An Integrated Approach to Currency Factor Investing*

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Abstract

Using the G10 currencies, we show that parametric portfolio policies can help guide an optimal currency strategy when tilting towards cross-sectional factor characteristics. While currency carry serves as the main return generator in this tilting strategy, momentum and value are implicit diversifiers to potentially balance the downside of carry investing in flight-to-quality shifts of foreign exchange investors. Drawing insights from a currency timing strategy, according to time series predictors, we further examine the parametric portfolio policy's ability to mitigate the downside of the carry trade by incorporating an explicit currency factor timing element. This integrated approach to currency factor investing outperforms a naive equally weighted benchmark as well as univariate and multivariate parametric portfolio policies.

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Investors favor global investment portfolios because of the diversification benefits associated with investing in less correlated, international markets. These portfolios usually engage in international bond and equity investments and are therefore directly exposed to and affected by foreign exchange (FX) rate fluctuations. To manage such currency exposures, currency factor strategies such as carry, value, and momentum have become popular among institutional investors. Currency factor models aim to measure the exposure of currencies to different factors, so that currency portfolios may be created dynamically or exchange rates may be predicted.

The choice of currency factors plays a crucial role since an uninformed choice of currency factors can heavily impact portfolio performance. Verdelhan (2018) suggests a two-factor model using U.S. Dollar (USD) 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, Mark, Sul and Wu (2018) also propose a two-factor model for predicting exchange rates. They conclude that the Dollar factor and the Euro factor drive exchange rates whereas the prominent carry factor does not.

The objective of this paper is to investigate an integrated approach to currency factor investing that optimally allocates currencies according to cross-sectional characteristics and time-series predictors. To this end, we build on the parametric portfolio policy (PPP) approach of Brandt and Santa-Clara (2006) and Brandt, Santa-Clara and Valkanov (2009) to assess the joint relevance of various potential predictors. Whilst the latter approach has been put forward by Barroso and Santa-Clara (2015) to construct optimal currency factor strategies based on carry, value and momentum characteristics, we contribute to this work by additionally incorporating the notion of timing. Firstly, we investigate currency timing in the parametric portfolio policy framework of Brandt and Santa-Clara (2006). Secondly, we expand the framework of Barroso and Santa-Clara (2015) to investigate the possibility of explicitly timing cross-sectional FX factors such as carry trade.

Our key results show that investing within the universe of G10 currencies using an optimal currency tilting strategy from February 1989 through December 2020 is more compelling and robust than the currency timing alternative. This finding comes mainly from stronger evidence of predictability in the cross-section of currency excess returns compared to time-series predictability with respect to the chosen fundamental variables and technical predictors. Unsurprisingly, the carry characteristic is the main driver of performance, yet the momentum and value characteristics help alleviate major carry drawdowns in volatile FX markets.

Extant literature on the carry trade, such as Menkhoff, Sarno, Schmeling and Schrimpf (2012a) and Brunnermeier, Nagel and Pedersen (2008), has examined the explicit timing of the profitability of carry trade. We investigate an extension of the tilting parametric portfolio policy to integrate the management of FX characteristics in light of meaningful conditioning information. Such currency factor investing not only offers the highest risk-adjusted performance, but also suggests that a PPP can be effectively adapted to overcome the drawbacks of models requiring forecasted expected returns.

The remainder of this paper is structured as follows: Section 1 reviews the FX literature and the common choice of factors used for currency tilting. Section 2 describes the optimal currency tilting based on the PPP framework of Brandt *et al.* (2009). Section 3 discusses relevant predictors for timing currencies and for timing currency factors. Section 4 introduces optimal currency timing and presents an integrated approach to currency factor timing. Section 5 concludes.

1 The Notion Of Currency Tilting

The idea behind characteristic-based tilting strategies is simple and straightforward. If we assume that the capital asset pricing model (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. However, follow-up studies (Fama and French (1992, 1993), Carhart (1997), Ang, Hodrick, Xing and Zhang (2006)) repeatedly find strong counterevidence for the relevance of equity factors beyond the market factor such as size, momentum, value, and low-volatility.

Several factors and factor models have garnered attention since the founding of the CAPM. Still, the efficacy of style factor-based portfolio allocation has been studied primarily in equity markets. Style investing has also become popular in other asset classes such as bonds, commodities, and FX. Extending factor-based strategies to FX markets is straightforward, and common factor strategies account for a large percentage of trading volumes in FX markets. Research on currency factors has identified some prominent reasons behind the success and widespread adoption of these strategies. For example, Burnside, Eichenbaum and Rebelo (2011) examine the profitability of the two most prominent FX strategies, carry and momentum. They confirm existing evidence that payoffs to currency strategies are skewed with fat tails and that conventional risk factors alone cannot account for these returns. The authors provide possible theoretical, microstructural, and behavioral explanations for their continued profitability, and acknowledge the uncorrelated payoff to carry and momentum strategies. Such correlation patterns offer a wide scope for investors to use multiple currency strategies simultaneously.

The performance of factor strategies in the last decade indicates that even well-established factors are prone to periods of poor performance during unfavorable market conditions. Still, the low correlation among factors and the resulting diversification benefits from combining multiple factors can help weathering tough times. Hence, in a portfolio setup, the choice of currency factors, and dynamically tilting towards or away from specific factors, play a crucial role as they can shield against adverse performance effects.

Following the approach of Brandt *et al.* (2009), we build an optimal currency tilting strategy by exploiting informative currency characteristics. The 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. Brandt *et al.* (2009)'s parametric portfolio policy tackles the issue of cross-sectional portfolio optimization by modeling the portfolio weights as a linear function of currency characteristics. In this study, we examine the three salient FX styles carry, value and momentum together with three additional currency factors, namely Dollar exposure, the Taylor rule and the output gap.

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 factors, such as market, value, and momentum. The carry trade portfolio is constructed by buying the highest-yielding currencies and selling the lowest-yielding currencies. Researchers have posited various explanations for the carry trade performance. Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan (2009) find that crash risk is responsible for 25% of carry trade returns in developed countries, while Caballero and Doyle (2012) find that carry trade returns can serve as compensation for systemic risk. They note that carry trade returns are highly correlated with equity market risk, especially during market downturns.

The carry factor seeks to exploit the failure of uncovered interest rate parity by banking on the interest rate differentials of high interest rate and low interest rate currencies. Having sparked interest in the early 1980s, Bilson (1981) and Fama (1984) attempted to solve the forward premium puzzle in order to identify the academic motivators behind carry trading in currencies. The FX carry trade strategy maintained its prominence over the years, see Galati and Melvin (2004) who attribute the surge in FX trading to the sudden rise in attractiveness of FX carry and momentum strategies. However, harvesting the FX carry trade has often been associated with collecting pennies in front of a steamroller. Researchers have identified certain cases of underperformance, for example, with liquidity squeezes (Brunnermeier, Nagel and Pedersen, 2008) or increased FX volatility (Menkhoff, Sarno, Schmeling and Schrimpf, 2012a).

To construct the FX carry factor, we take the forward discount (or premium) of a specific 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. We compute the forward discount as:

$$fd_t^i = \frac{F_t^i}{S_t^i} - 1, \tag{1}$$

where F_t^i is the price of one USD expressed in foreign currency units at time t and S_t is the spot price of one USD in foreign currency units at t.

1.2 FX Momentum

Momentum investing has been extremely popular among equity portfolio managers and has been a subject of intense academic study for decades, beginning with Jegadeesh and Titman (1993). In the realm of currencies, exploiting short-term price momentum effects is also relevant given that they are not subsumed by any other traditional risk factor. FX momentum effects can be detected for formation periods of between one and twelve months. But three months is a common choice, because it strikes a solid balance between the goodness of signal and strategy turnover.[1]

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 in order to capture the persistence of currency returns in the short term. We thus compute the momentum signal accordingly:

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

where S_t^i is the spot 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 that restrict the deployment of arbitrage capital to exploit this phenomenon. Equity markets also seem to play a predictive role in explaining the variations in currency momentum payoffs. Okunev and White (2003) capture momentum in the cross-section of currencies and find positive evidence for existence of profits from a cross-sectional momentum-based strategy. 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 they are less related to business cycle risk. They also confirm that FX momentum returns are much higher in currencies with high lagged idiosyncratic volatility and high-country risk ratings.

1.3 FX Value

To assess undervalued and overvalued currencies, FX value strategies seek to exploit long-term reversal effects in FX markets. However, there is no universally accepted rule for classifying

[1] The choice of a three-month formation period is consistent with Kroencke, Schindler and Schrimpf (2013) and Barroso and Santa-Clara (2015).

currencies this way, therefore we need to proxy for 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.

To construct an FX value factor, we use purchasing power parity as the measure of fundamental value, assuming that goods should cost the same across countries. Currencies whose real exchange rate (RER) deviates significantly from one may be viewed as undervalued or overvalued. The FX value strategy would then seek to exploit the likely reversal of currencies that have exceeded their purchasing power parity values. To determine which measure of purchasing power parity to use, we follow Asness, Moskowitz and Pedersen (2013) and use the 60 month deviation from uncovered interest rate parity. We thus compute the cumulative real depreciation of currency i as:

$$Q^i_{h,t} = \frac{S^i_t CPI^i_h CPI^i_t}{S^i_h CPI^i_t CPI^{US}_h}, \tag{3}$$

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 U.S. or for the other currency i; and S^i_t and S^i_h are the spot prices of one USD in foreign currency units at t or h, respectively.

1.4 Macro-Based FX Factors

The currency fluctuations of a given country are, at least theoretically, linked to its economic fundamentals. Engel and West (2005) argue that exchange rates reflect the expectations of changes in macroeconomic fundamentals. They use a present value model that allows for greater emphasis on future expectations of fundamentals and find evidence of weak forecasting ability. Numerous other studies in the exchange rate predictability literature find similar weak evidence in lieu of exploiting fundamentals for predicting currency returns. Rossi (2013) reviews the literature on exchange rate forecasting and concludes that it depends on a range of elements such as predictors, forecasting horizons, sample periods, models, and forecast evaluation methods. Rossi's paper also highlights the outperformance of linear models over their more complex counterparts.

Cochrane (2017) asserts the significance of the relationship between business cycles and currency returns and emphasizes that they are necessary for the empirical validation of risk-based models. Macroeconomic conditions can hence be leveraged to understand and explain currency excess returns. Apart from the style-based factors such as carry, value and momentum, we investigate three macro-based FX factors related to output gap, the Taylor rule and Dollar exposure, each of which is outlined below.

1.4.1 Output Gap

Macroeconomic theory postulates that currencies of strong economies tend to appreciate against those of weaker economies. The current strength of an economy can be deduced based on its position in the cycle, for example, whether the economy is approaching the peak of the cycle or is closer to the trough of the cycle. Specifically, a simple output gap measure can be used to capture the current state of an economy.

The output gap is defined as the difference between an economy's actual output and its maximum potential, measured as a percentage of its gross domestic product (GDP). As the output gap-based FX strategy targets loading on stronger countries with respect to the base currency USD, the strategy goes long currencies of countries with output gaps above that of the U.S. and vice versa. Colacito, Riddiough and Sarno (2020) thus sort currencies of 27 countries on the basis of output gap in order to capture the impact of business cycles on currency returns. The resulting strategy generates a Sharpe ratio of 0.74, and a similarly high Sharpe ratio in a multivariate model with carry, value, momentum, and Dollar carry. Their output gap portfolio shows zero correlation with the carry trade portfolio, thereby suggesting diversification benefits.

We follow Colacito, Riddiough and Sarno (2020) and Bartram, Djuranovik and Garratt (2020) in constructing the output gap-based FX factor. As the output gap is not directly observable, we use detrended monthly industrial production (IP) for each country in our sample. Specifically, we use the linear projection method of Hamilton (2018) that gives the detrended output as the residuals from the regression of log IP_t on a constant and on $IP_{t-13:t-24}$ using an expanding window estimation so as to include all the data available at time t.

1.4.2 The Taylor Rule

The Taylor rule evaluates changes to monetary policy based on inflation and real activity by tracking the Fed's decisions on adjusting short-term interest rates post-1987 (see Taylor (1993) for empirical application of macroeconomic policy evaluation). Therefore, the rule posits that nominal interest rates are based on the current inflation rate, the inflation gap, the output gap, and the equilibrium interest rate. Following Castro (2011), the linear representation of Taylor rule can be written as,

$$i_t^* = \bar{r} + \pi^* + \beta(\pi_t - \pi^*) + \gamma(y_t - y^*) \tag{4}$$

where $\bar{r}$ is the is the equilibrium real rate.

Thus, according to the Taylor rule, the nominal short-term interest rate (i_t^*) would increase if inflation (π_t) exceeds a target inflation rate (π^*) or if output (y_t) increases above its trend or potential value (y^*). Therefore, the coefficients β and γ denote the sensitivity of interest rate policy to deviations in inflation and to the output gap respectively.

Engel and West (2005) offer a sound reasoning for the relevance of the Taylor rule strategy for exchange rate predictability. They posit that the currencies of economies where current output is above their potential are expected to appreciate. The Taylor rule has shown consistent short-term out-of-sample forecasting ability in various follow-up studies (Mark (2009); Molodtsova and Papell (2009); Wang and Wu (2012); and Molodtsova, Nikolsko-Rzhevskyy and Papell (2008) among others). The Taylor rule-based factor is constructed from the output gap and an implicit output deflator by simply summing 1.5 times the deflator and 0.5 times the output gap.

1.4.3 Dollar Exposure

Building on the work of Lustig, Roussanov and Verdelhan (2014), Verdelhan (2018) develops a Dollar exposure factor that measures the average change in the USD versus other currencies, which distinguishes the local shocks from the global shocks. The Dollar exposure factor is simply the coefficient of the Dollar factor in the regression of a currency's rate change on a constant, the interest rate differential, the carry factor, the interaction between the interest rate differential and the carry factor, and the Dollar factor using 60-month rolling windows. The Dollar factor represents the average change in exchange rate across all currencies. As in Verdelhan (2018), this factor goes long when the average forward discount of a country's currency is positive and short otherwise and helps in assessing the riskiness of currencies.

2 Optimal Currency Tilting

Modeling optimal portfolio weights involves evaluating a wide range of risk-reward trade-offs and investment constraints. Brandt *et al.* (2009) exploit the cross-sectional characteristics of equity returns to obtain optimal portfolio weights assuming a linear portfolio policy that models optimal portfolio weights as the sum of a benchmark weight, plus a deviation term depending on chosen characteristics. We next leverage their parametric portfolio policy framework to gauge the currency characteristics needed to generate a currency allocation and to harness the associated premia.

2.1 Parametric Portfolio Policy Framework

The parametric portfolio policy (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 *et al.* (2009) consider an investor seeking to maximize the conditional expected utility of her portfolio return, $r_{p,t+1}$:

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u(r_{p,t+1})\right] = E_t\left[u\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}\right)\right], \tag{5}$$

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:

$$w_{i,t} = w(x_{i,t};\phi) = \overline{w_{i,t}} + \frac{1}{N_t}\phi' x_{i,t}, \tag{6}$$

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 must be estimated as part of the utility maximization, and $x_{i,t}$ is the vector of cross-sectionally standardized characteristics of asset i at date t. Parameterization (6) implicitly assumes that the chosen characteristics fully capture the joint distribution of asset returns. The portfolio policy is embedded in the idea of estimating the weights as a function of the characteristics, which 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. Thus, deviations from the benchmark are equivalent to a zero-investment portfolio. The portfolio parameterization implies that the chosen characteristics convey various aspects of the joint distribution of returns. We rewrite the optimization problem in terms of ϕ-coefficients as follows:

$$\max_{\phi} E\left[u(r_{p,t+1})\right] = E\left[u\left(\sum_{i=1}^{N_t} f(x_{i,t}, \phi) r_{i,t+1}\right)\right] \tag{7}$$

where we parameterize the optimal portfolio weights as a function of the chosen currency characteristics. The first-order condition of the maximization problem is then given by:

$$\frac{1}{T}\sum_{t=0}^{T-1} h(r_{t+1}, x_t; \phi) \equiv \frac{1}{T}\sum_{t=0}^{T-1} u'(r_{p,t+1})\left(\frac{1}{N_t}\hat{x}_t' r_{t+1}\right) = 0, \tag{8}$$

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

$$\Sigma_{\phi} \equiv AsyVar[\hat{\phi}] = \frac{1}{T}[G'V^{-1}G]^{-1}, \tag{9}$$

where

$$G \equiv \frac{1}{T}\sum_{t=0}^{T-1} \frac{\partial h(r_{t+1}, x_t; \phi)}{\partial \phi} = \frac{1}{T}\sum_{t=0}^{T-1} u''(r_{p,t+1})\left(\frac{1}{N_t}\hat{x}_t' r_{t+1}\right)\left(\frac{1}{N_t}\hat{x}_t' r_{t+1},\right)' \tag{10}$$

and V is a consistent estimator of the covariance matrix of $h(r, x; \phi)$ and u'' is the second derivative of the utility function.

2.2 Naive Currency Portfolio Construction

To benchmark the performance of the PPPs, we construct naively weighted currency portfolios for each of these currency characteristics. To construct such portfolio, we rank the G10 currencies according to each characteristic. The top and bottom three currencies form the long and short legs of the portfolio, respectively, based on an equal-weighting scheme, see Kroencke, Schindler and Schrimpf (2013). Specifically, we will use the characteristics x_t defined in the previous section. The long ($\mathcal{L}_t^j$) and short ($\mathcal{S}_t^j$) legs with $N = 9$ sets of currencies are defined as follows:

$$\mathcal{L}_t^j = \begin{cases} 1 & \text{if} \quad x_t^j \geq q(x_t)_{1-p} \\ 0 & \text{if} \quad x_t^j < q(x_t)_{1-p}, \end{cases} \tag{11}$$

and

$$\mathcal{S}_t^j = \begin{cases} 1 & \text{if} \quad x_t^j \leq q(x_t)_p \\ 0 & \text{if} \quad x_t^j > q(x_t)_p, \end{cases} \tag{12}$$

where $q(x_t)$is the p-quantile of x_t and $p = \frac{3}{9}$.

2.3 Empirical Results

We next implement the parametric portfolio policy for a mean-variance investor. The currency investment universe is comprised of the G10 currencies with USD as the base currency and the following countries' currencies: Australia (AUD), Canada (CAD), Germany (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), and the United Kingdom (GBP). All the spots, forward and CPI data come from Bloomberg. We use the OECD industrial production data to compute the output gap. Our sample period spans between February 1989 through December 2020. We define the currency excess returns in USD for currency i as follows:

$$r_{t+1}^i = \frac{F_t^i}{S_{t+1}^i} - 1, \tag{13}$$

where F_t^i is the price of one USD expressed in foreign currency units and S_{t+1}^i is the spot price of one USD in foreign currency units. We choose a conservative risk aversion coefficient of $\gamma = 10$ for the analysis to represent moderate risk aversion.

The value characteristic (measured via the real exchange rate, RER) is computed against the USD using the spot exchange rate and the consumer price index (CPI). Bloomberg provides monthly CPI data, except for Australia and New Zealand, where only quarterly data are available. For these two countries, the most recent values are carried forward to the subsequent months until the new quarterly data become available. Because we consider the EUR as the currency for Germany, we take the CPI into account only for Germany. To account for the deviation from uncovered interest rate parity, we exclude 60 months of observations, so that our sample for the value characteristic $Q_{h,t}^i$ spans between February 1994 through December 2020. In addition, we use an initial period of five years in the PPP optimization to determine the optimal coefficients. Our backtest thus begins from February 1999. The portfolios are rebalanced monthly, with an expanding window of 60 months. We also construct one-month and twelve-month cross-sectional momentum factors using the same method as for the three-month momentum.

Table 1 gives the estimation results and performance statistics for the six univariate PPPs, the multivariate PPP, and the naive models. In Panel A, we test all the chosen factors univariately. Carry and value characteristics are positively significant at the 5% level, while the Taylor rule-based factor is positively significant at the 1% level. This indicates that the PPP methodology correctly identifies the expected direction of the respective trades. In this vein, the one- and twelve-month momentum characteristics indicate price momentum effects, yet all momentum coefficients are insignificant.[2] The FX carry strategy offers the best risk-return trade-off in terms of the Sharpe ratio (0.44) followed by the Taylor rule-based strategy (0.34) and the FX value strategy (0.31). However, it is important to note that the FX carry strategy is vulnerable to crash risk as indicated by its 27% drawdown.

In Panel B, we show FX factor performance when driven by the naive portfolio construction paradigm laid out in Section 2.2. Across the six FX characteristics, we note that risk-adjusted performance is slightly elevated relative to the optimized factor-PPPs from Panel A. In defense of the latter, we rationalize that naive factor portfolios come with the benefit of hindsight bias; while naive factor portfolios are designed to follow the prescribed rationale of a given factor throughout the sample, the PPPs have to first learn this rationale from the data before going "all-in".

Next, we investigate multivariate PPP strategies to leverage diversification benefits across FX characteristics. As a benchmark, we consider a simple 1/N-portfolio that equally weights the six naive FX factors from Panel B. This aggregate strategy gives a Sharpe ratio of 0.5. Panel C shows the results for the multivariate PPP that aims to capture the contributions and diversification coming from all six characteristics. In this context, we find carry and value to be significant (at the 1%-level). Moreover, we note that the multivariate PPP has a lower risk-adjusted performance than the naive 1/N aggregate (Sharpe ratio of 0.35 versus 0.5 for the 1/N-portfolio). To further investigate this outcome, we look into a fundamentals-only PPP in Panel D. Therein, value and Taylor-rule characteristics are significant at the 5%-level. Yet, the Sharpe ratio of this combination is similar to the performance of the respective univariate PPPs, suggesting little room for diversifying across fundamental FX factors. Against this backdrop, we lastly test a PPP that focuses on one fundamental characteristic only (namely value) together with carry and momentum. This "classic" FX factor combination produces a Sharpe ratio of 0.47 which is on par with the naive 1/N combination.

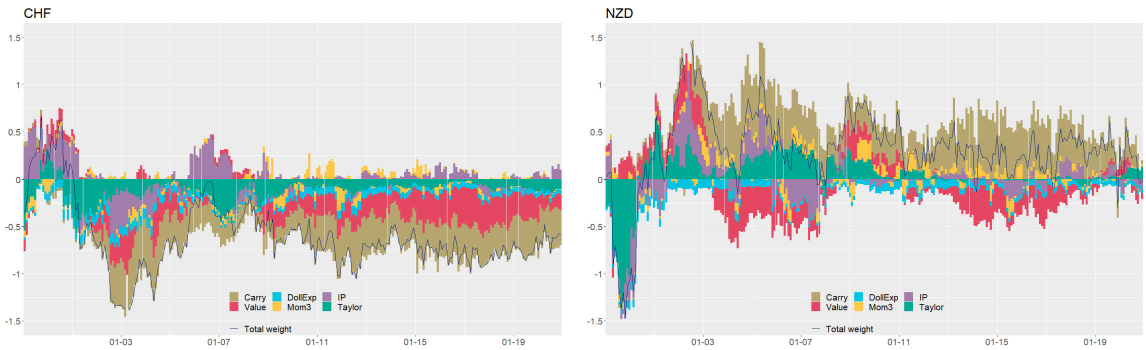
To foster intuition about how the parametric portfolio policies work, we decompose each currency weight by the six characteristics. Figure 1 illustrates the optimal weights for two

[2] Barroso and Santa-Clara (2015) observe a significant momentum coefficient (before transaction costs) when using a larger currency universe, including emerging markets, and over a longer investment horizon.

Table 1: Currency Tilting: Performance Panel A gives the estimated results of the univariate PPPs as well as the performance statistic of each investment style. Panel B gives the performance statistics for the naive portfolio construction of the six investment styles. Return, volatility and maximum drawdown figures are measured in percentage terms. Panel C groups the factors based on economic fundamentals. Panel D and E give the estimated results for the multivariate optimization with three and six factors, respectively. The sample period is February 1994 through December 2020. *, ** and *** represents significance at 10%, 5% and 1% levels, respectively.

	$\hat{\phi}$	S.E.	Return p.a. (%)	Vola p.a. (%)	Sharpe ratio	Max Draw-down (%)
Panel A: Univariate models						
Carry	1.58**	0.60	5.29	7.20	0.44	26.59
Value	1.57**	0.64	3.90	5.70	0.31	8.89
CS1Momentum	0.05	0.62	1.85	1.80	-0.17	3.93
CS3Momentum	-0.01	0.63	2.06	3.30	-0.02	7.10
CS12Momentum	0.39	0.61	2.32	3.80	0.05	10.50
DollarExposure	0.83	0.57	2.73	4.00	0.15	15.86
OutputGap	0.82	0.80	2.29	2.60	0.06	7.15
TaylorRule	1.86***	0.71	5.24	9.10	0.34	34.24
Panel B: Naive models						
Carry			5.79	7.85	0.46	23.57
Value			5.17	7.39	0.41	12.08
CS3Momentum			0.97	7.71	-0.15	39.13
DollarExposure			3.43	5.51	0.23	15.05
OutputGap			3.21	5.78	0.18	17.42
TaylorRule			5.09	7.02	0.42	26.19
Aggregate Portolio (1/N)			3.94	3.62	0.50	7.15
Panel C: 6-Factor PPP						
			6.31	12.00	0.35	35.00
Carry	2.09**	1.07				
Value	1.51**	0.67				
CS3Momentum	0.12	0.64				
DollarExposure	-1.21	0.88				
OutputGap	1.02	0.87				
TaylorRule	0.77	1.16				
Panel D: Fundamentals PPP						
			6.00	11.30	0.34	39.04
Value	1.24*	0.65				
OutputGap	0.82	0.86				
TaylorRule	1.66**	0.73				
Panel E: Carry, Value & Momentum PPP						
			6.11	8.38	0.47	18.55
Carry	1.59***	0.60				
Value	1.60**	0.62				
CS3Momentum	0.25	0.25				

Figure 1: Decomposing optimal currency tilting weights. The figure shows the currency tilting allocation over time and the contribution of each conditioning variable. The right-hand chart is for CHF; the left-hand chart is for NZD. The sample period is February 1994 through December 2020.

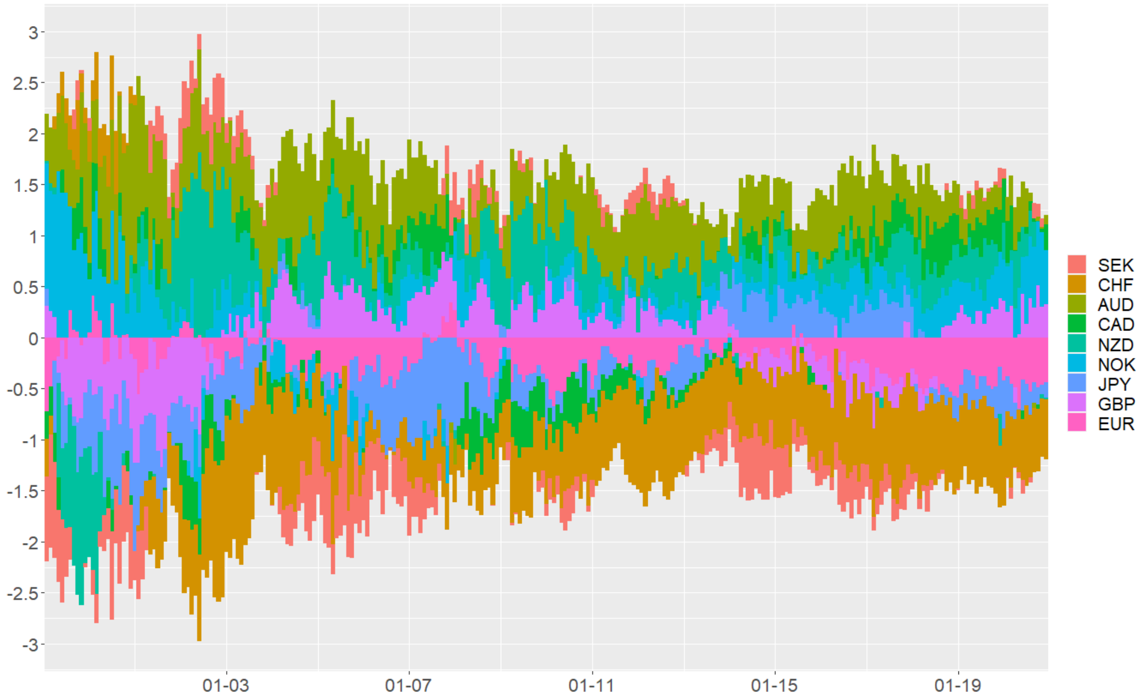


currencies, CHF and NZD, over time.[3] The CHF weights are almost always negative, and are mainly driven by the carry characteristic, as expected, but also by the three fundamental characteristics value, Dollar exposure and the Taylor rule. In contrast, the NZD weights are typically positive; naturally, this outcome is mainly driven by the large carry contribution. For the remaining characteristics, contributions vary in magnitude and sign through time.

Figure 2 shows the aggregate currency allocations according to the parametric portfolio policy with no restrictions on portfolio weights. High carry currencies such as AUD and NZD have predominantly long positions; low carry currencies, such as CHF, EUR, and JPY, constitute almost the entire short leg. The SEK oscillates modestly between positive and negative weights when compared with the other currencies. CHF, followed by EUR and JPY, represent the major short positions with average weights of -60.80%, -23.69%, and -19.15% respectively. AUD, NZD, and NOK hold major long positions, with weights averaging 54.87%, 31.71%, and 24.05% respectively. Note that Figures 1 and 2 display a de-levering of carry trades during the 2008 period, thanks to factor diversification. This shift in allocation also reflects a desire for moderate risk aversion, and, as a result, a reduced emphasis on the carry trade. To check the robustness of these results, we vary the risk aversion parameter. In unreported results, we find that the carry and value characteristics remain significant for risk-loving and risk-averse investors alike. The other characteristics also exhibit similar behavior, in line with our findings in Panel E of Table 1. In summary, the PPPs are effective in utilizing cross-sectional currency characteristics to guide an optimal portfolio.

[3]The results for all other currency pairs are available upon request.

Figure 2: Aggregate optimal currency tilting allocation. The sample period is February 1994 through December 2020.



3 The Notion Of Currency Timing and Currency Factor Timing

3.1 Currency Timing

In this section, we first turn to time-series information that could inform an optimal currency timing strategy in order to estimate optimal currency portfolio weights according to the PPP framework of Brandt and Santa-Clara (2006). Whether macroeconomic and financial variables can forecast FX returns is still widely debated. Nevertheless, there is evidence on the relevance of fundamental variables, interest rate-related variables (Cornell and Dietrich, 1978), and technical indicators (Cotter, Eyiah-Donkor and Potì, 2017) in forecasting FX returns. Second, rather than timing individual currencies we investigate timing the cyclicality of currency factors, focusing on the carry trade. Specifically, we illustrate how to incorporate this notion of factor timing into a PPP for optimal currency tilting as implemented in Section 2.

3.1.1 Fundamental Variables

We consider 14 predictor variables, as suggested by Welch and Goyal (2008)[4]: 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 lagged variables could exhibit very high first-order autocorrelations. Ferson, Sarkissian and Simin (2003) suggest "stochastic de-trending" of the lagged variable in order to avoid the bias that can result 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. Furthermore, there are few standardized fundamental variables that attain extreme values, which we truncate at ± 5.

3.1.2 Technical Indicators

Technical indicators can time trades by recognizing the drivers of international financial markets from a behavioral perspective. Similar to Hammerschmid and Lohre (2018), we include 11 technical indicators based on two sets of trading rules related to the general concepts of momentum (MOM_k) and moving averages (MA_{s-l}).

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}, and a sell signal otherwise.

$$MOM_k = \begin{cases} 1 & \text{if} \quad S_t > S_{t-k} \\ 0 & \text{if} \quad S_t \leq S_{t-k} \end{cases} \tag{14}$$

   where 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 at a given time t over j months is given by

$$MA_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} S_{t-i} \quad \text{for} \quad j \ = \ s,\ l, \tag{15}$$

[4]The dataset is available at `http://www.hec.unil.ch/agoyal/`

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 $l = 9, 12$ is for long-term moving averages. 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 otherwise:

$$MA_{s-l} = \begin{cases} 1 & \text{if} \quad MA_{s,t} > MA_{l,t} \\ 0 & \text{if} \quad MA_{s,t} \leq MA_{l,t} \end{cases} \tag{16}$$

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

3.1.3 Predictor Variables Selection

Now that we have carefully chosen 14 fundamental variables and 11 technical predictors, it is essential to check for multicollinearity. Figure 3 shows the correlation structure (using the currency pair USD/EUR[5] as an example) for the fundamental variables and technical indicators for our entire sample from February 1989 through December 2020. As expected, and as the bottom right of the chart shows, the technical indicators are highly correlated. The fundamental variables display a heterogeneous 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 a complementary predictive ability and suitability for our analysis.

To reduce the number of predictors, we follow Neely, Rapach, Tu and Zhou (2014) and Hammerschmid and Lohre (2018) and apply principal component analysis (PCA) separately to the fundamental and technical indicators. This procedure eliminates the noise within the predictors and also provides orthogonal predictors, which helps avoid multicollinearity. The PCA results confirm our findings from the correlation map: It takes the first three principal components of the fundamental variables to jointly explain 56% of the data variation. Conversely, we only need the first principal component of the technical indicators to explain about 86% of the data variation.[6] Hence, for our analysis we use the first three principal components of the fundamental variables (denoted as F_t^{Fun1}, F_t^{Fun2}, and F_t^{Fun3}), and the first principal component of the technical indicators (denoted as F_t^{Tec}).

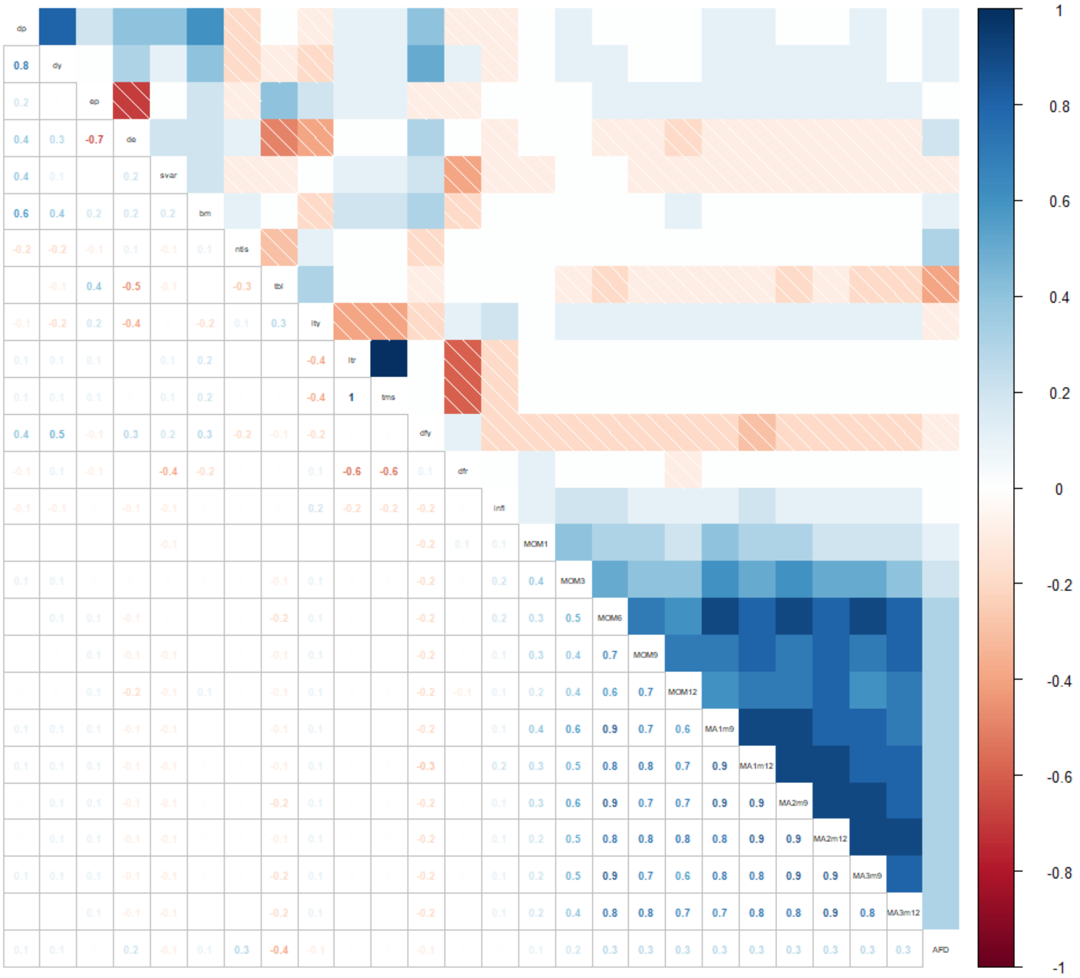
In addition to fundamental and technical indicators, we follow Bartram, Djuranovik and Garratt (2020) and construct a signal representing the Dollar carry trade as per Lustig, Roussanov and Verdelhan (2014). The Dollar carry trade strategy goes long on foreign currencies when-

[5]We will use the USD as the benchmark currency, and we refer to each currency pair only by its matched currency, thus denoting USD/EUR as EUR.

[6]Note that these results largely hold for all currencies. For the sake of space, we do not include them here, but they are available upon request.

ever the average foreign short-term interest rate is above the U.S. interest rate (for example during U.S. recessions). It shorts all foreign currencies otherwise. This measure captures the variations in the country-specific price of risk that the standard carry trade would fail to capture. To construct this predictor variable, we compute the average forward discount (AFD) by averaging the naive carry characteristic cross-sectionally across our currency universe.

Figure 3: Correlation matrix of predictor variables. The correlation between fundamental variables is shown in the top left corner. The bottom right corner shows the correlation structure of the technical indicators for EUR. The sample period is February 1989 through December 2020.



3.2 Currency Factor Timing

Section 2 documents that a PPP for currency tilting can successfully exploit cross-sectional currency characteristics. Still, we know that these factor strategies come with cyclicality that can be capitalized if anticipated in advance. Specifically, the carry trade is prone to crash risk in flight-to-quality events. Diversifying the carry signal by combining it with momentum and value signals is a viable approach in this context. However, momentum strategies can be an expensive hedge. Thus, we explore whether there are alternative ways to navigate the downside risk of the carry trade by investigating integrated parametric tilting policies conditional on carry timing signals.

Recent FX literature has explored the possibility of timing carry strategies with different indicators, such as FX volatility-based exchange rate regimes, the bid-ask spread, equity/bond returns, and the Cboe Volatility Index (VIX). Christiansen, Ranaldo and Söderlind (2011), Clarida, Davis and Pedersen (2009) offer insights into the economic consequences of high versus low distress periods, business cycles, and specific events on the carry trade. Ideally, we could condition a currency tilting policy on such information, which effectively represents an integrated approach to currency factor investing. For example, the model may anticipate the unwinding of carry trade positions during the 2008 global financial crisis. Moreover, this integrated approach could offer a deeper understanding of the variations 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 as follows:

$$w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T(z_t \otimes x_{i,t}), \tag{17}$$

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. 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 parametric equity portfolio policy in order to time size, value, and momentum factors. They model the coefficients as a function of the yield curve slope, so that the effect on the joint distribution of returns can vary depending on the business cycle (as measured by the slope of the yield curve).

3.2.1 Liquidity- And Volatility-Based Indicators To Time The Carry Trade

We need to identify relevant predictors for timing the carry trade, which univariately has not only higher returns but also the highest risk, as seen before. Bekaert and Panayotov (2020) distinguish currency carry trades based on the Sharpe ratio and highlight the relevance of equity market risk factors for the G10 currencies between 1984 and 2014. Their results show that carry trades are driven by certain subsets of the G10 currencies. In contrast, Christiansen *et al.* (2011) use a currency volatility-based regime-dependent pricing model to capture the time-varying systematic risk of carry trades. Clarida *et al.* (2009) also explore the volatility-regime based sensitivity of carry trades. They use an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model during the Russian financial crisis period of 1997–1998 versus the non-crisis period and establish volatility regime sensitivity of the carry trade. Jordà and Taylor (2012) also turn to a regime-based model and conclude that such models better explain carry trades.

Carry trade returns and crash risk have also been linked consistently by numerous researchers. 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. Such evidence from the literature supports the notion of liquidity-based sensitivity of carry trades. Thus, we look for indicators that capture both liquidity and volatility, which in turn can be used for timing the carry trade.

3.2.1.1 TED Spread

The TED spread is a common proxy for money market liquidity and is defined as the difference between the three-month LIBOR Market Model and three-month Treasury bill. It 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. It has been observed that the TED spread naturally has a positive correlation with currency crashes.

3.2.1.2 FX Volatility

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 an exponential decay parameter λ of 0.95, which denotes a half-life in the exponential weights of 14 days in a three-month window for constructing our volatility estimates.

4 Optimal Currency Timing And Currency Factor Timing

4.1 Currency Timing

In this section, we present the Brandt and Santa-Clara (2006) framework that lends itself naturally to deriving optimal currency timing strategies. Specifically, we leverage classic timing signals as given by the fundamental variables and technical indicators introduced in Sections 3.1.1 and 3.1.2.

4.1.1 Methodology Of Brandt and Santa-Clara (2006)

Brandt and Santa-Clara (2006) consider a risk-averse investor who maximizes a mean-variance utility function over next period's wealth:

$$\max_{w_t} E\left[w_t' r_{t+1} - \frac{\gamma}{2} w_t' r_{t+1} r_{t+1}' w_t\right], \tag{18}$$

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 are linear in a column vector z_t of K state variables, thereby capturing time variation in expected returns as follows:

$$w_t = \theta z_t, \tag{19}$$

where θ is an $(N \times K)$ matrix of parameters. Replacing the linear portfolio policy, w_t, in (18) yields:

$$\max_{\theta} E_t \left[(\theta z_t)' r_{t+1} - \frac{\gamma}{2} (\theta z_t)' r_{t+1} r'_{t+1} (\theta z_t) \right]. \tag{20}$$

with

$$(\theta z_t)' r_{t+1} = z'_t \theta' r_{t+1} = vec(\theta)' (z_t \otimes r_{t+1}), \tag{21}$$

where $vec(\theta)$ is a vectorization of the matrix θ into a column vector and $\otimes$ is the Kronecker product. Using $\tilde{w} = vec(\theta)$ and $\tilde{r}_{t+1} = z_t \otimes r_{t+1}$, the objective function (20) can be rewritten as:

$$\max_{\tilde{w}} E_t \left[\tilde{w}' \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}' \tilde{r}_{t+1} \tilde{r}'_{t+1} \tilde{w} \right]. \tag{22}$$

Hence, the original dynamic optimization problem is transformed into a static problem that can be applied to the augmented asset space represented by $\tilde{r}_{t+1}$. This represents 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 (22) is equivalent to:

$$\max_{\tilde{w}} E \left[\tilde{w}' \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}' \tilde{r}_{t+1} \tilde{r}'_{t+1} \tilde{w} \right]. \tag{23}$$

Based on the information embedded in the state variables we can determine the corresponding portfolio policy. An additional benefit of this methodology is that the PPP expresses the portfolio problem in an estimation setup. This allows for the calculation of the standard errors of portfolio weights to assess 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:

$$\frac{1}{\gamma^2} \frac{1}{T \; - \; N \times K} (\iota_T - \tilde{r}\tilde{w})' (\iota - \tilde{r}\tilde{w}) (\tilde{r}' \tilde{r})^{-1}, \tag{24}$$

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

4.1.2 Empirical Results

In addition to using the AFD characteristic, we build on the PCA analysis in Section 3.1.3 and select three fundamental principal factors and one technical principal factor. Thus, we are considering five conditioning variables in total (F_1^{Fun}, F_2^{Fun}, F_3^{Fun}, F^{Tec}, AFD). The portfolio optimization will be performed out-of-sample over an expanding window. We will first use an initial window of nine 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 aversion parameter γ is again fixed at ten. We implement a long-short strategy, so that long positions cancel out short positions to mimic a zero-investment strategy.

Panel A of Table 2 shows the univariate performance statistics of the AFD-only strategy, the fundamentals-based and the technicals-based strategy. The performance of a strategy using fundamental variables has a much higher drawdown than the AFD-only or the technicals-only strategy. The technicals-only strategy offers the highest return and highest Sharpe ratio with the lowest drawdown amongst the others. We constrain the weights of the PPP portfolio to 200% (in absolute terms) in order to ensure the results are comparable to those of currency tilting (Panel E of Table 1). The performance of the univariate technical strategy has a Sharpe ratio of 0.35 for the unconstrained version and 0.30 for the constrained version. Because our technical PCA is composed of indicators that capture the trend, the methodology can indeed pick up the time-series momentum phenomenon.

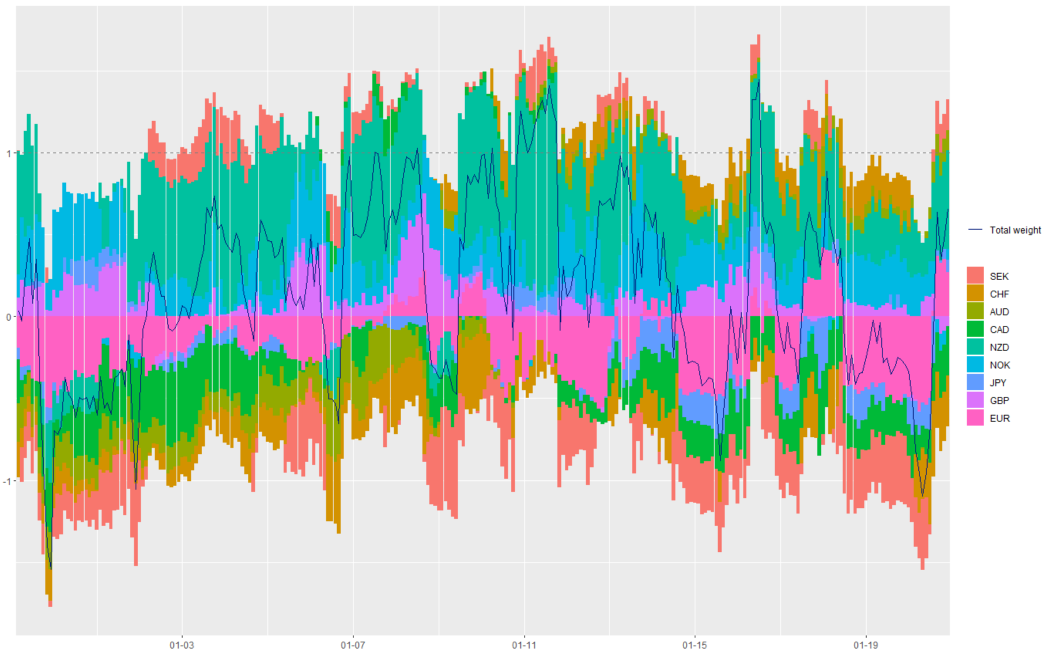
Table 2: Currency timing policy: θ coefficients and performance analysis Panel A shows the univariate performance analysis (returns, volatility, Sharpe ratio and maximum drawdown) from the PPP optimization. The sample period is February 1994 through December 2020. Panel B shows the multivariate performance analysis for the parametric portfolio policy. The performance analysis includes annualized returns and volatility, Sharpe and information ratios, and maximum drawdown for the unconstrained and constrained versions. The weights in the constrained version are restricted to 200% (in absolute terms). *, **, and *** represents significance at 10%, 5% and 1% levels, respectively.

Panel A	Return p.a. (%)	Vola p.a. (%)	Sharpe Ratio	Max Drawdown (%)
AFD PPP	3.19	17.92	0.06	51.93
AFD PPP (Constrained)	1.96	5.93	-0.03	23.26
$F_{1,2,3}^{Fun}$ PPP	3.15	29.50	0.03	70.40
$F_{1,2,3}^{Fun}$ PPP(Constrained)	1.71	5.13	-0.08	13.80
F_1^{Tec} PPP	9.26	20.48	0.35	43.19
F_1^{Tec} PPP (Constrained)	4.63	8.24	0.30	15.91
Panel B	**Return p.a. (%)**	**Vola p.a. (%)**	**Sharpe Ratio**	**Max Drawdown (%)**
MV PPP	14.07	48.72	0.24	88.69
MV PPP (Constrained)	2.43	6.17	0.05	20.80

Panel B combines the average forward discount and the fundamental and technical PCA factors in a multivariate setup and reports the performance of the PPP strategy. We observe that the multivariate strategy offers a return of around 14% with a volatility of 49%. The drawdown of the unconstrained strategy is around 89% while that of the constrained strategy is only 21%.[7] Although currency tilting is a better alternative when comparing the constrained strategy results in Panel E of Table 1 and Panel B of Table 2, our main takeaway from Table 2 is the relevance of technical indicators in currency timing.

Figure 4 shows the aggregate optimal currency timing policy allocation timed with technical indicators (F_1^{Tec}). Given that the unconstrained version is highly leveraged, we focus on a constrained strategy in which the sum of absolute weights is bound by 200%. Still, unlike the currency tilting strategy depicted in Figure 2 where some currencies take consistent long and short positions, Figure 4 lacks any such consistent patterns. Of course, this is expected because we are investigating a trend strategy for which portfolio weights are oscillating more. As visible from the constrained version, SEK is characterized by large short positions whereas NOK and NZD predominantly take long positions towards the end of the sample period. EUR oscillates throughout the sample, with large weights in both long and short legs.

Figure 4: Aggregate optimal currency timing allocation. The sample period is February 1999 through December 2020. The figure shows the allocation for the constrained version where the weights are restricted to 200%.



[7] In unreported results, we perform simple robustness tests for the multivariate timing portfolio for different values of the risk aversion parameter and find similar results as above.

We observe a marked change in the form of a reduction in both the overall allocation and the allocation across individual currencies during the 2008–09 period. For instance, the allocations for GBP drastically reduces post-2008 and even more so after the announcement of Brexit, whereas the overweight allocations in NZD and EUR revert to their pre-2008 allocations after 2009. Consistent with the fluctuations in the cumulative returns of JPY over the entire sample period, the allocations in JPY oscillate throughout the sample, with small weights in both long and short legs. Notably, we find in unreported results that all currencies contribute positively to the timing strategy's performance. The highest performance contribution is found for the NZD positioning, followed by SEK and CHF. Additionally, the first half of the sample period is characterized by higher timing returns, suggesting weaker efficacy of timing signals in the latter half of the sample period.

Although the currency timing PPP delivers higher returns, it is highly leveraged and hence, as expected, the associated risk is very high. In line with the extant literature, trend signals emerge as the strongest currency timing signals and can successfully be operationalized in the presented PPP framework. This motivates us to next investigate currency tilting in a way that operationalizes factor timing.

4.2 Currency Factor Timing Through Conditional Currency Tilting

Using the learnings from the previous subsection, we combine the notion of timing with the methodology followed in Section 2.1 to design an integrated currency factor timing strategy. This second look at Brandt et al. (2009)'s parametric portfolio policy suggests reconsidering the assumption of time-invariant coefficients.

In this subsection, we create a liquidity regime-based model indicator that is constructed as a dummy variable from the TED spread. Specifically, we build two carry characteristics: the first carry characteristic is set to zero for illiquid months (as defined by the TED spread) and equals the original characteristic otherwise. Vice versa, the second carry characteristic is equal to the original carry characteristic in illiquid months and is zero in liquid months. In the same vein, we construct FX volatility indicators where two regimes are created to differentiate between turbulent periods characterized by extreme volatility versus periods of normal volatility. We use a cut-off of 85% such that the indicator captures the 15% most volatile times.

We use the first five years of the sample period to initialize the parametric portfolio optimization and re-estimate the parameters on a monthly basis with an expanding window. Panel A of Table 3 includes our univariate estimation results for PPPs timing carry, along with the untimed univariate carry trade in Panel B. To first provide a proof of concept of the proposed methodology, we create a "crystal ball" indicator based on future carry trade returns. To do this, we construct a regime indicator that equals one if next month carry returns are positive, and zero otherwise. Intuitively, the regimes from this perfect foresight indicator should perfectly time the carry trade; at the very least, the conditional currency tilting policy is enabled to perfectly learn from this information as it unfolds in an expanding window estimation. Indeed, given this "crystal ball", we obtain a highly significant positive coefficient in the good regime, and likewise a significant negative coefficient in the bad regime, indicating that the PPP can distinguish between good and bad regimes. Naturally, we observe abnormal performance for the associated dynamic tilting policy, as evidenced by the Sharpe ratio of 3.77. In turn, we are confident in using this framework to test our chosen carry timing indicators.

Table 3: Currency factor timing results. Panel A presents the estimated results of the univariate parametric portfolio policy, and the performance statistics of the carry strategy timed with different indicators. Panel B gives the estimated result for the univariate carry strategy from table 1. Panel C gives the estimated results when using different indicators to time the carry trade in a multi-factor setup including the crystal ball exercise. The sample period is February 1994 through December 2020. *, ** and *** represents significance at 10%, 5% and 1% levels, respectively.

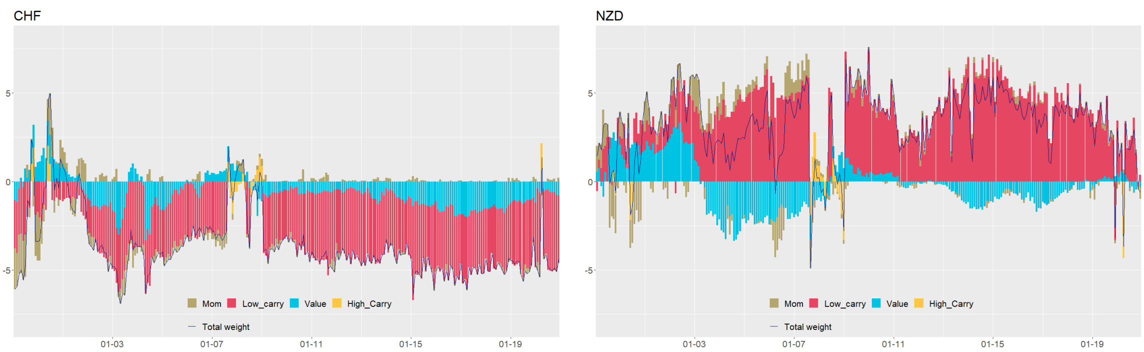
	$\hat{\phi}$	S.E.	Return p.a. (%)	Vola p.a. (%)	Sharpe ratio	Max Drawdown (%)
Panel A: Univariate models						
Crystal ball-timed PPP			161.06	42.14	3.77	19.01
Carry x $I(low\ FutureCarry)$	-15.12***	1.48				
Carry x $II(high\ FutureCarry)$	20.48***	1.93				
TED-timed PPP			9.00	9.97	0.69	16.06
Carry x $I(low\ TED)$	2.57***	0.65				
Carry x $II(high\ TED)$	-2.22**	1.09				
FX Vol-timed PPP			4.61	7.87	0.31	28.70
Carry x $I(low\ Vol)$	1.67***	0.66				
Carry x $II(high\ Vol)$	1.27	1.37				
Panel B: Benchmark model						
Carry(Tilting)	1.58**	0.60	5.29	7.20	0.44	26.59
Panel C: Timing carry (Multivariate)						
Optimal Portfolio (Crystal-ball)			163.95	43.20	3.75	18.98
Momentum	-0.31	1.42				
Value	-1.19	1.26				
Carry x $I(low\ FutureCarry)$	-15.45***	1.51				
Carry x $II(high\ FutureCarry)$	20.84***	1.99				
Optimal Portfolio (TED-timed)			8.20	9.97	0.61	17.21
Momentum	-0.31	0.70				
Value	0.81	0.70				
Carry x $I(low\ TED)$	2.44***	0.72				
Carry x $II(high\ TED)$	-1.78	1.48				
Optimal Portfolio (FX Vol-timed)			5.26	8.49	0.37	23.21
Momentum	0.23	0.65				
Value	1.54***	0.62				
Carry x $I(low\ Vol)$	1.62**	0.67				
Carry x $II(high\ Vol)$	1.47	1.41				

Panel A further reports the performance statistics and the coefficients of carry portfolios timed with different liquidity and volatility indicators. Compared to the original carry portfolio, the integrated strategy timing the carry trade with the TED spread delivers a higher Sharpe ratio of 0.69 (versus 0.44 for the original carry tilting strategy). Moreover, the maximum drawdown is reduced from 26.59% to 16.06%, evidencing that the TED spread indicator helps mitigate crash risks. The estimated ϕ coefficient is significant for both low and high TED regimes but with opposite signs. This indicates the different impact of the carry characteristic on the joint distribution of returns during periods of high and low market liquidity. The positive ϕ coefficient of the low TED spread regime further stipulates the tilting of the optimal currency portfolio towards carry currencies during liquid periods. In contrast, the negative coefficient hints the tilting of the optimal portfolio towards low interest rate currencies during illiquid periods.

Next we inspect the ability of the FX volatility indicator to time the currency trade. We find a significantly positive coefficient in the low volatility regime; yet, unlike the TED spread indicator, the high volatility regime is still characterized by a positive coefficient, albeit insignificant. Hence, one is not unwinding the carry trade in these periods but though reducing the sizing of carry trade positions. In terms of strategy returns, one however experiences a reduction in risk-adjusted returns relative to the untimed version. Panel C shows the performance of a multi-factor setup wherein the carry trade is timed using the TED spread. Comparing this multivariate result with that in Panel D of Table 1, we observe a marked improvement in the Sharpe ratio (going from 0.47 to 0.61), and a reduction in the drawdown. This highlights the improvements offered by an integrated portfolio policy approach.

To rationalize the mechanics of the integrated approach, we again consider the two carry currencies, the CHF and NZD. In Figure 5, we analyse the decomposition of their optimal weights. Carry considerations dominate the short and long positions of CHF and NZD, respectively, during normal times. This confirms our results in Section 2. Here, the integrated

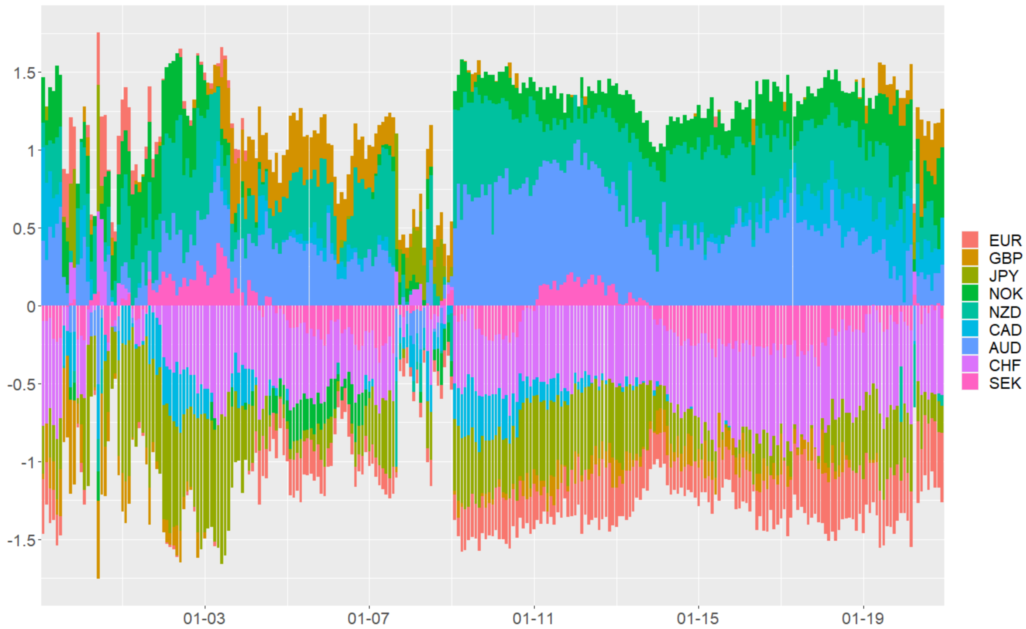
Figure 5: Decomposition of the optimal currency weights. The figure shows the currency weights decomposition in the PPP timed with FX liquidity indicator, the TED spread and the contribution of each conditioning variable. The left-hand chart is for CHF; the right-hand chart is for NZD. The sample period is February 1999 through December 2020.



parametric portfolio policy minimizes the crash risk by varying with market liquidity conditions as proxied for by the TED spread. In the same figure, we note that this timing feature was also active in 2001 during the stock market downturn. Hence, the carry trade positions get automatically adjusted whenever there is an expected drop in liquidity during such periods of financial distress. Adding further support is the expected opposite weight distribution of the high carry currency (NZD) and low carry currency (CHF).

Figure 6 shows the weights on an aggregate portfolio level. It depicts the eventual reduction of the carry trade positions, especially during the global financial crisis. It also shows the expected significant reduction in all currency weights, backed by a full investment in the risk-free rate. We also note a significant increase in the exposure to safe heaven currencies since 2000.

Figure 6: Currency factor timing: Aggregate Allocation. The sample period is February 1999 through December 2020.



5 Conclusion

Extant literature on currency investing has explored the choice and relevance of style-based and macroeconomic variables mostly using univariate factor approaches or static allocations. We take a different route by focusing on a dynamic approach and a multivariate framework that combines well-known FX factors. We rely on the PPP of Brandt and Santa-Clara (2006) and Brandt *et al.* (2009), which allow for both tilting and timing currencies using salient FX characteristics and time-series indicators, respectively. As for currency tilting, we exploit cross-sectional information by using factors such as value, momentum, carry, and macro-based factors. As for currency timing, we confirm the prominent role of technical indicators whilst fundamental variables are found to add little value.

In sum, we find evidence in favor of such dynamic portfolio allocation strategies, especially for an optimal currency tilting strategy with carry, value and momentum. Yet, such optimized currency factor allocations do not outperform equal-weighted factor allocations. Such outcome prompted calibrating an integrated strategy that embeds timing carry trade positions. A TED spread-based regime indicator helps navigate the downside of the carry trade, improving the overall risk-adjusted performance of the currency allocation. From a practitioner perspective, this framework is straightforward to implement in real-time. It offers the flexibility to be used with or without conditioning variables, univariate or multivariate, and can help capture diversification benefits in a multi-factor setup.

References

Akram, Q. F., Rime, D. and Sarno, L. (2008). Arbitrage in the foreign exchange market: Turning on the microscope. *Journal of International Economics*, **76** (2), 237–253.

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, **61** (1), 259–299.

Asness, C. S., Moskowitz, T. J. and Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, **68** (3), 929–985.

Barroso, P. and Santa-Clara, P. (2015). Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis*, **50** (5), 1037–1056.

Bartram, S. M., Djuranovik, L. and Garratt, A. (2020). *Currency Anomalies*. Working paper, University of Warwick.

Bekaert, G. and Panayotov, G. (2020). Good carry, bad carry. *Journal of Financial and Quantitative Analysis*, **55** (4), 1063–1094.

Bilson, J. F. (1981). The speculative efficiency hypothesis. *Journal of Business*, **54** (3), 435–451.

Brandt, M. W. and Santa-Clara, P. (2006). Dynamic portfolio selection by augmenting the asset space. *Journal of Finance*, **61** (5), 2187–2217.

—, — and Valkanov, R. (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *Review of Financial Studies*, **22** (9), 3411–3447.

Brunnermeier, M. K., Nagel, S. and Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual*, **23** (1), 313–348.

Burnside, C., Eichenbaum, M. and Rebelo, S. (2011). Carry trade and momentum in currency markets. *Annual Review of Financial Economics*, **3** (1), 511–535.

Caballero, R. J. and Doyle, J. B. (2012). *Carry trade and systemic risk: Why are FX options so cheap?* Tech. rep., National Bureau of Economic Research.

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*, **52** (1), 57–82.

Castro, V. (2011). Can central banks' monetary policy be described by a linear (augmented) Taylor rule or by a nonlinear rule? *Journal of Financial Stability*, **7** (4), 228–246.

Christiansen, C., Ranaldo, A. and Söderlind, P. (2011). The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis*, **46** (4), 1107–1125.

CLARIDA, R., DAVIS, J. and PEDERSEN, N. (2009). Currency carry trade regimes: Beyond the Fama regression. *Journal of International Money and Finance*, **28** (8), 1375–1389.

COCHRANE, J. H. (2017). Macro-finance. *Review of Finance*, **21** (3), 945–985.

COLACITO, R., RIDDIOUGH, S. J. and SARNO, L. (2020). Business cycles and currency returns. *Journal of Financial Economics*, **137** (3), 659–678.

CORNELL, W. B. and DIETRICH, J. K. (1978). The efficiency of the market for foreign exchange under floating exchange rates. *Review of Economics and Statistics*, **60**, 111–120.

COTTER, J., EYIAH-DONKOR, E. and POTÌ, V. (2017). Predictability and diversification benefits of investing in commodity and currency futures. *International Review of Financial Analysis*, **50**, 52–66.

ENGEL, C. and WEST, K. D. (2005). Exchange rates and fundamentals. *Journal of Political Economy*, **113** (3), 485–517.

FAMA, E. F. (1984). Forward and spot exchange rates. *Journal of Monetary Economics*, **14** (3), 319–338.

— and FRENCH, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, **47** (2), 427–465.

— and — (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, **33** (1), 3–56.

FARHI, E., FRAIBERGER, S. P., GABAIX, X., RANCIERE, R. and VERDELHAN, A. (2009). *Crash risk in currency markets*. Working paper, National Bureau of Economic Research.

FERSON, W. E., SARKISSIAN, S. and SIMIN, T. (2003). Spurious regressions in financial economics? *Journal of Finance*, **58** (4), 1393–1413.

GALATI, G. and MELVIN, M. (2004). *Why has FX trading surged? Explaining the 2004 triennial survey*. Tech. rep., BIS Quarterly Review, December 2004.

GREENAWAY-MCGREVY, R., MARK, N. C., SUL, D. and WU, J.-L. (2018). Identifying exchange rate common factors. *International Economic Review*, **59** (4), 2193–2218.

HAMILTON, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, **100** (5), 831–843.

HAMMERSCHMID, R. and LOHRE, H. (2018). Regime shifts and stock return predictability. *International Review of Economics & Finance*, **56**, 138–160.

HANSEN, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, **50**, 1029–1054.

JEGADEESH, N. and TITMAN, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, **48** (1), 65–91.

JORDÀ, Ò. and TAYLOR, A. M. (2012). The carry trade and fundamentals: Nothing to fear but FEER itself. *Journal of International Economics*, **88** (1), 74–90.

KROENCKE, T. A., SCHINDLER, F. and SCHRIMPF, A. (2013). International diversification benefits with foreign exchange investment styles. *Review of Finance*, **18** (5), 1847–1883.

LUSTIG, H., ROUSSANOV, N. and VERDELHAN, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, **111** (3), 527–553.

MARK, N. C. (2009). Changing monetary policy rules, learning, and real exchange rate dynamics. *Journal of Money, Credit and Banking*, **41** (6), 1047–1070.

MENKHOFF, L., SARNO, L., SCHMELING, M. and SCHRIMPF, A. (2012a). Carry trades and global foreign exchange volatility. *Journal of Finance*, **67** (2), 681–718.

—, —, — and — (2012b). Currency momentum strategies. *Journal of Financial Economics*, **106** (3), 660–684.

Molodtsova, T., Nikolsko-Rzhevskyy, A. and Papell, D. H. (2008). Taylor rules with real-time data: A tale of two countries and one exchange rate. *Journal of Monetary Economics*, **55**, S63–S79.

— and Papell, D. H. (2009). Out-of-sample exchange rate predictability with taylor rule fundamentals. *Journal of International Economics*, **77** (2), 167–180.

Neely, C. J., Rapach, D. E., Tu, J. and Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, **60** (7), 1772–1791.

Okunev, J. and White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis*, **38** (2), 425–447.

Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature*, **51** (4), 1063–1119.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, **39**, 195–214.

Verdelhan, A. (2018). The share of systematic variation in bilateral exchange rates. *Journal of Finance*, **73** (1), 375–418.

Wang, J. and Wu, J. J. (2012). The Taylor rule and forecast intervals for exchange rates. *Journal of Money, Credit and banking*, **44** (1), 103–144.

Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, **21** (4), 1455–1508.