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# Accessing Currency Returns Through Intelligent Currency Factors

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## ABSTRACT

In the early 2000s, the popularity of investing into currency alpha products and currency hedge funds began to grow. With this came the need for an independent means by which to assess currency alpha performance. Because there is no natural benchmark in the world of currencies, this led to the creation of currency "beta" indexes that were built to reflect the main trading styles used in the currency industry.

The primary goal of such beta or style indexes was to provide a way to objectively assess the performance of currency alpha managers. Investors increasingly saw the indexes as a cost-effective way of accessing currency returns and demand increased for investable versions.

The appeal of these indexes was their simplicity, transparency, and systematic nature. However, one major drawback of many investable currency beta indexes is their inability to react or adjust to changes in the risk environment. In addition, the majority of investable indexes currently in existence allocate equal trading weights to the currencies selected to trade regardless of the strength of the underlying trade signal. Both characteristics can lead to increased drawdowns and inferior performance.

In this paper, a methodology is presented for the construction of three "intelligent" currency beta factors based around the popular trading styles of carry, value, and trend/momentum together with a multi-style factor combining all three. The methodology is termed "intelligent" because we demonstrate how, in the case of the carry factor, applying a binary filter to determine risk environment and adjusting trade sizes in periods of risk aversion can lead to improved drawdown and enhanced performance statistics versus more naïve carry factors. In addition, for all three single-style factors we demonstrate how establishing a relationship between the resulting trade weight per currency and the magnitude of the underlying trade signal's information coefficient can enhance performance versus other currency beta factors that apply an equal trading weight per currency regardless of the strength of signal.


## CURRENCY: MORE THAN JUST A RISK PROVIDER?

The foreign exchange (FX) market is the largest and most liquid in the world with approximately $5.1 trillion traded a day.[1] What makes the FX markets unusual and unlike many other markets though, is the high proportion of participants such as central banks and companies that trade currency as a result of necessity as opposed to being motivated by returns. For example, Sarno and Taylor (2002) and Sager and Taylor (2006) argue that the currency markets are characterized by heterogeneous rather than homogenous participants who act on different information and risk tolerances than the common rationality and risk-neutral investor behavior that is commonplace in most other markets. This phenomenon can create market inefficiencies that in turn can create the potential for generating returns.

## THE MAIN DRIVERS OF CURRENCY RETURNS

During the 2000s, interest in currency as an asset class increased, which motivated many FX researchers to perform quantitative analysis in order to ascertain the main trading styles used by such players. Middleton (2005) and Pojarliev and Levich (2007) found that a large proportion of the returns generated by currency hedge funds could be explained by three trading styles, namely: carry, value, and trend/momentum.

### CARRY

Carry is based on the economic theory of uncovered interest rate parity (UIP) and, more specifically, the failure of the parity condition to hold empirically. The UIP theory asserts that the currencies of countries with higher interest rates should depreciate against currencies of countries with lower interest rates (Feenstra and Taylor 2008; Mishkin 2006). This in turn means that a risk-averse investor should be indifferent, from a returns' perspective, as to whether to deposit cash domestically or overseas. Or, put another way, the nominal interest rate on a domestic risk-free government bond should be equal to the nominal interest rate of a comparable foreign risk-free government bond plus the expected change in the nominal exchange rate between those two countries over the duration of the bond.

Under UIP, the forward rate of a currency pair should be an unbiased predictor of its future spot rate. However, empirically, the converse has been shown to be true. For example, Delcoure et al. (2003), Pojarliev (2007), and Engel (2016) found that currencies of countries with higher interest rates tended to appreciate against currencies of countries with lower interest rates. This relationship has become referred to commonly as the "forward rate bias" and has led to the popularity of the "carry trade" in which an investor buys a currency with a high interest rate and funds this by selling a currency with a lower interest rate, with the expectation that the former will appreciate against the latter.

*Although there is no fundamental economic reason why trends should exist in the currency markets, behavioral science suggests that herd mentality and investors' beliefs that the winners of the past will be the winners of the future may explain the behavior.*

### VALUE

Value is based on the economic premise of the "law of one price," or what is more commonly referred to as purchasing power parity (PPP). PPP states that a basket of goods in one country should cost the same as an identical basket of goods in another country with the exchange rate between those two countries being the mechanism by which such equilibrium holds.

Froot and Rogoff et al. (1995), Taylor and Taylor (2004), and Taylor (2006), for example, conclude that, over the shorter term, currencies may deviate from their long-run equilibrium or PPP values, but over the medium to long run, currencies tend to revert to fair value. This mean reversion opens the possibility for trading opportunities for currency because an investor can buy an undervalued currency and sell an overvalued currency with the expectation that each will, over time, revert to their fair values.

### TREND/MOMENTUM

The random walk theory states that the path a price follows cannot be predicted by knowledge of the path it took in the past. However, empirical evidence often suggests otherwise and that past returns can be useful in predicting future returns. In fact, trend-following/momentum has been one of the most popular forecasting strategies used within the currency markets. Although there is no fundamental economic reason why trends should exist in the currency markets, behavioral science suggests that herd mentality and investors' beliefs that the winners of the past will be the winners of the future may explain the behavior. Nonetheless, simple trend-following strategies have been shown to be profitable in the currency markets going back to Taylor (1990), LeBaron (1992), Levich and Thomas (1993), and more recently Toner (2014), Orfanakos (2016), and Rohrbach et al. (2017).

## CURRENCY FACTORS: KEY OBJECTIVES AND PARAMETERS

### OBJECTIVES

The key objective of a currency factor is to offer, in an investable form, a product that has been designed to reflect a key trading style used with the currency industry. Key to the success of such factors is that the strategies and rules underpinning the return streams need to be easy to understand and transparent. In addition, it is paramount that clarity also surrounds the construction of the factors with respect to which currencies can be traded and how trade signals are transformed into actual positions.

This section will cover the construction of the currency factors in terms of currency universe and trading frequency and the following section will discuss the systematic rules that underpin the trade signal generation.

### FACTOR PARAMETERS

#### *Currency universe*

We have created three currency factors that have been designed to encompass the styles of carry, value, and trend/momentum. With respect to the carry and value factors, the universe of currencies permissible for trading is the G10: Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK) all versus the U.S. dollar (USD).

The currency universe for the momentum factor is slightly different; it is concentrated on G4 currencies, namely: EUR, GBP, and JPY versus the USD. The reason for this concentration is two-fold: (1) generally trend/momentum strategies tend to perform better on currencies that exhibit fairly high buy-and-hold volatility; and (2) although currencies such as AUD, NZD, and CAD meet the high-volatility criteria, their price action tends to be driven much more by fundamentals.

#### *Trade generation*

For the purposes of the hypothetical back test of performance, we assume that trade signals are generated on the last business day of the month using data as of the 4 p.m. London close. All trades are placed against the USD using the one-month forward. The positions of each factor are held static throughout the month until new signals are regenerated at the next month-end and the positions are adjusted as necessary.

VOLUME 19
NUMBER 1
2019

## INTELLIGENT CURRENCY FACTORS SIGNAL AND TRADE GENERATION

We discussed above the economic rationale and theory behind the three main drivers of currency returns: carry, value, and trend/momentum. Here we demonstrate how we have developed these economic theories into the systematic trading rules that underpin each of the factors.

### THE INTELLIGENT CARRY FACTOR

#### *The rule*

A simple carry strategy buys the currency with the highest interest rate and sells the currency with the lowest interest rate. For example, at the end of June 2019 the one-month deposit rate in the United States was 2.38 percent and its equivalent in Europe was –0.41 percent. For a simple carry strategy, the resulting signal would be one that is short EUR and long USD.[2]

In theory, the interest rate differential (IDF) derived by comparing the London Interbank Offered Rate between two currencies should be equivalent to the carry implied from comparing the forward rate of the currency pair to its spot.

However, since the Great Financial Crisis (GFC) this relationship does not always appear to hold. The difference between the IDF and the carry implied from the forward rate often is referred to as the "cross currency basis" and it typically has been exaggerated in times of market stress.

Deriving a signal for carry based on one-month IDFs offers the benefit of simplicity, but the downside of such an approach is that it does not capture this anomaly. As such, the signals underpinning the carry factor have been derived by calculating the forward premium or discount to spot because this will ensure that any prevailing cross-currency basis has been captured fully within the signal.

Using the forward premium or discount to obtain a signal for a carry trade would work as follows: If the forward price of a currency is trading at a discount to spot, i.e., the forward points are negative, then this indicates that the interest rate of the left hand side (lhs) currency is higher than the interest rate of the right hand side (rhs) currency. For example, at the end of June 2019 the one-month forward rate of USD/CHF was trading at a discount to the USD/CHF spot rate, thus indicating that the lhs currency, USD, had a higher one-month interest rate than the rhs currency, CHF, at that time.

The resulting trade signal would be a buy signal for the lhs currency (USD) and a sell signal for the rhs (CHF) currency. The converse would be the case if the forward price was trading at a premium, i.e., the forward points were positive. This rule is summarized as:

$$\text{Forward Discount or Premium} = \frac{F_t - S_t}{F_t} \quad (1)$$

Where: $F_t$ = the one-month forward rate at time $t$
$S_t$ = the spot rate at time $t$
$t$ = last business day of most recent month-end

Although carry is a popular trading strategy, it is widely acknowledged (and empirically witnessed) that the strategy suffers in periods of risk aversion or "risk off." This is because the source from which the carry strategy extracts its signal, i.e., interest rates, is not able to adjust quickly enough (or at all) to reflect the change in market environment. Therefore, carry trade signals can be quite sticky or nonreactive and, as a result of this, the drawdowns suffered often are significant in such risk-off periods and impact performance substantially.

This can be seen in figure 1, which shows the net asset values of two available simple carry currency factors—the Russell Conscious Currency Carry Index and the Deutsche Bank (DB) Currency Carry Index. Both carry factors suffered losses of roughly 30 percent during the GFC of 2007–2008 and experienced drawdowns in other risk-off periods too.

Figure 1 clearly demonstrates how, empirically, very simple or naïve carry strategies can suffer significant drawdowns due to their inability to adjust or adapt quickly enough to changes in the market's risk environment.

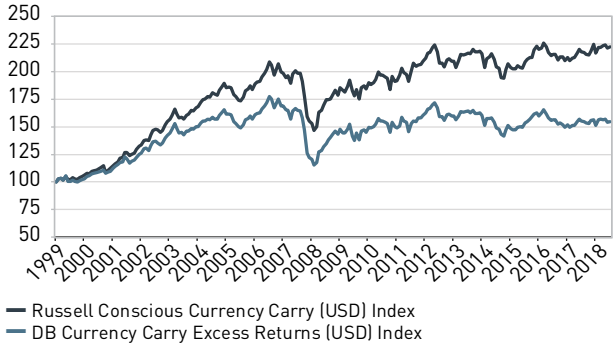
Our research has concentrated on asking whether these drawdowns can be reduced if it were possible, in a systematic way, to detect changes in risk sentiment and then adjust the underlying trade signals appropriately.

#### *Risk filter*

It is commonplace for investors to use risk indicators to gauge sentiment toward risk that may impact their market and ultimately change their investment decisions. In the case of equities,

Figure 1

**NET ASSET VALUE OF NAÏVE CARRY STRATEGIES**




*Source: Bloomberg, Mesirow Financial. Performance from January 1999–June 2019.*

for example, the CBOE Volatility (VIX) index measures the expected price fluctuations in S&P 500 options over the next thirty days and this often is used as an indicator of market risk appetite. Likewise in the bond markets, investors may look at changes in measures such as the TED spread (the difference between the U.S. three-month Treasury bill rate and the U.S. three-month interbank rate) and credit default swaps to gauge risk sentiment.

Although these individual indicators of risk are useful, for the carry factor our intention was to use a risk indicator that encapsulated risk sentiment across many different asset markets and not just the market we are investing in, i.e., currency. In addition, it was important for transparency reasons that we used a publicly available risk indicator.

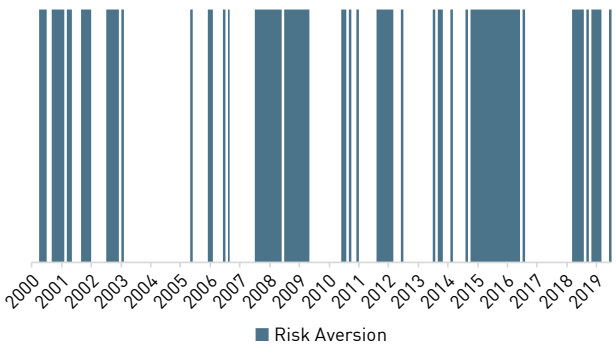
Several across-asset and publicly available risk indexes exist. For the purposes of this study, we use the Citi Macro Risk Index (MRI).[3] The MRI consists of several proxies for market risk such as FX volatility, TED spread, and VIX and is a systematic means to indicate which "state," i.e., risk aversion or risk seeking, the market is currently in. The index is constructed with upper and lower bounds of 0 and 1 and the Citi methodology deems an index value higher than 0.5 is indicative of a risk-aversion state.

The blue bars of figure 2 show an empirical representation of the periods of risk aversion as indicated by the MRI. This spans from the tech bubble and U.S. recession in 2001, the Worldcom/Enron accounting scandals of 2002, to the GFC of 2007–2008, the "taper tantrum" of 2012, the China and equity sell-off of 2015–2016, to more recently the uncertainty of Brexit and U.S./China Trade Wars in 2018–2019.

Although the MRI is by no means a panacea for risk, it nonetheless provides a means to gauge, in a quantitative and systematic manner, the risk appetite or state of the market. Our methodology for utilizing the MRI within the intelligent carry factor is described below.

Figure 2

**CITI MACRO RISK INDEX (MRI) PERIODS OF RISK AVERSION**




*Source: Bloomberg, MRI Index Performance from December 1999–June 2019.*

### *Trade generation*

Let us now consider in more detail how the signals from the carry rule are translated into actual trade weights.

First, we use equation 1 to calculate the size of the premium or discount to spot for each of the G10 currencies in our permissible universe. The USD is included in this ranking. These ten values then are ranked in order of magnitude and the six currencies ranking 1–3 and 8–10 are selected to be traded with the remaining four currencies omitted for trading for the month.

The methodology behind the construction of many currency factors is to allocate an equal trade weight to those currencies selected for trading. For example, in the case of six currencies selected to be traded the resulting buy and sell positions would be plus or minus 33 percent, 33 percent and 33 percent. An implicit assumption in this type of methodology is that the magnitude of information strength of the signal is equal regardless of where the currency appeared in the ranking, i.e., the information signal from a currency that ranked 1 is indifferent to a currency that ranked 3 and therefore equal trades should be used.

Our belief is that the equal-weighting approach discards much of the information and benefit brought about by ranking in the first place. As such, our methodology for assigning trade weights differs significantly from other currency factors because it places a higher buy (sell) trade weight on rank 1 (10) than rank 2 (9) than rank 3 (8) because we believe that there is benefit in translating the information coefficient of the underlying trading signal, detected through the ranking, into the resulting trading positions.

The resulting trade weights we assign are as follows:

Rank 1 = short 50%
Rank 2 = short 33%
Rank 3 = short 17%
Rank 4 = zero
Rank 5 = zero
Rank 6 = zero
Rank 7 = zero
Rank 8 = long 17%
Rank 9 = long 33%
Rank 10 = long 50%

To explain this further, let us illustrate with an example. In table 1, we have calculated the forward discount or premium (via equation 1) of each of the G10 currencies against the USD at the end of June 2019 and ranked these values in order of size.

The negative values in column 2 indicate that the USD has a higher one-month interest rate than the rhs currency, with the converse being true for positive values. The resulting ranks can be seen in column 3 with USD/CHF having the largest discount to spot for that month and this is therefore allocated rank 10.

VOLUME 19
NUMBER 1
2019

Table 1

## EXAMPLE CARRY FACTOR TRADE CONSTRUCTION JULY 2019

| Currency (USD versus CCY) | Forward Discount/ Premium Scaled by Forward* | Rank (1 to 10) | Position Size (USD/CCY)† |
|---|---|---|---|
| USD/CHF | –0.30% | 10 | +50% |
| USD/EUR | –0.26% | 9 | +33% |
| USD/JPY | –0.25% | 8 | +17% |
| USD/SEK | –0.24% | 7 | 0% |
| USD/GBP | –0.16% | 6 | 0% |
| USD/NOK | –0.12% | 5 | 0% |
| USD/AUD | –0.10% | 4 | 0% |
| USD/CAD | –0.08% | 3 | –17% |
| USD/NZD | –0.07% | 2 | –33% |
| USD/USD | 0.00% | 1 | –50% |

** As of end of June 2019; † Position for the month of July 2019.*
*Source: Bloomberg, MRI Index.*

Table 2

## ADJUSTMENTS TO JULY'S CARRY TRADE POSITIONS IF THE MRI INDICATED RISK AVERSION

| Currency (USD versus CCY) | Original Position Size (USD/CCY)* | Deleveraged Position Size (USD/CCY) if in Risk Averse State* |
|---|---|---|
| USD/CHF | +50% | +25% |
| USD/EUR | +33% | +16.5% |
| USD/JPY | +17% | +8.5% |
| USD/SEK | 0% | 0% |
| USD/GBP | 0% | 0% |
| USD/NOK | 0% | 0% |
| USD/AUD | 0% | 0% |
| USD/CAD | –17% | –8.5% |
| USD/NZD | –33% | –16.5% |
| USD/USD | –50% | –25% |

** Position for the month of July 2019.*
*Source: Bloomberg, MRI Index*

Once the ranking is complete, we next allocate a specific trade weight to the USD versus the rhs currency and this can be seen in column 4. Any currencies with ranks 4–7 automatically are excluded from trading positions for the month, i.e., for the month of July no positions would be taken in USD versus SEK, GBP, NOK, or AUD. Only currencies with ranks 1–3 and 8–10 would be traded in July, i.e., long USD/CHF 50 percent, long USD/EUR 33 percent, and long USD/JPY 17 percent and short USD/CAD 17 percent, short USD/NZD 33 percent, and finally short USD/USD 50 percent. Obviously, the latter currency cannot be traded and would represent the net USD position for that month.

Once we have our baseline trading weights, we then need to consider which risk state we are in, i.e., risk seeking or risk aversion. We do this by consulting the signal from the MRI. If this shows we are in a risk-averse state, then our baseline carry positions would be deleveraged by half. The rationale being that naïve carry strategies tend to incur losses in such periods, so by reducing the position size we help minimize such losses.

If the MRI indicates a "normal" or risk-seeking environment, the baseline carry position sizes remain untouched.

Returning to the previous example, table 2, column 3, shows what adjustments would have been made to the original trading sizes if the MRI indicated a risk-averse state at the end of June 2019. All trading positions would have been deleveraged by a factor of one-half and, as such, would reduce the exposure of the factor in environments where carry strategies tend to perform negatively.

### THE INTELLIGENT VALUE FACTOR

#### *The rule*

The fair value or PPP value of a currency may be calculated in numerous ways. Transparency was a key objective when designing the methodology of the intelligent currency factors, so the value factor is based upon PPP data that is publicly available and published by the Organisation for Economic Co-operation and Development (OECD).[4]

The first step in constructing a trade signal for the value factor is to calculate the over- or undervaluation of a currency pair. The methodology we use to do this is to calculate the average of the past three month-end spot prices of each currency against the USD and compare this to its OECD's PPP value.

It is important to note that PPP values are updated only annually, and in the case of the OECD, the values are usually available by the end of the first quarter of the following year. So, for example, 2018 PPP values will not be published until sometime between January and March 2019.

To ensure that the methodology encapsulates this delay in availability, our trading rule uses a lag of fifteen months for the PPP value, equation 2.

$$\text{Under/Overvaluation} = \frac{\frac{1}{3}\sum_{t}^{-2} S_t}{PPP_{t-15}} \quad (2)$$

Where: $S_t$ = the spot rate at time $t$
$PPP_{t-15}$ = the OECD PPP rate at time $t$–15
$t$ = last business day of most recent month-end

*Although the permissible universe of currencies for the intelligent carry and intelligent value factors is G10, for the intelligent momentum factor it is concentrated on the G4 currencies of EUR, GBP, JPY, and USD.*

### *Trade generation*

The methodology for constructing the trade weights for the value factor is similar to that of the carry factor described above. At the end of each month, the percentage over/undervaluation for each of the G10 currencies against the USD is calculated and then ranked in terms of magnitude. Long USD positions with weights of 50 percent, 33 percent, and 17 percent are established for the top three most-undervalued currencies against the USD and short positions of the same magnitude for the three most-overvalued currencies against the USD. Again, the four currencies assigned ranks 4–7 are not traded that month. These positions then are held for the forthcoming month and adjusted, if required, once the trade weights are recalculated at the end of that month.

## INTELLIGENT MOMENTUM FACTOR

### *The rule*

Our momentum factor is created slightly differently from the carry and value factors. Although the permissible universe of currencies for the intelligent carry and intelligent value factors is G10, for the intelligent momentum factor it is concentrated on the G4 currencies of EUR, GBP, JPY, and USD. For carry and value we applied a specific trading rule to all currencies, ranked, and then selected the top/bottom three currencies to trade; for momentum we instead calculate the trade signal per currency as an average of three time-weighted signals for the currency.

This is depicted in equation 3, which shows how for each of USD versus EUR, GBP, and JPY we compare the most recent month-end spot price with its value three-months prior, six-months prior, and twelve-months prior. This results in three trade signals per currency, with "+1" indicating a USD/CCY2 long position and "–1" indicating a short USD/CCY2 position. From this we then take an average and arrive at a trade weight for the specific currency pair for that month.

$$\text{Momentum Signal} = \frac{(\text{If } S_t > S_{t-3} \textit{ then } 1,-1) + (\text{If } S_t > S_{t-6} \text{ then } 1,-1) + (\text{If } S_t > S_{t-9} \text{ then } 1,-1)}{9} \quad (3)$$

Where: $S_t$ = the spot rate at time $t$ (CCY2/USD)
$t$ = last business day of most recent month-end
1 = buy USD/CCY2
–1 = sell USD/CCY2

### *Trade generation*

To explain this further, let us consider an example. Table 3A shows the spot rates for EUR/USD, GBP/USD, and USD/JPY as of June 2019 month-end alongside their corresponding values three, six, and nine months prior.

We next assess whether the value of the current month-end USD/CCY2 spot has appreciated or depreciated versus its prior three, six, and nine month-end spot value. A "+1" is assigned if USD/CCY2 has appreciated and a "–1" if it has depreciated (see table 3B). The final step is to apply a third weighting on each time horizon's signal to arrive at an average trading signal for each USD/CCY2 currency pair for the month of July (see table 3C).

## INTELLIGENT CURRENCY FACTORS PERFORMANCE

We discussed the methodology for creating the intelligent currency factors above. Here, we show the hypothetical performance of the factors using monthly data over the period end of December 1999 to end of June 2019.

In addition to showing the performance of the intelligent carry, value, and momentum currency factors, we also show the performance achieved by equally weighting the returns of each factor into a combined or intelligent multi-strategy currency factor.

The diversification benefits of a multi-strategy approach can be seen in the correlation coefficients between the factors (see table 4). As the trade signals for each of the single-style

VOLUME 19
NUMBER 1
2019

Table 3

## EXAMPLE MOMENTUM FACTOR TRADE CONSTRUCTION FOR JULY 2019

| (A): Spot Rates (quoted in market convention) | | | | |
|---|---|---|---|---|
| | | 3 Month | 6 Month | 9 Month |
| | June 28, 2019 | March 29, 2019 | December 31, 2018 | September 29, 2018 |
| EUR/USD | 1.1373 | 1.1229 | 1.1432 | 1.615 |
| GBP/USD | 1.2696 | 1.3031 | 1.2736 | 1.3041 |
| USD/JPY | 108 | 111 | 110 | 114 |

| (B): Momentum Signals (quoted as USD vs. CCY2) | | | | |
|---|---|---|---|---|
| | | 3 Month | 6 Month | 9 Month |
| USD/EUR | | -1 | 1 | 1 |
| USD/GBP | | 1 | 1 | 1 |
| USD/JPY | | -1 | -1 | -1 |

| (C): Momentum Final Positions (quoted as USD vs. CCY2) | | | | | | |
|---|---|---|---|---|---|---|
| | | 3 Month | 6 Month | 9 Month | Average | |
| USD/EUR | | -33% | 33% | 33% | 11% | Long USD/EUR |
| USD/GBP | | 33% | 33% | 33% | 33% | Long USD/GBP |
| USD/JPY | | -33% | -33% | -33% | -33% | Short USD/JPY |

*Source: Bloomberg, Mesirow Financial.*

Table 4

## INTELLIGENT CURRENCY FACTORS CROSS-CORRELATION

| | Carry | Value | Momentum |
|---|---|---|---|
| Carry | 1 | 0.04 | -0.13 |
| Value | | 1 | -0.17 |
| Momentum | | | 1 |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Table 5

## INTELLIGENT CURRENCY FACTORS HYPOTHETICAL PERFORMANCE

| | Intelligent Currency Factors | | | |
|---|---|---|---|---|
| | Multi-Strategy | Carry | Value | Momentum |
| Annualized Return | 3.96% | 4.14% | 5.09% | 2.64% |
| Annualized Standard Deviation | 3.46% | 6.56% | 7.54% | 5.13% |
| Return/Risk | 1.14 | 0.63 | 0.67 | 0.51 |
| Maximum Drawdown | -4.86% | -20.07% | -14.53% | -8.91% |
| Maximum Month | 3.55% | 4.39% | 7.96% | 5.95% |
| Minimum Month | -2.45% | -7.20% | -6.60% | -4.63% |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Performance is hypothetical and does not represent actual client activity. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

currency factors are generated from different sources, i.e., interest rates, fundamentals, and price, the resulting cross-correlation between the returns of factors is either low or negative, making a combination of the factors an attractive offering for the purposes of diversification.

### PERFORMANCE OF THE INTELLIGENT CURRENCY FACTORS

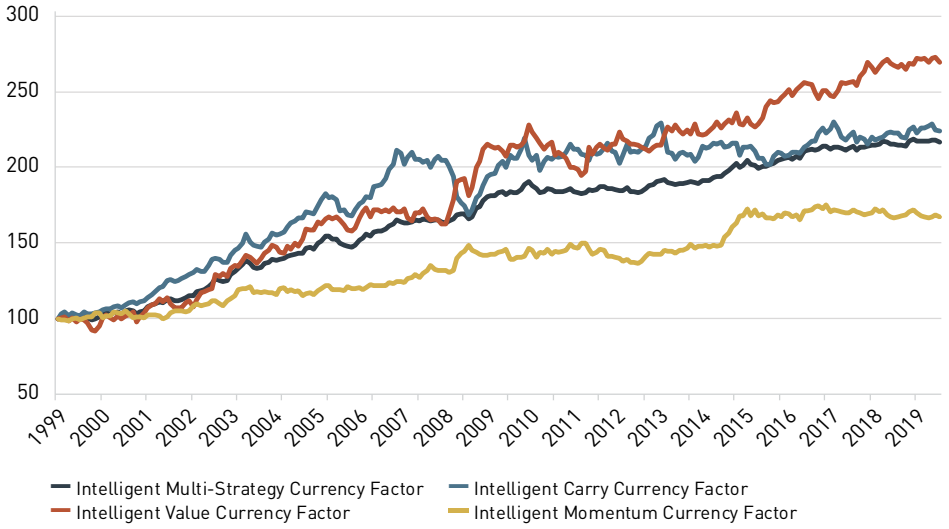
Table 5 shows the annualized hypothetical performance statistics for the intelligent carry, value, and momentum currency factors over the period end of December 1999 to end of June 2019. Table 5 also shows the performance of the intelligent multi-strategy factor, the returns of which are equally weighted across the three single-style factors.

The intelligent value currency factor performed best during the period with a return-to-risk statistic of 0.67. The intelligent momentum currency factor exhibited the lowest performance of the three single-style factors, although a return-to-risk ratio of 0.51 over an almost nineteen-year period is still strong.

The return-to-risk of the intelligent carry currency factor lay in-between value and momentum at 0.63 and this factor had the largest of the maximum drawdowns at 20 percent

Figure 3

## INTELLIGENT CURRENCY FACTORS HYPOTHETICAL NET ASSET VALUES




*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019.*
*Performance is hypothetical and does not represent actual client activity. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Table 6

## INTELLIGENT CURRENCY FACTORS CORRELATION VERSUS TRADITIONAL ASSET CLASSES

| | Intelligent Factors | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Multi-Strategy** | **Carry** | **Value** | **Momentum** | **Equities** | **Bonds** | **Commodities** |
| Multi-Strategy | 1 | 0.59 | 0.66 | 0.29 | 0.10 | –0.08 | –0.04 |
| Carry | | 1 | 0.04 | –0.13 | 0.44 | 0.09 | 0.39 |
| Value | | | 1 | –0.17 | –0.13 | –0.27 | –0.27 |
| Momentum | | | | 1 | –0.17 | 0.11 | –0.19 |
| Equities | | | | | 1 | 0.26 | 0.48 |
| Bonds | | | | | | 1 | 0.29 |
| Commodities | | | | | | | 1 |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Equities are the MSCI World-ex USD; bonds are the Barclays Global Aggregate-ex USD; and commodities are the Thomson Reuters CRB Commodity Index. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

during the period. As previously discussed though, the carry strategy can be susceptible to losses in periods of risk aversion and this specific drawdown occurred in the GFC of 2007–2008.

This can be seen more clearly in the net asset value chart in figure 3. However, if we contrast this to the 30-percent drawdowns suffered by the DB and Russell carry factors (see figure 1) we see that applying the risk filter, and deleveraging positions in risk-averse periods, reduced drawdown by one-third.

Turning our attention now to the intelligent multi-strategy currency factor, the diversification effect of combining the three strategies can be seen in the performance statistics. Looked at in isolation, the standard deviation of the single-style currency factors ranged from 5.13 percent (intelligent momentum) to 7.54 percent (intelligent value) while the standard deviation of the combined factor (intelligent multi-strategy) was just 3.46 percent. The maximum drawdown of the intelligent multi-strategy currency factor also benefitted significantly from the favorable correlation coefficients between the individual factors and was approximately 5 percent versus approximately 9 percent for momentum, 14.5 percent for value, and 20 percent for carry.

The benefit of investing in a diversified intelligent multi-strategy currency factor can be seen more clearly in the net asset values in figure 3. It is unrealistic to think that any one single-style currency factor will perform well all the time but, by combining non-correlated currency factors, periods of losses can be minimized. For example, in 2007–2008 we see in figure 3 that the intelligent carry currency factor suffered; however, during that same period the intelligent value currency factor excelled. The correlation between the returns of these two factors over this specific time period was close to –1.

VOLUME 19
NUMBER 1
2019

Table 7

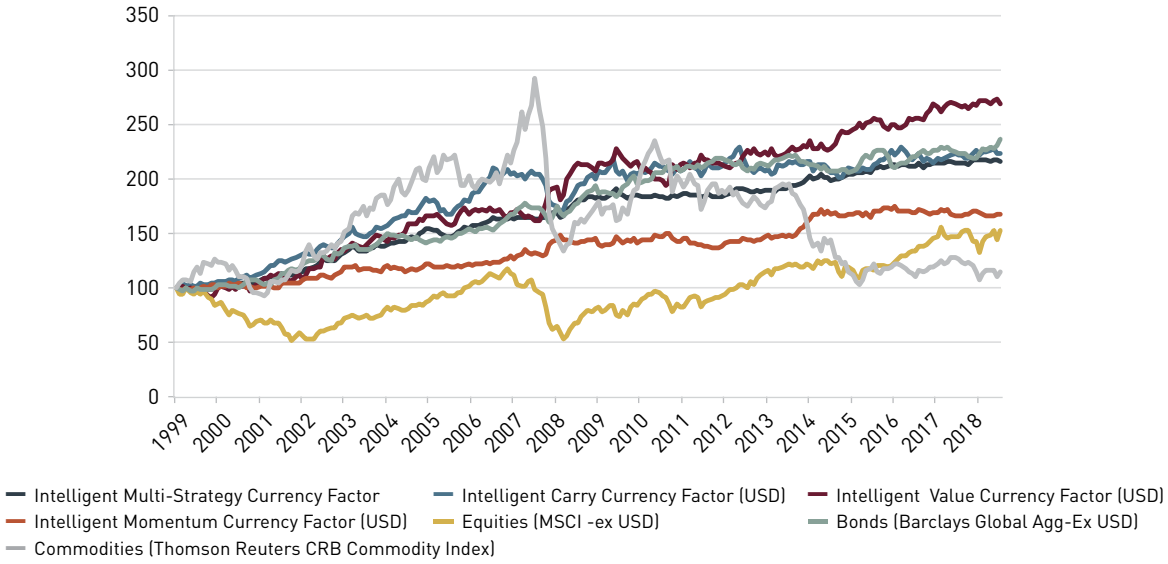
## INTELLIGENT CURRENCY FACTORS HYPOTHETICAL PERFORMANCE VERSUS OTHER ASSET CLASSES

| | Intelligent Factors | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Multi-Strategy** | **Carry** | **Value** | **Momentum** | **Equities** | **Bonds** | **Commodities** |
| Annualized Return | 3.96% | 4.14% | 5.09% | 2.64% | 2.19% | 4.42% | 0.71% |
| Annualized Standard Deviation | 3.46% | 6.56% | 7.54% | 5.13% | 15.28% | 5.55% | 16.58% |
| Return/Risk | 1.14 | 0.63 | 0.67 | 0.51 | 0.14 | 0.80 | 0.04 |
| Maximum Drawdown | -4.86% | -20.07% | -14.53% | -8.91% | -55.37% | -10.08% | -64.73% |
| Maximum Month | 3.55% | 4.39% | 7.96% | 5.95% | 10.35% | 6.03% | 12.92% |
| Minimum Month | -2.45% | -7.20% | -6.60% | -4.63% | -21.13% | -4.05% | -25.26% |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Equities are the MSCI World-ex USD; Bonds are the Barclays Global Aggregate-ex USD; and Commodities are the Thomson Reuters CRB Commodity Index. Performance is hypothetical and does not represent actual client activity. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Figure 4

## INTELLIGENT CURRENCY FACTORS NET ASSET VALUE VERSUS OTHER ASSET CLASSES




*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Performance is hypothetical and does not represent actual client activity. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Although the diversification effect improves the overall return-to-risk ratio, negative correlation also can dampen returns versus that of a single-style strategy. Whether an investor prefers to allocate to just one of the single-style intelligent currency factors or prefers to invest in the more diversified intelligent multi-strategy currency factor, figures 2 and 3 show that performance has been acceptable over the medium to long term for either choice.

### PERFORMANCE VERSUS TRADITIONAL ASSET CLASSES

Unfortunately, currency often is overlooked as an investment possibility in many asset allocation exercises. This is usually underpinned by a belief that currency is a zero-sum game and that it is not possible to make returns by investing in currency. These are unfortunate assumptions though because, as we have seen, returns can be made in currency. In addition, currency often is negatively correlated with equities and bonds and therefore can offer exceptional diversification benefits when combined with more-traditional asset classes. This latter point is demonstrated in table 6, which shows low or negative correlation between the intelligent currency factors and equity, bond, and commodity indexes over the period in question.

Table 7 shows the hypothetical performance of the intelligent currency factors alongside that of proxies for equities, bonds, and commodities over the period end of December 1999 to end of June 2019. As we discussed earlier, one of the main justifications for not considering currency within an asset allocation exercise is the belief that it is a zero-sum game and it is not possible to generate returns. Table 7 demonstrates this is clearly not the case because the intelligent currency factors have, overall, achieved superior performance compared to the proxies for equities, bonds, and commodities. This is further highlighted by the net asset value chart in figure 4, which highlights that the hypothetical returns generated by the intelligent currency factors have been steadier and more consistent, too.

The only exception to this perhaps is bonds, although over the past five to six years performance has in fact been flat.

*Adding currency to a traditional asset allocation split*

As we have seen, the intelligent currency factors have exhibited better or comparable risk-to-return statistics versus passive equities and bonds during the period under study. In addition, the correlation between the returns generated by the currency factors and equities and bonds has been low or negative. This suggests that an allocation to a currency factor within an equity/bond portfolio may result in diversification benefits.

*It is staggering that almost one-quarter of the risk of a typical USD-based equity portfolio is invested in something that is essentially unintentional and also considered to be uncompensated, i.e., the belief that the impact of currency "washes out" over time.*

In table 8, column 5, we show the performance of a traditional asset allocation portfolio where the investment is split 60-percent equities and 40-percent bonds. In table 8, column 6, we repeat this exercise, but this time reduce the equity and bond allocation to 40 percent and 30 percent, respectively, and allocate the remaining 30 percent to the intelligent multi-strategy currency factor.

Immediately the diversification benefits of adding currency to a traditional asset split are apparent with the risk of the portfolio being reduced by approximately one-third and similar reductions seen in maximum drawdown and worse-month statistics.

The result of this is an improvement of return-to-risk during the period from 0.31 in the traditional equity/bond portfolio to 0.49 in the alternative equity/bond/currency portfolio.

## CURRENCY FACTORS WITHIN AN OVERLAY FRAMEWORK

It is commonplace nowadays for portfolios to be invested internationally. However, this creates exposure to the foreign currencies in which the overseas assets are denominated and, if left unhedged, can add volatility to the portfolio. Unfortunately, many investors are unaware of the amount of risk that currency can contribute to the overall portfolio and therefore exposures often are left unhedged.

In table 9 we show the performance statistics of an unhedged USD-based MSCI World portfolio over the period end of December 1999 to end of June 2019. We also calculate the amount of risk that leaving the currency unhedged contributed to the overall risk of the portfolio, namely 23 percent.

It is staggering that almost one-quarter of the risk of a typical USD-based equity portfolio is invested in something that is essentially unintentional and also considered to be uncompensated, i.e., the belief that the impact of currency "washes out" over time. A more sensible approach could be to hedge out the currency exposure and risk and reallocate that risk budget to an alternative stream of returns.

Table 9 shows that by hedging 100 percent of the currency exposure of the USD-based MSCI World portfolio the overall risk has been reduced from approximately 16.5 percent to 14 percent with the risk now contributed by currency close to zero. The next step would be to take that "risk saving" and reallocate it to one of the intelligent currency factors. For the purposes of this analysis, we show the impact of making an allocation to the intelligent multi-strategy currency factor given it is diversified across the three currency styles.

Table 8

**HYPOTHETICAL PERFORMANCE OF A TRADITIONAL ASSET ALLOCATION PORTFOLIO VERSUS AN ALTERNATIVE ASSET ALLOCATION PORTFOLIO**

| | Equities | Bonds | Intelligent Multi-Strategy Currency Factor | Traditional Asset Allocation (60% Equities, 40% Bonds) | Alternative Asset Allocation (40% Equities, 30% Bonds, 30% Currency) |
|---|---|---|---|---|---|
| Annualized Return | 2.19% | 4.42% | 3.96% | 3.08% | 3.39% |
| Annualized Standard Deviation | 15.28% | 5.55% | 3.46% | 9.99% | 6.89% |
| Return/Risk | 0.14 | 0.80 | 1.14 | 0.31 | 0.49 |
| Maximum Drawdown | -55.37% | -10.08% | -4.86% | -38.20% | -27.03% |
| Maximum Month | 10.35% | 6.03% | 3.55% | 6.57% | 5.03% |
| Minimum Month | -21.13% | -4.05% | -2.45% | -14.18% | -9.05% |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999-June 2019. Equities are the MSCI World-ex USD; Bonds are the Barclays Global Aggregate-ex USD; and Commodities are the Thomson Reuters CRB Commodity Index. Performance is hypothetical and does not represent actual client activity. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

VOLUME 19
NUMBER 1
2019

Table 9

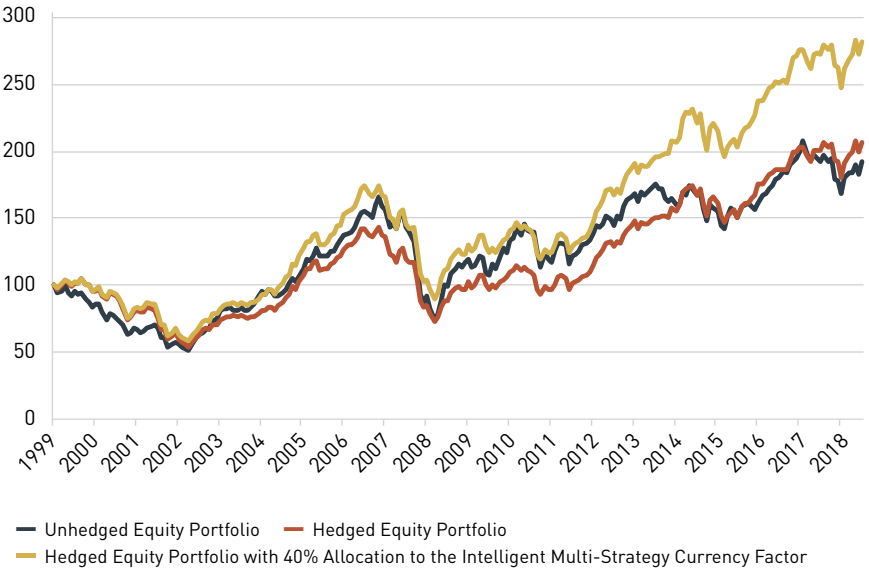
## ALLOCATION TO INTELLIGENT MULTI-STRATEGY CURRENCY FACTOR WITHIN AN OVERLAY FRAMEWORK

| | Unhedged Equity Portfolio | Hedged Equity Portfolio | Hedged Equity Portfolio + 40% Allocation to Currency Factor |
|---|---|---|---|
| Annualized Return | 3.34% | 3.74% | 5.32% |
| Annualized Standard Deviation | 16.56% | 14.02% | 14.30% |
| Return/Risk | 0.20 | 0.27 | 0.37 |
| Maximum Drawdown | –55.30% | –49.36% | –48.99% |
| Maximum Month | 12% | 10% | 10% |
| Minimum Month | –22% | –16% | –15% |
| Risk Contributed by Currency | 23% | 0.04% | 2.44% |

*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Equities are the MSCI World-ex USD. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Figure 5

## ALLOCATION TO INTELLIGENT MULTI-STRATEGY CURRENCY FACTOR WITHIN AN OVERLAY FRAMEWORK, NET ASSET VALUE




*Source: Bloomberg, Mesirow Financial. Performance from December 1999–June 2019. Past performance is not necessarily indicative of future results. Actual results may materially differ. See final disclaimer.*

Table 9, column 4, shows that a 40-percent allocation to the intelligent multi-strategy factor enhanced overall returns by 198 basis points (bps) versus the unhedged portfolio, 150 bps versus the hedged portfolio, and helped to improved return-to-risk from 0.20 and 0.27, for unhedged and hedged, respectively, to 0.37.

The impact of such an allocation strategy can be seen more clearly in figure 5, which shows the net asset values of the MSCI portfolio from the perspectives of being unhedged, passively 100-percent hedged, and hedged with an allocation to the intelligent multi-strategy currency factor.

Clearly, from a risk-budgeting perspective, leaving the currency exposure of an internationally invested portfolio unhedged is not particularly compelling. A more conducive proposition for utilizing the risk budget more effectively would be to hedge out the risk caused by the unintentional exposures and then reallocate those risk savings to an intelligent currency factor.

## CLOSING REMARKS

This paper presented a methodology for building three "intelligent" currency beta factors that encompassed the most popular trading styles used with the currency industry, namely: carry, value, and momentum. In addition, we demonstrated how the returns of these individual factors could be combined into a multi-strategy factor that offers the advantage of diversified returns.

We showed how using a risk filter to determine risk environment and then adjusting the position size of the carry strategy accordingly could help improve its performance versus a simple carry strategy without risk filter. In addition, we presented a methodology for linking trading size with the magnitude of information

coefficient of the trading signal versus adopting an equal trading weight per currency regardless of strength of signal.

Through the empirical analysis we showed how the three individual intelligent currency factors had positive performance during the period under study and how, by combining the three single-style factors into an intelligent multi-strategy currency factor, return-to-risk was improved due to the diversification benefits.

We also showed how currency is a suitable addition to a traditional asset allocation approach due to its low or negative correlation with equities and bonds and, potentially, superior performance in terms of returns.

The final part of the empirical analysis showed how a simple risk-budgeting exercise that re-allocated the risk caused by unintentional currency exposure in a portfolio to an allocation to the intelligent multi-strategy currency factor could enhance the returns of an internationally invested equity portfolio without increasing overall risk from being hedged.

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## ENDNOTES

1. "Bank of International Settlements Triennial Report 2016," https://www.bis.org/publ/rpfx16.htm.
2. Source: Bloomberg, www.bloomberg.com.
3. For more information, see "Citi Risk Aversion Indicator: Index Methodology," Citi Investment Strategies (October 16, 2015), https://investmentstrategies.citi.com/citicis/eppublic/docs/us/Citi_Risk_Aversion_Indicator_Index_Conditions.pdf.
4. For more information, see "Purchasing Power Parities (PPPs), Data and Methodology," https://www.oecd.org/sdd/prices-ppp/purchasingpowerparitiespppsdata.htm.

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