carry x $I(low\ Carry)$	-13.42***	1.85				
Carry x $I(high\ Carry)$	18.64***	2.15				
Carry x VIX			5.16	7.96	0.37	24.04
Carry x $I(low\ VIX)$	1.79*	1.08				
Carry x $I(high\ VIX)$	1.74*	1.00				
Carry(Tilting)	1.76**	0.79	5.94	7.48	0.50	26.58
Panel B: Multivariate model (tilting)						
Optimal Portfolio			7.12	8.22	0.60	18.56
Momentum	0.71	0.63				
Value	1.96***	0.63				
Carry	1.90***	0.60				
Panel C: Multivariate model (integrated)						
Optimal Portfolio			8.92	9.67	0.69	15.73
Momentum	0.05	0.72				
Value	1.33*	0.70				
Carry x $I(low\ TED)$	2.80***	0.76				
Carry x $I(high\ TED)$	-3.83**	1.71				
Panel D: Multivariate model (integrated)						
Optimal Portfolio			7.60	8.72	0.62	14.08
Momentum	0.20	0.67				
Value	1.87***	0.62				
Carry x $I(low\ Vol)$	1.97	1.31				
Carry x $I(high\ Vol)$	0.87	1.00				
Panel E: Multivariate model (integrated)						
Optimal Portfolio			6.27	7.91	0.51	19.13
Momentum	0.68	0.65				
Value	1.98***	0.63				
Carry x $I(low\ VIX)$	1.67*	0.94				
Carry x $I(high\ VIX)$	2.09***	0.79				
Panel F: Multivariate model (Crystal Ball)						
Optimal Portfolio			151.57	42.87	3.57	18.04
Momentum	0.23	1.37				
Value	-1.18	1.26				
Carry x $I(low\ Carry)$	-13.87***	1.51				
Carry x $I(high\ Carry)$	18.96***	1.80				

Figure 7: Decomposition of the optimal currency weights. The figure shows the currency weights decomposition in the parametric portfolio policy timed with FX liquidity indicator, the TED spread and the contribution of each conditioning variable. The left chart is for the CHF and the right one for the NZD currency. The sample period is between 1994-02 and 2017-12.

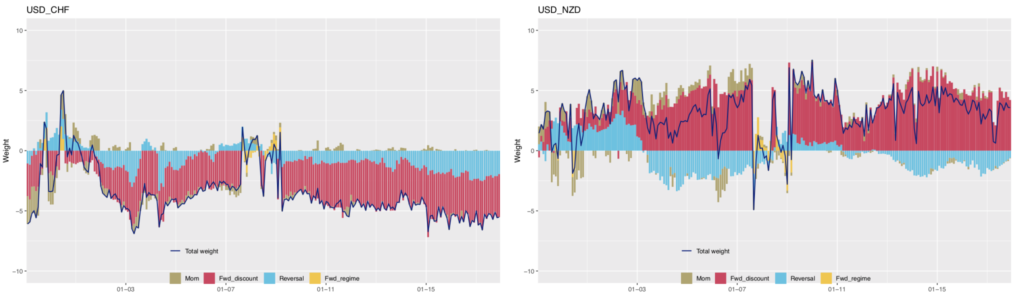


Figure 8: Currency factor timing: Aggregate Allocation. The sample period is between 1994-02 and 2017-12

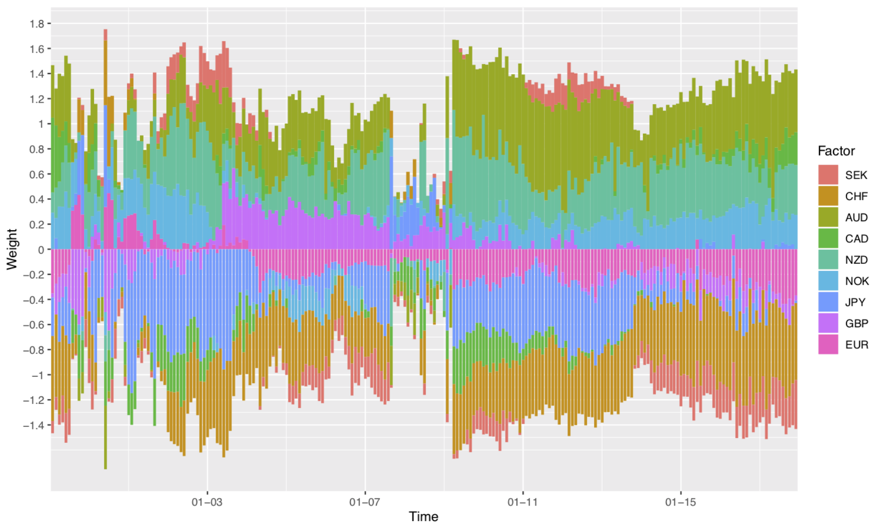


Figure 8 shows the weights on an aggregate portfolio level. This not only depicts the unwinding of the carry trade positions especially during the financial crisis but also shows the expected significant reduction in all currency weights, backed by a full investment in the risk free rate. We also observe a significant increase in the exposure towards the safe heaven currencies since 2000. Overall, we observe that the liquidity measure perform better in timing the carry trades than the volatility measures.

6 Conclusion

The gamut of studies on currency factor investing elaborates on the choice and relevance of style-based and macroeconomic variables. Whereas most of the studies use univariate factor approaches, we focus here on a multivariate framework and an integrated one. In our study, we focus on efficient currency portfolio allocation and rely on parametric portfolio policies by Brandt and Santa-Clara (2006) and Brandt *et al.* (2009) that allow for both tilting and timing currencies using carefully chosen characteristics and variables respectively. For the tilting exercise, exploiting information in the cross-sectional dimension, we use 3 different factors: value momentum and carry. For factor timing exercise which exploits the time series information we rely on fundamental and technical indicators as predictors and perform a PCA analysis to reduce the number of variables and extract common factors embedded in all predictor variables.

We find evidence in favor of such sophisticated portfolio allocation strategies, especially for an optimal currency tilting strategy. The choice of broader underlying fundamental and technical factors could be a possible reason for the poor performance of our optimal currency timing strategy. Nonetheless, this pushes our study in the direction of developing an integrated strategy which could help time the carry/value/momentum strategies. Testing such an integrated portfolio policy highlights the predictability of market liquidity proxy for timing carry trades, thereby motivating us to experiment with various other conditioning variables.

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