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DYNAMIC FACTOR ALLOCATION – AN APPLICATION TO ACTIVE CURRENCY INVESTING

By: Luc de la Durantaye, Michael Lewis, and Michael Sager[1] November 2018

1. SUMMARY

Interest in factor risk premia continues to grow amongst asset managers, and these now represent the foundation of many rules-based quantitative investment processes. For many clients, the motivation to focus on factor risk premia—or factors, for expediency—remains opaque. In this paper we discuss the merits of utilizing a rules-based factor investment process, in the context of Active Currency investing. We focus on three questions:

- Can we identify and exploit a set of well-defined factor risk premia to generate persistent returns to an active currency mandate?
- Do these factors exhibit macroeconomic or risk-based performance biases, and if they do, can we use this information to adjust the conditional risk of active currency mandates to maximize performance?
- Can we measure and use the attractiveness of factors themselves through time to add an additional, alpha source of returns to active currency mandates by dynamically allocating risk between factors?

We conclude that factor investing represents a significant advance in portfolio construction, allowing investment managers to more efficiently allocate ex ante portfolio exposures to those factor risk premia that exhibit the most desirable return characteristics. We also find that the performance of factors is robust to most macroeconomic states, but that it exhibits vulnerability to periods of heightened risk aversion. Finally, we conclude that it is possible to identify a robust relationship between characteristics of individual factors and the magnitude of future returns achieved by a risk allocation to each factor. Exploiting this information in live trading using dynamic factor allocation is difficult, but the resulting portfolio performance improvement is intuitive and economically relevant.

2. WHY CONSIDER RULES-BASED FACTOR INVESTING?

Investment portfolios are traditionally organized across securities for single asset products, and by asset class for multi-asset products. This approach is well-established and intuitive. It is also arguably sub-optimal and arbitrary. As Maeso and Martinelli (2017) discuss, investors are not interested per se in the individual securities or asset classes they own. These are means to achieve an end objective; namely, an optimal allocation of investment capital to a set of identifiable and rewarded risk factors. This set of risk factors includes equity, interest rate, credit, and inflation risk. It also includes Alternative Risk Premia that have an associated positive expected return, such as Value, Carry, and Momentum.[2] Exposure to these factor risk premia is achieved through appropriate combinations of asset holdings.

The primary benefit of factor investing is an increase in the efficiency and transparency of portfolio construction. Factor investing reduces the dimensionality of the portfolio optimization problem from many

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[2] Factor risk premia are typically defined as long-only strategies. Alternative Risk Premia (ARPs) are market-neutral long/short strategies. Given our focus on active currency investing, we concentrate upon ARP strategies henceforth. But we use the terms factors and ARPs interchangeably.

securities or asset classes to a small, well-defined set of factors (Kinlaw et. al., 2017). It allows investors to directly target ex ante allocations to desired risk factors, and to more efficiently identify and eliminate idiosyncratic, unrewarded risks. In a portfolio organized by securities or asset classes, these exposures can only be targeted on an ad hoc, ex post basis. Factor investing also enhances an investor's understanding of the drivers of portfolio performance, as returns are expressed as a function of exposures to targeted risk factors (Amenc, Coqueret, and Martellini, 2015). And available evidence suggests that portfolios constructed on the basis of factor exposures have achieved more effective diversification, particularly when it is needed most during significant equity market drawdowns (Ilmanen and Kizer, 2012).[3]

3. ACTIVE CURRENCY FACTOR INVESTING

Factor risk premia have a long history in Active Currency investing. Overlay and Absolute Return managers, including CIBC Asset Management, have traditionally built currency investment processes on a foundation of well-established, theoretically rigorous factors. These include Value, Carry, Cycle, and Momentum. Figure 1 defines each of these four currency risk premia, and provides an indicative investment horizon over which each is expected to accrue a positive return. It also reports the Information Ratio (IR) that would have been realized by a risk allocation to each of these factor risk premia, over the sample period December 2002 to June 2018.[4] In line with theoretical prediction, IRs are positive, and generally statistically significant.

In many cases, the positive return associated with identified factors represents compensation paid to investors for assuming one or more identified, undiversifiable risks from other, more risk averse market participants. That is, factors reward investors for accepting exposure to 'bad times'.[5] For Carry, these risks include inflation as well as Skewness risk, whereby episodic funding constraints inhibit market participants engaged in Carry trades, leading to abrupt negative changes in exchange rates (Chernov et. al., 2014). The Value factor represents compensation for assuming exposure to the risk of value traps, whereby apparently cheap assets trade at a persistent discount to estimated intrinsic value because underlying fundamentals are actually distressed. The Turkish lira in 2018 is an example. And the Cycle factor represents compensation for assuming exposure to both the risk of equity market selloffs and interest rate risk.

In other cases, factor risk premia capture persistent behavioral anomalies associated with the failure of market efficiency. This includes the Momentum factor, which exploits the observed tendency of investors both to exhibit herding behavior, and to initially under-react to and then subsequently over-price news flow (Barberis, Schleifer, and Vishny, 1998; Hong and Stein, 1999). Similar to Carry, Momentum is subject to episodic Skewness risk.

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[3] It is also important to understand what factor investing does not offer. In particular, factor investing does not uncover a previously untapped, additive source of expected return. In an unconstrained portfolio optimization, the empirical superiority of a factor or asset-based approach will be data dependent. As one can be derived from the other, neither has an inherent, theoretical advantage (Idzorek et. al., 2013). Another motivation cited by some investors for factor investing is to replace active managers with passive indices representative of a choice of factors that exhibit long-term positive expected returns. (Shirbini, 2018). We disagree with this motivation, and consider skilled active investing to be an important diversifying source of expected returns.

[4] IR measures the return per unit of risk generated by an active manager in excess of its benchmark. We use a sample beginning in December 2002 throughout our analysis as it covers the period during which Luc de la Durantaye has been the lead currency portfolio manager at CIBC Asset Management. We construct all factors and portfolios to encompass 32 Developed (DM) and Emerging Market (EM) currencies at each time t.

[5] Equivalently, Alternative Risk Premia represent the price that an investor has to pay in order to hedge against a specified undiversifiable risk (Baltas, 2018).

Figure 1 – Active Currency Alternative Risk Premia

Currency Factor	Investment Rationale	Investment Horizon	15-Year IR
Carry	- Higher-yielding currencies tend to outperform lower-yielding currencies. - Construction: yield derived from implied rates in currency forwards.	6-12 mths	0.51
Value	- Relatively cheap currencies tend to outperform relatively expensive currencies. - Construction: PPP adjusted for Terms of Trade and productivity differentials.	2-3 years	0.65
Cycle	- Currencies of cyclically strong countries tend to outperform those of weaker countries. - Construction: Trend extraction based on panel of leading and confirming variables	6-12 mths	0.85
Momentum	- A currency's recent relative performance tends to persist in near future. - Construction: total returns over specified look-back period.	3 mths	0.37

Sources: Bloomberg and CIBC Asset Management Inc. The performance of each factor is based on a hypothetical portfolio constructed by CIBC AM on the basis of proprietary rules. Performance is gross of fees and net of estimated transaction costs. Sample: December 2002 to June 2018; Factors based on CIBC Asset Management Inc. research. This hypothetical scenario is shown for illustrative purposes only and is not indicative of future results. Please refer to the Disclaimer page for further information.

Each of our factors represents compensation for a different non-diversifiable risk or market anomaly. They often exhibit a different investment horizon to one another. These characteristics suggest significant diversification benefits will accrue to a portfolio that combines exposure to these factors. And in all cases, the currency factors that we consider can be expressed with minimal parameterization. This makes them strong candidates for inclusion in a transparent rules-based investment process, and means that they have limited vulnerability to in-sample overfitting and data mining. This is not always the case for factor investing. Harvey, Liu, and Zhu (2016) identify 316 factor risk premia that have been proposed in the academic literature across all asset classes. They consider this number to be an under-estimate of the entire factor population, and argue that many of these factors have been discovered through a non-rigorous process of data-mining.

3.1. Carry factor construction

Currency Carry risk premia models are typically constructed to be consistent with the notion of Forward Rate Bias, which argues that currencies with relatively high (low) interest rates tend to appreciate (depreciate) over time. Similar to Koijen et. al. (2013), we can define the Carry risk premium as,

$$Carry_{i,t} = \left(\frac{S_{i,t} - F_{i,t}}{F_{i,t}}\right) * \frac{1}{\sigma_{i,t}} \tag{1}$$

where $S_{i,t}$ is the USD spot exchange rate for currency i at time t, and $F_{i,t}$ is the 3-month outright USD forward exchange rate for currency i at time t. $\sigma_{i,t}$ is the 3-month implied volatility of currency i at time t and is included to normalize the magnitude of carry opportunities across our currency universe.

3.2. Value factor construction

The concept of intrinsic value has a rich history in exchange rate theory and was first formalized by Cassel (1918) as Purchasing Power Parity (PPP). The investment horizon of PPP factor premium models tends to be too long for many active currency investors; for instance, Taylor and Taylor (2004) conclude that PPP holds with an investment horizon of 10 years or more. To shorten this horizon, we amend PPP to incorporate greater sensitivity to cyclical changes in currency intrinsic value. Our Value factor model is calculated using a multivariate cointegrating pooled regression that expresses US dollar (USD) real exchange rates (y_t)[6] as a function of relative country Terms of Trade ($X'_{i,t}$) and productivity differentials ($Z'_{i,t}$),

$$y_{i,t} = \beta X'_{i,t} + \gamma Z'_{i,t} + \theta_i D'_{i,t} + \varepsilon_{i,t} \qquad (2)$$

Estimated coefficients β and γ are homogeneous across all countries in our pool. $D'_{i,t}$ are a set of fixed effect terms included in regressions to capture country idiosyncrasies in the relationship between real exchange rates and our explanatory variables. We assume monthly rebalancing, at which time spot exchange rates are compared with the output of the model to generate estimates of currency misvaluations.

3.3. Cycle factor Construction

Unlike the other factor risk premia, the cycle model is proprietary to CIBC Asset Management. As Figure 1 explains, it is constructed using trend extraction techniques that exploit a broad set of leading and coincident indicators. Further details are available on request.

3.4. Momentum factor Construction

Cross-sectional momentum factor models exploit the strength of trailing trends in total returns across a set of currencies,

$$M_{i,t} = \left(\frac{F_{i,t}}{F_{i,t-j}} - 1\right) * \frac{1}{\sigma_{i,t}} \qquad (3)$$

where $M_{i,t}$ is the total return to currency i at time t. Lag length j is typically defined to be 3, 6, or 12 months.

3.5. Factor Portfolio Performance

These factor models can be used to form four rank-ordered market-neutral long/short currency portfolios. In general terms, raw factor inputs are cross-sectionally ranked, so that the most (least) attractive assets at each time t for each model have the highest (lowest) rank. These ranks are then centered around zero by subtracting the cross-sectional mean,

$$Sig_{j,t}^{xs,i} = rank(ARP_{j,t}^{i}) - \frac{N_t+1}{2} \qquad (4)$$

where $\mathbf{Sig}_{\mathbf{j,t}}^{\mathbf{xs,i}}$ is the cross-sectional rank of asset j at time t for each factor model i.

The dispersion of raw currency factor data around cross-sectional means at each time t contains information for expected currency returns at time t+1. We exploit this insight in our model construction. We then impose a sum-to-zero constraint, so that the sum of longs for each model equals the absolute sum of shorts at each time t. We also impose a unit risk constraint so that factor models are directly comparable to one another in each period and can easily be combined into an aggregate portfolio. In this paper, for simplicity, we combine factors using a simple 1/N risk allocation, where N equals the number of individual factor models. Portfolios are rebalanced on the last day of each calendar month.

Cumulative performance of individual and combined factor portfolios is shown in Figure 2. All factors demonstrate a standalone ability to add value to an investment portfolio over an extended period. In addition, and as expected, returns to individual factors are diversifying; performance is relatively stronger and more consistent for the combined factor portfolio than for any of the individual models. This diversification effect reflects the attractive and relatively stable pairwise correlation structure that exists between factor models (Figure 3). As the various factors capture returns based upon different rewarded risks and anomalies, over different time horizons to one another, a strong diversification benefit to combining factors in a single portfolio was expected.

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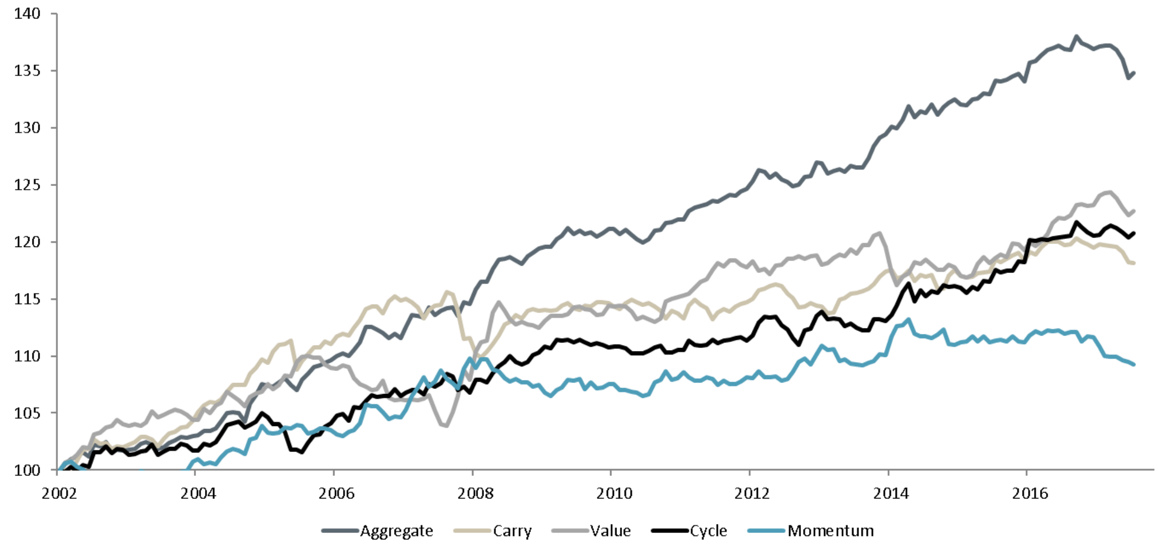
[6] We define exchange rates in terms of units of US Dollar per foreign currency. An increase in an exchange rate is therefore consistent with a weakening in the US Dollar.

Figure 2 – Cumulative Performance of Individual ARP Portfolios, and Combined Equally Weighted Portfolio



The performance of each factor is based on hypothetical portfolios constructed by CIBC AM on the basis of proprietary rules. Returns are rescaled to 5% Annualized Risk. Performance is gross of fees and net of estimated transaction costs. Sample: December 2002 to June 2018; Factors based on CIBC Asset Management research.

Sources: Thomson Reuters Datastream, Bloomberg and CIBC Asset Management Inc.. This hypothetical scenario is shown for illustrative purposes only and is not indicative of future results. Please refer to the Disclaimer page for further information.

Returns to factor risk premia vary through time. But factor portfolios typically exhibit a relatively lower macroeconomic environmental bias than portfolios organized by security or asset class (Figure 4). To demonstrate this, we follow Ilmanen et. al. (2014) and define four macroeconomic environments according to the behavior of inflation and real GDP growth over our sample period. Other than Carry and Momentum in an environment of rising inflation and growth, our individual factors have achieved relatively consistent, positive performance across the various environments. And so has the equally weighted factor portfolio. By contrast, as is well known, equity performance is relatively inconsistent; strong in periods of rising growth, but weak in periods of falling growth.

Figure 3 – Pairwise Factor Correlations

Pairwise factor correlations (Dec 2002 – June 2018)

	Carry	Value	Cycle	Mom
Carry	1			
Value	-0.22	1		
Cycle	0.32	0.09	1	
Mom	-0.16	-0.18	0.09	1

Pairwise factor correlations (Dec 2002 – July 2007)

	Carry	Value	Cycle	Mom
Carry	1			
Value	-0.20	1		
Cycle	0.29	0.18	1	
Mom	0.14	-0.13	0.05	1

Pairwise factor correlations (Oct 2009 – June 2018)

	Carry	Value	Cycle	Mom
Carry	1			
Value	0.08	1		
Cycle	0.39	-0.01	1	
Mom	-0.21	-0.26	0.24	1

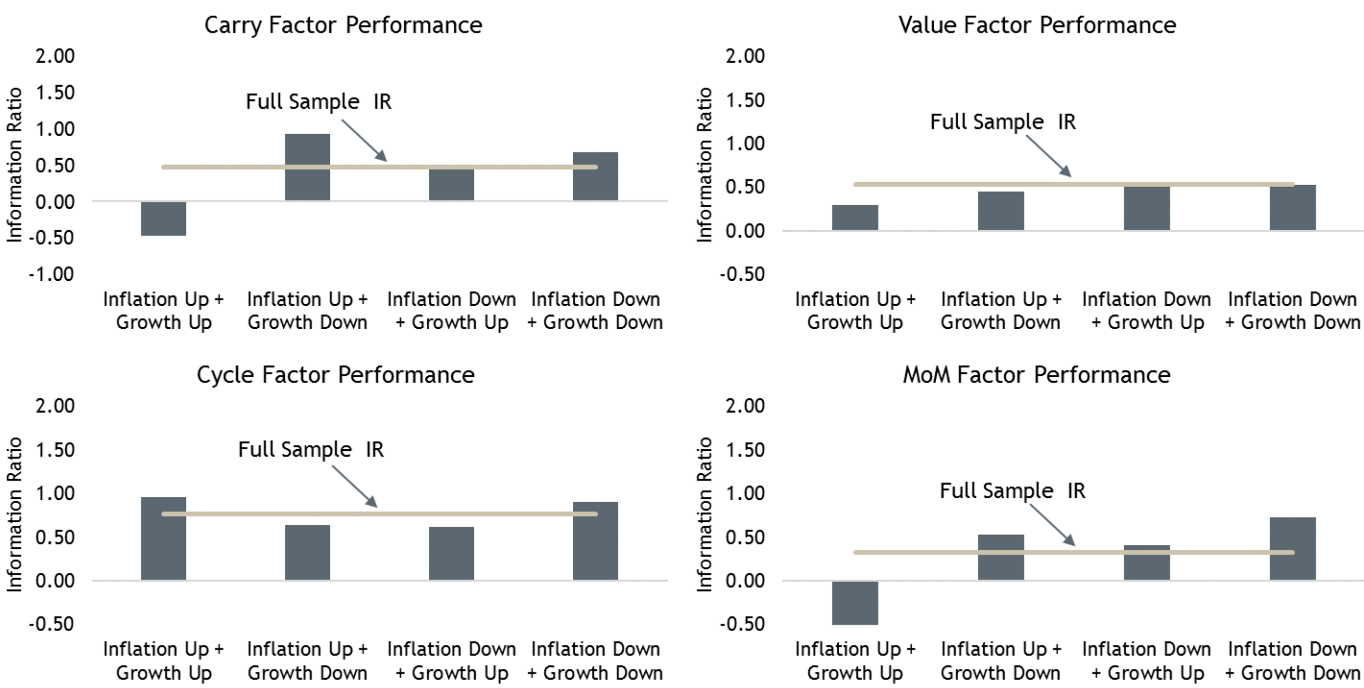
Pairwise factor correlations during recessions and risk aversion*

	Carry	Value	Cycle	Mom
Carry	1			
Value	-0.45	1		
Cycle	0.12	0.12	1	
Mom	-0.46	-0.12	-0.17	1

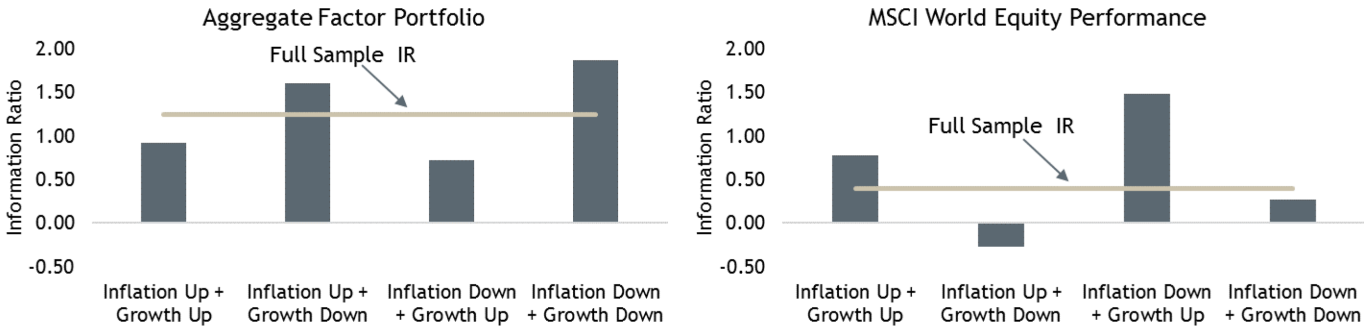
Source: Thomson Reuters Datastream, Bloomberg and CIBC Asset Management Inc.. *Risk Aversion defined as periods during which the Vix Index is above its 70th percentile. The performance of each factor is based on a hypothetical portfolio constructed by CIBC AM on the basis of proprietary rules. Performance is gross of fees and net of estimated transaction costs. Sample: December 2002 to June 2018; Factors based on CIBC Asset Management research.

Currency factors do exhibit greater performance bias to the prevailing level of investor risk appetite. Periods of risk aversion tend to be relatively persistent, consistent with the notion that risk is easier to forecast than returns (Merton, 1980). As Kinlaw (2011; Figure 5) reports, even twenty days following the onset of a risk aversion event, its impact upon asset volatilities continues to lie close to levels initially observed. We measure investor risk appetite using a proprietary quantitative CIBC AM tool that incorporates various global volatility metrics.[7] Consistent with theoretical priors, the performance of our factors indicates that Carry, particularly, is vulnerable to Skewness risk, which typically occurs during periods of heightened risk aversion (Figure 6). Our results also suggest that the Value, Cycle, and Momentum factors also tend to perform less well during periods of relatively high investor risk aversion.

Figure 4 – Factor Performance Across Macroeconomic Environments



[7] The CIBC AM proprietary Risk Index is a mix of spreads and option implied volatility from various asset markets, with an emphasis on FX volatility, as is appropriate for our analysis in this paper. The index is constructed to be bounded by [0, 100].



The performance of each factor is based on a hypothetical portfolio constructed by CIBC AM on the basis of proprietary rules. Performance is gross of fees and net of estimated transaction costs. Sample period: December 2002 to June 2018. Factors based on CIBC Asset Management research.

Sources: Thomson Reuters Datastream, Bloomberg and CIBC Asset Management Inc.. Global Equities: MSCI World Index. Inflation UP (DOWN) = y/y US CPI above (below) its trailing 4-quarter moving average. Growth UP (DOWN) = y/y Real US GDP growth above (below) its trailing 4-quarter moving average.

The insight that the prevailing risk environment has systematic information for the future performance of our factor models is one we return to in the next section.

Expected factor performance also appears to be conditional on the starting valuation and carry of the factors themselves.[8] Expected returns associated with our various factor models embed the concept of mean reversion around a longer-term equilibrium risk premium (Figure 7). Just as an individual security or asset class exhibits periods of trading cheap or rich to its long-term intrinsic value, so do factors. This means that an understanding of where a factor is currently trading relative to its own intrinsic value can provide important insight into its expected performance in future periods. For instance, if the valuation of our factor portfolios is currently high, the probability of a further increase in their value becomes progressively lower. And if the factor portfolios offer a higher starting carry, chances are that they will attract capital flows that will boost their expected return in subsequent periods.

Figure 5 – Periods of Heightened Investor Risk Aversion are Persistent

	Next 5 Days		Next 10 Days		Next 20 Days		10th Percentile Threshold
Global Assets	2.31	(7%)	2.22	(8%)	2.13	(9%)	1.93
US Assets	2.98	(5%)	2.90	(5%)	2.79	(6%)	1.95
US Sectors	3.12	(5%)	3.04	(6%)	2.87	(6%)	2.03
Currency	2.08	(8%)	1.93	(9%)	1.80	(11%)	1.83
US Fixed Income	4.05	(4%)	3.85	(5%)	3.60	(5%)	2.12
US Treasuries	3.19	(5%)	3.13	(6%)	2.96	(6%)	2.00
US Credit	4.17	(4%)	4.09	(4%)	3.69	(4%)	1.61

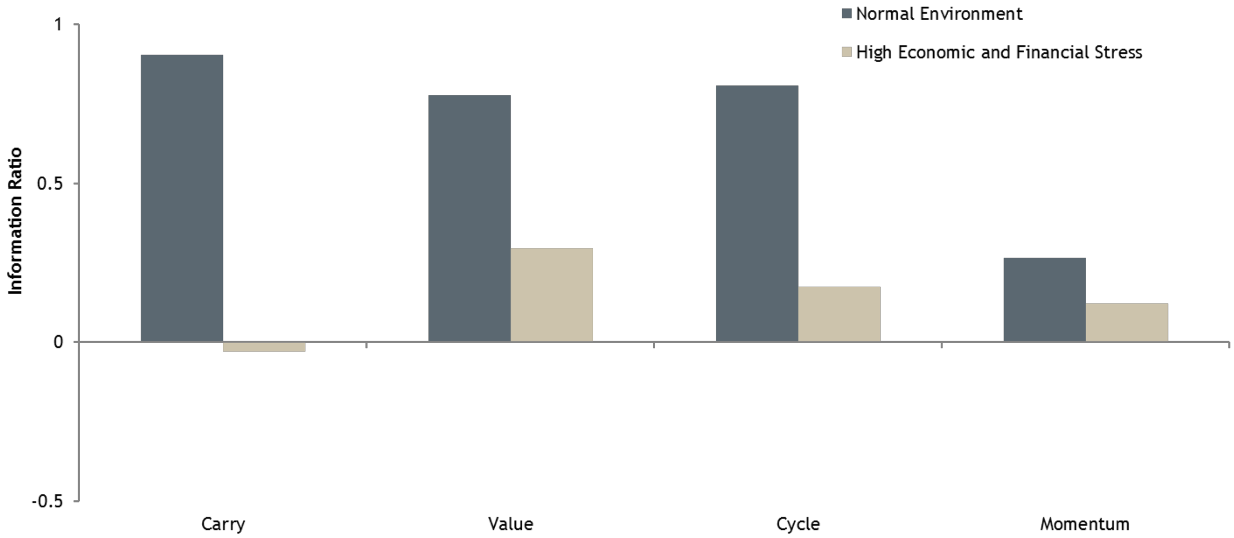
Source: Kinlaw, W. (2011). Each value in parentheses shows where the average level of market turbulence falls, as a percentile from the maximum turbulence value.

To test our intuition, we follow the same portfolio construction process as above, but then divide the cross-sectional rank of currencies for individual factor models into quintiles at each time t. We then compute the median value misalignment and carry for each quintile, as well as the interquintile range (IQR) for both series, of both factors.[9] Our null hypothesis is that valuation and carry IQRs at time t are correlated with subsequent

[8] For expositional simplicity, in the following analysis we focus on our Value and Carry factor models, and exclude both Momentum and Cycle.
[9] The IQR is defined as the median value of the highest quintile minus the median value of the lowest quintile.

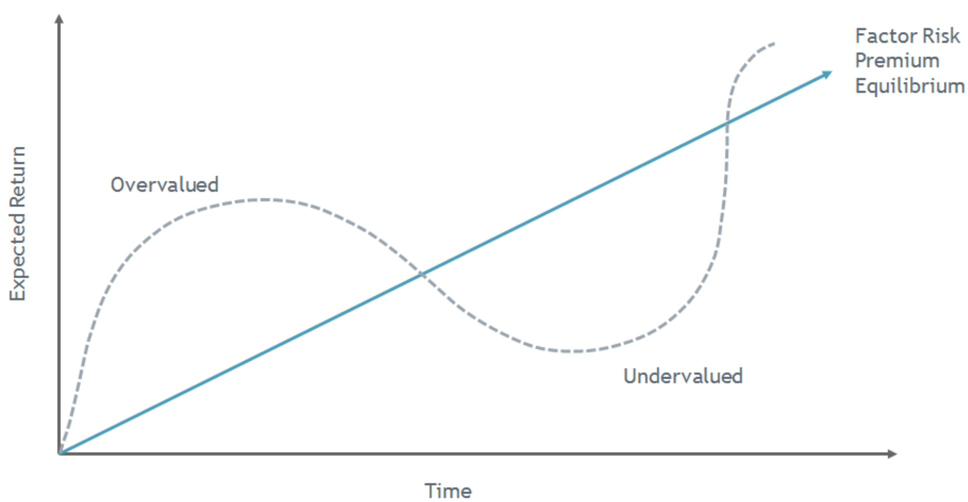
returns to each factor portfolio. High (low) factor valuation at time t is expected to be consistent with relatively low (high) factor returns in the future. Conversely, high (low) factor carry at time t is expected to be consistent with relatively high (low) future factor returns. Figure 8 provides visual support for our hypothesis, using the value of our Value factor to illustrate. The left-hand chart plots the correlation between starting value and 12-month ahead returns to our Value factor. An increasingly negative IQR, indicative of a widening valuation spread between the top and bottom quintiles of our currency universe, is associated with higher future returns to the Value factor. This is confirmed by the right-hand chart in Figure 8, which plots 12-month ahead returns by valuation spread quintile; there is a marked performance difference between the first (widest valuation spread) and fifth (narrowest) quintiles.

Figure 6 – Hypothetical Factor Risk Premium Portfolio Performance during Periods of Normal and Heightened Investor Risk Aversion



Source: CIBC Asset Management Inc., Thomson Reuters Datastream, Bloomberg. Sample: December 2002 to June 2018. Hypothetical scenario shown for illustrative purposes only, and not indicative of future results. P-values indicate the statistical significance of differences in Information Ratios between the two states.

Figure 7 – Stylised Factor Risk Premium Through Time



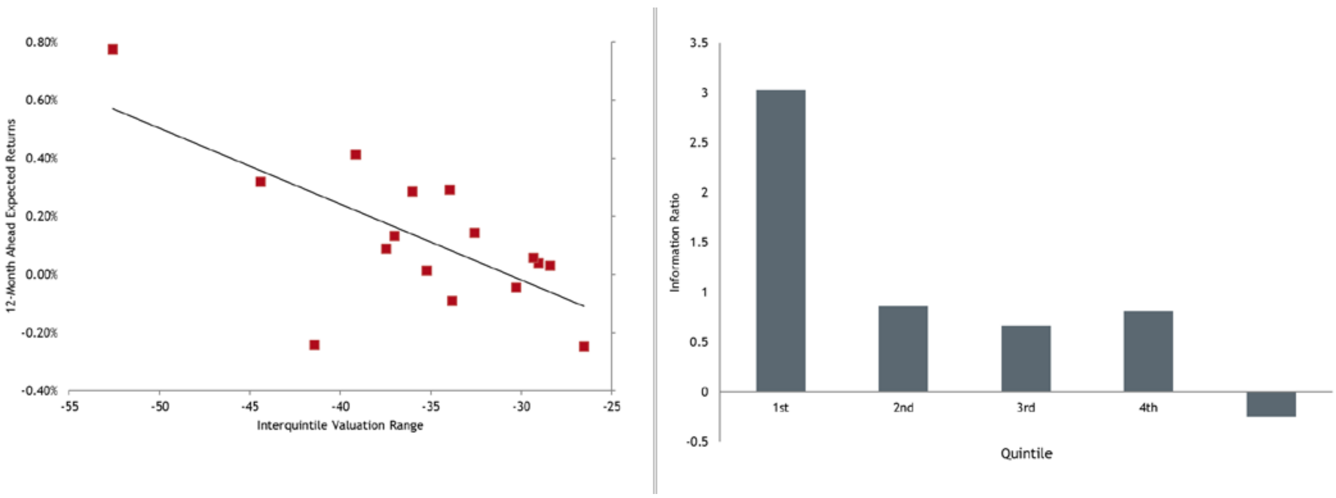
For Illustrative purposes only

4. DYNAMIC FACTOR ALLOCATION

The preceding discussion demonstrates the merits of an active currency investment process built upon a foundation of simple, rules-based factor models. It also motivates an investigation to determine whether skilled investors can extract an additional source of return from factors by systematically conditioning the use of active risk budgets upon two characteristics of the factors themselves—starting valuation and carry—as well as the prevailing risk environment. We call this approach Dynamic Factor Allocation (DFA).

To test the ability of DFA to improve the performance of a factor portfolio, we focus on our Value and Carry factor models. The value of our conditioning variables at time t will determine the magnitude of active risk tilts, and therefore our aggregate factor portfolio exposures, at each time t+1. To ensure that our strategy is investible, we assume a gradual shift in active risk due to DFA through time, rather than a strategy that aggressively switches back and forth between long and short tilts. In a similar vein, total active tilts, $\mathrm{DFA}_{\mathrm{f,t+1}}$, are constrained to lie within a +/-50% range around our initial factor allocations. Consequently, the bulk of portfolio exposures will continue to be driven by our underlying factor risk premia. This is intuitive, as the underlying factors are constructed to be exposed to identified, diversifying systematic risk premia that we believe will persist in the long term, and which will continue to reward investors willing to be exposed to them.

Figure 8 – Correlation of Interquintile Valuation with 12-Month Ahead Value Portfolio Returns and IR



Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. Sample: December 2002 to June 2018. Non-overlapping samples. Results incorporate 5% annualized risk target.

Also to ensure that our DFA strategy is investible, we focus on a parsimonious model specification to generate our active tilts. At the beginning of each month, we estimate the following regression using monthly data, rolling five-year sample windows, and only incorporate information available at time t,

$$r_{f,t+1} = \sum_{i=1}^{N} \beta_i C_{i,t} + \varepsilon_t \quad (5)$$

where $r_{f,t+1}$ is a vector of expected returns to factor f at time t+1, and where f is defined as either our Value or Carry factor model. $C_{i,t}$ is a matrix of our conditioning variables at time t, and β_i is a vector of estimated loadings on $C_{i,t}$. We use two versions of C in our regression analysis,

C = {Factor Portfolio IQR Valuation Spread, Factor Portfolio IQR Carry} *(6)*

and:

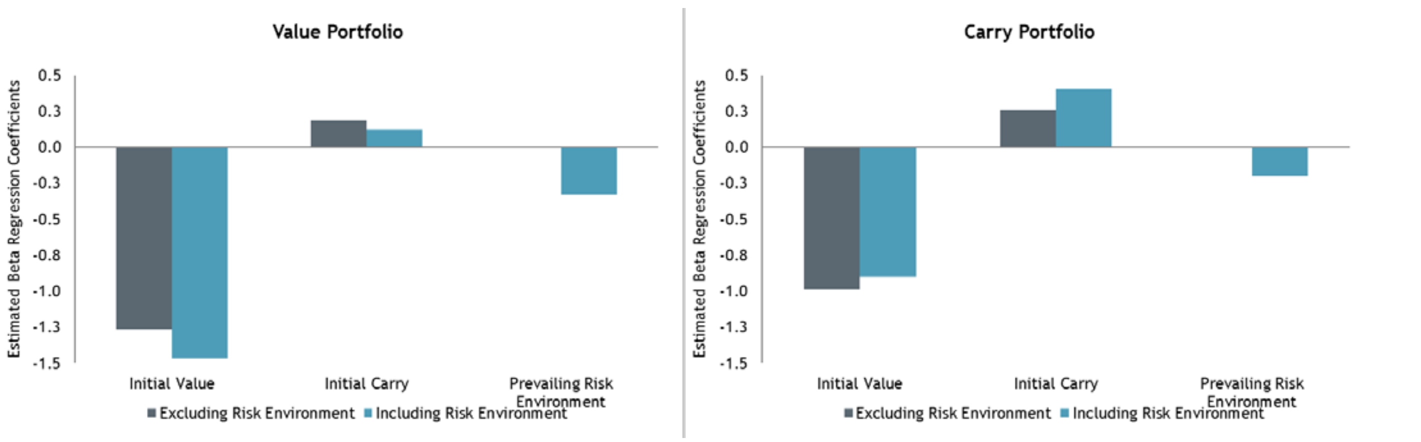
C = {Factor Portfolio IQR Valuation Spread, Factor Portfolio IQR Carry, Risk Environment} *(7)*

Including a measure of the prevailing risk environment adds complexity to the design and implementation of a DFA strategy. But the interplay of an evolving risk environment with various fundamental themes, factors, and idiosyncratic risks is the reality of any active investment strategy and we view the complexity as worth the benefit of achieving a more thorough analysis.

At each time t, we multiply $r_{f,t+1}$ by the R^2 of the regression in (5) to derive the conditional expected returns that determine the size and sign of active risk tilts in period t+1.[10] Thus, the extent to which conditional risk-taking deviates from our unconditional factor risk budget depends on the accuracy of our forecasting model—our proxy for investment conviction—as well as the value of our conditioning variables. If portfolio valuation and carry, and the prevailing risk environment, all at time t, have no significant explanatory power for future factor portfolio returns, our DFA strategy will not introduce active tilts relative to the original positioning of our factor portfolios.

Figure 9 plots estimated beta coefficients from (5) above. Our three conditioning variables are transformed to have a mean of zero and standard deviation of one. Accordingly, estimated betas can be interpreted as reflecting the change in expected portfolio returns due to a one standard deviation increase in each of our conditioning variables above their average over the past five years.[11]

Figure 9 - Sensitivity of Value and Carry Portfolio Expected Returns to Initial Valuation and Carry of Each Portfolio, and the Prevailing Risk Environment



Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. Beta coefficients multiplied by 1000. Sample period: December 2002 to June 2018.

Results are consistent with a priori expectations. Expected returns to the Value factor portfolio are greater when the starting valuation of this portfolio is cheap, and when its starting carry is relatively high.[12] These results hold whether we exclude (dark blue bars) or include (light blue bars) the risk environment from our regression framework. When the risk indicator is included in the regression, a high-risk index value—synonymous with relatively high-risk aversion—is negative for expected returns to the Value factor, again consistent with our null hypothesis. Intuitively, risk aversion encourages a flight to safer assets, and away from potential value traps. In terms of magnitudes, starting factor valuation is substantially more important to expected returns than either starting portfolio carry or the prevailing risk environment. Again, this makes intuitive sense.

10 R^2 is a common measure of the explanatory power of a regression. We also apply a scalar to the time series of conditional expected returns to ensure active risk allocated to this strategy is always consistent with the allocated risk budget.

[11] To verify the robustness of results, we replicate our analysis using the percentile rank of each conditioning variable, again calculated using rolling 5-year samples. We found results to be directionally similar, but slightly less significant. These results are not reported here but are available on request.

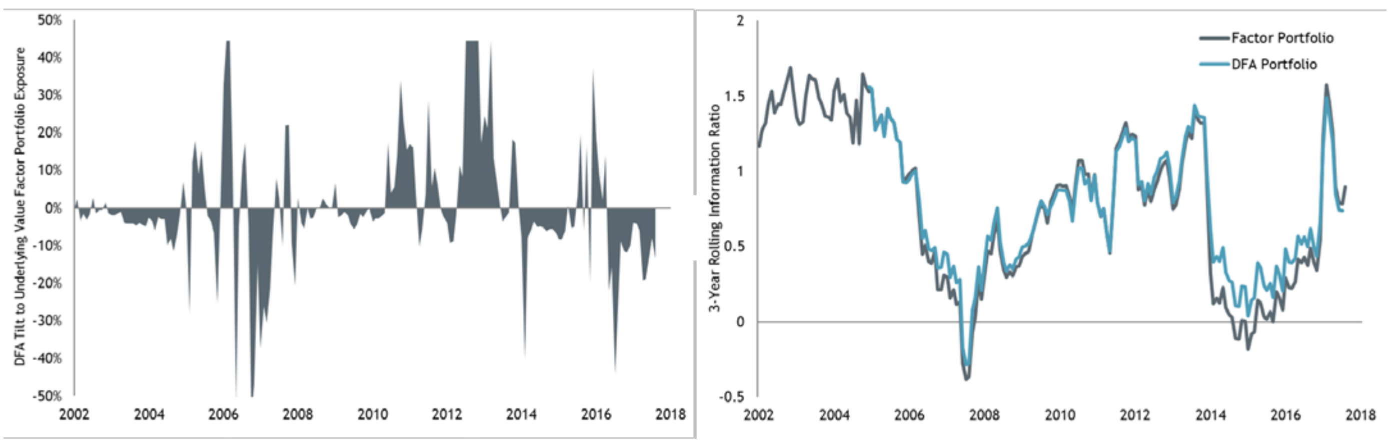
[12] According to our definition, more attractive starting portfolio valuations are synonymous with an increasingly negative IQR. As a result, a negative estimated beta multiplied by an increasingly negative IQR value is synonymous with an increasingly positive expected portfolio return in period t+1.

We find similar results for the Carry factor model. The relationship between future expected returns and starting portfolio carry is interesting. Without inclusion of the risk environment (dark blue bars) relativity high starting carry is consistent with positive expected returns. This is what we expected to find. But once we include our measure of the prevailing risk environment (light blue bars), the sign of this coefficient becomes more positive, and the estimated loading on our risk environment conditioner is negative. Together, these results suggest some interplay between starting carry and risk environment related to Skewness risk. As discussed above, this risk is identified by the academic literature as one explanation for the existence of a positive long-term currency Carry risk premium. It typically crystallizes during periods of acute market stress, consistent with a high observation for our measure of the risk environment. Consequently, it seems that only once we control for the probability of observing Skewness risk is the hypothesized relationship between starting carry and subsequent Carry factor portfolio returns fully revealed.

The left-hand charts of Figures 10 and 11 report DFA exposures to our individual Value and Carry factor portfolios, based upon a model specification that incorporates all three of our conditioning variables, and relative to the positioning of the underlying factor portfolios. The right-hand chart of each figure reports 3-year rolling IRs to original (dark blue line) and DFA tilted positioning (light blue line).

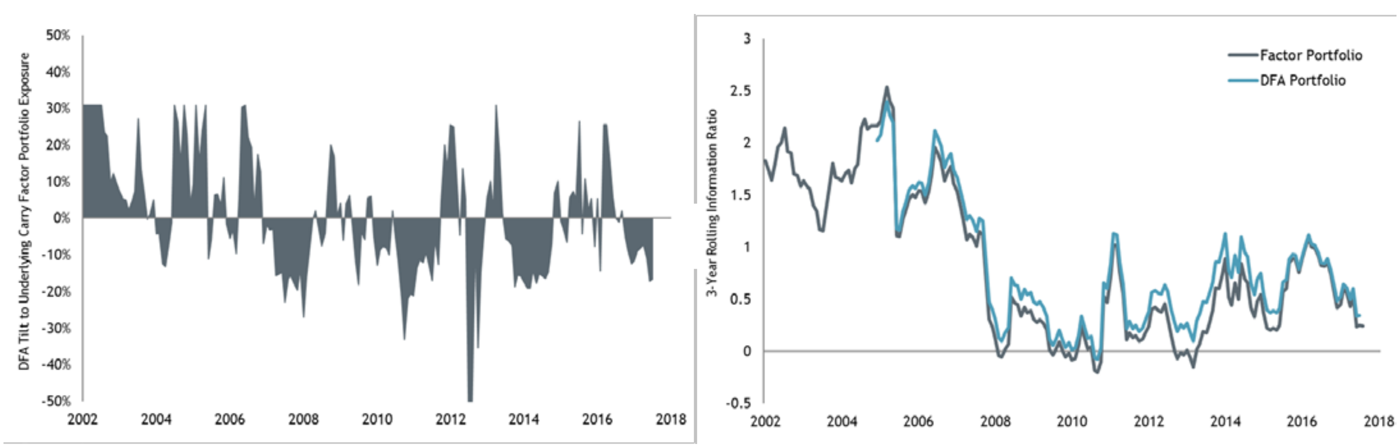
The magnitude of the performance improvement due to our rules-based DFA tilting strategy is modest for each model, but commensurate with the explanatory power of conditioning variables used to create our dynamic factor tilts. It is also consistent with the findings of Asness et. al. (2017) and Bender et. al. (2018).

Figure 10 – DFA Exposure and Rolling IRs of Value Factor Portfolio



Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. Sample period: December 2002 to June 2018. The rolling IR series for the DFA portfolio only begins in 2005 to allow for the initial accumulation of 3 years of data.

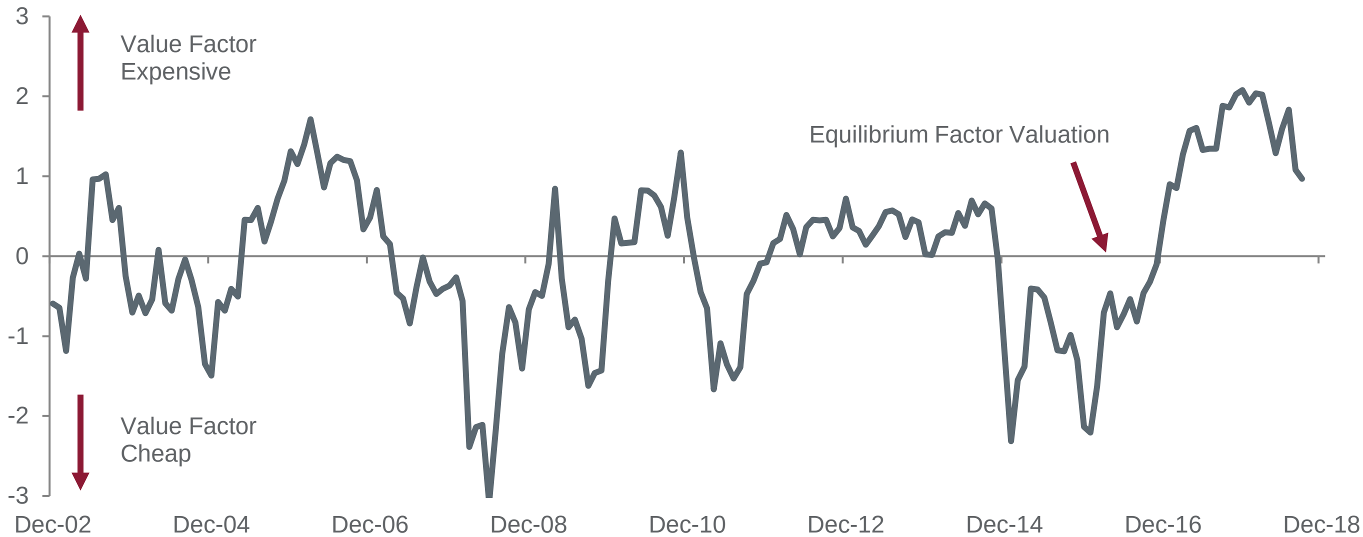
Figure 11 - DFA Exposure and Rolling IRs of Carry Factor Portfolio



Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. Sample period: December 2002 to June 2018. The rolling IR series for the DFA portfolio only begins in 2005 to allow for the initial accumulation of 3 years of data.

For our Value factor portfolio, there are two noteworthy periods when DFA tilts add incremental value. First, in 2007-2008 our DFA strategy underweights the original Value factor portfolio. This is intuitive. 2006 marked a local high in the valuation of our Value factor (Figure 12); the factor was expensive, and the expected return from a risk allocation to it was low. Thereafter, the factor's valuation became progressively cheaper as the Global Financial Crisis (GFC) erupted and played out. The magnitude of carry attached to the Value factor portfolio was generally low during the GFC. And our proprietary risk index identified an increasingly negative environment for factor risk premia strategies as the GFC intensified.

Figure 12 - Valuation of Value Factor Portfolio



Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. The Valuation of the Value Factor Portfolio is reported as a z-score, normalized using full-sample average and standard deviation statistics, and is shown for illustrative purposes only. Sample period: December 2002 to June 2018.

This combination of expensive but improving factor valuation, low factor carry, and high-risk aversion was not propitious for the expected performance of a Value-based strategy. Accordingly, the rolling 3-year IR of the Value factor portfolio was increased by our DFA underweight. That said, it is a moot question whether simulated gains were achievable in practice during this period, given a backdrop of low market liquidity and abnormally high transaction costs. We observe a similar DFA experience during 2018. In an environment of elevated risk aversion, expensive factor valuation, and factor carry only around its average level, DFA tilts moved to underweight our Value factor portfolio.

Second, in 2013-2016 DFA Value factor tilts were often positive. For much of this period, the Value factor was cheap relative to its own intrinsic valuation (Figure 12), the risk environment was benign, and the carry attached to the Value factor portfolio was typically close to its sample average. DFA tilts persistently boosted the rolling IR of the Value factor during this period.

The relative improvement in Carry factor portfolio performance due to active DFA tilts is noteworthy, but does not significantly change the weak performance of this factor since the onset of the GFC. Central bank efforts to lower the cost of capital in response to this crisis shrunk the magnitude of the currency carry risk premium. These efforts are only now tentatively being unwound, led by the US Federal Reserve. Cyclical deviation between DM countries, and by implication DM interest rates, validates the continued existence of a positive expected Carry risk premium. And the carry premium attached to EM currencies within our investment universe persists. But from a steady-state perspective, expected DM interest rate differentials are much narrower now than historically, as macroeconomic and institutional similarities across the DM country universe continue to increase. Accordingly, the level of expected return associated with this factor has likely experienced a decline that may persist for some time. DFA does not materially change this conclusion.

Figures 13 and 14 present the portfolio-level performance that results from our approach to DFA. For ease of comparison, reported returns are standardized to a 5% annualized risk target. A number of observations are pertinent. First, as discussed above, an equally-weighted factor portfolio encompassing Carry and Value risk premia outperforms each individual model portfolio. As the expected return to each factor derives from a different fundamental source, and their associated investment horizons are also different, combining them in a portfolio is diversifying. Second, a further IR improvement is possible based on a dynamic weighting of factors (final column of Figure 13); some, modest alpha is available from systematic conditional portfolio risk allocation. This alpha equates to around 70bps per annum, assuming an annualized risk target of 5.0%.[13] As Campbell and Thompson (2008) argue, although this additional return is not *statistically* significant, even relatively small performance improvements can be *economically* meaningful to investors, particularly in the current low expected return environment. Third, and as discussed above, Figure 14 emphasizes that this additional alpha is not specific to a particular sub-sample but instead appears to cumulate throughout our sample; the blue and gray lines in Figure 14 gradually diverge as our sample expands.

Fourth, and arguably most important, DFA achieves a noteworthy improvement in portfolio skew and kurtosis (Figure 13). Portfolio risk is often summarized using only the standard deviation of returns. In reality, we think beyond this simplistic level when managing client assets, and also consider, inter alia, the normality of expected returns, and particularly their skewness. From this perspective, the value of a DFA strategy lies in its ability to systematically recognize environments in which particular factor risk premia are likely to underperform, and to make appropriate adjustments to conditional factor risk allocations. In these environments, our results suggest that DFA can help preserve clients' capital. This conclusion is confirmed by the drawdown statistics in Figure 13. The maximum drawdown experienced by the factor portfolio including DFA over our sample period is 25% shallower than the maximum drawdown of the equally-weighted factor portfolio. This is an economically meaningful improvement, and emphasizes the value of considering DFA in addition to an underlying rules-based factor investment strategy.

Figure 13 - Summary Performance Results

	Carry	Value	Carry + Value	DFA
Annualized Return	2.9%	3.3%	5.0%	5.7%
Annualized Volatility	5.0%	5.0%	5.0%	5.0%
Information Ratio	0.57	0.66	1.00	1.15
Skewness	-1.23	0.27	0.07	0.22
Kurtosis	4.29	2.47	1.09	0.69
Max DD, %	-13.9%	-13.1%	-8.6%	-6.5%
Length of Max DD (months)	53	29	20	19
Win Rate, % months	60.66%	60.11%	60.66%	64.48%
Average Win / Loss Return Ratio	1.06	1.19	1.57	1.48

Source: The information was prepared by CIBC Asset Management Inc. based on/using data from the following third-party service providers: Bloomberg, Thomson Reuters Datastream. Sample period: December 2002 to June 2018.

5. CONCLUSION

Rules-based factor models have long been successfully exploited by active currency investors as a way to construct portfolios that target exposures to a set of rewarded factor risk premia on an ex ante basis. These premia include Carry, Value, Cycle, and Momentum. In our analysis, we have shown that the performance of

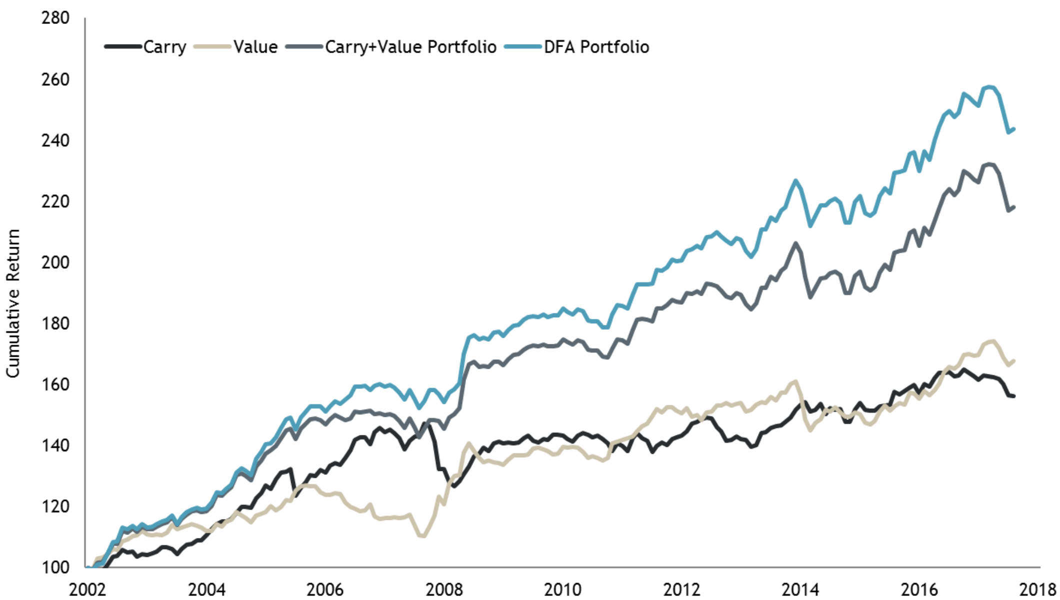
[13] Since our results can be scaled linearly, this is equivalent to a return improvement of 14 basis points per each 1% of risk.

single and combined factor portfolios have historically provided an attractive source of risk-adjusted currency returns. The extent of time variation in this performance appears muted compared to asset-based, and typically equity-centric, portfolios, as is the performance impact of changes in macroeconomic conditions.

Changes in market risk environment appear more impactful for factor portfolio performance. We use this observation, as well as the relationship between the starting valuation and carry of factor portfolios and subsequent portfolio returns, to develop a conditional set of Dynamic Factor Allocation decision rules to tilt risk exposures around our initial factor portfolios through time. We report a modest, but economically significant, improvement in portfolio performance, and a particularly relevant improvement in portfolio skew and drawdown characteristics.

In this paper, we have isolated the opportunity to add value to investment portfolios relying exclusively upon rules-based factor risk premia models. An alternative approach is to also implement active tilts based upon rigorous discretionary risk-taking. Discretionary active investing is difficult to do well. Only a small cohort of currency managers has demonstrated persistent ability to add value from this investment style. But if implemented with skill and discipline, the advantage of disciplined discretionary risk taking is its potential to exploit a wider array of fundamental and non-fundamental currency risks than those that can be captured by quantitative factor strategies. These variables can include the conditioning variables that we have already exploited, but also macroeconomic fundamentals related to current account flows, microstructure variables such as market liquidity and position crowding, as well as geo-political event risk. A foundational set of transparent rules-based factor models combined with disciplined quantitative and discretionary tilts—both to the aggregate level of active risk through time, as well as to risk allocations between factor risk premia and assets at any given time—represent the totality of the CIBC AM active currency investment process.

Figure 14 - Cumulative Returns to Individual Factors and Factor Portfolios



Source: Performance is gross of fees and net of estimated transaction costs. Returns are rescaled to 5% Annualized Risk. Performance is gross of fees and net of estimated transaction costs. Sample period: December 2002 to June 2018. Factors based on CIBC Asset Management research. Sources: Thomson Reuters Datastream, Bloomberg and CIBC Asset Management Inc.. This hypothetical scenario is shown for illustrative purposes only and is not indicative of future results. Please refer to the Disclaimer page for further information.

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