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FX Cookbook: A Recipe for Systematic Investing in Currency Markets

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This is the twentieth edition of our Quantcraft series. This periodical outlines new trading and analytical models across different asset classes.

Foreign exchange is present in most institutional portfolios and corporate balance sheets. That said, it often receives less attention than deserved, therefore often being a source of risk but not a source of reward. This *Quantcraft* aims to change that.

This report introduces a **"cookbook"** for systematic investing in the asset class, with recipes of short, medium and long-term signals. Importantly, we also describe a broad framework for strategy selection, implementation and rebalancing. Issues such as market neutrality versus directionality, signal smoothing and filtering, and portfolio tranching are carefully addressed.

We describe 4 short-term signals: Momentum Spill-Over from the interest rate market, DTCC positioning (COFFEE), CFTC Momentum and CFTC Reversal.

We also describe 2 medium-term signals and 1 long-term signal: Momentum and Carry, and Value.

We describe optimal implementation for absolute return portfolios and for currency hedging, thereby covering a broad scope of currency market participants.

Figure 1: FX Cookbook

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FX Cookbook: A Recipe for Systematic Investing in Currency Markets

1. Introduction

Foreign exchange is present in most institutional portfolios and corporate balance sheets. That said, it often receives less attention than deserved, therefore often becoming a source of risk but not reward. Earlier in May we showed that the presence of non-profit seeking participants provides scope for harnessing value from currency markets. This "cookbook" provides some suggestions on how to do so systematically.

Section 2 uses econometrics to describe the drivers of contemporaneous and future market returns, as well as the interactions between them across multiple horizons. Section 3 introduces a framework for estimating predictive power in a more dynamic, signal-specific format that guides us on major implementation aspects. Section 4 describes how we build signals from each driver and implement them in absolute return portfolios. In total, we introduce 7 signals that cover short, medium and long term horizons. Section 5 applies a subset of these signals for currency risk management, where we introduce 4 informed dynamic currency hedging methods. Section 6 concludes.

1.1 Our dataset

Unless stated otherwise, we utilize 1-month forwards in 24 USD/FX[1]. Positions are executed at the NY close, 1 business day after they have been calculated (t+1). Thus if a target portfolio is calculated at the end of Tuesday October 2nd, 2018, the respective trades are only executed at the close on Wednesday October 3rd, 2018. We apply fixed bid-ask spreads, estimated as the long-term historical average multiplied by 1.5x, as our transaction cost estimate.

1.2 Risk estimation

We estimate risk – volatilities, correlations and betas – primarily through covariance matrices of historical currency returns.[2]

These are built using the classical (historical sample) method but with an exponential decay parameter. We seek a balance between robustness and adaptivity when choosing parameter values; off-diagonal elements utilise a 3-year decay while the elements of our main diagonal use a 1-year decay. This is in line with the view that volatility estimates should be highly adaptive, while correlation estimates should be stable.

Finally, unless otherwise stated, we use 3-day non-overlapping asset returns[3], as opposed to daily returns, so as to reduce noise and timezone differences.

2. Identifying the Investment Factors

Our first task is to identify the most important factors explaining foreign exchange returns; in other words, the drivers of the asset class. We focus on explaining returns over short, medium and long-term frequencies using all our historical data. This allows us to get a better feel for factor persistence.

We apply two tools: principal component analysis and panel regressions. The first focuses on explaining contemporaneous returns, while the second evaluates which factors are better return predictors.

[1] USD vs AUD, EUR, GBP, CHF, SEK, NOK, NZD, CAD, JPY, BRL, CZK, KRW, MXN, PLN, RUB, SGD, TRY, TWD, ZAR, CZK, HUF, ILS, INR and THB.

[2] We use historical, as opposed to implied currency returns. While currency markets are unique in providing implied correlation data between currency pairs, thus allowing us to compute a market-implied covariance matrix, we opted against that approach due to data limitations - especially with regards to implied correlations between reference asset portfolios (or the PC1 of the asset class) and each currency pair. The risk that using options market data would yield an over-conservative risk estimate also played a role in our final choice, given the bias in implied volatilities and correlations when predicting their future empirical statistics. Risk estimation is a key part of our work, as seen in Ward et al (2016), Natividade and Brehon (2009) and Natividade et al (2017), and new methodologies will be considered for implementation in this context should they look promising.

[3] Specifically, we estimate 3 separate matrices of 3-day non-overlapping returns. Each starts one day after the other. The final covariance matrix is the average of the 3.

2.1 Principal Component Analysis (PCA)

Following the standard recipe found in quant cookbooks, we first apply PCA to better understand the common variations of currency market returns. This is a useful tool in that it "distills" large data pools into a smaller set that represents the main variations of the whole dataset.

We ran this exercise on a slightly larger set of 27 currencies; it may still look small for the cross-asset investor, but FX is unique in that it can imply a lot more than just 27 time series. Currencies are traded in pairs, and therefore there are potentially 351 return streams[4] to be analysed. Each stream - say, EUR/JPY for instance - reflects the driving forces of both currencies (the EUR and the JPY in this case). Therefore, in order to isolate the returns attributed to each separate currency, one must consider baskets of pairs with that currency in common so as to better understand its own specific drivers.

As such, we built 27 separate baskets, each formed using pairs with one common base currency, and applied PCA on each of those.[5] This particular multi-basket PCA exercise was conducted on daily returns and revealed significant correlations between each USD/FX rate and each of the respective PC1s - which explain, on average, 52% of the variations in each basket – a high number in the context of other asset classes.[6] In other words, most returns in each currency group - for instance, the ZAR/FX basket - are already captured in the USD exchange rate - in this case, USD/ZAR.

This should not come as a surprise as the USD crosses are often the most liquid[7], and hence the first port of call for incorporating new market information. Figure 2 shows these correlations in more detail.

This finding allowed us to condense the number of inputs going into our multi-currency, multi-frequency, multi-start date study. Instead of 27 individual baskets, the remaining steps of this study focused therefore on USD/FX returns alone.

The next step was to apply PCA to a USD/FX basket, accounting for multiple frequencies as we are interested in multiple horizons. As some of the horizons are long-term, we also applied re-sampling in order to reduce discretization error.[8]

Figure 2: Long-term correlation of daily returns between base currency PC1 and CCY/$ pair

$/FX	PC1
USD	0.70
EUR	-0.74
JPY	-0.67
CHF	-0.72
GBP	-0.66
AUD	-0.86
NZD	-0.83
CAD	-0.67
NOK	-0.80
SEK	-0.80
PLN	-0.94
MXN	-0.83
BRL	-0.92
TRY	-0.90
ZAR	-0.29
SGD	-0.26
TWD	-0.27
KRW	-0.79
THB	-0.24
INR	-0.47
MYR	-0.46
IDR	-0.79
ILS	-0.53
CZK	-0.91
HUF	-0.95
RON	-0.87
RUB	-0.87

Data since 1971 or as per Section 1.The correlations are broadly negative as we assessed FX/$ as opposed to $/FX. Source: Deutsche Bank

The results of our multi-frequency PCA exercise point to the following:

- The first principal component is dominant across return frequencies, explaining an average of 54% of the total return variation as shown in Figure 3. It has a positive and stable loading onto each asset, as is

[4] That is, all possible pairwise combinations of 27 currencies (27*26/2).

[5] For completeness, we also ran the exercise on the full combination of base and quote currencies in G-10 (45). The first principal component explained circa 30% of the variations across horizons below 2 years, and the loading of each currency pair related to its interest rate differential. The second principal component, which explained circa 25% of the variations across horizons, correlated more strongly to the US dollar despite much of the direct USD effect being cancelled out by the inclusion of all other cross exchange rate variations.

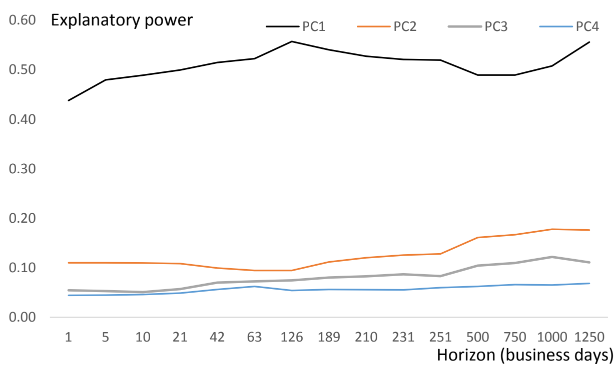
[6] For context, the share of common variations in equity indices is circa 45%, 30% in bond futures, 25% in commodity futures, and 33% in US corporate credit CDS. See Natividade et al (2013) and Gonzalez et al (2018) for details.

[7] A few European currencies are the exception, where most liquidity is in the EUR/FX cross. But even there, the volatility in EUR/FX is typically lower; PC1 correlates highly with the USD/FX pair as it also picks up EUR/USD volatility.

[8] Discretization error in the sense that using different start dates could produce different results. In our re-sampling, we repeated the PCA multiple times, using all available unique start dates. We used, for instance, 4 start dates to analyse weekly returns and 249 start dates to analyse annual returns, generating 4 and 249 separate PCAs outputs, of which we calculated the average. This allowed us to reduce any bias associated with the exact dates that market data was snapped.

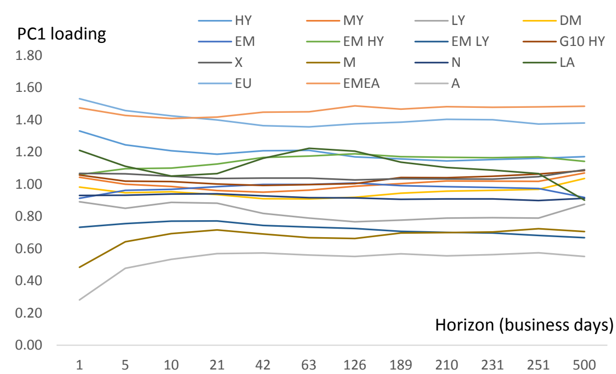
typical when delineating the *market factor* of an asset class. In this context, we interpret PC1 as representing the *US dollar factor*.

Figure 3: Explanatory power by principal component for various horizons (USD/FX basket)



Source: Deutsche Bank

Figure 4: PC1 loading (USD/FX baskets) according to horizons and classification



Currency baskets: HY: high yield, MY: medium yield, LY: low yield, DM: developed markets, EM: emerging markets, EM HY: EM high yield, EM LY: EM low yield, G10 HY: developed high yield, X: exporters, M: importers, N: neutral, LA: Latin America, EU: Europe, EMEA: Europe, Middle East and Africa, A: Asia. Source: Deutsche Bank

- The second principal component explains an additional 13% of the variations in returns across frequencies. The sign and intensity of how it loads onto each currency relates strongly to the interest rate differential between the USD and that currency. This strongly indicates a link between PC2 and the carry trade, and hence we interpret it as the *carry factor*.
- The sign of the PC2 loadings inverts as we move from short to long-term frequencies. Figure 5 plots the cross-sectional beta of interest rate differentials to PC2 loadings. Importantly, as shown in Figure 6, the beta flips from heavily positive in frequencies under 9 months to notably negative in frequencies beyond 5 years. This negative relationship between loadings and frequencies - and therefore short-term PC2 and long-term PC2 - is concomitant to the argument that covered interest rate parity is more likely to hold in the long run than in the short term. To the extent that high interest rate countries also witness high inflation, this finding suggests that *high inflation countries should see their currencies depreciate in the long run - a standard claim from traditional currency valuation models*.
- The way that higher order principal components load onto each currency pair is unstable as we change the return frequencies. This suggests that PC3 and above are more likely to be picking up noise. Figure 7 shows examples for PC3 and PC4.

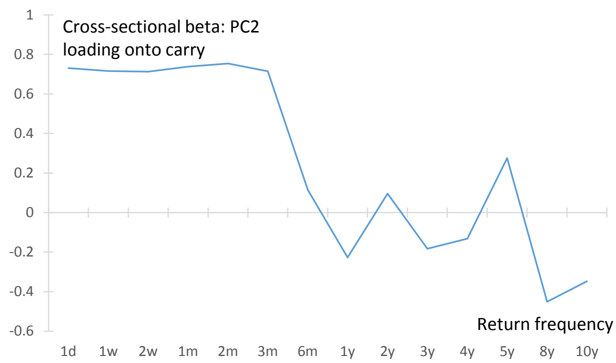
Figure 5: PC2 loading versus interest rate differentials (1M and 10Y returns)

Note: both X and Y values have been cross-sectionally standardized. Source: Deutsche Bank

These results suggest that the two key factors of interest are the US dollar and carry; they are the two broad drivers of the foreign exchange asset class.

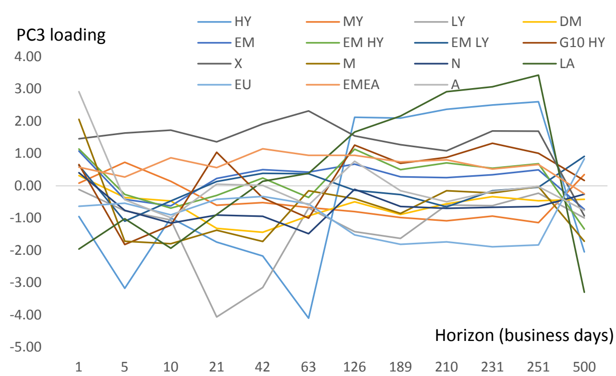
This statement should not surprise the reader. Verdelhan (2012, 2018) also outlines the influence of both US dollar and carry as key determinants of exchange rate variations, although the former is formulated differently[9]. The two factors are also often used as control variables when authors look to introduce new currency drivers. Finally, it also concurs with prior DB research - see, for instance, Giacomelli and Zhang (2016) and Natividade et al. (2013).

Figure 6: Sensitivity of PC2 loadings to interest rate differentials versus the USD according to return frequency



Note: both X and Y values have been cross-sectionally standardized. Source: Deutsche Bank

Figure 7: Average PC3 loading of currency groups according to return frequency



Currency baskets: HY: high yield, MY: medium yield, LY: low yield, DM: developed markets, EM: emerging markets, EM HY: EM high yield, EM LY: EM low yield, G10 HY: developed high yield, X: exporters, M: importers, N: neutral, LA: Latin America, EU: Europe, EMEA: Europe, Middle East and Africa, A: Asia. Source: Deutsche Bank

That the direction of the dollar is the most important driver of the currency market is widely agreed upon, but not enough. A proper understanding of the asset class requires understanding the fundamental forces behind the US dollar itself, and that is far harder. Broadly speaking, drivers can be broken down into short-term, medium-term and long-term factors. Short-term factors would tend to be dominated by positioning, speculative sentiment, market microstructure and idiosyncratic FX flows. Medium-term factors include the monetary and fiscal policy outlook, relative growth rates, terms of trade shocks, current accounts, and capital flow trends. Long-term factors include shifts in purchasing power parity, productivity trends and changes to saving-investment imbalances.

This rich pool of variables notwithstanding, the academic literature has had little success in building a coherent modelling approach to exchange rates that outperforms the random walk in what has come to be known as the "exchange rate determination puzzle"[10].

Our favoured interpretation of this result[11] is that the FX market and "dollar trend" suffers from high levels of complexity that make the application of a unified modelling technique particularly difficult. The closest equivalent to this observation in the physical world would be what are known as "complex systems" such as the global climate or human brain. These systems, similar to FX, are characterized by non-linearities, feedback loops and a high-sensitivity to initial conditions that makes the application of a unified modelling approach particularly challenging.

More importantly, the presence of a dynamic system does not preclude FX from being a profitable asset class. As we have demonstrated elsewhere[12] and this paper will expand upon there is strong evidence on the presence of excess returns in FX over time. Importantly, however, we must also ensure that our modelling approach is flexible and inclusive.

2.2 Panel Regressions

Having *explained* the main variations through statistical factors, we now seek to apply factor analysis to *predict* future FX returns. For that, we apply panel regressions. This approach not only allows us to introduce future FX returns as dependent variables, but also add peripheral, tangible factors to the mix. Addressing multi-collinearity is key, as the causality effects often work both ways.

In choosing our explanatory variables we opted for a combination of fundamental and market data, as dictated by the academic literature. After careful scrutiny, we opted for a small set of representative variables as opposed to the wide, "kitchen sink" approach.[13] The candidates we opted for are:

[9] Verdelhan (2015, 2018) uses the term *slope factor* to characterise the same US dollar factor; the author formulates it as the cross-section of dollar beta-sorted currency returns.
[10] See Cheung et al (2002).
[11] Another interpretation is that the USD trend itself is truly random.
[12] See Saravelos et al (2018).
[13] Our choice is somewhat in line with recent efforts in both academia and industry to apply greater scrutiny when choosing investment factors. A good example of that is in Harvey and Liu (2018), where the authors advocate using bootstrap-based re-sampling as a way to decide which

(1) The *market factor*, represented by the first principal component of a USD/FX basket.[14]

(2) A *sentiment factor*, represented by a basket of USD/FX implied volatilities.[15]

(3) Dummy variables representing regional and trade balance characteristics.[16]

(4) A *price action factor*, calculated on currency returns orthogonal to the market factor.[17] The lookback window for cumulative returns is the same as our regression frequency.

(5) A *long-term price action factor*, calculated on 5-year currency returns orthogonalised against the market factor.[18]

(6) A *carry factor*, calculated according to the percentage distance between the 6-month USD/FX forward and spot.[19]

(7) A *monetary policy factor*, calculated as the change in nominal 6-month interest rates over a period equal to our regression frequency.[20]

(8) The *long-term forward*, as a potential measure of currency valuation.[21]

(9) *Purchasing power parity* (PPP), as estimated by the BIS, as another measure of currency valuation.[22]

(10) A *macroeconomic growth factor*, proxied by our *DB Nowcast Beat* indicators for country growth.[23]

Having decided on the explanatory variables, the next step was to define the regression format. We opted for panel regressions as they capture both the time series and cross-sectional aspects of the asset class without suffering from data shortage. We also opted against the Fama-McBeth[24] approach as not only we lacked cross-sectional breadth, but we were not as interested in evaluating how the investor is compensated from exposure to any particular driver; such is addressed separately in Sections 3 and 4.

We evaluated multiple horizons of future returns, ranging from daily to 9 months.[25] For a given frequency, the regression steps were as follows:

1. We set future USD/FX returns (from current to next evaluation date) as the dependent variable, and the current value of each of the 10 explanatory variables above as independent variables.

factors to include. We opted for a simpler method - stepwise regressions - as the number of candidate regressors is already small.

[14] Using a "market factor" is common practice in the finance literature, given the use of CAPM-type models in investment research. We proxied it by using the PC1 of a basket of global USD/FX pairs, rolled monthly, where the covariance matrix is built using 1 year of rolling daily returns and assumes unit variance. We calculate the 5-year rolling time series sensitivity of each USD/FX pair to this PC1, and the corresponding beta becomes the market factor for each currency pair - i.e. the market "score".

[15] We proxy "sentiment" through a time series that collates 3-month realised volatility of the USD/FX PC1 described above from Sep-80 to Jan-91, and the 3-month DB Currency VIX (CVIX3I Index on Bloomberg) from Jan-91 onwards. We opted not to add other option market variables given their strong link to the CVIX itself, as per Natividade et al. (2015). Therefore we believe this variable also encompasses the *volatility factor* in Menkhoff et al. (2010) and Christiansen et al. (2010)), the *global factor* in Lustig et al. (2011), the *skewness factor* in Rafferty (2012), and the *correlation factor* in Mueller et al. (2013). We also note that some of these factors were constructed in order to explain the returns of FX Carry portfolios, as opposed to currency returns. The sentiment "score" for each asset is estimated in the same way as the market score.

[16] The dummy variables characterise currencies according to region (G-10, Asia, EMEA, EU and LatAm) and trade (exporters and importers). It partly follows the approach used in Giacomelli and Zhang (2016). We omit one of the descriptors (EM FX) in order to remove perfect collinearity. For clarity, the import currencies are: EUR, INR, JPY, KRW; the export currencies are: AUD, NZD, BRL, CAD, CLP, COP, MYR, NOK, PHP, RUB, ZAR.

[17] This is, in essence, a measure of *residual momentum* (or *residual reversal*) and is in line with the equity market literature (Gutierrez and Pirinsky (2007), Kasssam et al (2010), Blitz et al (2011) and Chaves (2012)), and credit market literature (Jostova et al. (2013) and Haesen et al. (2017)). It also helps reduce the collinearity between the market and price action factors. We believe this partly covers the *momentum factor* in Gutierrez and Kelley (2008), Burnside et al. (2011), Menkhoff et al. (2011) and Raza et al. (2013).

[18] We use it as a simple version for currency valuation, as it is based on the premise of long-term reversion in currency returns. This is partly based on Engel and Hamilton (1990).

[19] The FX carry factor has been widely mentioned in the academic literature, most recently under the label of *slope factor* in Lustig et al (2011) and Verdelhan (2015, 2018) due to a slight difference in construction. We opt for using 6-month implied yields due to the smoothness and historical length.

[20] Currency analysts often use relative interest rate changes as input to their short-term views - see, for instance, Rosenberg (2002). Yield curve determinants have been more generally addressed in Chen et al. (2009), Ang et al. (2010), Georges et al. (2014), Natividade et al. (2014) and Natividade et al. (2015).

[21] It is a (simple) version for currency valuation if one considers the premise that interest rate parity holds over long horizons.

[22] Purchasing Power Parity models have been used to explain long-term reversion in currency values, with Rogoff (1996) and Neely (1998) serving as good reference. As such, we use it as a potential explanatory factor of currency returns. They are also often used as input to currency valuation strategies, with Hafeez (2007), Serban (2010) and Asness et al. (2013) serving as recent examples. We used BIS USD PPP values prior to 1994, and BIS REER values (translated into USD PPP via matrix inversion) post 1994. We lagged the data by 2 months so as to remove the time lag between applicable date and reporting date. We avoided using other estimates of valuation - such as BEER, FEER and DBEER - as we did not have enough history for those.

[23] The *DB Nowcast Beat* indicators, introduced in Natividade et al. (2014), extract the first principal component of a basket of both hard and soft growth data in 26 countries and regions. Examples include retail sales, industrial production, unemployment, trade and GDP growth as hard data, and consumer sentiment and business sentiment as soft data. Albeit unsuccessful in our use of the *Beat* indicators for building single currency strategies, we added them to this analysis given how they proxy - well or poorly - other potential explanatory variables shown in the literature. Examples of the latter include: the *consumption growth factor* in Lustig and Verdelhan (2007, 2011), the *surplus-consumption risk factor* in Riddiough (2014), the *size factor* in Hassan (2013), and the *economic momentum factor* in Dahlquist and Hasseltoft (2016). We also note that some literature points to currencies driving future macroeconomic performance, and not the other way around; see, for instance, Engel and West (2005) and Sarno and Schmeling (2013).

[24] Fama and MacBeth (1973).

[25] We removed longer horizons due to the significant shrinkage of time series breadth in the data.

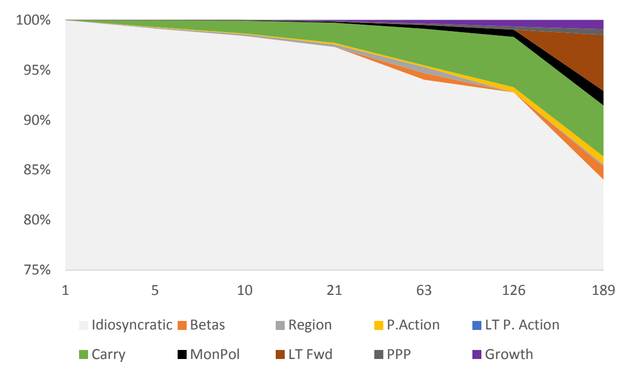
2. We apply cross-sectional standardisation in both the dependent and independent variables, thereby reducing the effect of outliers. We apply an inverse z-score standardisation method as described in Natividade et al. (2014).
3. We apply a *stepwise regression* algorithm to address multicollinearity between explanatory variables. [26] This step narrows the number of potential explanatory variables to a much smaller set.
4. We re-run the stepwise regressions, but now using only the qualifying explanatory variables from Step (3). The procedure is different in that we now run a sequence of *univariate* stepwise regressions, evaluating the marginal contribution of each regressor in explaining the residual returns from the previous univariate regression. We tested all available sequences, and calculated the average results. This extra step allowed us to better estimate the influence of each individual regressor.

As was the case with the PCA study, our panel regressions were repeated with different start dates so as to reduce the noise coming from data discretization. The final results use an average of all regressions.

Figure 8 shows the results of our panel regressions; marginal R-square values are plottted according to varying time horizons. We highlight the following observations:

- Most of the systematic variations in the asset class are not *predicted* by the regressors chosen. The share predicted by the academically-backed regressors is smaller than what we witness, for instance, in equities and corporate credit. [27] But rather than challenging our choice of drivers, we note that currency markets are notoriously hard to predict. The reader may recall past statements by Alan Greenspan on the topic. [28] Not only that, but it also alludes to the time-varying importance of each individual driver, as one would expect in a dynamic system as alluded to earlier.
- The predictive power of our regressors grows as the return horizon grows. This is in line with lower frequency data being less noisy.
- Carry is the foremost driver, and more influential than any of the others across horizons. Other drivers become increasingly important under longer horizons.

Figure 8: Marginal explanatory power from panel regressions according to independent variable and forecast horizon (days)



Source: Deutsche Bank

These results both confirm and contradict those from Section 2.1. First, they confirm the relevance of the carry factor; in addition to being a key factor explaining the *current* variations of the asset class, it is also the top *predictor* of future returns.

On the other hand, these results are also discouraging on the US dollar. It may be the biggest factor explaining contemporaneous returns, but it fails to explain much of the future variations in the asset class. This lends further support to our previous allusion to complex systems, where different factors are intertwined. The USD factor is often entangled with alternative drivers such as valuations, monetary policy and market sentiment, which are also - as our regressions show - clear drivers of the US dollar as well.

By adding clarity on other factors, which were not immediately clear from the PCA exercise and which also help drive the US dollar, we are now able to bridge the gap between drivers – in other words, predictors – and investment strategies. We will use them not only to define cross-sectional portfolios that are neutral to the US dollar, but to also take positions on the US dollar through time series portfolios. Specifically:

- Market and sentiment factors, and price action: these will be captured through our Momentum and Positioning signals. Sections 4.1, 4.5 and 4.6 show we effectively capture directional moves in the asset

[26] The algorithm, implemented through the function stepwisefit in Matlab, iterates through the different potential explanatory variables using their p-value as metric.

[27] See, for instance, Capra et al. (2018).

[28] We highlight two famous quotes. The first is "Having endeavored to forecast exchange rates for more than half a century, I have understandably developed significant humility about my ability in this area", dated 2001. The second is from 2002: "We at the Federal Reserve have spent an inordinate amount of time trying to find models which would successfully project exchange rates [...]. It is not the most profitable investment we have made in research time. Indeed, it is really remarkable how difficult it is to forecast."

class as a whole as well as in individual currencies, using both price and non-price data.

- *Carry*: this factor has now been validated by both PCA and panel regressions. Section 4.2 goes through our proposed implementations.
- *Monetary policy*: we proxy this driver through our Momentum Spill-Over factor, previously addressed in our research (Natividade et al. (2015)) and revised in detail in Section 4.4.
- PPP, long-term interest rate parity and long-term past returns: these will be captured through our *Value* signal. Section 4.3 will show how our fundamental valuation signal, albeit more complex than a long-term price-based signal, captures the long-term reversal phenomena more accurately.

3. Assessing Predictive Power and Rebalancing Implications

Having identified the core drivers of currency returns, we next devise an analytical framework that assesses predictability from a practical angle. For every factor, we first calculate a *signal*; in other words, a noise-filtered estimate of what the factor is "saying" about each asset.

Once the signal is defined, our framework uses the *term structure of its predictive power* to identify each signal's optimal implementation format.

For a given asset, we evaluate the covariance between future returns and current signal value, using the whole signal history. We calculate the statistic for the asset class as a whole, either using the original asset-specific signals or their values as a spread to the cross-sectional median. This therefore allows us to conclude on the most optimal portfolio implementation format - be it time series, cross-sectional or both.[29]

This particular implementation question is key to the systematic investor. Cross-sectional constructs imply market neutrality – that is, returns should be unrelated to the US dollar. In this case, the notional (or risk) capital allocated to the short positions normally equate that of the longs. Time series constructs are unconstrained and can take significant directional exposures to the USD. The CTA community is known for implementing time series strategies, while the equity long-short community is known for the cross-sectional approach.

But there are other applications to this framework. Repeating the exercise across multiple horizons[30] allows us to assess the speed of signal decay. We may therefore determine whether the signal requires extra treatment - such as filtering and noise control, as is the case with fast signals - or how often we should rebalance a strategy that implements this signal.

It also allows us to better assess the complementary ability of a given signal in a multi-strategy context, adding multi-horizon diversification to our multi-factor, multi-asset currency portfolio.

We estimate two versions of these *modified information coefficients (MIC)*[31]: time series and cross-sectional. For the former, the MIC is estimated as follows:

$$\tilde{S}_t^i = \frac{S_t^i}{\sum_{j=1}^{N} |S_t^j|}$$

$$MIC_{t,h}^{TS} = E[r_{t+h}^i \tilde{S}_t^i]/h$$

where S_t^i is the raw signal for a given currency pair at a given point in time, r represents future returns and h is the horizon of future returns. In the case of the cross-sectional MIC:

$$\tilde{S}_t^i = S_t^i - median(S_t\ )$$

$$\tilde{S}_t^i = \frac{\tilde{S}_t^i}{\sum_{j=1}^{N} |\tilde{S}_t^j|}$$

$$MIC_{t,h}^{CS} = E[r_{t+h}^i \tilde{S}_t^i]/h$$

The MICs introduced in this section will be applied to each signal introduced in Section 4, thereby allowing us to design strategies that capture its information content more accurately.

An important observation worth highlighting is that our implementation decisions are subjective; we do not apply hypothesis tests to define the significance of our MIC estimates. This is because the relationship between current signal and future asset returns may be regime-

[29] While information coefficients have been carefully addressed as far back as Grinold and Kahn (1999), we found Hassan and Mano (2013) to be the most useful recent reference. The authors use this technique - based on covariances and not correlations - to dissect the carry trade and forward bias anomalies. According to the authors, the covariance between future FX returns and current signal can be decomposed into (a) a static component, (b) a dynamic component and (c) a US dollar (market) component. Cross-sectional strategies capture (a) and (b), whereas time series strategies capture (b) and (c).

[30] As with Section 2, we apply statistical averaging for horizons other than daily. This is done through a sampling procedure; for a given horizon, each MIC estimate is generated using non-overlapping returns with distinctly different start dates. For example, the final 3-month MIC is an average of 63 separate MIC estimates, each generated using a separate start date.

[31] Information coefficients are typically estimated using correlations, and not co-variances. We made this modification to allow for a comparison between time series and cross-sectional implementations.

dependent, which is not captured by current estimates. This will be covered in future research.[32]

Finally, we also assess the impact of portfolio rebalancing assumptions on the performance of our return streams. While we do not discuss market impact models in this report[33] - they are arguably less crucial for low frequency strategies applied to highly liquid markets - we evaluate the impact that different rebalancing assumptions have on return characteristics.

We do so because for every strategy there is a fine balance between turnover control, which dampens cost, and turnover enhancement, which increases adaptivity. There is no widely agreed formula for estimating signal-to-noise ratios in finance,[34] but we can observe the relationship between these two forces by looping through different assumptions on portfolio rebalancing and tranching. In addressing this question we ultimately seek to identify the optimal rebalancing frequency for every factor portfolio introduced.

4. Building Absolute Return Portfolios

Having identified the core drivers of currency returns, and a framework for optimal implementation, we now build absolute return strategies.

Given the unconstrained nature of such portfolios, we will exploit market directional and market neutral strategies alike. As mentioned earlier, our decision criterion is largely based on the predictivity characteristics of each signal; in other words, it is based on a form of *feature importance*.[35]

We will introduce each factor strategy according to relevance and horizon, starting with the medium-term base factors (Trend and Carry) and moving to long-term Value and short-term factors later.

All factors have a "global" and a "local" element to them[36], in the sense that they can affect all assets in a similar direction – i.e. USD-related – but also that there may be key differences between how individual assets are impacted. As such, we implement both time series and cross-sectional strategies, and the MICs introduced in Section 3 allow us to see what is appropriate for each factor.

4.1 Momentum

Momentum is the first of our investment factors. It is based on the premise that assets that are rising in value will continue to rise, and those that are falling in value will continue to fall.[37]

4.1.1 Signal generation

Our trend signal is based on the premise that signal direction, not signal intensity, is what carries most predictive power - as highlighted in Natividade et al. (2013) and Natividade et al. (2016). The low entropy in signal intensity allows us to simplify the raw signal, and deploy complexity at later stages of the strategy.

As also highlighted in Natividade et al. (2013), our results suggest that fine tuning the signal training windows is less optimal relative to an approach that equally weights between short, medium and longer term training windows.[38] For a given currency pair, our signal is therefore built using the following steps:

(1) We calculate the total return - spot and carry - between $t-h$ and t, where $h \in \{21, \ldots, 252\}$ is measured in business days. This gives us 232 total return values.[39]

---

[32] We believe there are 3 ways a signal should be assessed: (a) *overall predictivity*, (b) *adaptivity* – predictivity under shorter horizons, under both calendar time and regime time, and (c) *diversification potential* – predictivity under distinct market regimes. The current assessment focuses exclusively on (a) and parts of (b), as it only evaluates the linear relationship between current signal and future returns. Applying hypothesis tests on current MICs to define whether or not to use a signal would over-simplify the problem.

[33] The reader should refer to Grinold & Kahn (1999) and, to some extent, Weng (2017) for that.

[34] Lopez de Prado (2018), for instance, addresses somewhat related concepts through ratios based on a so-called "confusion matrix": *precision*, *recall*, *accuracy* and *F1 score*. The author also quotes various metrics pertaining to the entropy of a time series, which relate to this topic as well. Grinold and Kahn (1999) use information coefficients - the correlation between current signals and future cumulative returns, evaluated cross-sectionally in a portfolio at every point in time - as a somewhat analogous measure, as also used in Natividade et al. (2016). In electronic engineering, on the other hand, there is a widely agreed formulae for signal-to-noise ratios (see, for instance, https://en.wikipedia.org/wiki/Signal-to-noise_ratio).

[35] We use the terminology from Lopez de Prado (2018), though our assessments do not utilize his proposed cross-validation methods as we believe those are not applicable to our tests. Further, our signals do not involve optimized calibration.

[36] This terminology follows Baz et al. (2013). The authors argue that, assuming linear signals, cross sectional portfolio weights are equal to time series weights minus the cross sectional average, and this average can be considered as a global factor.

[37] This description may appear simplistic, but it an accurate summary. Theories of irrational preferences – under-reaction, herd behaviour and extrapolation – appear most popular among the explanatory factors behind the trend premium. The reader interested in the academic literature should check Jussa et al. (2012), Ilmanen (2011), Moskowitz et al. (2011) and Natividade et al (2013) for a review of the literature.

[38] The results from Section 4.1.2 may favour shorter training windows in foreign exchange relative to other asset classes, but we opt against it as the benefits of a one-size-fits-all algorithm for trend following across asset classes outweighs the losses. In our view, sub-1 month momentum dynamics in USD/FX should be captured via specific short-term momentum models, with different signal estimation, noise control, rebalancing and turnover characteristics.

[39] This signal is slightly different from the one introduced in Natividade et al. (2013), in that previously we used 9 lookback windows between 2 weeks and 1 year, thus generating 9 binary readings ({-1,+1}). We applied

(2) We record the sign of each total return value from Step (1). That is, $\tilde{s}_{t-h,t} = sign\left(r_{t-h,t}\right)$.

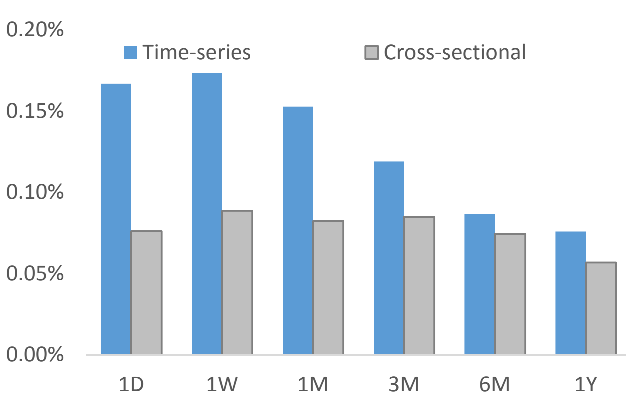
The raw signal is the average of all 232 signs from Step (2), i.e. $\bar{s}_t = \frac{1}{(251-32)} \times \sum_{h=32}^{251} \tilde{s}_{t-h,t}$. Note that $\bar{s}$ is bounded, that is, $\bar{s} \in [-1,1]$. We also record the volatility of $\tilde{s}$, $\tilde{\sigma}_t = \sqrt{\frac{1}{(251-32)} \times \sum_{h=32}^{251}\left(\tilde{s}_{t-h,t} - \bar{\tilde{s}}_t\right)^2}$, which will be used later for noise control. Finally, we also record the sign of the raw signal, $\hat{s}_t = sign(\bar{s}_t)$.

4.1.2 Signal predictive power

Having defined our Momentum signal, we now estimate modified information coefficients (MICs) so as to better understand its relationship to future asset returns. Such understanding will allow us to address general implementation questions, such as format - time series versus cross-sectional - and rebalancing, a function of signal decay.

Figure 9 shows the progression of our MICs over multiple horizons, using 28 years of data. It shows positive predictive power in both time series and cross-sectional formulations, with the former being notably higher than the latter especially in the shorter-term.

Figure 9: Momentum signal – modified information coefficient



Source: Deutsche Bank

The key argument favouring time series implementation lies in the tendency of the US dollar - the closest to a "market" concept for foreign exchange - to trend. Figure 10 shows the result of a long-term impulse-response function[40] applied to the first principal component of the USD/FX basket[41], with multiple look-back (impulse) windows and multiple look-ahead (response) windows[42]. The numbers in the cells correspond to univariate t-statistics.

Figure 10: Impulse-response function t-statistics, USD/FX PC1

	1W	2W	3W	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	1Y	2Y	3Y	4Y	5Y
1W	1.2	1.3	2.0	2.3	3.1	2.7	2.9	2.3	2.2	2.0	1.5	1.6	1.7	1.8	1.9	1.7	1.2	1.1	0.8
2W	0.9	1.4	1.9	2.4	2.8	2.6	2.6	2.1	2.1	1.8	1.4	1.5	1.6	1.8	1.8	1.7	1.2	1.1	0.7
3W	1.2	1.5	2.0	2.4	2.5	2.7	2.5	2.1	1.9	1.6	1.4	1.4	1.6	1.8	1.7	1.7	1.2	1.0	0.7
1M	1.1	1.6	2.0	2.3	2.3	2.5	2.3	1.9	1.8	1.4	1.3	1.3	1.5	1.7	1.6	1.7	1.2	0.9	0.6
2M	1.1	1.4	1.5	1.6	1.9	1.9	1.6	1.4	1.2	1.0	1.0	1.1	1.3	1.4	1.3	1.5	1.0	0.6	0.4
3M	0.8	1.1	1.3	1.5	1.6	1.5	1.3	1.1	0.9	0.8	0.9	1.0	1.1	1.1	1.0	1.3	0.9	0.5	0.3
4M	0.7	1.0	1.1	1.2	1.2	1.2	1.0	0.8	0.7	0.7	0.8	0.9	0.9	0.9	0.9	1.2	0.7	0.3	0.2
5M	0.6	0.8	0.9	1.0	1.0	0.9	0.7	0.6	0.6	0.6	0.7	0.8	0.8	0.8	0.7	1.1	0.6	0.2	0.1
6M	0.5	0.6	0.7	0.8	0.8	0.7	0.6	0.5	0.6	0.6	0.6	0.7	0.7	0.7	0.6	1.0	0.5	0.1	0.1
7M	0.4	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.6	0.6	0.6	0.6	0.5	0.9	0.5	0.1	0.0
8M	0.3	0.4	0.5	0.5	0.5	0.6	0.6	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.9	0.4	0.0	0.0
9M	0.3	0.4	0.4	0.5	0.5	0.7	0.7	0.6	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.4	0.0	-0.1
10M	0.3	0.4	0.5	0.5	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.7	0.4	0.0	-0.2
11M	0.3	0.4	0.5	0.5	0.6	0.6	0.6	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.7	0.4	0.0	-0.3
1Y	0.3	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.3	0.0	-0.3
2Y	0.2	0.3	0.3	0.4	0.4	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.1	-0.2	-0.5	-0.9
3Y	0.1	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	-0.1	-0.5	-0.8	-1.0
4Y	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.5	-0.7	-0.9
5Y	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3	-0.4	-0.4	-0.5	-0.7

Source: Deutsche Bank

The results show us that:

- The USD/FX PC1 exhibits trend properties across most horizons in the short and medium term, if the moves are evaluated relative to short and medium term history.
- At the same time, the USD/FX PC1 exhibits reversal properties across long-term horizons when the moves are evaluated relative to a long term history.
- The strongest trend properties lie in short-term horizons, under 3 months, and the strongest reversal properties lie in horizons beyond 3 years.
- The t-statistic values are generally low, but this is largely due to the use of one series alone (as opposed to a panel of multiple series), the fact that the data has not been smoothed (so as not to introduce memory effects), and the relatively short history (mostly affecting the long horizons).

Figure 9 validates taking a time series momentum approach to FX, but it does not remove cross-sectional momentum. The US dollar may be a key source of trendiness, but our MICs also suggest there may be enough non-USD momentum to validate the construction of a market neutral strategy.

this change so as to smooth out the signal and therefore require less noise control.

[40] In other words: $r_{t+1,t+A} = a + b \times r_{t-L,t} + \varepsilon_{t+A}$
where A is the look-ahead period (in days) and L is the look-back period (in days). We used data from January 1980 onwards. We applied non-overlapping windows and a sampling metric in line with that of Section 1, thereby reducing discretization error.

[41] Daily returns, includes both carry and spot returns.

[42] We opted for this simple, univariate impulse-response function as it makes it easier to visualise the relevant relationships. We also refer the interested reader to Natividade et al. (2015), where we apply a more hollistic multivariate, auto-regressive, regime-switching model to the same problem.

As such, we first isolate idiosyncratic momentum by focusing on residual returns; in other words, we strip out the USD-related returns from each USD/FX pair.[43] After that, we re-build the signal as defined in Section 4.1.1 but using residual returns instead.

4.1.3 Noise control

Noise control is a common feature in price action strategies, and is typically done either through smoothing the raw signal or attaching level thresholds below which the new signal is not executed.

We implement noise control for both time series and cross-sectional signals, and we do it in two steps. First, we apply a hysteresis-based threshold mechanism similar to that from Natividade and Anand (2016): if the absolute raw signal $|\bar{s}_t| < \theta = {}^{1}/_{3}$, we keep the old signal.[44] This adjustment leads to lower turnover versus a version with no turnover, which we favour.[45] The preliminary signal is, therefore:

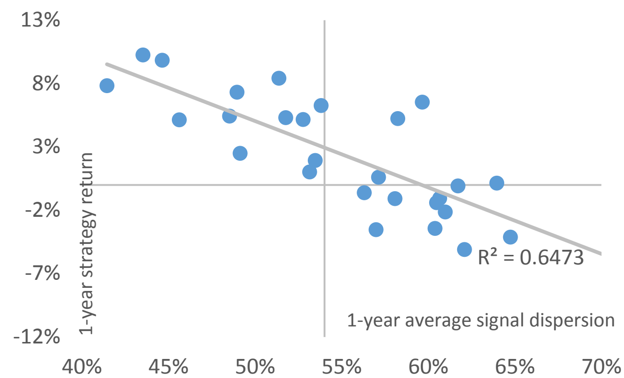
$$\hat{s}_t = \begin{cases} sign(\bar{s}_t), & \bar{s}_t \geq \theta \\ \hat{s}_{t-1}, & \bar{s}_t < \theta \end{cases}$$

Second, we deflate the preliminary signal by signal dispersion; in other words, we deflate it by the volatility of the raw signal as calculated in Section 4.1.2.[46] This second adjustment is new, and based on our experience diagnosing the differences between broad and narrow trend following programmes.[47] This gives our final signal:

$$s_t = \frac{\hat{s}_t}{\tilde{\sigma}_t}$$

Figure 11 plots the contemporaneous relationship between aggregate signal volatility and the annual returns of our trend following strategy, using data since 1991. The relationship is strong, as shown by the regression fit, thus validating the approach.

Figure 11: Contemporaneous relationship between dispersion of trend signals and returns of the portfolio



Source: Deutsche Bank

4.1.4 Weighting scheme: time series Momentum

As highlighted in Grinold and Kahn (1999), the risk-adjusted returns in a strategy are a function of the predictive power of its signals (the rank coefficient) and how diversified the positions are (the investment breadth).[48] As per Natividade et al. (2016), trend following signals tend to have low predictive power and we therefore aim to maximise breadth.

Therefore, in theory, one should aim to maximise breadth when building a trend following algorithm.

At the same time, we must be conscious of the risks of over-parameterisation and, crucially, also assess whether there exist thresholds *under* which breadth maximising methods are unlikely to add value.

To address these issues, we rigorously compared 2 weighting schemes: inverse volatility (IVW) and minimum correlation (MCW).[49] As our pool of assets is

[43] The residual returns are estimated as: $\varepsilon_t^i = r_t^i - \beta_t^i r_t^{\$} - \alpha_t^i \varepsilon_t^i = r_t \quad - \beta_t r_t^{\$} - \alpha_t \varepsilon_t^i = \beta_t r_t \quad - \alpha_t$, where r_t is the daily return in USD/FX, $r_t^{\$}$ is the daily return in the "market" factor (PC1 of USD/FX), and β_t^i, α_t^i are the slope and constant terms estimated by a regression using a 1-year lookback window.

[44] This is somewhat different from Natividade and Anand (2016) in that here we use symmetric thresholds to introduce long and short positions, as opposed to the prior asymmetric thresholds. The prior rationale, which reflected the regime-dependent noise profile of investment assets, was effective in addressing discretisation issues in the old signal. Such has become less relevant in the new signal as it is far more continuous. The threshold level of 1/3 followed what had been done in Natividade and Anand (2016), which in turn was based on our anecdotal evidence of typical noise thresholds among industry participants.

[45] Daily turnover fell from 5.9% to 5.7%, and the backtested historical Sharpe ratio rose from 0.35 to 0.4.

[46] We also set a lower boundary for this volatility estimate, which equals the 25th percentile of the distribution of signal volatility estimates across all assets. This is in order to ensure the final signal is not hyper-inflated due to this noise adjustment, as the adjustment goes in the denominator.

[47] For instance, the differences between the DB Cross Asset Trends Index (<DBCATUSD Index> on Bloomberg), which uses 17 assets, and the same version that uses 80 assets or the SG Trends Index (former New Edge Trend Following Index). The CAT version with 80 assets, as well as the benchmarks, underperformed the DB CAT index since its launch in May 2015 despite benefiting from greater investment breadth. This is largely due to the difference in noise characteristics.

[48] As per fundamental law of active management, $Sharpe \approx IC \times \sqrt{breadth}$ where IC is the information coefficient and, according to Grinold and Kahn (1999), breadth is defined as "the number of independent forecasts of exceptional return we make per year". As per authors, more breadth helps diversify residual risk.

[49] The reader may wonder why have we not attempted other risk-based weighting schemes, such as those shown in Mesomeris et al. (2012) and Natividade et al (2013). Our response is two-fold. First, we wanted to test two extremes: an algorithm that mostly heavily focuses on asset correlations (MCW), and one that fully ignores correlations (IVW). Other risk-based algorithms normally sit in between. Second, it is our anecdotal evidence - and evidence from simulated data in this project - that the less the number of assets, the less utility that complex weighting schemes have versus simpler schemes. The pool of assets used here is quite small compared to, say, the Equities or corporate fixed income pools.

fixed at 24 currency pairs, we used pairwise correlations as our measure of diversification potential and therefore evaluated the effect of changes in this metric on each weighting scheme.

IVW is the simplest risk-based position weighting scheme, and therefore a benchmark. It indirectly enhances diversification by ensuring that position sizes solely reflect the inverse of the volatility of the asset. Leaving aside time-related notations, for asset i where $i \in \{1, \dots, N\}$ and with returns r_i, the IVW weight is calculated as:

$$w_i^{(iv)} = \frac{1/\sigma_{r_i}}{\sum_{j=1}^{N} 1/\sigma_{r_j}}$$

MCW, on the other hand, directly targets diversification by overweighting positions that are less correlated to others. We implemented the algorithm in Varadi et al. (2012), as follows:

(1) Compute the exponentially weighted Pearson correlation matrix, ρ, of asset returns. For consistency, we used the same correlation matrix as elsewhere in the report, hence see Section 1.2 for details.

(2) Compute the mean, μ_ρ, and the standard deviation, σ_ρ, of all elements of the correlation matrix in Step (1).

(3) Create the adjusted correlation matrix, ρ_A, by transforming each element of the previous correlation matrix to a reading between $[0,1]$, where $-1 \rightarrow 0$ and $1 \rightarrow 1$. The mapping is done through the standard normal cumulative distribution: $w_T = 1 - normcdf\left(\rho_{i,j}, \mu_\rho, \sigma_\rho\right) w_a = 1 - normcdf\left(\rho_{i,j}, \mu_\rho, \sigma_\rho\right)$.

(4) Compute the average value for each row of the adjusted correlation matrix, ρ_A. These are the initial portfolio weight estimates from the transform w_T in Step (3).

(5) Compute the rank portfolio weight estimates: $w_{Rank} = \frac{Rank(w_T)}{\sum_i Rank(w_T)}$

(6) Combine the rank portfolio weight estimates from Step (5) with the adjusted correlation matrix from Step (3) by multiplication and standardisation:

$$\widehat{w} = \frac{w_{Rank} \times \rho_A}{\sum w_{Rank} \times \rho_A}$$

(7) Scale the portfolio weights by asset volatility and further standardise such that the sum adds to 1:

$$w_i = \frac{w_i/\sigma_i}{\sum_j w_j/\sigma_j}$$

One may rationally challenge the inclusion of IVW in our tests; if we are exclusively interested in maximising breadth, we should directly opt for diversification-maximising algorithms such as the MCW.

But our experience suggests that it is not as simple. As alluded to earlier, diversification-maximising algorithms may bring drawbacks such as more parameters and over-allocation to noisy assets. [50] And while we addressed the latter in Section 4.1.3, it does not decide which weighting scheme to choose for us.

The answer should, ideally, come from testing the sensitivity of our results to the diversification potential available in the asset pool. With that in mind, it is clear that historical backtests are not enough. [51] Recent literature may have shed some light, but the approaches proposed are also often less applicable to alternative risk premia strategies. [52]

As such, we opted for creating simulated data and using that to build portfolios, which were then compared to one another using different weighting schemes and correlation assumptions. Each of the 24 simulated time series had the same long-term return and volatility equal to that of the average of our currency pairs, [53] and interacted with one another through a correlation parameter that varied according to each trial. In other words:

$$dX_t = \mu_x X_t dt + \sigma_x X_t dW_t^x$$

$$dY_t = \mu_y Y_t dt + \sigma_y Y_t dW_t^y$$

$$dW_t^x dW_t^y = \rho dt$$

[50] Noisy assets are often less correlated and hence increase diversification. In this case, however, the overall impact is negative; the information coefficient drops by more than the (square root of) breadth rises.
[51] The two weighting schemes produce very similar risk adjusted returns. This alone may favour the IVW approach, as it has less parameters, but that is not enough as historical Sharpe ratios may not accurately reflect future Sharpe ratios.
[52] The recent literature typically focusses on fitting risks, and proposes methods based on cross validation and on deflating expected performance by the number of parameter combinations tried. Lopez de Prado (2018) is a good reference. The challenge in incorporating such techniques to low frequency, alternative risk premia strategies, is two-fold: (1) it is often difficult to document how many iterations have been tried on the same model, and what constitutes an independent iteration, and (2) it is often difficult to remove memory effects when preparing the data for a sampling exercise, as different parts of the model will have different memory dependencies.
[53] We opted for an individual long-term return and volatility estimate for all simulated series, as opposed to one for every simulated asset that corresponded to that of each real asset, in order to further isolate the effect of correlations in our results.

In each trial, we simulated 8,000 observations[54] for each of the 24 time series, with a given average correlation rho to one another. At each rebalancing date, which occurred at every new time unit, we applied the aforementioned trend following algorithm and aggregated positions according to both IVW and MCW schemes, therefore rebalancing all the prior positions. The process was repeated 150 times for each fixed correlation level. We then changed the correlation assumption above and verified the effect of that on the difference in risk-adjusted returns of the trend following portfolios using both IVW and MCW schemes.

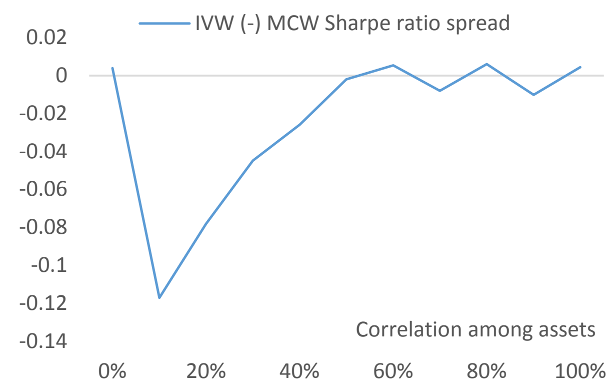
Figure 12 plots the result of our analysis. It shows the difference in Sharpe ratios between the simulated IVW trend following portfolio and the simulated MCW trend following portfolio, for a given assumption on the average correlation between constituents. It tells us that:

- When correlations are generally low, the MCW scheme underperforms IVW. *Higher diversification generally implies lower convexity*; if the portfolio is already diversified to start with, seeking further diversification leads to a drop in returns that outweighs the drop in volatility. To our surprise, the simulations suggest that the correlation threshold to switch between schemes is rather high - circa 50%.
- But when assets are heavily correlated to one another, the marginal diversification brought by MCW over IVW makes a material difference, and therefore it should be recommended. In a pool of 24 assets and when Trend Following (time series Momentum) is the strategy in question, the simulations suggest the threshold is circa 50%.

Given the results above, we opted to weight individual positions using the inverse volatility scheme. As such, at every rebalancing date, we divide the final signal calculated in Section 4.1.2 by the volatility of asset returns, which gives us the preliminary asset weight. We then modify this preliminary weight to account for constraints, thereby giving us the final weight.[55] In other words, for currency pair i of a total of N currency pairs:

$$w_{i_t}^{Trend} = \frac{s_{i_t}/\sigma_{i_t}}{\sum_j^N \left| s_{j_t}/\sigma_{j_t} \right|}$$

Figure 12: Difference in Sharpe ratios – IVW and MCW schemes using simulated data and different asset correlation assumptions



Notes: see main text for details. Source: Deutsche Bank

4.1.5 Weighting scheme: cross-sectional Momentum

Deriving asset weights in the cross-sectional Momentum strategy can be a simpler exercise; not only it should focus primarily on USD neutrality, but our previous results also showed there is no need for asset weights to reflect signal intensity.

The steps, at a given rebalancing date, are as follows:

(1) We rank currency pairs based on the signals estimated in Sections 4.1.1 and 4.1.3, but now utilizing *residual* returns (instead of original returns) and without the sign in the raw signal. In other words:

$$\hat{s}_{t,res} = \begin{cases} \bar{s}_{t,res}, & \bar{s}_{t,res} \geq \theta \\ \bar{s}_{t-1,res}, & \bar{s}_{t,res} < \theta \end{cases}$$

$$s_t = \frac{\hat{s}_{t,res}}{\tilde{\sigma}_t}$$

(2) We go long the top half and short the bottom half of assets in our pool, assigning equal weights to each asset such that the absolute sum of weights equals 100%. We opt for taking exposure to all a ssets so as to maximise factor exposure and avoid idiosyncratic risk.

(3) We re-adjust the weights from Step (2) such that the net beta to the US dollar is zero:

[54] Equivalent to 32 years of data, if daily, thereby resembling the length of much of our data.
[55] We attach upper and lower boundaries for each currency pair. The upper boundary is equal to the minimum of 15% and 2% of the currency's average daily volume for a portfolio of USD 1bn. The lower boundary is the same as the maximum, but with a negative sign. Absolute weights must sum to 100%.

$\arg\min \sum_i^N (w_i - \tilde{w}_i)^2$, such that $\sum_i^N w_i \beta_i^\$ = 0$. In this case, $\tilde{w}_i$ is the initial USD/FX weight and $\beta_i^\$$ is the beta of each currency pair to the PC1 of the asset class.[56]

The reader may question the need for beta neutralisation given that the original signal is already calculated using non-USD returns. While it is a fair question, our backtests strongly indicated the need for an additional adjustment. *USD-neutrality in the signals may not translate into USD-neutrality in the portfolio.*

4.1.6 Portfolio tranching

Having defined our signal and weighting schemes, we next move on to define the optimal rebalancing frequency for our Momentum portfolios.

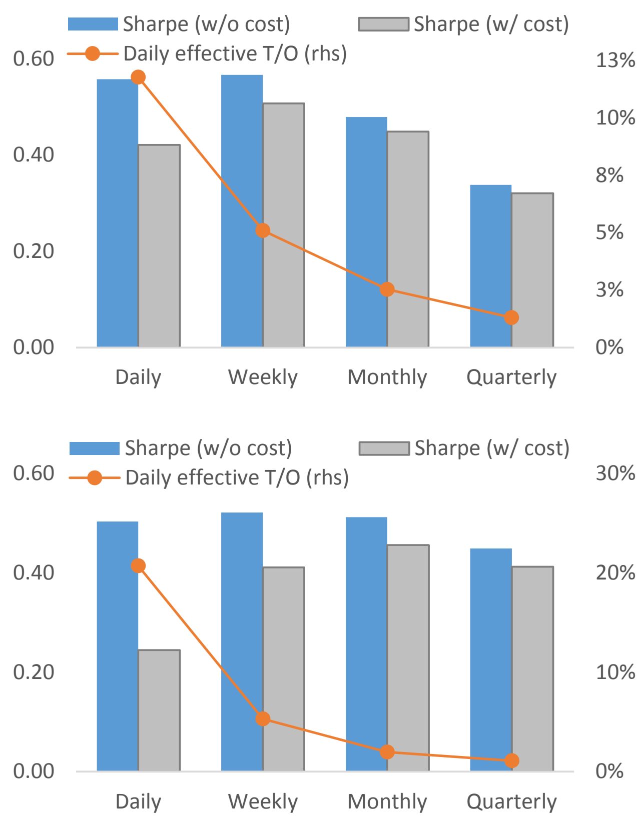
Figure 13 shows our results in more detail, as it evaluates the effect of our rebalancing assumptions on risk-adjusted returns, turnover and cost. The numbers are not surprising; backtests that rebalance more frequently generally show better risk-adjusted returns *before* costs, as per blue bars, but higher turnover, as per orange line. The higher turnover translates into higher costs.

As we aim to strike a balance between adaptivity and turnover, we choose the portfolio that rebalances monthly, using 20 daily tranches. Not only it maintains the high backtested Sharpe ratio, suggesting that signal entropy is still largely reflected in the positions, but the daily effective turnover also drops by more than three-quarters from the fastest rebalancing alternative. This particular momentum signal does not need to be "fast"; faster signals will be introduced later in this report. We make this decision for both time series and cross-sectional implementations.

4.1.7 Backtest performance

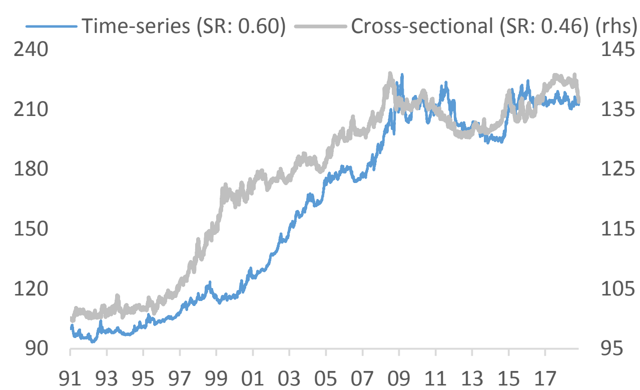
Figure 14 displays the historical backtest of our USD/FX Momentum strategies, with transaction costs included. The time series strategy is heavily market-directional; while long-term correlations to the USD Index reside at 6%, 1-year rolling correlations (of daily returns) swing significantly over time - as shown in Figure 15. The cross-sectional Momentum strategy is, however, far less correlated over time as expected given the explicit beta neutralisation.

Figure 13: Tranching results (time series followed by cross-sectional constructs) – Momentum portfolios



Source: Deutsche Bank

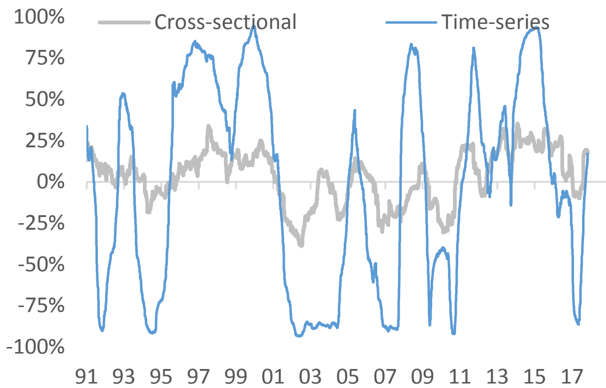
Figure 14: Time series and cross-sectional Momentum backtested returns (net of transaction costs)



Source: Deutsche Bank

[56] Another alternative for beta neutralization involves estimating the USD-beta of both long and short baskets separately and using these as hedge ratios. This approach would however require originally allocating equal risk weights for each asset as opposed to equal USD weights.

Figure 15: Rolling 1-year correlations to the US dollar (PC1 of the asset class)



Note: using daily returns. Source: Deutsche Bank

4.2 Carry investing

As shown in Section 2, Carry is an indisputable determinant of foreign exchange returns. It has also been a popular systematic strategy in the asset class over decades, and we refer the interested reader to Ilmanen (2011), Rosenberg (2013) and Koijen et al. (2013) for a detailed literature review.

Carry directly reflects interest rate differentials between countries, which - as noted in Anand et al. (2014) and alluded to in Section 2 - links to currency valuations through what higher interest rates imply about domestic economic conditions. If rates are rising due to deteriorating external balances or rising inflation, then - as we will show in Section 4.3 - standard valuations models will suggest that the currency should depreciate in order for the country to regain competitiveness.[57]

It also implies a strong link between the FX Carry trade and investor sentiment. To the extent that countries with higher interest rates also have higher current account financing requirements, they are more dependent on capital inflows and their currencies more sensitive to investor sentiment - particularly in emerging markets. As such, the investor typically requires a premium – in the form of positive carry – in order to be long currencies that are more vulnerable.

4.2.1 Signal generation

Estimating FX carry is straight forward. It is a model-free characteristic observed at the start of a trade, and represents the expected return of a static FX position assuming prices stay constant. It is normally[58] defined according to 2 exogenous, directly observable variables - domestic interest rates in the 2 countries. This interest rate spread defines the distance between spot and forward rate, thereby defining the carry.

Translating from carry to a signal is also straight forward, and in our view should reflect 3 characteristics. First and foremost, both *sign* and *size* of the carry value help predict future asset returns, and therefore carry intensity should be directly reflected on signal value.[59] Second, FX carry values are less noisy, at least as compared to price action signals; this allows us to apply looser noise control. Finally, carry and asset volatility typically bear a positive relationship and therefore the signal should be deflated by volatility, thereby resembling a modified ex-ante Sharpe ratio[60].

Our Carry signal is built as follows:

$$c_t^i = (S_t^i - F_t^i)/F_t^i$$

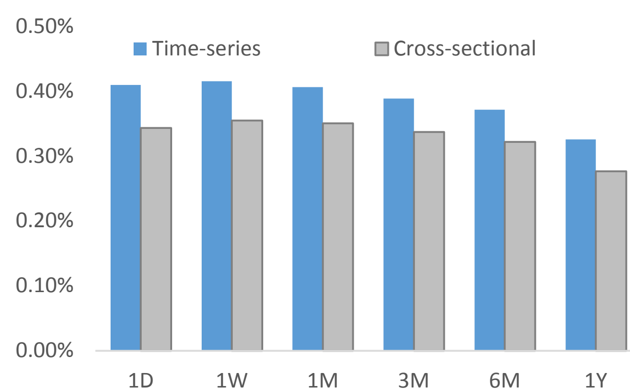
$$S_{i,t}^{Cr} = \sum_{h=0}^{N-1} c_{t-h}^i / N$$

$$S_{i,t}^{Cr} = S_{i,t}^{Cr} / \sigma_{i,t}$$

4.2.2 Signal predictive power

Figure 16 confirms our findings from Section 2. Not only is the Carry factor quite powerful – with higher MICs than any other signal – but its predictive power also persists across horizons.

Figure 16: Modified information coefficients – FX Carry signal



Source: Deutsche Bank

The numbers also suggest that both time series and cross-sectional implementations add value. The latter is commonplace in both academic and industry research, but the former has also gathered attention recently – see,

[57] This link helps explain why some authors label the FX Carry trade as FX Value; an example is Ang (2014).

[58] We say *normally* instead of strictly because this argument does not apply to non-deliverable (NDF) FX markets. In that case, onshore interest rates are often unavailable to the foreign investor and do not define the price of the FX forward.

[59] See Maurer et al. (2016) and Natividade et al. (2016).

[60] See Anand et al. (2014).

for instance, Koijen et al. (2013), Lustig et al. (2014) and Bartram et al. (2018).

4.2.3 Weighting scheme: time series Carry

As alluded to earlier, the time series implementation is akin to capturing the *dollar carry*; a term coined in Lustig, Rosanov and Verdelhan (2014). While not as common, we find this implementation just as valid as the cross-sectional version. Interest rates are a key variable driving the US dollar globally[61], and therefore could also be considered as a means of taking directional views on the first principal component of the asset class.

Having argued the need for *sign* and *size* to be both reflected into the Carry signal, we also directly translate these into portfolio weights. The weight allocated to each asset is therefore as follows:

$$w_t^i = s_{i,t}^{Cr}$$

$$w_t^i = {w_t^i}\Big/{\sum_j^N \left|w_t^j\right|}$$

Note that asset weights follow the same summation and boundary constraints as per Section 4.1.4.

4.2.4 Weighting scheme: maximum ex-ante Sharpe ratio

Our *market neutral* implementation of the Carry factor is inspired by Maurer et al. (2016); in other words, we seek to maximise the ex-ante risk-adjusted returns of our Carry portfolio. Therefore, our asset weights are set so as to maximise the ratio between portfolio carry and portfolio volatility. The procedure, for a given rebalancing date, is as follows:

$$\underset{w}{\arg\max} \frac{\sum_i^N w_i\, c_i}{\sqrt{\sum_i^N \sum_j^N w_i w_j \sigma_{ij}}}$$

subject to:

$$\sum_i^N w_i \beta_i^{\$} = 0$$

All other constraints, such as the absolute summation of weights equalling 100% and individual weights staying within boundaries, are the same as in Section 4.1.4.

This approach seeks to maximise the contribution of carry to final strategy returns, while also minimising the contribution of spot moves. The construct balances the relationship between risk, as reflected in how each asset co-varies with the portfolio, and reward, as reflected by asset carry. Therefore not only it favours assets with a high carry-to-volatility ratio but also assets whose diversification properties outweigh their lower carry.

The beta neutralisation constraint is also key to this construct. While FX spot returns are known to move in the direction of carry, and not against it[62], such feature should only be a part of our time series Carry implementation. As we show in Section 4.2.6, the constraint has also made quite a difference. It is an approach we follow in other asset classes as well.[63]

4.2.5 Portfolio tranching

Having derived our Carry weights, we now define the rebalancing assumptions by analysing the impact of tranching, just as we did in the Momentum factor. Figure 16 shows that the Carry signal does not exhibit fast decay, and therefore our rebalancing procedure should focus primarily on turnover - and hence cost - control.

The backtest results seem to favour weekly rebalancing, as per Figure 17. That said, the improvement in risk-adjusted returns is not notably significant and mainly attributed to volatility reduction. As such, we also opt for monthly rebalancing - tranched daily, with 20 tranches in total - as is the case in our Momentum portfolios. We also opted against slower rebalancing as that could have adverse implications to our beta estimation and hence market neutrality.

4.2.6 Backtest results

Figure 18 suggests that the Carry portfolios complement one another, which we also deduce from looking at how the combined portfolio outperforms the individual constructs in the backtest.

More importantly, the separate constructs allow us to take on USD exposure more efficiently. As shown in Figure 19, the *dollar carry* - time series - construct exhibits significant correlations to the US dollar over time, while the *market neutral* version is largely uncorrelated.

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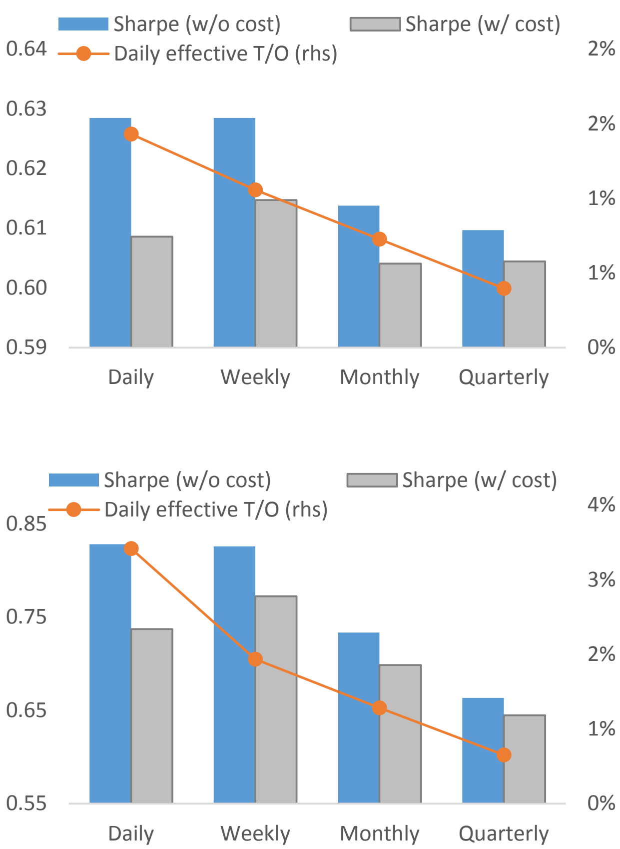
[61] We refer the reader, for instance, to our FX Blueprint reports over the course of the past 2 decades.

[62] See Koijen et al. (2013) and Rosenberg (2013). This is a standard finding of uncovered interest rate parity tests, which show that UIP does not hold over the long run. The poor recent performance of FX Carry, which reflects unconventional monetary policies and floored interest rates, suggests however that UIP has been holding in recent years,

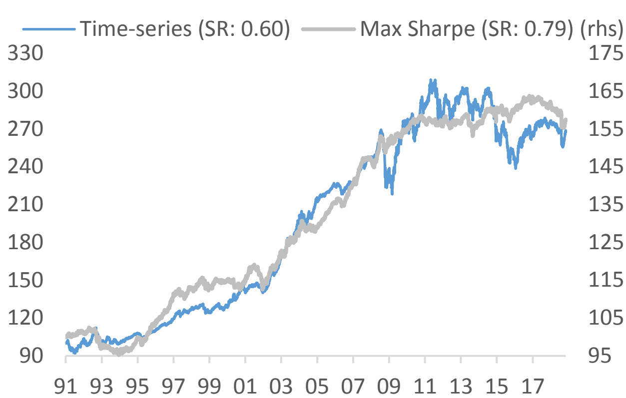
[63] See Anand et al. (2018). Note however that performance using a cross-sectional approach similar to our Momentum factor yields similar results as long as the market beta constraint is also present.

Figure 17: Tranching results (time series followed by max Sharpe constructs) – FX Carry portfolio



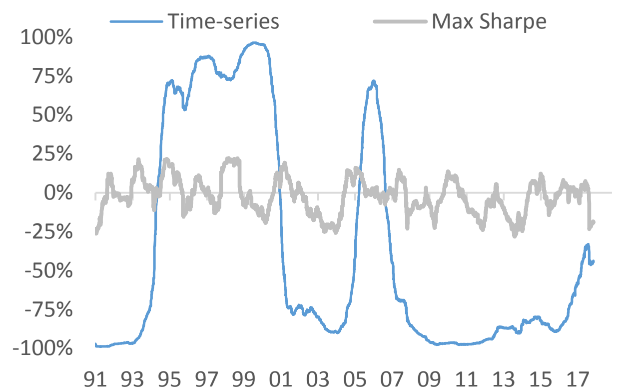
Source: Deutsche Bank

Figure 18: Time series and market neutral Carry backtested returns (net of transaction costs)



Source: Deutsche Bank

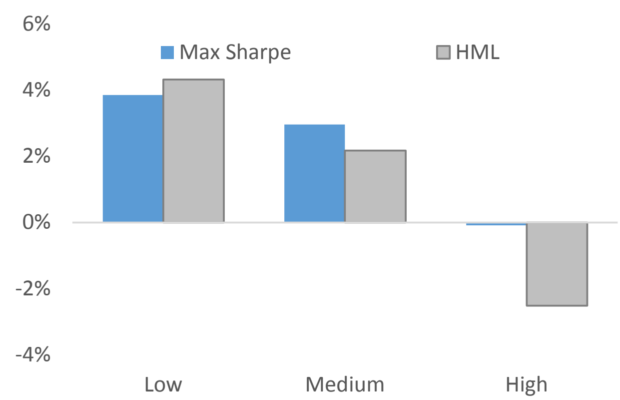
Figure 19: Return correlations to the US dollar, 1Y rolling



Note: US dollar proxied by the first principal component of the asset class (USD/FX). Source: Deutsche Bank

The decoupling between our market neutral portfolio and USD returns has an additional, positive consequence: the strategy was largely uncorrelated to global risk appetite. This results from the US dollar acting as a historical risk barometer[64], and therefore neutralising exposure also made the backtest returns more sentiment-agnostic. Figure 20 shows the distribution of monthly backtest returns across regimes in our Global Sentiment Indicator. The standard cross-sectional (HML) Carry factor[65] is far more sensitive to market regimes. This finding removes the need for timing mechanisms in our FX Carry factor, thereby changing our proposed implementation from Anand et al. (2014).

Figure 20: Monthly returns according to GSI terciles – market neutral versus standard HML Carry portfolio



Source: Deutsche Bank

[64] The US dollar has historically been a safe haven due to relative capital flows, especially at periods of market risk aversion, although this may not persist into the future.

[65] 24 USD/FX pairs, equally weighted, ranked by carry and with the same rebalancing assumptions as our proposed market neutral portfolio.

Finally, Figure 21 shows the relative contribution of carry and spot onto our time series and market neutral Carry portfolios. We highlight two findings:

- Spot moves contribute more in the time series construct, while carry is more influential in the market neutral construct.
- Spot has made a stronger impact in both portfolios since the end of last decade, as unconventional monetary policy suppressed global interest rates.

4.3 Value investing

Sections 2.1, 2.2 and 4.1.2 all suggest that currencies exhibit reversal properties over the long run. Value models help us comprehend such phenomena. They allow us to understand the long-term swings in the US dollar, the fact that uncovered interest rate parity often holds over the long run, and – importantly – why there are cases where this statement does not apply.

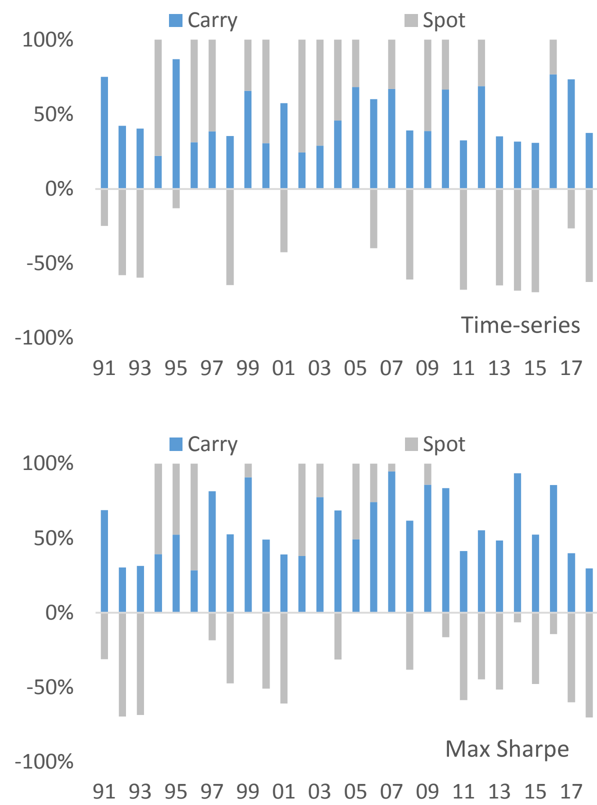
The most standard model of valuation is based on the *law of one price*: all identical goods must sell at the same price in a frictionless world. This creates an intimate link between domestic and foreign prices. Significant deviations should be offset by opposite moves in the exchange rate; if this hasn't occurred yet, it creates a value opportunity.

The best reference for the law of one price is the purchasing power parity exchange rate. In other words, the ratio of domestic prices in an identical basket of goods between two countries. It is generally agreed that nominal exchange rates should not diverge significantly from the PPP exchange rate, and indeed they do not for many comparable economies. But the less comparable the countries, the more that nominal exchange rates can persistently deviate from their PPP anchor.

Much of the work by fundamental currency researchers focuses on explaining why persistent deviations can (and do) occur, and whether those explanatory variables can be included in the original PPP estimate so as to generate a better, more universal fair value anchor for any exchange rate. A significant body of academic and industry literature exists on the topic; Ricci et al. (2008), Menkhoff et al. (2015), Ca'Zorzi and Rubaszek (2018) are good examples of the former, and Brehon (2013) and Kalani (2016) are flagship references of the latter.

The discussion often boils down to two questions: what estimation format to use and which extra variables best capture the divergences? Keeping in mind the challenges with data quality and parameterisation risks, we opted for a somewhat simple approach that is also based on the law of one price. Crucially, it also allows us to compare developed and emerging currencies as part of the same factor portfolio.

Figure 21: Annual return attribution to both time series and market neutral Carry portfolios



Source: Deutsche Bank

4.3.1 Signal generation

Fundamental Value models naturally carry significant overfitting risks, which we attribute to 3 reasons. First, they are based on long-term variables and a thorough assessment often requires more history than is available. Second, the revised nature of some inputs may introduce look-ahead bias. Third, there is often a significant degree of subjectivity among analysts on which variables to include in the model. This is not a problem specific to foreign exchange; Mesomeris et al (2018), for instance, point out similar issues in Equity Value.

With that in mind, we opt for a parsimonious signal that is largely based on Kalani (2016). We first estimate each currency's fair value and misalignment on a trade-weighted basis. We then convert to its respective USD/FX exchange rate and adjust for risk. At a given rebalancing date, which occurs once a month, the steps are as follows:

(1) We take the Bank for International Settlements (BIS) real broad effective exchange rate (REER) for each country. This will be used as dependent variable in our panel regressions.

(2) We estimate a reduced-form long-run relationship between the REER and macroeconomic variables in question. We regress the REER on 2 variables: productivity differentials and terms of trade, using a dynamic OLS model:

$$\log(REER_{i,t}) = \alpha_i + \beta_p^1 \times PROD_{i,t} + \beta_p^2 \times TOT_{i,t} + \theta + \epsilon_{i,t}$$

$$\theta = \sum_{s=-1}^{s=1} (\gamma_s^1 \Delta PROD_{i,t} + \gamma_s^2 \Delta TOT_{i,t})$$

$$PROD_{i,t} = \log\left(\frac{GDP_{i,t}}{\overline{GDP}_{i,t}}\right)$$

$TOT_{i,t} = \log(TOT_{i,t})$, where $\frac{GDP_{i,t}}{\overline{GDP}_{i,t}}$ is the ratio of real GDP per capita for country i over the weighted average of real GDP per capita of the basket of countries. This ratio is our proxy for productivity differentials, thereby addressing the Balassa-Samuelson effects. $TOT_{i,t}$ is the terms of trade index for country i.[66] α_i captures country fixed effects. The regressions are done in panel format, with 5 separate panels (p): EM commodity exporters, EM commodity importers, East Asian "tigers", G-10 commodity exporters and G-10 commodity importers.

(3) For a given country, we take its REER misalignment value, $\varepsilon_{i,t}$, and convert it to its equivalent USD/FX exchange rate misalignment.[67] This is our signal, $s_{i,t}$.

4.3.2 Signal predictive power

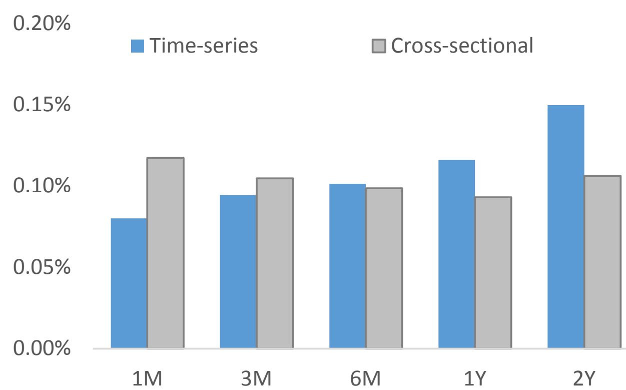
Figure 22 confirms our earlier assumptions that fundamental Value signals are of a long term nature. The predictive power does not decay; in fact, it grows with time. This is also in line with academic literature, which points to a PPP misalignment half-life of more than 2 years.[68]

Interestingly, the time series MICs are of similar levels as the cross-sectional MICs, which validates implementing both strategy constructs. While the latter is commonplace, the former is not but gives us a view on broad US dollar over or under-valuation.

4.3.3 Weighting scheme: time series Value

Our time series weighting scheme directly reflects the signal value, but adjusted for asset volatility. Some assets may look more misaligned simply because they are more volatile, and therefore we need to adjust for volatility mismatches. Further, the (risk-adjusted) weight intensity directly reflects both signal sign and size, as both add value in this particular investment factor.[69] This is also in line with the *lines in the sand* approach to currency misalignments [70]; very significant misalignments matter far more than smaller ones.

Figure 22: Modified information coefficients – FX Value



Source: Deutsche Bank

The weights in our time series construct are derived as follows:

$$s_{i,t}^{Vl} = {s_{i,t}}\big/{\sigma_{i,t}}$$

$$w_{i,t} = {s_{i,t}^{Vl}}\Big/{\sum_j^N \left|s_{j,t}^{Vl}\right|}$$

4.3.4 Weighting scheme: cross-sectional Value

The cross-sectional weighting scheme seeks to achieve 2 objectives: adjust position sizes for specific misalignment values and achieve market neutrality. The first is tricky; equal dollar weights or risk weights would not distinguish currencies that are far misaligned. A raw signal weighting scheme could also lead to misspecification; in other words, too much model risk.

To address this issue, we applied a linear weighting scheme that reflects the ranks of the risk-adjusted currency misalignment.[71] This construct therefore goes long the top half of assets, which are most comparatively undervalued, and short the other half. The weight allocated to each asset is a linear reflection of where it ranks versus the other assets in the same half.[72]

[66] Terms of trade is the ratio of export over import prices. We use different TOT sources depending on whether the country is a commodity exporter or not. If so, we use the Citibank Commodity Terms of Trade Indices. If not, we use national source TOT indices.

[67] We convert into USD/FX using 2 methods: matrix inversion and least squares. Cline (2008) explains the approach in detail.

[68] See, for instance, Lothian and Taylor (2000) and Ricci et al (2008). Winkler (2017) also provides an in-depth review of reversals to PPP exchange rates.

[69] See Natividade et al. (2016).

[70] See Chadha and Nystedt (2006).

[71] A non-linear weighting scheme might have increased idiosyncratic risk too much, especially given the small number of assets in the investment pool.

[72] Take for instance a basket of 12 currencies that the portfolio is long, as these are comparatively undervalued in the basket of 24. The most undervalued gets a weight of $\widetilde{w}_1 = 0.5 \times 12/(12 + 11 + \cdots + 1) = 7.7\%$ while the least undervalued currency gets the respective weight of $\widetilde{w}_{12} = 0.5 \times 1/78 = 0.6\%$. The same calculation applies to the short basket, with opposite signs.

As with the previous market neutral portfolios, we re-adjust the asset weights so as to target a neutral beta to the US dollar, as proxied by the PC1 of the asset class.

The beta adjustment works as follows:

$$\arg\min_{w} \sum_{i}^{N} (w_i - \widetilde{w}_i)^2$$
$$\sum_{i}^{N} w_i \beta_i^{\$} = 0$$

where $\widetilde{w}_i$ is the linearly-ranked weight for a given asset and $\beta_i^{\$}$ represents the currency beta to the USD. The other constraints are the same as with cross-sectional Momentum.

4.3.5 Portfolio tranching

Figure 23 is in line with our prior findings; slower rebalancing generally outperforms faster rebalancing. As such, we opt for annual rebalancing, tranched monthly, in the case of the time series portfolio construct.

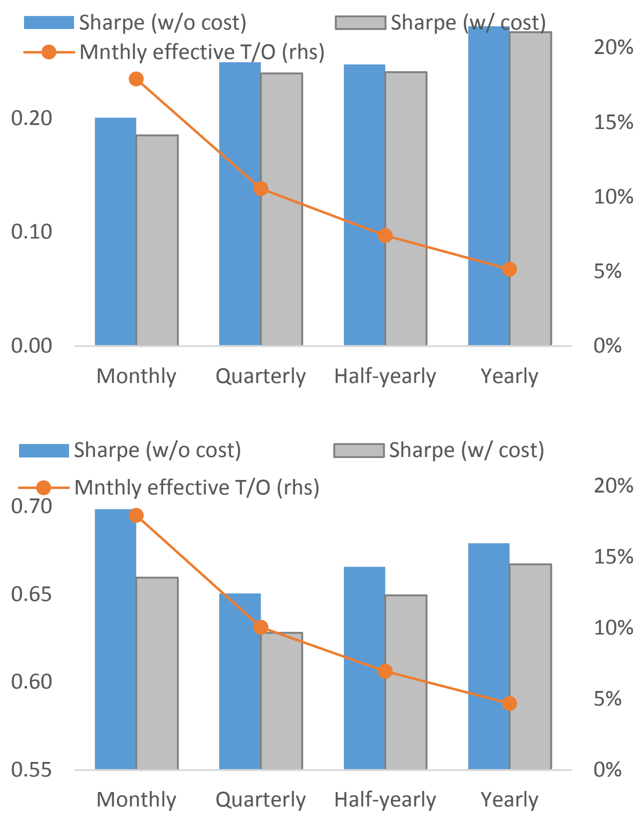
The cross-sectional portfolio is, in contrast, rebalanced monthly, but we do so only in order to ensure our hedge ratios are sufficiently adaptive and therefore allow for market neutrality. Note that, due to the nature of our data sources, monthly is also our fastest available rebalancing frequency.

4.3.6 Backtest results

As is the case with prior factor portfolios, the time series and cross-sectional implementations complement one another. As further highlighted by the rolling correlations the time series portfolio bears significant USD directionality while the cross-sectional portfolio is largely market neutral.

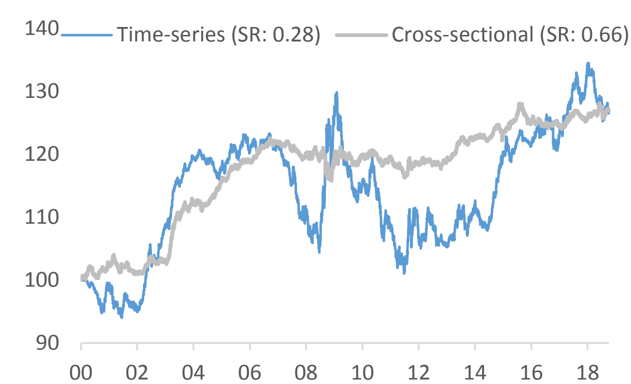
Key to the Value factor, however, is the convexity exhibited by the time series construct. This feature is particularly attractive, and often sought after in FX Value portfolios. Its defensiveness - particularly to variations in the US dollar - can be particularly attractive for currency risk management programmes.

Figure 23: Tranching results (time series followed by cross-sectional constructs) – Fundamental Value portfolio



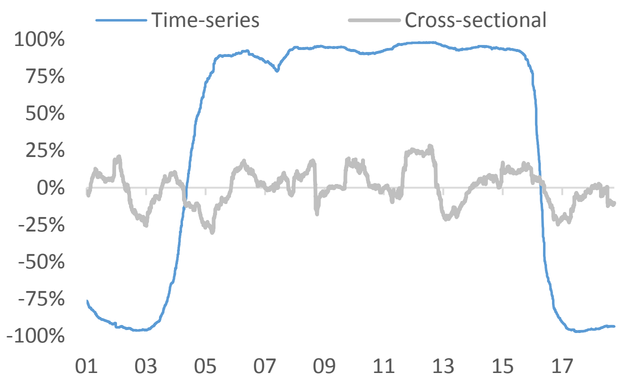
Source: Deutsche Bank

Figure 24: Time series and market neutral Value backtested returns (net of transaction costs)



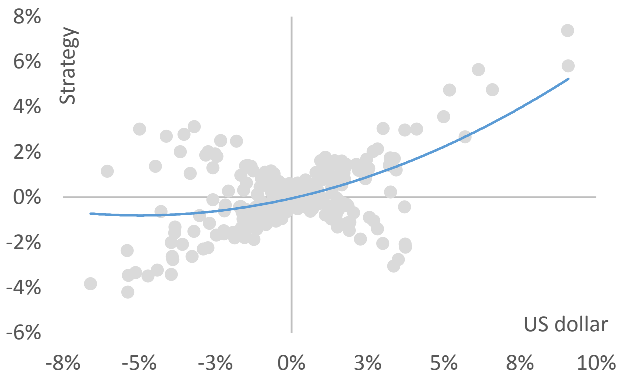
Source: Deutsche Bank

Figure 25: Return correlations to the US dollar, 1Y rolling



Source: Deutsche Bank

Figure 26: Convexity – monthly Value portfolio returns against monthly US dollar returns



Notes: US dollar proxied by the PC1 of the USD/FX basket, as before. Source: Deutsche Bank

4.4 Rates Momentum spill-over

Short-term, or "fast" factors are our final area of coverage. Not only Section 2 alluded to the presence of short-term patterns, but the liquidity and depth of foreign exchange markets also suggests we should be able to capture them systematically.

Most of the signals in this category point towards short-term momentum. But not only they do not correlate heavily with short-term price action momentum, they also exhibit certain attractive characteristics not seen in price action signals – namely smoother data and less memory dependency.

We start with our *momentum spill-over* (MSO) signal. It is based on the argument that interest rates have predictive power in FX, as they directly reflect perceived shifts in monetary policy and inflation targets.[73] Given the strong predictive power of interest rate spreads on FX – as per our discussion on Carry – it is no surprise that its first derivative also contains useful information, even if it decays fast.

4.4.1 Signal generation

The signal, launched in Natividade et al. (2015), is built using the following steps:

(1) Calculate the interest rate spread between a given country and the US as per 6-month FX forwards. Record the change over the past 21, 42 and 63 business days, and annualise these changes.

(2) Calculate the annualised volatility of daily changes in 6M interest rate differentials, using the same lookback windows as in Step (1).

(3) Calculate the ratio of changes, as per Step (1), over volatility, as per Step (2), for all 3 windows, and take the average of these 3 ratios.

(4) Apply noise control by taking the 1-month average of the measure calculated in Step (3). This average is our signal, S_i^{MSO}.

As with our Value factor, the spill-over signal requires further treatment in order to be applicable to a wide pool of currency pairs. This is because the *sign* of the relationship between rates momentum and FX returns often depends on *country risk premium*: the higher the risk, the more that rising rates hurt the currency. That identity, explained in detail in Natividade et al. (2015), goes in opposite direction to the pattern we are trying to capture: that relative central bank hawkishness should lead to relative currency appreciation.

As such, we implemented a filter that removes currency pairs from the investment pool when needed. We calculate the 1-year correlation between (past) 1-day interest rate spread moves and (future) 1-day FX returns for each currency pair; if the correlation is negative, that pair is removed.[74]

4.4.2 Signal predictive power

Figure 27 shows how the modified information coefficients in our momentum spill-over signal change across horizons. Not only it decays fast, but the levels

[73] The interested reader should refer to Rosenberg (2002), Chen et al. (2009), Ang et al. (2010), and Georges et al. (2014

[74] This is a slight modification from the original signal from Natividade et al. (2015). We formerly ranked all assets according to the signal, allocated capital according to the ranks, and then re-distributed the capital only to those assets that passed the filter. The ranking now only takes place after filtering.

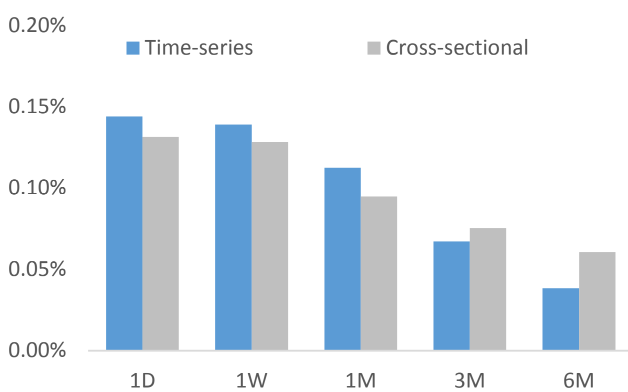
are generally low. This confirms both the short-term and momentum nature of the signal. Interestingly, the time series construct exhibits a shorter term profile than the cross-sectional construct.

4.4.3 Weighting schemes: time series and cross-sectional

The spill-over signal resembles traditional Momentum in terms of modified information coefficients, which are also low, and in nature, as it also points towards continuation. These similarities led us to move away from our original weighting scheme, introduced in 2015[75], and instead implement the same approach as introduced in Sections 4.1.4 and 4.1.5. Other arguments also favour an implementation that focuses on signal sign and not on signal size:

- Low MICs imply that signal intensity is less informative.
- Portfolio turnover is already high due to the fast nature of this signal. The weighting schemes applied in our Momentum portfolios help reduce unnecessary turnover, and therefore cut costs.

Figure 27: Momentum spill-over signal – modified information coefficient



Source: Deutsche Bank

At a given rebalancing date, the weight allocated to a given asset in the time series Momentum Spill-Over portfolio is calculated as follows:

$$w_i = sign(s_i^{MSO}) \times \frac{1/\sigma_{r_i}}{\sum_{j=1}^{N} 1/\sigma_{r_j}}$$

As for the cross-sectional MSO portfolio, the asset weights are calculated using the same approach as with the standard Momentum portfolio. In other words:

(1) We rank currency pairs based on the signals estimated in Section 4.4.1.

(2) We go long the top half and short the bottom half of assets in our pool, assigning equal weights to each asset such that the absolute sum of weights equals 100%. We opt for taking exposure to all assets so as to maximise factor exposure and avoid idiosyncratic risk.

(3) We re-adjust the weights from Step (2) such that the net beta to the US dollar is zero:

$\arg\min \sum_i^N (w_i - \tilde{w}_i)^2$, such that $\sum_i^N w_i \beta_i^{\$} = 0$. In this case, $\tilde{w}_i$ is the initial USD/FX weight and $\beta_i^{\$}$ represents the currency beta to the USD.[76] The other constraints are the same as with the factor portfolios described earlier.

4.4.4 Portfolio tranching

Rebalancing portfolios of fast factors is tricky as one needs to preserve signal entropy while also curtailing noise and costs.

On one hand, the fast signals primarily add value by adapting quickly to changing market conditions. They make the total portfolio more adaptive, and therefore keep the user from trying to accelerate other signals that are supposed to be slow.

On the other hand, fast factors can be noisy and costly, and we need to address both issues. The first has already been covered in Section 4.3.1, as we apply a moving average to the original signal. But the second is also pertinent. Figure 28 shows significant decay in risk-adjusted returns after accounting for transaction costs, assuming daily rebalancing (i.e. no tranching).

We therefore opt for weekly rebalancing in both time series and cross-sectional constructs. This allows us to safeguard signal entropy, while also seeing a significant drop in average daily turnover and, therefore, costs. The weekly rebalancing also allows us to keep the hedge ratios in the cross-sectional portfolio adaptive, and therefore more market neutral.

4.4.5 Backtest results

The first clear finding from our backtests is that this factor produces worse expectancy than the others. That said, it also provides positive convexity, with Sortino ratios that are on average 1.4x the Sharpe ratios[77], which reflects the fast adaptivity desired in short-term factor

[75] Natividade et al. (2015) uses a non-linear ranked weighting scheme for capital allocation. The signal was only implemented in a cross-sectional format, and with no beta targets.

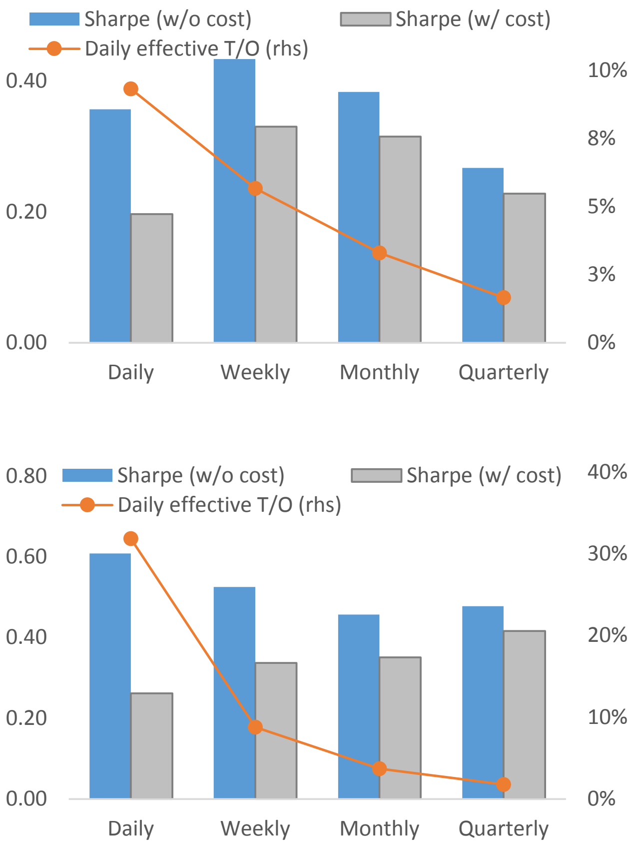
[76] Another alternative for beta neutralization involves estimating the USD-beta of both long and short baskets separately and using these as hedge ratios. This approach would however require originally allocating equal risk weights for each asset as opposed to equal USD weights.

[77] The backtested Sharpe ratios for the time series and cross-sectional MSO portfolios are, respectively, 0.33 and 0.34. The Sortino ratios are 0.46 and 0.48.

portfolios. The two constructs also complement one another.

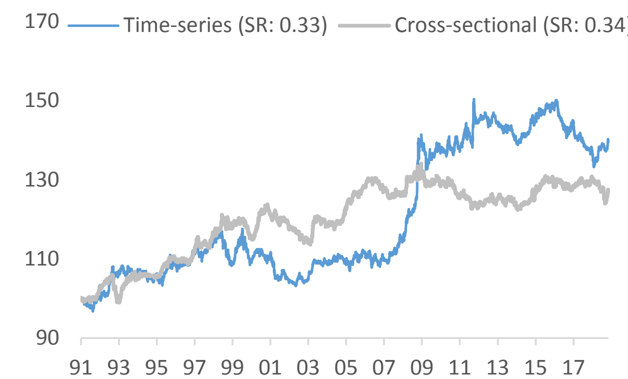
Finally, Figure 30 shows that constraining our beta exposures also led to market neutralisation even in shorter term factors. We note that the initial strategy from Natividade et al. (2015), despite being implemented under a cross-sectional scheme of *capital* neutrality, correlates more with the time series version of the new construct than the cross-sectional version.

Figure 28: Tranching results (time series followed by cross-sectional constructs) – Rates Momentum Spill-Over portfolio



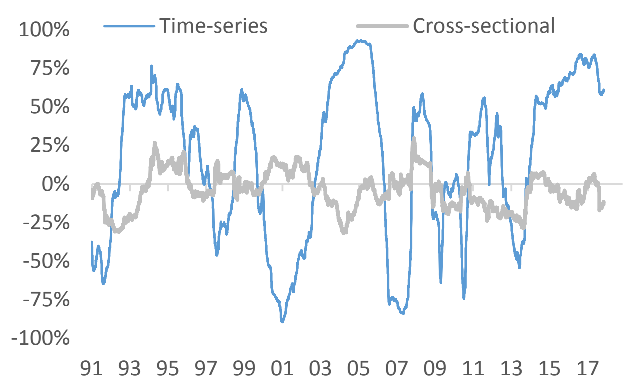
Source: Deutsche Bank

Figure 29: Time series and market neutral MSO backtested returns (net of transaction costs)



Source: Deutsche Bank

Figure 30: Return correlations to the US dollar, 1Y rolling



Source: Deutsche Bank

4.5 Positioning factors: COFFEE

We now move on to signals linked to investor positioning, based on exchange traded contracts and are hence publicly available.

Our first positioning signal is dubbed COFFEE[78]. It was introduced in Weng and Grover (2017) and is based on DTCC options flow data. It is based on findings from the FX literature - notably Evans and Lyons (2002) - that order flow is an important determinant of exchange rates. The premise is that so-called "smart money", or leveraged fund order flows, lead price action, and we use options volume data to proxy such order flow.

We base the signal on two assumptions, which are backed by an analysis of randomised trade samples with internal data:

[78] Categorised Option Flow in Foreign ExchangE.

- Distinct types of participants have distinct preferences for strikes. Funds seeking speculative opportunities and effective leverage favour higher delta strikes, whereas corporate hedgers tend to prefer lower delta options.[79]
- Most investors are net buyers rather than sellers of options.[80]

The signal therefore reflects our proxy for leveraged flow, using higher delta option volumes. We apply it to a subset of our original asset pool, namely USD exchange rates against G10, KRW, PLN, SGD, MXN, ILS, TRY, RUB and ZAR.[81]

4.5.1 Signal generation

As per Weng and Grover (2017), the signal for a given currency pair is calculated daily, as follows:

(1) We calculate option deltas for all European options expiring in less than one year[82], and select options whose (absolute) deltas range between 0.25 and 0.75.

(2) We calculate the difference between notional volumes, traded on aggregate over the past 4 weeks, of the calls and puts from Step (1). This smoothed measure controls for noise and gives us the base notional volume imbalance.

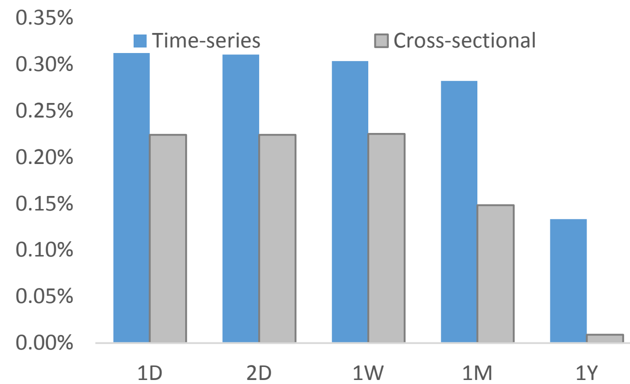
(3) We standardise the imbalance measure calculated from Step (2) by dividing it by its 1-year historical volatility. This gives us the signal, S_i^{COFFEE}.[83]

4.5.2 Signal predictive power

Figure 31 indicates that the COFFEE signal has been quite powerful, with MIC levels that are almost as high as those in the Carry factor and which are not matched by any of our other short-term signals.[84]

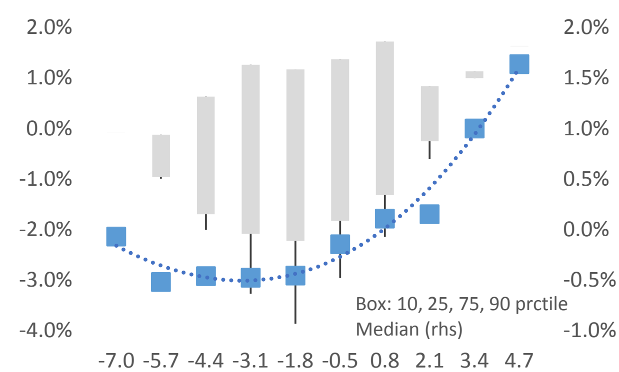
Figure 32 also confirms its relationship with Momentum. The more that calls are favoured over puts, the higher the signal value, and the more likely the asset is to rise over the next 1 month. It also suggests signal returns can be more convex when predicting US dollar depreciation.

Figure 31: COFFEE signal – modified information coefficient



Source: Deutsche Bank

Figure 32: COFFEE signal – relationship between signal level and future 1-month asset returns



Source: Deutsche Bank

4.5.3 Weighting schemes: time series and cross-sectional

We apply the same weighting schemes as those from the Momentum Spill-Over portfolios, thereby focusing primarily on turnover control and cost reduction. This also implied under-utilising signal intensity, an unfortunate side effect given the high MICs shown in Section 4.5.2.

[79] As supporting evidence, Weng and Grover (2017) documented that volume data on higher delta options correlated more positively with CFTC futures data associated with non-commercial participants.
[80] This may seem like a stronger assumption, but note that the variance risk premium in foreign exchange is much lower than in other asset classes. Not only was it backed by randomised internal trade samples, but also frequently observed in our option surveys as published in the DB Global FX Gamma Reports since 2008 (see, for instance, Natividade (2008)).
[81] While CNH was in the original pool, we removed it from this research paper as it is not part of the other signals.
[82] And not expiring at the date of signal evaluation, i.e. non-expiring options.
[83] The COFFEE signals are available on Bloomberg.
[84] While it doesn't reduce its value-add, one could argue the high MICs are due to its short-term history and less straight forward access. For a review of the typical life cycle of a new signal, see Ilmanen (2011).

At a given rebalancing date, the weight allocated to a given asset in the time series COFFEE portfolio is calculated as follows:

$$w_i = sign(s_i^{COFFEE}) \times \frac{1/\sigma_{r_i}}{\sum_{j=1}^{N} 1/\sigma_{r_j}}$$

As for the cross-sectional COFFEE portfolio, the asset weights are calculated using the following steps:

(1) We rank currency pairs based on the signals estimated in Section 4.5.1.

(2) We go long the top half and short the bottom half of assets in our pool, assigning equal weights to each asset such that the absolute sum of weights equals 100%. We opt for taking exposure to all assets so as to maximise factor exposure and avoid idiosyncratic risk.

(3) We re-adjust the weights from Step (2) such that the net beta to the US dollar is zero:

arg min $\sum_i^N (w_i - \tilde{w}_i)^2$, such that $\sum_i^N w_i \beta_i^{\$} = 0$. In this case, $\tilde{w}_i$ is the initial USD/FX weight and $\beta_i^{\$}$ represents the currency beta to the USD.[85]

Note that we keep the asset and portfolio boundary constraints as before in both time series and cross-sectional constructs.

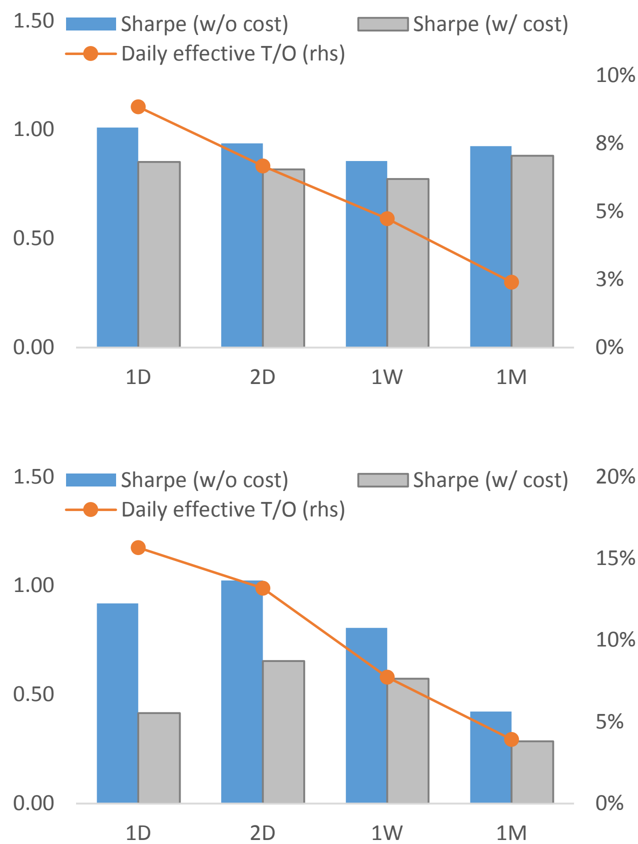
4.5.4 Portfolio tranching

We opted for weekly rebalancing, with daily tranching, as in line with our Momentum spill-over portfolios. Figure 33 suggests that a slightly faster rebalance would lead to higher risk-adjusted returns, but not enough to compensate for the turnover pick-up.

4.5.5 Backtest results

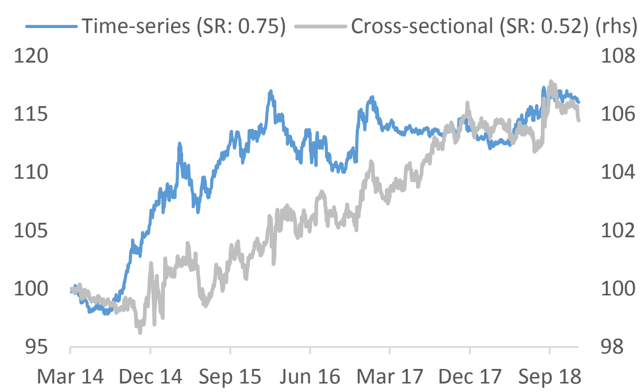
As with prior factor portfolios, Figure 34 suggests that the COFFEE time series and cross-sectional portfolios complement one another. But perhaps more important is the fact that the time series factor portfolio has been primarily long USD for much of the backtest period. Figure 35 shows the weighted average COFFEE signal over time; given that asset weights only account for signal sign (and not size) it is no wonder that the time series portfolio has been heavily correlated to the PC1 of the asset class[86].

Figure 33: Tranching results (time series followed by cross-sectional constructs) – COFFEE portfolio



Source: Deutsche Bank

Figure 34: Time series and market neutral COFFEE backtested returns (net of transaction costs)

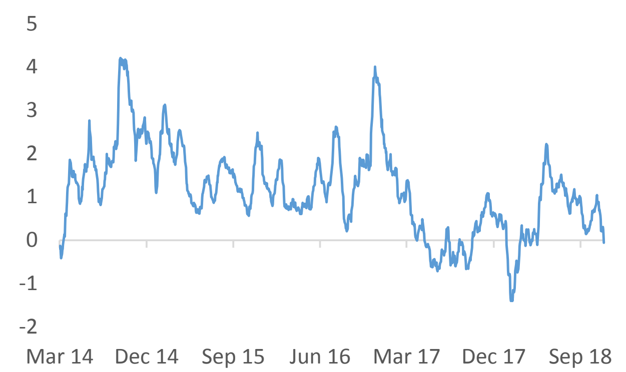


Source: Deutsche Bank

[85] Another alternative for beta neutralization involves estimating the USD-beta of both long and short baskets separately and using these as hedge ratios. This approach would however require originally allocating equal risk weights for each asset as opposed to equal USD weights.

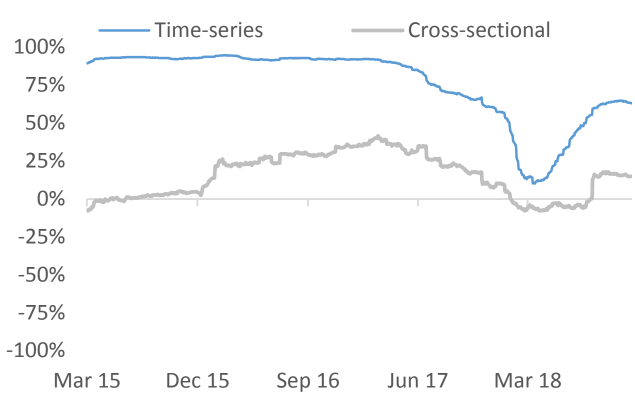
[86] We note that adjusting positions for signal intensity would have led portfolio turnover to double.

Figure 35: Weighted US dollar COFFEE signal



Source: Deutsche Bank

Figure 36: Return correlations to the US dollar, 1Y rolling



Source: Deutsche Bank

4.6 Positioning factors: CFTC

Staying within the context of market positioning, our final short-term signal is based on open interest data on exchange-traded currency futures contracts as recorded by the Commodity Futures Trading Commission (CFTC). The motivation comes from studies suggesting that CFTC data is a good proxy for the investor community as a whole, and therefore potentially useful in price prediction.[87]

We start with 2 behavioural-based priors:

- First order dynamics – i.e. net positioning – by non-commercial participants point towards price momentum, reflecting the likelihood that this class of market participants are trend followers.
- Second order dynamics – in other words, changes in these positions – point towards price reversal. This reflects the likelihood that abnormally high flows lead to overshoot and subsequent retracement in asset prices.

Testing these priors can be challenging due to how CFTC data is made publicly available. Weekly Commitment of Traders (COT) reports[88] are released on Friday at 15:30 EST with information related to prior Tuesday's close. Conservative backtesting therefore assumes the signal is executed the following Monday, a delay of 4 business days. Further, the low frequency with which the data is made available – one weekly snapshot – also introduces discretisation error. The two shortcomings are especially detrimental to signals that decay fast, as is arguably the case with short-term reversals – our second prior above.

As is the case with the COFFEE signal, our CFTC signals are applied to a subset of the original pool of assets, due to data availability. The assets are: EUR/USD, AUD/USD, GBP/USD, USD/CAD, USD/JPY, NZD/USD, USD/CHF, USD/BRL, USD/MXN and USD/RUB.

4.6.1 Signal generation

We create 2 signals from the CFTC data: a continuation and a reversal signal. Both are calculated once a week, as the COT data is made available.

The continuation signal for a given asset is calculated as follows:

$$L_i^{NC} = \sum_{h=0}^{3} l_{i,t-h}^{NC}$$

$$S_i^{NC} = \sum_{h=0}^{3} s_{i,t-h}^{NC}$$

$$s_i^{CFTC,C} = \frac{L_i^{NC} - S_i^{NC}}{L_i^{NC} + S_i^{NC}}$$

where $l_{i,t}^{NC}$ represents long positions for week t from non-commercial traders, sometimes known as "large speculators", and $s_{i,t}^{NC}$ represents short positions from the same non-commercial traders. Note that we apply a 4-week sum as noise control measure, just as is the case in the COFFEE signal introduced earlier.

[87] Upperman (2006), in his book, discussed various ways to understand and use COT data through different trading strategies. Sanders et al. (2006) investigated the forecasting ability of CFTC's Commitments of Traders data. He found that traders' positions do not show a systematic tendency to lead returns and the positions follow returns. Wang (2003) found that over intervals from one to twelve weeks, that non-commercial traders' positions forecast price continuations and commercial traders forecast price reversals.

[88] The report provides a breakdown of aggregate positions held by three different types of traders: "commercial traders," "non-commercial traders" and "non-reportable." "Commercial traders" are sometimes called "hedgers", "non-commercial traders" are sometimes known as "large speculators," and the "non-reportable" group is sometimes called "small speculators".

The reversal signal for asset i is calculated using the following steps:

(1) Calculate the z-score of the current net position ($l_{i,t}^{NC} - s_{i,t}^{NC}$ above) for the asset, using 3 lookback windows for z-score estimation: 1, 2 and 3 months.

(2) Calculate the average of the 3 z-scores from Step (1).

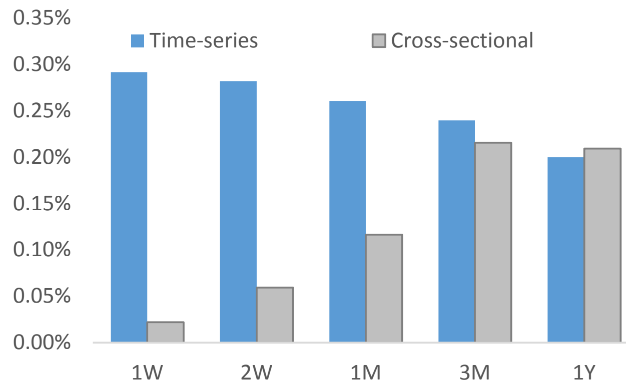
(3) Calculate the volatility of daily asset returns over the past 6 months. The final signal, $s_i^{CFTC,R}$, is the ratio of the average z-score from Step (2) over asset volatility, multiplied by -1 so as to represent reversal and not continuation. We apply no noise control to this signal so as to preserve its speed.

4.6.2 Signal predictive power

As with all other cases, we estimated modified information coefficients introduced in Section 3 for the CFTC signals above. The MICs reiterate our priors: the first signal points to continuation, or momentum, and the second to reversals. Three other observations are worth noting:

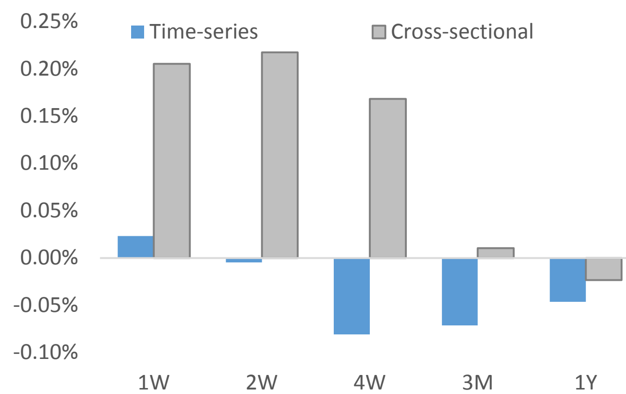
- The time series version of the reversal signal does not exhibit any predictive power. It highlights that this reversal factor should be captured as a *relative* phenomenon. This is shown in Figure 38.
- The cross-sectional version also shows a clear difference in speed: the reversal signal is faster while the continuation signal is slower. This is shown in Figure 39.
- Its slower nature favours the continuation signal, as it becomes less vulnerable to discretisation error and reporting lag. We also note that its MIC values are higher than what we found in the price action momentum signal, which reiterates our argument that price action signals coming from alternative market data may at times be better than those coming from price action data. A comparison between Figure 37 with Figure 9 also highlights this point.

Figure 37: CFTC continuation signal – modified information coefficient



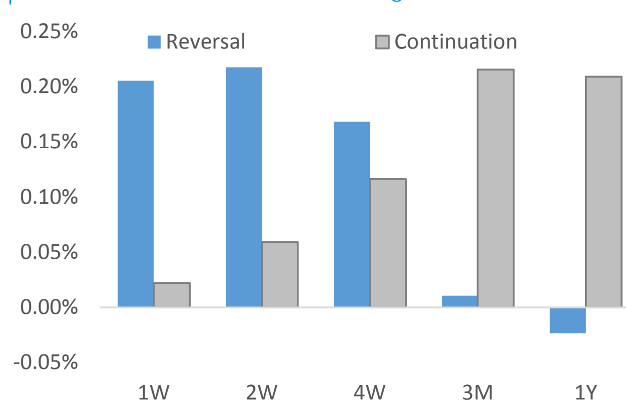
Source: Deutsche Bank

Figure 38: CFTC reversal signal – modified information coefficient



Source: Deutsche Bank

Figure 39: MICs for cross-sectional versions of the CFTC continuation and reversal signals



Source: Deutsche Bank

4.6.3 Weighting schemes: time series and cross-sectional

The weighting schemes used in our CFTC continuation signals are the same as those applied in other short-term signals: inverse volatility weights for the time series implementation, and equal notional weights, with a target beta to the USD, in the cross-sectional version.

With regards to the CFTC reversal signal, however, we remove the time series construct – Section 4.6.2 shows it lacks predictive power – and remove the beta target constraint from the cross-sectional construct, as the unconstrained version has already been historically market neutral.

The weighting scheme for our time series continuation signal is calculated as follows:

$$w_i \ = sign(s_i^{CFTC,C}) \times \frac{1/\sigma_{r_i}}{\sum_{j=1}^{N} 1/\sigma_{r_j}}$$

The weighting scheme for the cross-sectional CFTC signals is calculated as follows:

(1) We rank currency pairs based on the signals estimated in Section 4.6.1.

(2) We go long the top half and short the bottom half of assets in our pool, assigning equal weights to each asset such that the absolute sum of weights equals 100%. We opt for taking exposure to all assets so as to maximise factor exposure and avoid idiosyncratic risk.

(3) Specifically in the case of the CFTC continuation portfolio, we re-adjust the weights from Step (2) such that the net beta to the US dollar is zero:

$\arg\min_{w} \sum_i^N (w_i - \widetilde{w}_i)^2$, such that $\sum_i^N w_i \beta_i^{\$} = 0$. In this case, $\widetilde{w}_i$ is the initial USD/FX weight and $\beta_i^{\$}$ represents the currency beta to the USD.[89]

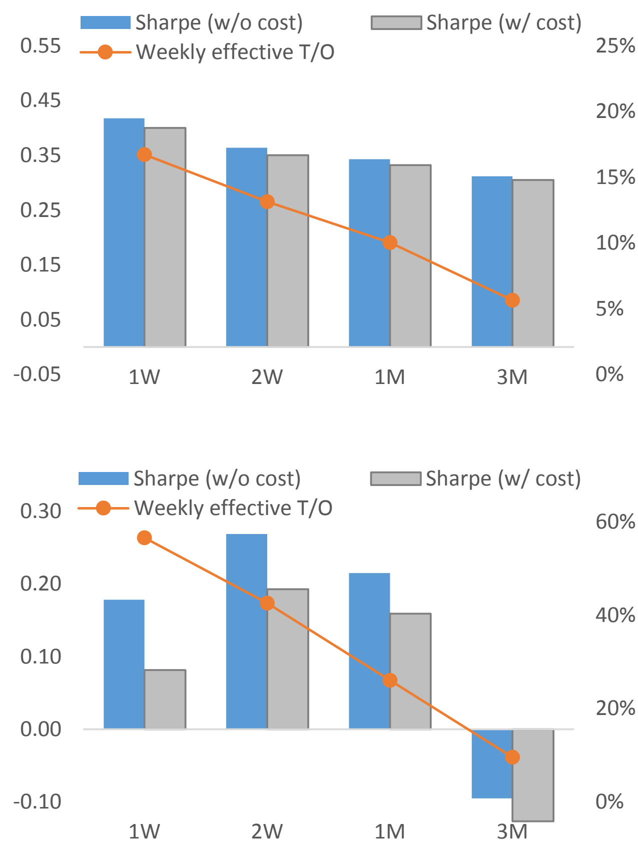
Note that we keep the asset and portfolio boundary constraints as before in both time series and cross-sectional constructs.

4.6.4 Portfolio tranching

Figure 40 plots the effects of different rebalancing windows, all tranched weekly, on performance and turnover for both CFTC signals, using both time series and cross-sectional implementations.

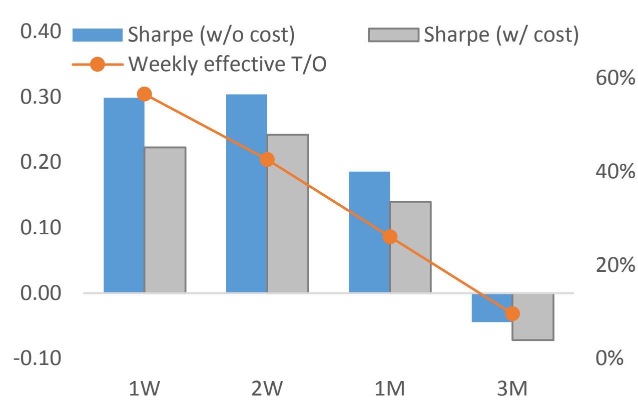
The rebalancing effects do not look highly significant, but the fast overall nature of this signal leads us to favour weekly rebalancing. This keeps it consistent with our other short-term factor portfolios.

Figure 40: Tranching results (time series followed by cross-sectional constructs) – CFTC continuation portfolio



Source: Deutsche Bank

Figure 41: Tranching results – CFTC reversal portfolio



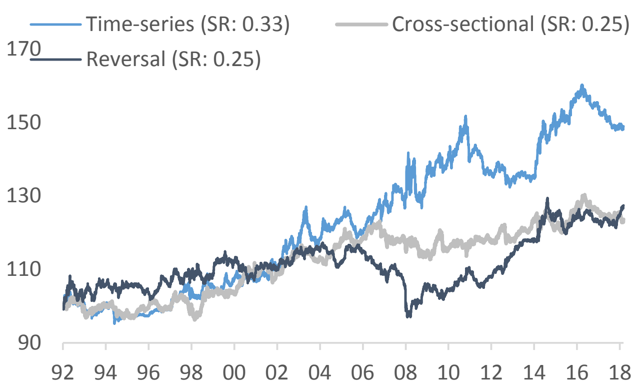
Source: Deutsche Bank

[89] Another alternative for beta neutralization involves estimating the USD-beta of both long and short baskets separately and using these as hedge ratios. This approach would however require originally allocating equal risk weights for each asset as opposed to equal USD weights.

4.6.5 Backtest results

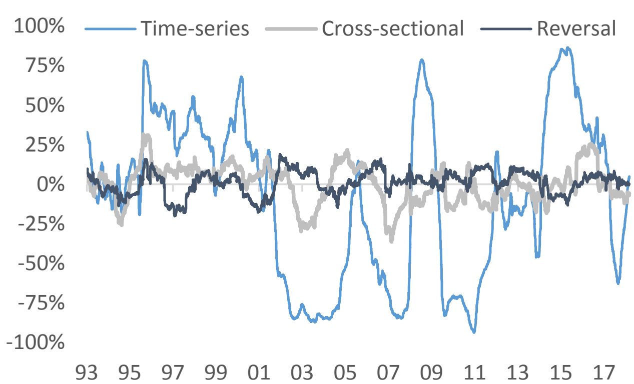
Figure 42 shows the backtested results of our 3 qualifying CFTC porttfolios, and Figure 43 shows how they correlate to the broad US dollar over time.

Figure 42: Time series and cross-sectional CFTC backtested returns (net of transaction costs)



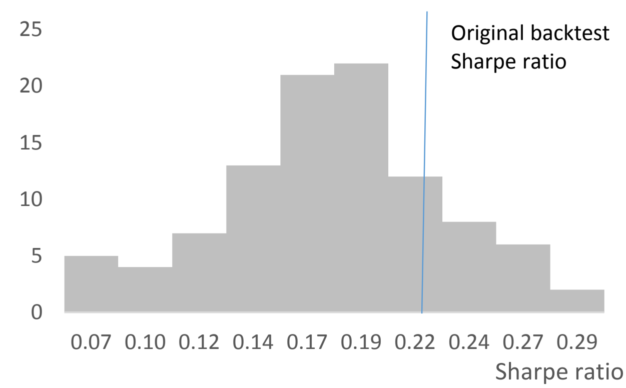
Source: Deutsche Bank

Figure 43: Return correlations to the US dollar, 1Y rolling



Source: Deutsche Bank

Figure 44: Distribution of Sharpe ratio estimates for the CFTC reversal portfolio after 100 simulations with bumped signals (bump size = 5th percentile)



Source: Deutsche Bank

4.6.6 Discretisation risk in the CFTC reversal portfolio

As we highlighted earlier, the fast decay in our cross-sectional reversal signal raises concerns given that CFTC data can only be snapped weekly. This rewarded an extra exercise to evaluate the risk of discretisation errors in the way the signal is built.

In order to test for this risk, we conducted an exercise where we randomly bumped the original reversal signal for each asset (and for each rebalancing date) by a small fixed quantity, which could be interpreted as sampling error.[90] The exercise was repeated for 100 simulated "backtests", thus providing us with a new distribution of Sharpe ratios.

The results of this exercise suggest that we cannot ignore the risk of discretisation error. After accounting for costs, the interquartile range of the distribution of Sharpe ratios sits at 0.19-0.21, and the backtested Sharpe ratio using the original signals is at 0.22 (85th percentile). If we change the bump assumptions to a slightly wider random number[91], the interquartile range becomes 0.15-0.21 and the backtested Sharpe ratio moves to the 78th percentile. In other words, slight changes in our estimate of market positioning - which can occur as we snap the data at a low frequency - may have meaningful effects on our factor portfolio. As such, we suggest exercising caution when allocating capital to this particular reversal signal.

[90] Equal to the 1st percentile of the distribution of absolute signal levels.

[91] 5th percentile instead of the 1st percentile. Note that we also applied the same exercise in the cross-sectional CFTC momentum signal as a check, and the results suggest there is far less discretisation risk in that case.

5. Currency Risk Management

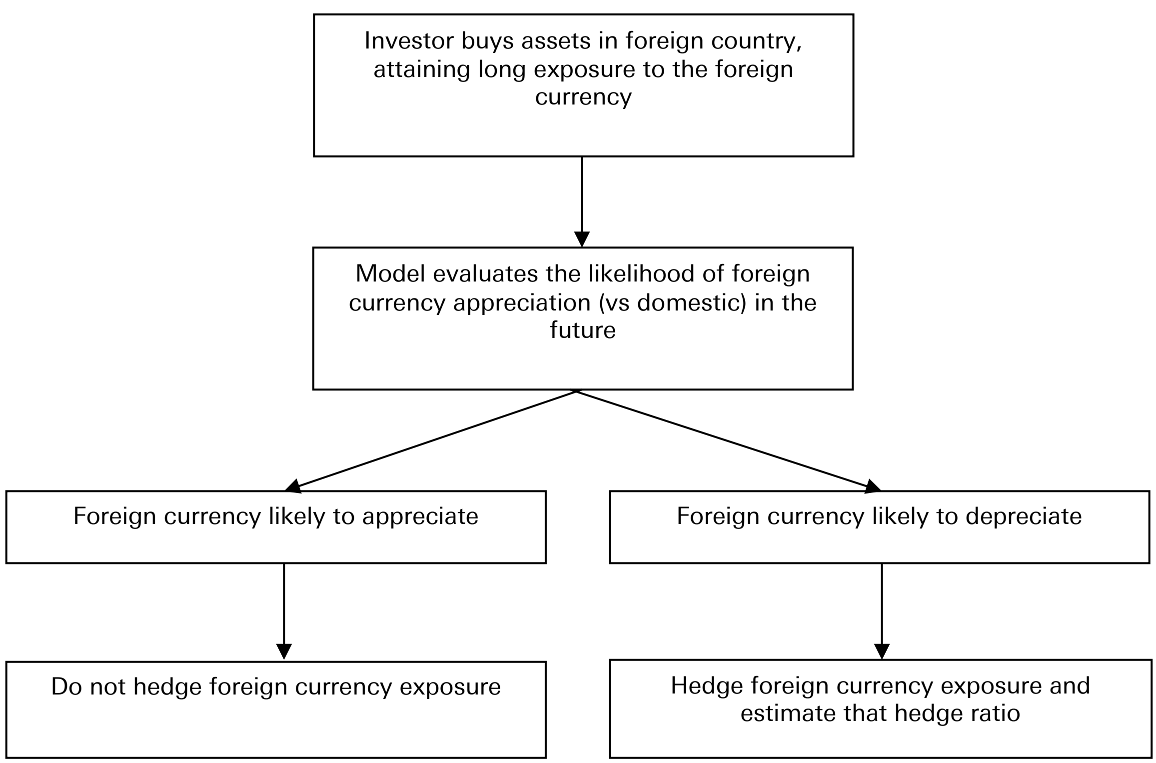
Managing currency risk is of key interest to cross-border investors. Poor management can negate a large portion of the gains from diversifying into a portfolio of foreign assets.

In addition, the immediate alternative – cancelling out currency risk through forward contracts – can be sub-optimal. It may not only remove economic gains, but also *increase* the risk in the total portfolio.

A good example is that of the Australia-based investor who buys Japanese equities and is therefore short AUD/JPY. The negative correlation between FX and equity exposures makes it such that being un-hedged is more risk-reducing to the combined position than neutralizing FX risk through AUD/JPY forwards. A sell-off in Japanese equities typically coincides with a weaker AUD (versus the JPY), and the natural short AUD/JPY position, if un-hedged, cushions the losses coming from Japanese equities. As such, being un-hedged would have offered a better risk profile.

This section outlines our new Informed Dynamic Currency Hedging (IDCH) framework. The hedging decisions are based on the following flow process:

Figure 45: Hedging flow process



Source: Deutsche Bank

Currency hedging has also received significant treatment in both academic and industry literature, of which we reference Campbell et al (2009), Brown and Zhang (2012), Brehon (2013), Chen et al (2013), Saravelos and Harvey (2013), Karolyi and Wu (2017), Bucher (2017), Opie et al (2018). There are 3 steps to our IDCH framework: risk estimation, return estimation, and hedge ratio estimation. The first part was outlined in Section 1.2, and hence we focus on the latter 2.

5.1 Return estimation

Predicting whether a foreign currency is likely to rise or fall should be an integral part of the FX hedging exercise – the more likely it is to rise, the less likely one is to hedge a (long) exposure to it. Keeping in line with hat thought, we use the investment factors from Section 4 as our predictors. But in order to ensure all currency pairs in the original pool are covered, we also focus on a smaller set: Momentum Spill-Over, Carry and

Momentum, and Value. These cover short, medium and long-term horizons respectively.

In each case, we take the weights built using the *time series* construct to define each factor's directional view on a given currency. We use, therefore, the weights defined in Section 4.4.3 for the Momentum Spill-Over factor, Section 4.1.4 for the Momentum factor, Section 4.2.3 for the Carry factor and Section 4.3.3 for the Value factor.

We opt for the time series weights so that their sign directly reflects the sign of the respective signals. In other words, we do not force long-short weights as is typical of cross-sectional strategies. This is in order to avoid positions that go against the direction of the original signal. If we expect all foreign currencies to appreciate against the USD, for instance, we should not hedge any of those exposures, as opposed to having half of them un-hedged (those that we are most bullish) and half hedged (those that we are least bullish).

Having defined our input factors, the preliminary currency weight at a given rebalancing date is the simple average of the individual factor weights:

$$w_{i_t}^{Prelim} = \frac{\sum_q^Q w_{i_t}^{(q)}}{Q}$$

where $Q = 4$ is the number of weights applicable to currency i.

5.2 Estimating hedge ratios

Having defined our risk and return estimates, we are now ready to define our hedge ratios; in other words, the weights defining how much the investor should go short each foreign currency in order to hedge the long exposure naturally incurred when she bought equities from those countries.

Note that we do not apply leverage in the methods introduced here. In other words, the investor cannot go long the foreign currency in the FX hedge portfolio – she is already long FX in the equities portfolio. Further, the size of the short position cannot exceed the size of the respective long exposure from the equities portfolio.

We present 4 methods, which vary according to complexity. The first 2 methods build hedge ratios on a currency-by-currency basis, therefore not accounting for the interactions between currencies – and between currencies and equities – in the portfolio. The final 2 methods apply a basket approach, thereby evaluating all joint risk exposures before deciding on the final hedge portfolio. The first 2 methods tend to be in line with the thought process of corporate hedgers, while the latter 2 tend to be more popular with institutional investors.

5.2.1 Method 1: sign-weighted IDCH

The first method is the simplest, as it focuses only on the sign (and not the size) of the individual factor weights.

This method has 2 variations, or "schemes": the proportional hedge ratio and the aggregate hedge ratio. The first assesses the proportion of the bearish signals to the total number of signals, while the second calculates the sum of the signs of all signals.

In other words, the first scheme is as follows:

$$w_{i_t}^H = \frac{1}{Q}\sum_{q=1}^{Q} \mathbf{1}_{\{w_{i,t}^{(q)}<0\}}$$

The second scheme is as follows:

$$w_{i_t}^H = \begin{cases} 1 \; if \; \sum_{q=1}^{Q} sign(w_{i,t}^{(q)}) < 0 \\ 0 \qquad\qquad otherwise \end{cases}$$

The first scheme is more conservative as the investor stays hedged most of the time, at varying quantities, while the second approach is more aggressive.

5.2.2 Method 2: size-weighted IDCH

The second method accounts for factor size; in other words, it also evaluates how much each factor favours a particular foreign currency. This methods has an element of "relativity" to it, as each factor allocates a finite amount of capital across currencies depending on which ones it favours. That said, the hedge ratios are still calculated on a currency-by-currency basis.

As before, we introduce 2 schemes. The first scheme is calculated as follows:

$$w_{i_t}^H = \frac{1}{\sum_q^Q \left|w_i^{(q)}\right|} \times \sum_{q=1}^{Q} w_i^{(q)} \times \mathbf{1}_{\{w_{i,t}^{(q)}<0\}}$$

The second scheme is calculated as follows:

$$w_{i_t}^H = \begin{cases} 1 \; if \; \sum_{q=1}^{Q} w_{i,t}^{(q)} < 0 \\ 0 \qquad otherwise \end{cases}$$

5.2.3 Methods 3 and 4: size-weighted FX-only IDCH and full IDCH

Method 3 builds from the earlier methods in that not only it takes information from our investment factors, but it also evaluate the co-movements between the currencies that need hedging. It can be applied to corporations with multi-national currency exposure.

Method 4 goes a step further and adds the relationship between the pool of currencies and the portfolio of assets that the market participant may be exposed to, thereby being applicable to international equity and fixed income portfolio investors. The steps to both methods follow below.

We define S_{i_t} as the USD price per unit of foreign currency i at time t, and P_{i_t} as the price of the asset (including dividends) in the foreign currency i at time t.

The unhedged return on that foreign investment measured from time $t-1$ to t is given by:

$$r_{i_t}^{uh} = \frac{P_{i_t} * S_{i_t}}{P_{i_{t-1}} * S_{i_{t-1}}} - 1$$

$$r_{i_t}^{uh} = (1 + r_{i_t}^{A})(1 + r_{i_t}^{S}) - 1$$

where $r_{i_t}^{A}$ and $r_{i_t}^{S}$ are one-period returns on the foreign asset (in local currency) and the currency spot (expressed in USD per unit of foreign currency – in other words, FX/USD).

For case 3, we ignore asset returns, so the unhedged return is simply the currency return: $r_{i_t}^{uh} = r_{i_t}^{S}$.

The one-period return on a long FX forward contract expressed as a function of the current spot exchange rate is defined as:

$$f_{i_t} = \frac{S_{i_t} - F_{i_{t-1}}}{S_{i_{t-1}}}$$

where F_{i_t} denotes the one-period forward dollar price of foreign currency i.

The hedged return on investment in country i is therefore given by:

$$r_{i_t}^{h} = r_{i_t}^{uh} - h_{i_t} f_{i_t}$$

where h_{i_t} is the hedge ratio of the investment in country i at time t. We define $h_{i_t} \in [0,1]$, therefore allowing each foreign currency exposure to be hedged up to 100%. The investor invests in N+1 assets, where "+1" represents the domestic (USD-denominated) asset, and is exposed to N foreign currencies with the USD as base currency.

Let $R = [r_{1_t}^{uh}, r_{2_t}^{uh}, \dots, r_{N_t}^{uh}, r_{N+1_t}]'$ be an (N+1) x 1 vector of unhedged returns in USD from all countries, with r_{N+1_t} being the return from the domestic (USD-denominated) asset.

W denotes an (N+1) x 1 vector of portfolio weights w_{i_t} with w_{N+1_t} being the weight allocated to the domestic asset. These correspond to the weights defined in Table 1, and in this context they vary according to the frequency that MSCI weights rebalance.

f denotes an N x 1 vector of forward currency returns f_{i_t}, and h is an N x 1 vector of hedge ratios h_{i_t}. The hedged gross portfolio return is given by:

$$R_{P_t}^{h} = W'R - h'(w \odot f)$$

In other words,

$$R_{P_t}^{h} = (W'R - w_h{}'f)$$

where w is an N x 1 vector of portfolio weights w_i excluding the weight of the U.S and $\odot$ represents element-by-element multiplication. w_h is an N x 1 vector of hedge positions (or hedge weights). These are the weights we solve for in our optimisation.

Note that the second term is subtracted from the first term because all hedge positions imply going short the foreign currency.

Representing the above equation differently,

$$R_{P_t}^{h} = (\sum_{i=1}^{N+1} w_{i_t} * r_{i_t}^{uh} - \sum_{i=1}^{N} w_{i,h} * f_{i_t})$$

In order to estimate the optimal hedge ratio, we solve for w_h to maximise the following objective function:

$$\arg\max_{w_h} \frac{w_h{}' w^{Prelim}}{\sigma_{R_P^h}}$$

or, put differently,

$$\arg\max_{w_h} \frac{\sum_{i=1}^{N} w_{i,h} * w_i^{Prelim}}{\sigma_{R_P^h}}$$

such that:

$$\sum_{i=1}^{N} w_{i,h} \le (1 - w_{N+1_t})$$

Finally, we also add a constraint[92] so that we do not hedge exposure to a foreign currency if that currency is expected to appreciate against the base currency (USD in the present case). In other words:

$$w_{i,h} = \begin{cases} 0, & w_i^{Prelim} > 0 \\ [0, w_{i_t}], & w_i^{Prelim} \le 0 \end{cases}$$

5.3 Results

We now document the results of various IDCH methods. Our baseline participant is an equity market investor long international equities with exposures equivalent to those of the MSCI World, as standardised in Table 46[93]. We start with the assumption that the investor is US-domiciled, and later also show results assuming the

[92] This constraint assumes full "alpha risk"; in other words, we do not differentiate between strong and moderate positive weights on the foreign currency. This condition, however, can be relaxed. One way is to modify the condition according to weight intensity thresholds. Another way would be to change the hedge ratio at the outside. An example of the latter could be that if the combined signals favour a currency then we allow to hedge that currency between 0 and 50%. Otherwise, if combined signals dislike a currency then we look for a hedge ratio between 50% and 100%.

[93] Note that we have removed exposures that are very small.

investor is based in Europe, Japan and Australia, but focus exclusively on Method 4.

Figure 46: MSCI World weights reference table

Countries	Weights	Std. weights
United States	50.65%	57.01%
Japan	7.80%	8.78%
United Kingdom	5.55%	6.25%
France	3.41%	3.83%
Canada	3.22%	3.62%
Germany	3.21%	3.61%
Switzerland	3.17%	3.56%
Australia	2.33%	2.62%
South Korea	1.80%	2.02%
Hong Kong	1.55%	1.75%
Taiwan	1.37%	1.55%
Spain	1.09%	1.22%
Sweden	0.97%	1.09%
Brazil	0.89%	1.00%
South Africa	0.80%	0.90%
Russia	0.39%	0.44%
Mexico	0.38%	0.43%
Poland	0.16%	0.18%
Turkey	0.13%	0.14%
Total	88.85%	100.00%

Weights current as of Q3 2017. Note that these weights change at every rebalancing date. Source: Deutsche Bank

In this exercise, we use 1-month forward contracts to hedge exposure to foreign currencies versus as given domestic currency. Similar to our approach in earlier sections, we rebalance our portfolio every month and apply tranches on a daily basis to reduce sampling error.

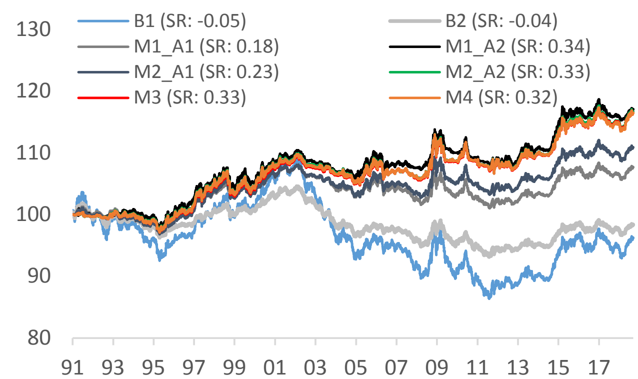
We compare our dynamic hedging methods with two benchmarks:

- A 100% static hedge: the investor uses 1M forwards to fully neutralise her foreign currency exposure; in other words, the size of each short position is equal to the natural (long) FX exposure in the equities portfolio.
- A 50% static hedge: the investor uses 1M forwards to hedge half of her foreign currency exposure. The 50% hedge is often called a "point of no-regret".

5.3.1 US-based investor

Figure 47 outlines the backtested performance of the hedge portfolios in the 4 methods proposed earlier, in addition to the two benchmarks.

Figure 47: Currency hedge portfolio backtests – transaction costs included



Source: Deutsche Bank

These results indicate the following:

- All IDCH methods outperform the benchmarks in the backtest. While the first benchmark hedge fully eliminates currency risk from the equities portfolio, it also suffers from periods of USD depreciation. The second benchmark, which applies a 50% hedge, reduces part of that underperformance.
- The more conservative alternative in our first IDCH method tracks the benchmarks more closely, given that it has less room to manoeuvre.
- Other methods outperform, which are more flexible and allow for the investor to better capture our investment factors and estimate cross-market (and cross-asset) risks. Methods that are more complex tended to yield better risk-adjusted backtested returns.
- Methods 3 and 4 are highly correlated to the first 2, despite also utilising our covariances to better manage the risk exposure. This suggests most of the value-add comes from the factors introduced in Section 4, and that the efficacy of the hedge programme depends heavily on that. This is intuitive due to the return-seeking nature of our objective function. Had we opted for a different utility target, the results could have been different.[94]

5.3.2 Non-US based investors

We now move onto investors domiciled elsewhere, and focus on Method 4 for currency hedging. As the reader would expect, co-movements between the domicile currency and international equities will lead to distinctly

[94] Another potential objective function seeks to minimise total portfolio variance: $\min_{w} var[r_A + r_{FX}(w)]$, with the same constraints as used earlier. This approach follows the premise that currency risks are not rewarded, but can be used to reduce total portfolio volatility and free risk capital that can be allocated elsewhere.

different conclusions depending on the country in question.

Our next investor of interest is Europe-based. Method 4 therefore accounts for how the Euro and global equities co-vary over time, in addition to utilising our predictive factors when deciding exposures. The backtests shown in Figure 48 suggest these would have made a particularly positive difference in the late 1990s and early 2000s.

Hedging global equity exposure for the Japan-based investor is also an important case study, due to the negative correlation between the JPY and global equities and the high cost of hedging due to low domestic interest rates. If unhedged, the Japanese investor suffers even more from global equity weakness; if hedged, they suffer from high hedging costs. Figure 48 shows that the IDCH Method 4 would have favoured being globally unhedged over long periods of time.

Finally, we present backtest results for the Australia-based investor, whose currency overlay challenges are often opposite to those of the Japanese investor. Not only the AUD is positively correlated to global equities, which cushions losses during risk aversion, but short AUD/FX positions are cheaper to hedge given the high domestic interest rates. In this case, Method 4 suggests hedging a greater proportion of the currency exposures historically as per high correlation with the first benchmark method.

6. Conclusions

This reports outlined a recipe for systematic investing in foreign exchange. We started by outlining the common variations and drivers of the asset class across different horizons. Once these drivers were understood, we then created a framework to assess how to optimally attain exposure for both absolute returns and currency hedging purposes. All the main implementation aspects – signal generation, aggregation, rebalancing and risk – were addressed carefully in each section.

We introduce 7 signals in this report:

- Rates spill-over momentum, DTCC positioning and CFTC positioning (momentum and reversal): these cover short-term price action and sentiment dynamics.
- Momentum and Carry: these have better predictive power medium-term horizons.
- Value: covering fundamental currency dynamics and whose impact spans over longer horizons.

Most signals are implemented through both time-series and cross-sectional constructs, therefore distinctly addressing the drivers of the US dollar and of other currencies. The two constructs are highly complementary to one another. Further, in currency hedging, we show 4 methods to achieve optimal currency exposure through the above factors, with implications to both corporates and institutional investors.

Figure 48: IDCH Method 4 currency hedging portfolios – Europe, Japan and Australia-based investors

Source: Deutsche Bank

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Appendix 1

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