# Dissecting Investment Strategies in the Cross Section and Time Series

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**Abstract**

We contrast the time-series and cross-sectional performance of three popular investment strategies: carry, momentum and value. While considerable research has examined the performance of these strategies in either a directional or cross-asset settings, we offer some insights on the market conditions that favor the application of a particular setting.

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# 1 Introduction

In quantitative cash equity strategies, momentum is almost always traded across assets (relative value) whereas in futures trading, momentum is typically applied directionally. Why? Our goal is to better understand the performance of three popular strategies, carry, momentum and value in different implementations: time-series vs. cross-sectional.

Consider the following motivating example. Suppose we do a principal components decomposition of a set of cash equity returns and extract the first 10 factors. The first factor is dominant and will resemble the market return. In a cross-asset strategy that is market neutral, the dominant factor is effectively hedged out. If predictability is driven by the other nine factors, this is exactly the way you want to implement your investment strategy. However, if the first factor plays an important role in predictability, perhaps a time-series implementation is preferred. In our example, if the market factor is trending, then it is more likely time-series momentum will be profitable than cross-sectional momentum.

Although there is considerable research on each of these popular strategies, there is little work that compares cross-asset and directional strategies for a wide variety of asset classes. For example, Moskowitz et al. (2012) focus on time-series momentum. Asness et al. (2013) look at cross-sectional performance of value and momentum. We fill this gap by providing an analysis of both the time-series and cross-section using a broad number of asset classes: equity, fixed income, currencies and commodities. We measure the relative performance of directional vs. cross-asset strategies as well as strategies that combine the information in each dimension.

In order to understand performance differences between the implementations, it is important to start with first principles. We begin our analysis with the theoretical underpinnings of each of these popular strategies. Next we compare the time-series and cross-sectional performance across a wide variety of assets.

We show that these strategies are largely profitable over our sample - and the best performance is when these strategies are combined. However, we are very aware of the critique in Harvey et al. (2015) with respect to factor proliferation. Indeed, we are testing three strategies that are select - they are popular because they have worked. Importantly, our focus is not to document the most profitable trading strategy; our goal is to explore the conditions where any particular strategy has the best shot of working. Indeed, there are many conditions that drive the difference between directional and cross-asset performance. Important drivers are the correlation of asset returns, the correlation of the information that drives markets (some of which is unobservable), as well as the correlation of the trading signals. These drivers will be explored in a future paper.

Our paper is organized as follows. In the second section, we present the theoretical underpinnings of each of the three strategies. Our data are described in the third section. The empirical comparison of the different strategies in directional and cross-asset implementations is presented in the next section. In the fifth section, we offer some thoughts on the underlying drivers of the differential performances. Finally, we offer some caveats about the average return performance of these strategies.


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# 2 Economic Foundations of the Strategies

Before implementing any strategy, it is important to understand the theoretical basis. That is, why would carry, momentum and value perform on a priori grounds? The economic foundation may also be useful in determining why certain strategies work better in the time-series, while others are best applied in the cross-section and vice versa.

## 2.1 Carry

We define carry as the difference between the spot and the forward price of an asset – in other words the profit on a long forward position if prices do not change. A simple version of the carry trade consists in buying the asset forward if the carry is positive or selling it forward if the carry is negative.

Carry trades exploit the difference between the expected spot price at expiry and the forward price.[1] Why would a forward price be different from an expected spot price? It is actually straightforward to show why.

Suppose that the forward prices were unbiased estimators of future spot prices (both forward and spot prices expressed as units of asset A per unit of asset B):

$$F_{t,T} = E_t(S_T) \tag{1}$$

where $F_{t,T}$ is the forward price at time t for expiry at time T and $S_T$ is the asset price at time T. It is then said that the forward bias, the difference between the expected spot price and the forward price, is zero. Then, if this is a general principle, this should apply to all relative prices, including units of asset B expressed per unit of asset A:

$$\frac{1}{F_{t,T}} = E_t(\frac{1}{S_T}) \tag{2}$$

And it should follow that:

$$\frac{1}{E_t(S_T)} = E_t(\frac{1}{S_T}) \tag{3}$$

which cannot happen by Jensen's inequality. This means that forward prices cannot be unbiased predictors of future spot prices. This should be true for all asset classes, although it is most intuitive for foreign exchange. In currency markets, the above means that uncovered interest rate parity cannot hold.

Can we say something about the magnitude of the forward bias and about the carry trade using basic finance theory?

Consider a dividend paying financial asset. By standard arbitrage, the forward price is equal to the spot price compounded at the risk-free rate minus the dividend yield:

$$F_{t,T} = S_t e^{(r-d)(T-t)} \tag{4}$$

[1]For practical purposes, readers can think of forwards and futures as equivalent in this section.

where $d$ is the continuously compounded dividend yield and $r$ is the continuously compounded risk-free rate. Note that the carry is positive (negative) if the interest rate is greater (smaller) than the dividend yield.

To calculate the expected return on a long forward position, we need to use an asset pricing theory. With the standard Capital Asset Pricing Model (CAPM), then the expected spot price is:

$$E_t(S_T) = S_t e^{(r+\beta\pi-d)(T-t)} \tag{5}$$

where $\beta$ is the asset beta and $\pi$ is the equity risk premium.

If the asset beta is positive as is generally the case, the forward price is lower than the expected spot price:

$$\frac{E_t(S_T)}{F_{t,T}} = e^{\beta\pi(T-t)} > 1 \tag{6}$$

Then, the expected P&L on a forward trade is:

$$E_t(S_T) - F_{t,T} = S_t e^{(r-d)(T-t)}[e^{\beta\pi(T-t)} - 1] > 0 \tag{7}$$

We can now draw two conclusions from a basic CAPM:

- There is a systematic forward bias. Forward prices are lower than expected spot prices for positive beta assets, that is most assets.
- The sign of the forward bias is independent of carry: the ratio of expected spot to forward depends on $\beta\pi$, not on $r - d$.

To link carry and forward bias requires richer asset pricing models. Suppose, for example, that expected returns are determined not just by the market factor but also by the dividend factor:

$$E_t(S_T) = S_t e^{(r+\beta\pi+\gamma[d-\overline{d}]-d)(T-t)} \tag{8}$$

Here, $\gamma$ is the dividend factor loading and $\overline{d}$ is the market dividend yield. It follows that:

$$\frac{E_t(S_T)}{F_{t,T}} = S_t e^{(\beta\pi+\gamma[d-\overline{d}])(T-t)} \tag{9}$$

With the dividend factor - a proxy for the value factor as we shall see below - the forward bias is now correlated with carry. The higher the dividend yield, the higher the carry, the lower the forward compared to the expected spot price, the more profitable the carry trade.

The CAPM and its derivative models apply in principle to all assets. For example, in Lustig and Verdelhan (2007), high-yielding currencies tend to depreciate whereas low-yielding currencies hold their own in low domestic consumption states. This hedging property of low-yielding currencies translates in lower expected returns relative to high yielders. Breeden (1986) derives equilibrium relationships between interest rates, growth and other parameters from optimal consumption and production models (more on this in the value sub-section).

Koijen et al. (2013) study the carry strategy across asset classes and find the strategy is relatively uncorrelated with factors such as value and momentum but is partially explained by recession and volatility risk. Other researchers have made conjectures about the carry strategy that are of a more ad hoc nature and tend to reflect idiosyncrasies in specific asset classes.

In currencies, the carry trade, also known as the bird-in-the-hand trade, consists in buying high-yielding currencies against low-yielding currencies. This trade can be profitable because high-yields are associated with non-diversifiable risk factors such as political turmoil or wavering property rights or persistently high inflation. In the extreme, the yield differential can remunerate a so-called peso effect, meaning that jump risk can be very real even though it has not materialized. Alternatively, a high yield on a currency can reflect a central bank just about to gain or regain anti-inflation credentials that will make its currency more desirable.

In commodities, the positive difference between spot and futures prices - also known as backwardation - was interpreted by Keynes as the result of producers selling futures to insure themselves against price falls. If this is the case, there is a structural excess supply of futures contracts relative to spot transactions: curves will tend to be backwardated; and futures prices will tend to roll up toward spot prices until they converge at expiry date. This is the so-called theory of insurance or theory of normal backwardation. But as observed empirically, backwardation is not the norm, particularly today. Indeed, hedging transactions can go both ways: hedgers can sell futures as Keynes asserted; alternatively, they can be naturally long futures if they are short the underlying commodity (e.g., airline companies are short fuel and need to buy futures for hedging purposes). In this case, the curve is contangoed and speculators are paid to be short futures. In other words, speculators are incented by hedgers to sell contangoed futures and buy backwardated futures. In a competing explanation, the theory of storage links backwardation to tight inventories. A low level of inventories may result in a high convenience yield, hence a backwardation (Working, 1933; Kaldor, 1939 and Schwartz 1997). Because inventories take time to rebuild, profits from the carry trade can be persistent.

In fixed income, the term structure is, more often than not, upward sloping. Conventional explanations range from the liquidity theory of rates - investors should be compensated for the higher risk of holding long bonds, hence the upward sloping yield curve - to the theory of preferred habitats - investors prefer short bonds to long bonds. Rates tend to roll down the curve: this translates into excess returns for fixed income investors.

## 2.2 Momentum

Momentum refers to persistence in asset returns: winners tend to continue to do well and losers continue to do badly. The conventional trade (at least for academic purposes) is to buy assets that outperformed and sell assets that underperformed over the previous year. Asset returns appear to exhibit negative autocorrelation over very short periods (less than one month) and longer time periods (more than three years) while the sweet spot for momentum, or positively auto-correlated, strategies is around 6-12 months.

Theories of momentum range from the risk-based to the behavioral. On the risk end of the spectrum, momentum performs because high-momentum assets are more sensitive to macroeconomic factors such as, for example, the growth rate of industrial production (Liu and Zhang, 2008); it can also perform because, to the extent realized and expected returns are highly correlated, then a cross-section of past winners with high realized returns has higher expected returns and ends up outperforming a cross-section of past losers (Conrad and Kaul, 1988). On the behavioral end, investors underreact to news either because they display conservatism bias and are slow updating their beliefs (Barberis, Shleifer and Vishny, 1998) or because they do not receive and update information at the same time (Hong and Stein, 1999). Alternatively, it is claimed that prices can overreact to news and feed upon themselves with noise traders deepening the mis-pricing. Furthermore, behavioral biases can generate momentum when fund flows exhibit inertia and the market under-reacts to expected future flows. Price returns will then show persistence until large deviation from price fundamentals result in a market reversal (Vayanos and Woolley, 2013). The so-called disposition effect can also help explain momentum returns. Investors tend to sell their winning stocks too early while holding on to their losers. Grinblatt and Han (2002) present a model where the disposition effect drives the market clearing price. Let there be a population of rational investors (fraction $\mu$) and a population of disposition investors (fraction 1-$\mu$) with the following demand curves:

$$\begin{cases} D_t^r = 1 + \beta(F_t - P_t) \\ D_t^d = 1 + \beta(F_t - P_t) + \alpha(P_{t-1} - P_t) \end{cases} \tag{10}$$

$D_t^r$ and $D_t^d$ are the demand functions of rational and disposition investors. $F_t$ is the fundamental price at t and $P_t$ is the market clearing price. A positive $\alpha$ describes the disposition effect: the lower today's price relative to yesterday's, the more disposition investors hold on to their assets, the higher the excess demand for that asset. A positive $\beta$ indicates that rational investors demand for an asset decreases with the difference between its market price and its fundamental price. The asset supply is equal to one unit. Then aggregating both demand functions, we obtain:

$$\mu D_t^r + (1-\mu) D_t^d = 1 \tag{11}$$

Therefore,

$$P_t = wF_t + (1-w)P_{t-1} \text{ , where } w \equiv \frac{1}{1+\mu\alpha} \tag{12}$$

At equilibrium, today's price is positively correlated to yesterday's price and only partially reflects the fundamental asset value.

Some market participants have been trying to evaluate the merit of these competing explanations in the current environment (AHL/MSS Academic Advisory Board, 2014). Is momentum behavioral? Do today's markets foster behavioral biases? The answer to both questions is a qualified yes. Because recent policy moves (negative nominal rates, open-ended quantitative easing, implicit policy focus on wealth effects) are unprecedented and unfamiliar, people rely more on heuristics: instinctive thinking may dominate investors' more deliberative mode of thinking. This can result in significant trends from anchoring and other behavioral biases. Behavioral biases, combined with more liquid markets and more efficient information diffusion, tend to favor persistence of slow momentum.

## 2.3 Value

Value can be defined as the difference between a fundamental asset price and its prevailing market price. This begs two questions: is there such a thing as the fundamental price of an asset?

What mechanisms cause market prices to deviate from and revert to fundamental prices? We answer these questions by looking in turn at interest rates, stocks, currencies and commodities.

A simple two-period consumption model yields the following inter-temporal equilibrium condition:

$$E_t\left[e^{(r-\rho)}\frac{U'(C_{t+1})}{U'(C_t)}\right] = 1 \tag{13}$$

where $r$ is the real interest rate, $\rho$ is the rate of preference for the future and $\frac{U'(C_{t+1})}{U'(C_t)}$ is the ratio of the marginal utility of consuming a real dollar at t+1 to the marginal utility of consuming it today. The expression $e^{-\rho}\frac{U'(C_{t+1})}{U'(C_t)}$ is commonly called a stochastic discount factor. With logarithmic utility functions and a log-normally distributed consumption, we can solve for the equilibrium real interest rate [2]:

$$r = g + \rho - \sigma^2 \tag{14}$$

where $g$ is the instantaneous real consumption growth and $\sigma$ is the volatility of consumption growth. In a deterministic model where people are indifferent between spending today or tomorrow:

$$r = g \tag{15}$$

Another value metric for interest rates is the differential between domestic and foreign real rates. When capital is free to move across countries, there is evidently a tendency for real rates of return to converge. Higher domestic real rates will result - all else equal - in an excess demand for domestic fixed income assets.

How about equity? A stock price can be viewed as the present value of its dividends:

$$P = \int_0^\infty D e^{g_d t} e^{-Rt} dt = \frac{D}{R - g_d} \tag{16}$$

where $D$ is the dividend today, $g_d$ the long term real continuous dividend growth rate (we assume for convenience that the dividend growth rate is equal to the consumption growth rate $g$) and $R$ the long term real continuous equity yield. From this equation, one may infer the implied equity yield:

$$R = g + \frac{D}{P} \tag{17}$$

meaning that the equity yield is the sum of the dividend growth and the dividend yield. The implied equity risk premium is:

$$ERP = R - r = g - r + \frac{D}{P} \tag{18}$$

By further assuming that $r = g$, then the implied equity risk premium is simply the dividend yield:

$$ERP = \frac{D}{P} \tag{19}$$

[2] As mentioned, $U(C_t) = ln(C_t)$ and $C_{t+1} = C_t e^{(g-\frac{\sigma^2}{2}+\sigma\varepsilon)}$, and noting that $E_t(e^{-\sigma\varepsilon}) = e^{\frac{\sigma^2}{2}}$, the result follows. For a broader class of so called constant relative risk aversion (CRRA) utility functions of form : $U(C_t) = \frac{C_t^{1-\gamma}-1}{1-\gamma}$, the real interest rate at equilibrium is $r = \gamma g + \rho - \gamma^2\sigma^2$. Note that CRRA utility functions become logarithmic for $\gamma = 1$.

Dividend yields can therefore be used as a measure of value for broad equity markets. High dividend yields may indicate that stocks are cheap against bonds [3]. Another measure of value is the price-to-book ratio. The price-to-book is a close cousin of Tobin's Q, another statistic used by investors to gauge value in stocks. Tobin's Q is defined as the ratio of the market cap to the replacement cost of assets. A Q that is greater than 1 means that an investor is better off replicating the assets of a company rather than buying it. It indicates that a company is expensive. Similarly, high price-to-book ratios are a presumption of expensiveness.

We now turn to commodities. Commodity prices exhibit mean reversion for a number of reasons: first, high (low) commodity prices incentivise producers to boost (reduce) supply which in turn results in downward (upward) pressure on prices. Second, in competitive commodity markets, prices will be pulled toward production costs. This would all suggest that value investing in commodity space is tantamount to positioning for long mean-reversion cycles.

Currencies also have their garden-variety value indicators. Among these, purchasing power parity (PPP) has the most intuitive appeal. Absolute PPP theory states that all products must sell at the same price in a frictionless world. It follows that an exchange rate $e$ (units of domestic currency per foreign currency unit) is the ratio of the domestic price index $p$ to the foreign price index $p*$. In the same vein, absolute PPP states that the percentage change in $e$ is approximately equal to the difference between domestic and foreign inflation, all measured over the same period. One can see how PPP is more a tautology than a theory - the only issue being how much frictions - such as transportation costs, tariffs, sticky prices, capital flows and economic policies - cause real exchange rates to deviate from PPP in practice.

We still need to answer the question: what explains the value premium? Much like theories of momentum, theories of value can be based on rational or behavioral stories.

Dornbusch's overshooting model (1976) is an example of a rational story that explains large deviations from PPP. The model is quasi-deterministic, assumes rational expectations, sticky prices in goods and services, fully flexible asset prices, a Keynesian money demand function, a PPP long-term equilibrium and uncovered interest rate parity (UIP). Here are two key equations of the model - UIP and money demand:

$$\begin{cases} E[ln(e)] - ln(e) = r - r^* \\ ln(m) - ln(p) = f(r, Y) \end{cases} \tag{20}$$

UIP states that the expected currency appreciation is equal to the differential between domestic and foreign interest rates. And demand for real money balances is a decreasing function of the interest rate (which acts as an opportunity cost) and an increasing function of income $Y$. How does the exchange rate react to an unanticipated increase in money supply? Because prices and income are sticky, the only way for money demand to match the increased money supply is through an instantaneous decrease in the domestic interest rate. But then people rationally expect two apparently conflicting outcomes: first, the currency should appreciate in response to the lower domestic interest rate as UIP would predict; and second, as domestic prices gradually rise to reflect the money supply shock, the currency needs to depreciate ($e$ increases) in the long run to reach its PPP level. The solution that will

[3] Of course the dividend yield can be time-varying and thus not necessarily a measure of value. Also, when interest rates are lower than growth as is currently the case, dividend yields tend to underestimate the equity risk premium. But other factors, such as leverage, may indicate that the equity risk premium is less than meets the eye.

reconcile both expectations is an instantaneous depreciation of the exchange rate over and above that dictated by PPP. This explains the overshooting of exchange rates. This mechanism is reminiscent of the euro sudden depreciation in response to the unanticipated loosening of monetary policy in Europe recently. While this model is arbitrage free - the value premium is perfectly neutralized by the carry, it is easy to see how exchange rate overshooting can create value opportunities in asset markets that are slow to adjust: for example, real estate prices expressed in euros have been much stickier than currencies in response to the European monetary policy surprise.

In equities, risk-based value stories are plenty: for example, Hansen Heaton and Li (1998) attribute the out-performance of value portfolios (relative to growth portfolios) to a higher long term exposure to consumption risk.

Behavioral stories of the value premium are also plentiful: Lakonishok, Shleifer and Vishny (1994) argue that value strategies outperform glamour strategies because investors put excessive weight on past history and just equate well-run firms with good investments. Benartzi and Thaler (1995) explain how investors with prospect-theory type of utility end up buying large amounts of T-bills despite a large equity risk premium. Similarly, Maenhout (1999) shows that ambiguity aversion - in this case the probability distribution of stock returns is viewed as ambiguous - accounts partially for the large equity risk premium.

We now turn to the empirical investigation of carry, momentum and value.

# 3 Data and Backtesting

## 3.1 Data Collection

The data sources are Bloomberg, Global Financial Data and the Man-AHL proprietary database. The sample period starts in January 1990 and ends in April 2015. The data we use are detailed in the Appendix. We study 26 equity futures markets, 14 interest rate swap contracts, 31 currency pairs, and 16 commodity futures. All prices are in U.S. dollars. We used mid-market prices and do not therefore account for trading costs (which we discuss later).

## 3.2 Signal Construction

1. Carry

   <u>FX:</u>

   We used the 3 month FX-forward to imply the carry, as shown below:

$$Carry_t = 4 \times (\frac{Spot_t}{Fwd_{3M,t}} - 1) \tag{21}$$

Equity:

We used the first two futures of each index and computed a raw carry signal as follows:

$$Raw\_Carry_t = \frac{1}{(T_2 - T_1)} \times \frac{Fut_{t,T_1} - Fut_{t,T_2}}{Fut_{t,T_2}} \tag{22}$$

For every month $m$, we compute a seasonality adjustment which is the average difference between the raw carry and its 1Y moving average at time t for all the $m$-month business days in the sample:

$$Adj_t = \overline{[Raw\_Carry_t - 1Y\_MA(Raw\_Carry_t)]}_n \tag{23}$$

where n is the number of $m$-month business days in the sample until time t.
We then corrected the raw carry signal by subtracting the seasonality adjustment:

$$Carry_t = Raw\_Carry_t - Adj_t \tag{24}$$

Commodities:

Some commodities display significant seasonal effects (like agricultural and energies markets). Then, to remove this seasonal effect in the carry computation, we used the first future and the contract exactly expiring one year later.

$$Carry_t = \frac{Fut_{t,T_1+1} - Fut_{t,T_1}}{Fut_{t,T_1+1}} \tag{25}$$

Swap Rates:

Carry is meant as "carry + roll down". We used the following formula:

$$Carry_t = \underbrace{\frac{S_{10Y,t} - Fixing_t}{Duration_t}}_{\text{"Carry"}} + \underbrace{\frac{S_{10Y,t} - S_{7Y,t}}{3}}_{\text{"Roll"}} \tag{26}$$

$Duration_t$ is the modified duration, with:

$$Duration_t = \frac{1 - (1 + S_{10Y,t})^{-10}}{S_{10Y,t}} \tag{27}$$

2. Momentum

For all asset classes, we used a CTA-momentum signal, based on the cross over of exponentially weighted moving averages. The algorithm building that signal is the following:

(a) Select 3 sets of time-scale with each set consisting of a short and a long exponentially weighted moving average (EWMA)

(b) Here, we have chosen $S_k$=(8,16,32) and $L_k$=(24,48,96).
Those numbers are not look-back days or half-life numbers. In fact, each number (let's call it $n$) translates to a lambda decay factor ($\lambda$) of $\frac{n-1}{n}$ to plug into the standard definition of an EWMA. The half-life (HL) is then given by:

$$HL = \frac{log(0.5)}{log(\lambda)} = \frac{log(0.5)}{log(1 - \frac{1}{n})} \tag{28}$$

(c) For each k=1,2,3 calculate

$$x_k = EWMA[P|S_k] - EWMA[P|L_k] \tag{29}$$

(d) We normalize with a moving standard deviation as a measure of the realized 3-months normal volatility (PW=63)

$$y_k = \frac{x_k}{Run.StDev[P|PW]} \tag{30}$$

(e) We normalize this series with its realized standard deviation over the short window (SW=252)

$$z_k = \frac{y_k}{Run.StDev[y_k|SW]} \tag{31}$$

(f) We calculate an intermediate signal for each k=1,2,3 via a response function R

$$\begin{cases} u_k = R(z_k) \\ R(x) = \frac{x exp(\frac{-x^2}{4})}{0.89} \end{cases} \tag{32}$$

(g) The final CTA momentum signal is the weighted sum of the intermediate signals (here we have chosen equal weights $w_k = \frac{1}{3}$)

$$S_{CTA} = \sum_{k=1}^{3} w_k u_k \tag{33}$$

3. Value

FX:

We used relative PPP (purchasing power parity) as value indicator:

$$\begin{cases} Value_t = PPP_t = log(Spot_{Real,t}) - \overline{log(Spot_{Real,t})} \\ Spot_{Real,CCY1/CCY2,t} = Spot_{CCY1/CCY2,t} \times \frac{CPI_{CCY1,t}}{CPI_{CCY2,t}} \end{cases} \tag{34}$$

Equities:

We used dividend yield as value indicator:

$$Value_t = DivYield_t \tag{35}$$

Commodities:

Value is defined as today's deflated price divided by the deflated historical average price, where history is the expanding window of all prices available:

$$Value_t = \frac{Adj.Price_t}{\overline{Adj.Price_t}} \text{, with } Adj.Price_t = \frac{Price_t}{US\_CPI_t} \tag{36}$$

Swap Rates:

We defined value, in the rate space, as the difference between the 10Y swap rate and the most recent nominal GDP growth rate (release quarterly):[4]

$$Value_t = S_{10Y,t} - GDP_t \tag{37}$$

An alternative definition of value could have been the difference between the 10Y swap rate and the most recent yoy CPI inflation (consumer price index).

We tested both definitions and the results were quite similar. All the results presented in the remainder of the paper will use the GDP definition.

## 3.3 Portfolio Construction

1. Basic Construction : Cross Sectional Portfolio

   The portfolio construction is simple. For each combination of style and asset class, we ranked all the assets according to the magnitude of the signal and took long/short positions on the six most extreme assets (three on each side).[5] We used equal weights, meaning that the risk allocated to each position did not depend on the magnitude of the signals. The portfolio was rebalanced every trading day, except in particular cases that we discuss below.

   To give the example of equity value trades, at each rebalancing date, we ranked all indices by dividend yield, and took long positions on the three highest dividend paying indices and short positions on the three lowest dividend paying indices. These six positions were held for one business day until the next rebalancing date.

   Once every {"asset class", "style"} portfolio had been built, we looked at the diversification benefits by regrouping them.

   When we regrouped asset classes together, we computed the ex-ante volatility of each of the portfolios and scaled their allocations for an annualized volatility of 15% per portfolio. When we regrouped investment styles together, we used equal weighting. The reason is that the volatility of returns come mostly from the choice of the asset class rather than the choice of the investment style.

2. Basic Construction : Time Series Portfolio

   The time series portfolio construction uses the same carry, momentum and value indicators as the cross sectional portfolio. The main difference is that, within every asset class, we consider the universe of N assets and take positions equivalent to $\frac{1}{N}$. These positions will be long or short depending on the carry, momentum and value indicators. All details of the portfolio construction are similar otherwise in the time series and cross sectional portfolios.

[4] We used a three month lag for the GDP growth rate.

[5] We used the six most extreme assets. Afterwards, we tested for other configurations and the results were comparable

3. Complications

   We mentioned that every portfolio was fully rebalanced every trading day. {"FX", "carry"} and {"FX", "value"} are two exceptions here because mean reversion in FX is slower than in equity and commodities.

   We decided to rebalance 1/252 of the portfolio every trading day, in other words, the positions taken in January 2005 were closed in January 2006, those taken in February 2005 were closed in February 2006...This gives one year for value and carry to take effect.

# 4 Empirical Results

## 4.1 Cross Sectional Portfolio

The first step consists in running 12 strategies by crossing the value/carry/momentum styles with FX/equity/commodity/interest rates asset classes. Results are summarized in table Table 1 Panel A which shows the Sharpe ratio estimates for these trading strategies. We show the Sharpe ratios for specific combinations of styles and asset classes. We also show average Sharpe ratios for each style and each asset class. Lastly, the "All Asset" numbers refer to the Sharpe of each investment style when implemented across all asset classes, meaning that we then benefit from the diversification. With one exception, all the Sharpe ratios are positive with an average of 0.40 per asset class. As far as styles go, Sharpe ratios across all assets vary between 0.42 to 1.27, with carry emerging as the most profitable standalone style. As shown in panel B, maximum drawdowns per style are of order 1.8 to 3.1 times the volatility. The skew is positive for value and momentum and negative for carry.

**Table 1**: Cross Sectional Strategies using Individual Signals

*Panel A: Sharpe Ratios*

| Asset Class | Value | Carry | Mom. | Avg |
|---|---|---|---|---|
| FX | 0.42 | 0.67 | 0.74 | 0.61 |
| EQ | 0.39 | 0.33 | 0.01 | 0.24 |
| Commo | 0.07 | 0.77 | 0.45 | 0.43 |
| IR | 0.56 | 0.76 | -0.31 | 0.34 |
| Avg | 0.36 | 0.63 | 0.22 | |
| All Asset | 0.75 | 1.27 | 0.42 | |

*Panel B: Maximum Drawdowns divided by Volatility*

| Asset Class | Value | Carry | Mom. | Avg |
|---|---|---|---|---|
| FX | -3.3 | -3.1 | -2.5 | -3.0 |
| EQ | -3.2 | -3.9 | -4.1 | -3.7 |
| Commo | -3.1 | -1.7 | -1.9 | -2.2 |
| IR | -1.5 | -1.9 | -9.1 | -4.2 |
| Avg | -2.8 | -2.6 | -4.4 | |
| All Asset | -1.8 | -3.1 | -2.6 | |

| *Panel C: Monthly Returns Skew* | | | | |
|---|---|---|---|---|
| Asset Class | Value | Carry | Mom. | Avg |
| FX | 0.59 | -1.03 | -0.17 | -0.20 |
| EQ | 0.03 | 0.23 | 0.25 | 0.17 |
| Commo | -0.27 | 0.22 | 0.38 | 0.11 |
| IR | 0.15 | 0.36 | -0.50 | 0.01 |
| Avg | 0.13 | -0.06 | -0.01 | |
| All Asset | 0.09 | -0.39 | 0.10 | |

Looking at broad correlations, value is negatively correlated with both carry and momentum. As expected, value and momentum covary negatively in line with the proverbial battle between fundamental and technical traders (Table 2 Panel A). It is particularly interesting to investigate correlations among the various pairs of styles and asset classes. Here, three remarks are in order. First, correlations vary between roughly -50% and +50%, with most clustered between -10% and +10%. The average correlation, as evidenced from Table 2 Panel B, is close to zero, indicating great scope for diversification within a broad portfolio. Second, carry and momentum tend to be positively correlated. This is mostly due to the high correlation between commodity carry and commodity momentum as both a high carry and a strong momentum are caused by low inventory levels (Erb and Harvey, 2006). Also of notice is the very negative correlation between value and carry in commodity space: a low spot price (revealing deep value) goes hand in hand with a lower convenience yield (or higher carry[6]) as both are caused by a high level of inventories.

**Table 2**: Correlation of Cross Sectional Strategies

| *Panel A: Overall* | | | |
|---|---|---|---|
| | Value | Carry | Mom. |
| Value | 1 | | |
| Carry | -9.0% | 1 | |
| Mom. | -9.2% | 15.0% | 1 |

| *Panel B: Correlation by Investment Style and Asset Class* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Value | | | | Carry | | | | Momentum | | | |
| | FX | EQ | CO | IR | FX | EQ | CO | IR | FX | EQ | CO | IR |
| FX | 1 | | | | | | | | | | | |
| EQ | 1% | 1 | | | | | | | | | | |
| CO | 0% | 0% | 1 | | | | | | | | | |
| IR | -1% | -5% | -1% | 1 | | | | | | | | |
| FX | -7% | 0% | -1% | 0% | 1 | | | | | | | |
| EQ | -1% | -3% | 0% | 0% | -11% | 1 | | | | | | |
| CO | -1% | 0% | -48% | 1% | 0% | 2% | 1 | | | | | |
| IR | 2% | -1% | 0% | 16% | -12% | 2% | -1% | 1 | | | | |
| FX | 1% | -3% | -4% | -1% | 4% | 2% | 4% | 1% | 1 | | | |
| EQ | -1% | -7% | 1% | -2% | 2% | -3% | 0% | 0% | 5% | 1 | | |
| CO | -2% | -1% | -32% | 0% | -1% | 3% | 51% | -1% | 4% | 0% | 1 | |
| IR | 0% | -6% | 0% | 15% | -5% | 1% | 0% | 1% | 7% | 1% | 3% | 1 |

It is also interesting to see that most strategy pairs - each scaled for 15% volatility (in line with the S&P historical volatility) - are showing low S&P beta estimates, indicating a low correlation with the market, maybe with the exception of FX carry which, as most currency traders have experienced, displays a significant pro-cyclical behavior. Note that the carry strategy in both equity and interest

[6]Carry measure is $\frac{F_{t,T}}{S_t} = e^{(r+s-c)(T-t)}$, where $s$ and $c$ are the storage cost and convenience yield respectively

rates is countercyclical.

**Table 3**: Assessing the Market Risk of Cross Sectional Strategies

| *Panel A: Beta Coefficients and T-Statistics in Parenthesis* | | | | |
|---|---|---|---|---|
| Asset Class | Value | Carry | Mom. | Avg |
| FX | -1%(-1.2) | 36%(30.0) | -8%(-7.13) | 9% |
| EQ | -15%(-12.3) | -17%(-14.7) | 1%(0.5) | -10% |
| Commo | -1%(-0.6) | -3%(-2.3) | -3%(-2.6) | -2% |
| IR | 3%(1.9) | -11%(-8.8) | -5%(-3.4) | -4% |
| Avg | -4% | 1% | -4% | |
| All Asset | -4%(-5.9) | 2%(2.6) | -4%(-6.1) | |

The effect of low correlations between {"asset class","style"} pairs is displayed vividly in Table Table 4, Panel A, B and C. In panel A, the Sharpe ratios of all three styles are greatly enhanced when styles are aggregated across styles. The Sharpe ratio for each asset class is almost doubled as a result of this aggregation.

**Table 4**: Combining the Cross Sectional Signals

| *Panel A: Sharpe Ratios* | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | 0.82 | 0.83 | 0.97 | 0.87 | 1.07 |
| EQ | 0.51 | 0.27 | 0.24 | 0.34 | 0.42 |
| Commo | 0.83 | 0.43 | 0.71 | 0.66 | 0.83 |
| IR | 0.87 | 0.16 | 0.34 | 0.46 | 0.54 |
| Avg | 0.75 | 0.42 | 0.57 | | |
| All Asset | 1.49 | 0.86 | 1.08 | | 1.40 |

| *Panel B: Maximum Drawdowns divided by Volatility* | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | -2.9 | -1.8 | -2.5 | -2.4 | -2.3 |
| EQ | -0.7 | -3.2 | -3.4 | -2.5 | -3.9 |
| Commo | -2.0 | -2.9 | -1.9 | -2.3 | -2.0 |
| IR | -1.6 | -3.5 | -3.3 | -2.8 | -1.8 |
| Avg | -1.8 | -2.9 | -2.8 | | |
| All Asset | -1.3 | -1.5 | -3.6 | | -1.7 |

| *Panel C: Monthly Returns Skew* | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | 0.09 | 0.35 | -0.32 | 0.04 | 0.18 |
| EQ | 0.54 | 0.42 | 0.59 | 0.52 | 0.82 |
| Commo | 0.16 | 0.03 | 0.50 | 0.23 | 0.48 |
| IR | 0.49 | 0.22 | 0.14 | 0.29 | 0.67 |
| Avg | 0.32 | 0.26 | 0.23 | | |
| All Asset | -0.14 | 0.19 | 0.14 | | 0.20 |

As we explore Sharpe ratios and correlations, the central question is: how consistent are they over time? Figure 1 presents Sharpe ratio three year moving averages over time per asset class and investment style. Remarkably, performance is consistently positive for value. It is also uniformly positive for carry except for a brief episode in the middle of the 90s. The contrast, cross sectional momentum has suffered over the last few years.

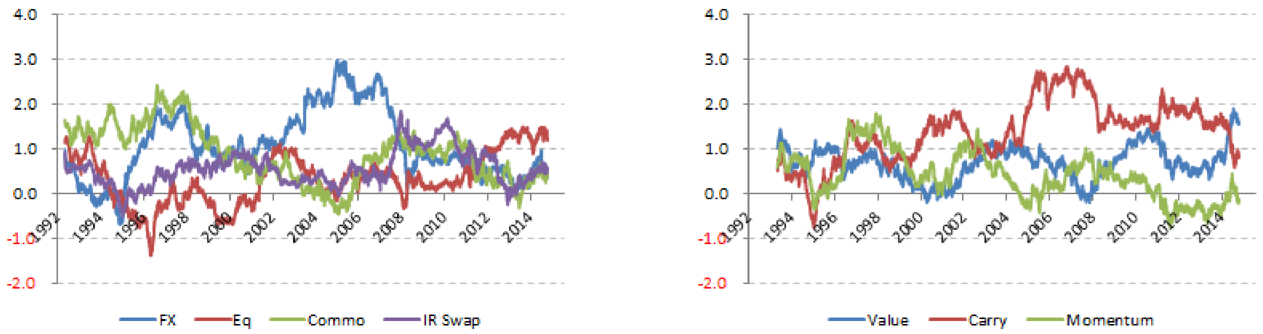



Figure 1. Cross Sectional: 3Y Rolling Sharpe per Asset Class (left) and per Investment Style (right)

In figure 2, it can be seen that correlations across styles are highly unstable, with value showing at times strong negative correlation with both carry and momentum.

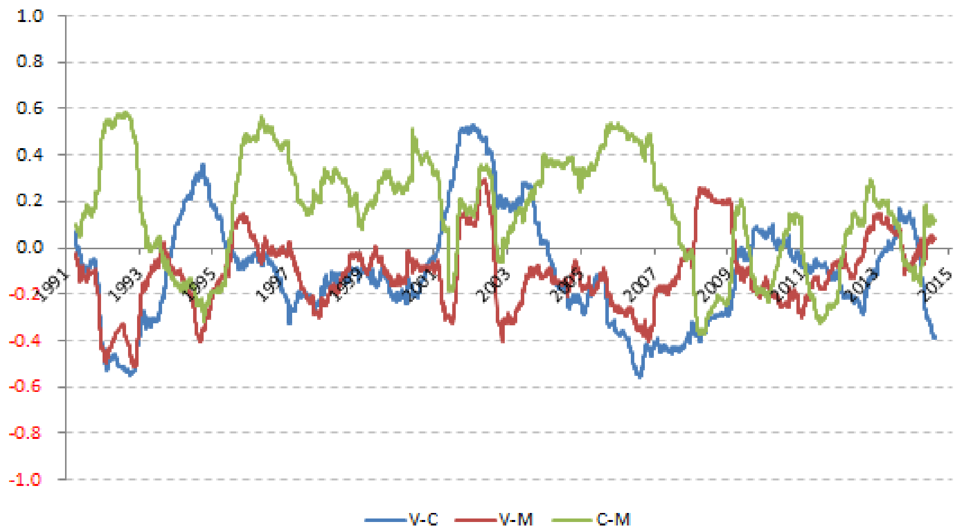



Figure 2. Cross Sectional: 1Y Rolling Correlations

Last but not least, figures 3 and 4 show the cumulative P&L, the 3Y rolling Sharpe ratio and its distribution when all strategy pairs are aggregated in a single portfolio. The overall Sharpe ratio is 1.40, with corresponding return and volatility of 6.88% and 4.92% respectively. The reader should be reminded however that the trading did not account for transaction costs. Figure 4 shows that the portfolio was never in the red on a 3yr rolling basis with a Sharpe ratio moving between 0 and 2.30 and hovering around 1.35 recently.

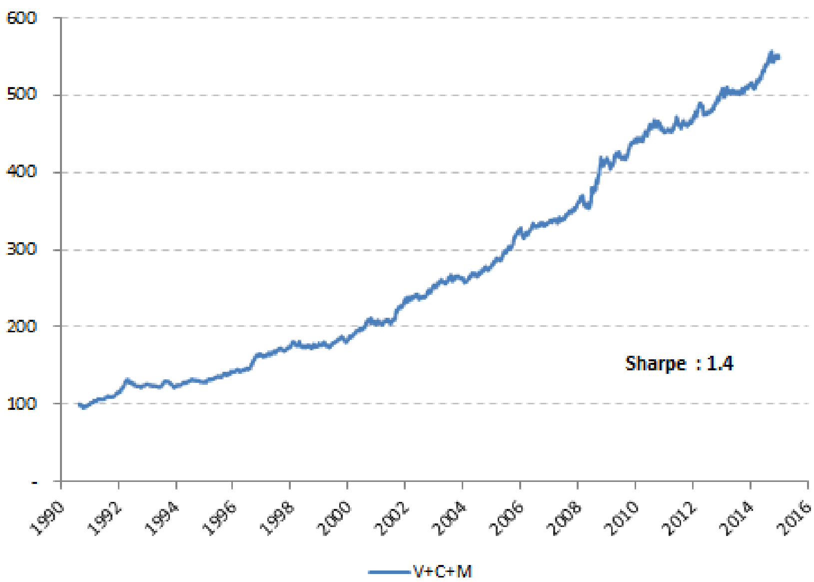
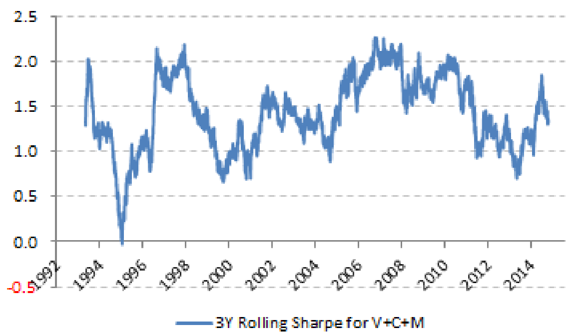



Figure 3. Cross Sectional: Value+Carry+Momentum Compounded P&L



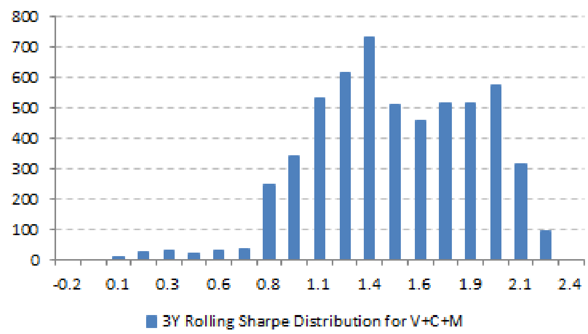




Figure 4. Cross Sectional: 3Y Rolling Sharpe (left) and its Distribution (right) for Value+Carry+Momentum

## 4.2 Time Series Portfolio

We now look at the time series approach: unlike the cross sectional portfolio, the time series portfolio is comprised of positions equivalent to $\frac{1}{N}$ in a universe of $N$ assets, with positions being long (short) if the signal is positive (negative). Therefore, if the signal is uniformly positive across an asset class, the portfolio position will be directionally positive in all assets.

As in the cross sectional portfolio, all styles exhibit overall positive Sharpe ratios in the time series. However, one major difference emerges: momentum more than doubles its Sharpe ratio from 0.42 to 0.96. The momentum drawdown to volatility ratio is lowest across styles in time series. As in the cross section, both value and momentum styles, unlike carry, are positively skewed. Overall, momentum exhibits substantially better risk return characteristics in time series than in cross section. One can surmise that momentum in a time series portfolio will capture more clearly market directionality, including reversals than in a cross sectional portfolio. Conversely, risk-adjusted performance is vastly worse for value in time series than in cross section. From Table 5 Panel A, it is readily apparent that equity is the prime culprit. Indeed, with stocks trending higher over the last

25 years, the value factor, which relies largely on mean reversion, was bound to underperform. In the same spirit, the Table 5 Panel B shows the deterioration in the drawdowns associated with value compared to Table 1 Panel B. It is also worth noting that both value and momentum display a high positive skewness (Table 5 Panel C).

**Table 5**: Time Series Strategies using Individual Signals

*Panel A: Sharpe Ratios*

| Asset Class | Value | Carry | Mom. | Avg |
|---|---|---|---|---|
| FX | 0.27 | 0.55 | 0.72 | 0.51 |
| EQ | -0.13 | 0.23 | 0.41 | 0.17 |
| Commo | 0.22 | 0.64 | 0.45 | 0.44 |
| IR | 0.48 | 0.83 | 0.77 | 0.69 |
| Avg | 0.21 | 0.56 | 0.58 | |
| All Asset | 0.28 | 1.25 | 0.96 | |

*Panel B: Maximum Drawdowns divided by Volatility*

| Asset Class | Value | Carry | Mom. | Avg |
|---|---|---|---|---|
| FX | -4.7 | -4.8 | -2.1 | -3.9 |
| EQ | -6.6 | -6.4 | -2.6 | -5.2 |
| Commo | -3.7 | -3.7 | -3.0 | -3.5 |
| IR | -4.5 | -5.3 | -1.9 | -3.9 |
| Avg | -4.9 | -5.0 | -2.4 | |
| All Asset | -4.4 | -2.5 | -2.4 | |

*Panel C: Monthly Returns Skew*

| Asset Class | Value | Carry | Mom. | Avg |
|---|---|---|---|---|
| FX | 1.36 | -1.20 | 0.34 | 0.16 |
| EQ | 0.41 | 0.18 | -0.07 | 0.18 |
| Commo | 0.02 | 0.64 | 0.64 | 0.43 |
| IR | -0.22 | -0.58 | 0.02 | -0.26 |
| Avg | 0.39 | -0.24 | 0.23 | |
| All Asset | 0.69 | -0.42 | 0.47 | |

Of note are the S&P betas and t-stats of {"asset class","style"} pairs in the time series (Table 7 Panel A): betas are more, yet weakly, negative and more significant in time series than in cross section. Specifically, carry strategies are well diversified across asset classes. FX carry is pro-cyclical as expected whereas equity carry, like equity value, boils down to buying market dips and selling market tops and will hence show a negative beta. From Table 6 Panel B, equity value and equity carry correlation is 51%, confirming that both strategies are similar in nature. Trading momentum and carry on a given asset class also shows a good degree of correlation. This is explained by the fact that momentum signals are computed on what amounts to a total return series. If a market exhibits a persistent carry premium this will accumulate though the total return and produce a momentum effect. The longer the lookback of the momentum signal, the more carry will accumulate and the higher the correlation between the signals. As in the cross sectional case, the average correlation in time series is close to zero, indicating substantial scope for diversification across styles and asset classes.

**Table 6**: Correlation of Time Series Strategies

| *Panel A: Overall* | | | |
|---|---|---|---|
| | Value | Carry | Mom. |
| Value | 1 | | |
| Carry | -3.1% | 1 | |
| Mom. | -10.2% | 23.6% | 1 |

| *Panel B: Correlation by Investment Style and Asset Class* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Value | | | | Carry | | | | Momentum | | | |
| | FX | EQ | CO | IR | FX | EQ | CO | IR | FX | EQ | CO | IR |
| FX | 1 | | | | | | | | | | | |
| EQ | -9% | 1 | | | | | | | | | | |
| CO | 1% | 9% | 1 | | | | | | | | | |
| IR | -1% | -6% | -2% | 1 | | | | | | | | |
| FX | -68% | 3% | 5% | 5% | 1 | | | | | | | |
| EQ | -7% | 51% | -4% | -9% | 0% | 1 | | | | | | |
| CO | 32% | -8% | -30% | 1% | -31% | 0% | 1 | | | | | |
| IR | 6% | -4% | -3% | 33% | -2% | -9% | 4% | 1 | | | | |
| FX | 8% | -17% | -11% | -2% | -2% | 6% | 9% | 4% | 1 | | | |
| EQ | 18% | -13% | -9% | -2% | -16% | 19% | 14% | 11% | 32% | 1 | | |
| CO | 13% | -18% | -31% | 0% | -11% | 3% | 46% | 1% | 33% | 24% | 1 | |
| IR | 6% | 3% | -2% | -1% | -2% | 2% | 5% | 20% | 9% | 16% | 8% | 1 |

**Table 7**: Assessing the Market Risk of Time Series Strategies

| *Panel A: Beta Coefficients and T-Statistics in Parenthesis* | | | | |
|---|---|---|---|---|
| Asset Class | Value | Carry | Mom. | Avg |
| FX | -29%(-25.1) | 37%(35.7) | -13%(-10.9) | -2% |
| EQ | -31%(-24.9) | -23%(-27.7) | -20%(-18.1) | -25% |
| Commo | 2%(1.5) | -18%(-14.4) | -10%(-8.1) | -9% |
| IR | 7%(8.5) | -9%(-9.6) | -9%(-9.9) | -4% |
| Avg | -13% | -3% | -13% | |
| All Asset | -13%(-25.3) | -3%(-6.5) | -13%(-18.5) | |

Combining signals, Sharpe ratios for time series are broadly in line with those for the cross section, with the proviso that individual style performances, as noted before, are significantly different. As in the cross section, the time series Sharpe is high at 1.37, while the 3Y rolling Sharpe ratio for a combined carry, momentum and value portfolio was always positive and varied between 0.1 and 2.7 over the past 21 years.

**Table 8**: Combining the Time Series Signals

| *Panel A: Sharpe Ratios* | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | 1.05 | 0.71 | 0.91 | 0.89 | 1.14 |
| EQ | 0.07 | 0.28 | 0.43 | 0.26 | 0.31 |
| Commo | 0.73 | 0.57 | 0.63 | 0.65 | 0.79 |
| IR | 0.81 | 0.89 | 1.03 | 0.91 | 1.04 |
| Avg | 0.66 | 0.61 | 0.75 | | |
| All Asset | 1.05 | 0.99 | 1.35 | | 1.37 |

| Panel B: Maximum Drawdowns divided by Volatility | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | -3.3 | -2.9 | -2.3 | -2.8 | -1.7 |
| EQ | -0.8 | -3.2 | -3.4 | -2.4 | -5.4 |
| Commo | -2.6 | -2.9 | -3.8 | -3.1 | -3.0 |
| IR | -5.9 | -2.4 | -1.9 | -3.4 | -3.6 |
| Avg | -3.2 | -2.8 | -2.8 | | |
| All Asset | -2.5 | -1.9 | -1.8 | | -1.9 |

| Panel C: Monthly Returns Skew | | | | | |
|---|---|---|---|---|---|
| Asset Class | V+C | V+M | C+M | Avg | V+C+M |
| FX | 0.48 | 1.40 | 0.04 | 0.64 | 0.58 |
| EQ | 0.25 | 0.16 | 0.38 | 0.26 | 0.51 |
| Commo | 0.61 | 0.61 | 1.47 | 0.90 | 1.87 |
| IR | -0.66 | 0.15 | 0.02 | -0.17 | -0.05 |
| Avg | 0.17 | 0.58 | 0.48 | | |
| All Asset | 0.18 | 1.25 | 0.34 | | 0.91 |

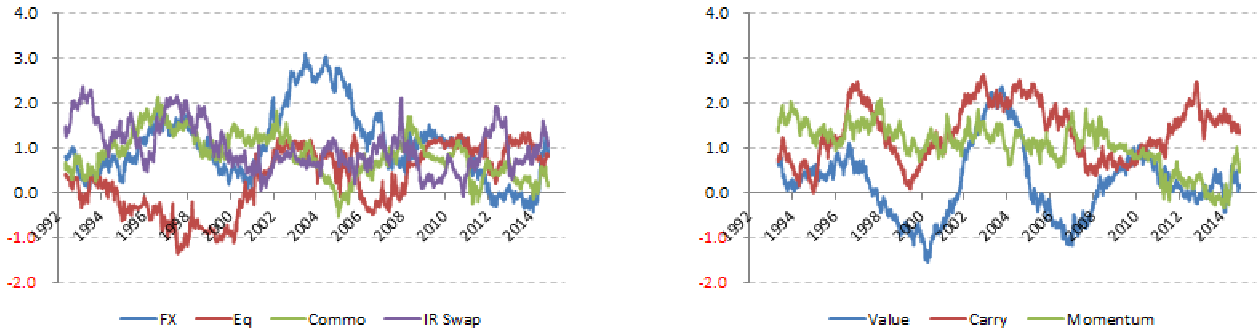



Figure 5. Time Series: 3Y Rolling Sharpe per Asset Class (left) and per Investment Style (right)

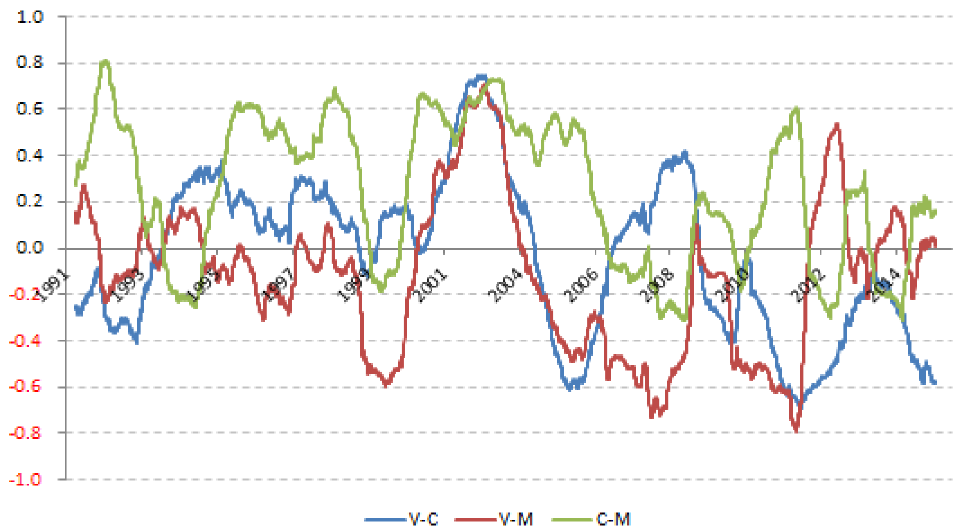



Figure 6. Time Series: 1Y Rolling Correlations

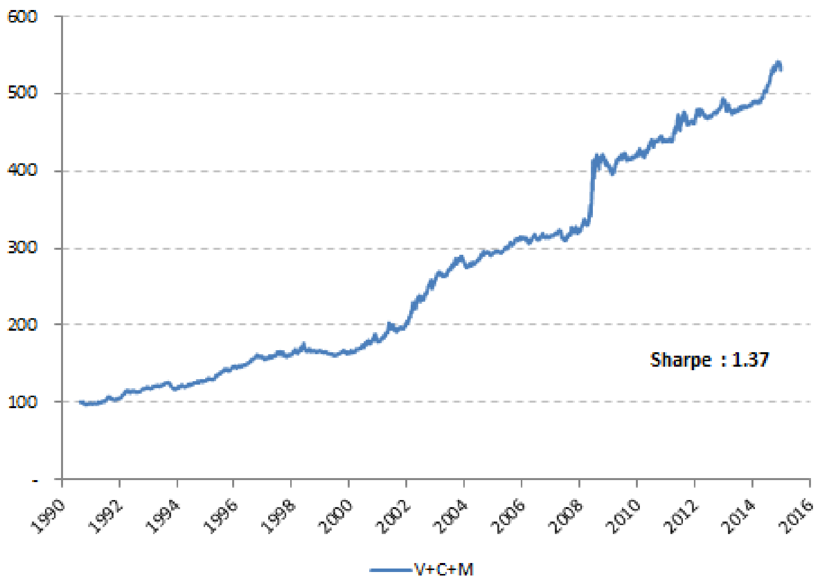



Figure 7. Time Series: Value+Carry+Momentum Compounded P&L

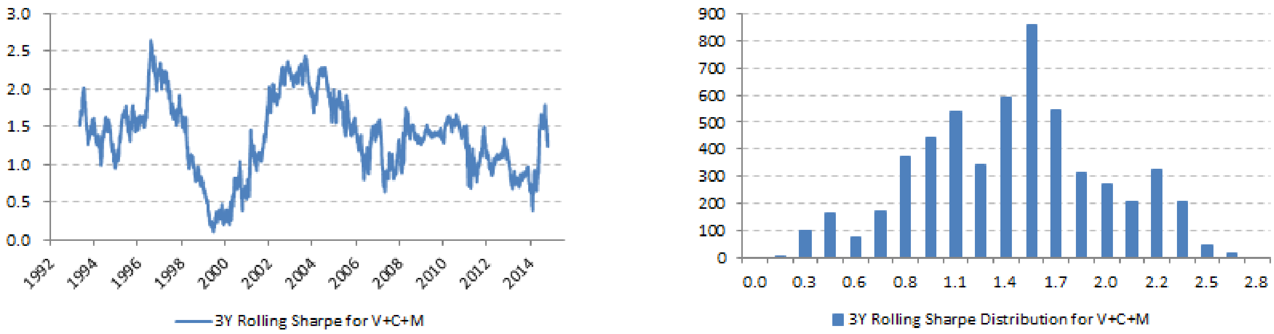



Figure 8. Time Series: 3Y Rolling Sharpe (left) and its Distribution (right) for Value+Carry+Momentum

Readers should be made aware of the fact that, in addition to the daily rebalancing with binary signals discussed so far, we also tested all of the above strategies using monthly rebalancing and linear signals. The monthly results are broadly consistent with the daily results.

## 4.3 A Few Thoughts on the Performance of Cross Section relative to Time Series

Contrasting Table 1 Panel A and Table 5 Panel A, we have quite different results for the three styles: value works well in the cross section, poorly in time series; carry works about equally well in both cross section and time series and momentum works well in time series, but poorly in the cross section.

At a basic level, assuming linear signals, cross sectional portfolio weights are equal to time series weights minus the cross sectional average. This average can be thought of as a global factor. Therefore, we can think of a cross sectional portfolio as a time series portfolio hedged for the global factor. Pursuing this line of reasoning, time series momentum will outperform cross sectional momentum to the extent that the global factor is trending. Alternatively, to the extent that the value indicator trades reversion to the mean, time series value investing will do better than cross sectional value investing when the global factor returns are negatively autocorrelated.

So how do we interpret the results from our data exploration? As stated above, momentum outperformance seems to go hand in hand with value underperformance in the time series versus the cross section. Although this result is difficult to interpret, we can offer three possible explanations.

The first is that momentum, unlike value, takes the price movements themselves as being informative and, as in such, may be better placed to assimilate any truly novel information about the global factor which may not be captured by the valuation model. In other words, the momentum model may account unwittingly for the factors omitted by the valuation model. This distinction between value and momentum is most prominent in the more correlated asset classes of equities and bonds.

In FX and commodities where a global factor is much less apparent the performance differences between the cross section and time series is much less. This makes sense, because in moving from time series to cross sectional portfolios we are essentially hedging out a single global factor. If this factor explains less, there will be less to hedge out and less difference between the portfolios (in either direction). This is exactly what we observe. Although this explanation may have merits, it does not help us understand why value performs better than momentum in the cross section.

Another explanation is that major global factors have exhibited very strong trends which have by definition hurt reversion based value predictors. It may even be claimed that the central purpose of stimulative public policies recently was to boost wealth effects by supporting a sustained rally in stocks and bonds, that in turn favored momentum over value in both asset classes.

A third explanation for time series versus cross sectional performance is the correlations of the signals, and how they compare to the correlations of the underlying markets. All else being equal, a cross sectional approach has more to gain when asset correlations are very high, as the above-mentioned global factor will dominate, and hedging this out will increase diversification by boosting exposure to a wider range of other factors. However, if signals are also highly correlated, a cross sectional approach will hedge out most of the (presumably informative) signals as well, potentially canceling out any gain from the diversification. Conversely if asset correlations are high, but signal correlations low, we will likely lose very little of the information in the signals by forcing them to be cross-sectional as their information already mostly relates to the non-global factors. This could potentially explain the outperformance of time series momentum against time series value in bonds and equities. Although both asset classes are internally highly correlated, the momentum signals on them are even more correlated, so moving to a cross-sectional framework will potentially hedge out more of the alpha from the signals than noise from the market. Correlations of value signals are notably smaller.

**Table 9**: Signal and Asset Average Correlations

| *Panel A: Signal and Asset Average Correlations* | | | | |
|---|---|---|---|---|
| Asset Class | Value | Carry | Mom. | Asset |
| FX | 48% | 23% | 40% | 24% |
| EQ | 44% | 23% | 66% | 51% |
| Commo | 30% | 3% | 19% | 7% |
| IR | 36% | 30% | 51% | 19% |
| Avg | 39% | 20% | 44% | 25% |

While all of the above explanations have appeal, the readers should note that value is traditionally traded in the cross section while momentum is traded in time series. So it would seem that traders have generally come to the "correct conclusions".

## 4.4 Cross Sectional Portfolio + Time Series Portfolio

We now try our hand at combining cross sectional and time series portfolios for all styles and asset classes. The overall correlation between the two portfolios is 43%. This translates into substantial diversification benefits. Also note that each style exhibits positive correlation (39%, 49% and 51% for value, carry and momentum respectively) between its cross sectional and time series incarnation (Table 11 Panel A). The Sharpe ratio of the combined portfolios is 1.61 (figure 11), while the 3Y rolling Sharpe ratio (figure 12) varied from 0.5 to 2.7 since 1994. One should note, however, overemphasize the diversification achieved by combining cross sectional and time series portfolios: indeed, it can be shown in a simple set-up that the combined portfolio is just the time series portfolio with half of the cross sectional mean hedged out.

**Table 10**: Combining the Cross Sectional and Time Series Signals

| *Panel A: Sharpe Ratios* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Asset Class | V | C | M | Avg | V+C | V+M | C+M | Avg | V+C+M |
| FX | 0.41 | 0.68 | 0.81 | 0.63 | 0.92 | 0.87 | 1.05 | 0.95 | 1.21 |
| EQ | 0.27 | 0.35 | 0.21 | 0.28 | 0.43 | 0.34 | 0.39 | 0.39 | 0.47 |
| Commo | 0.12 | 0.82 | 0.50 | 0.48 | 0.92 | 0.54 | 0.76 | 0.74 | 0.92 |
| IR | 0.60 | 0.88 | 0.04 | 0.51 | 0.98 | 0.42 | 0.65 | 0.68 | 0.80 |
| Avg | 0.35 | 0.68 | 0.39 | | 0.81 | 0.54 | 0.71 | | |
| All Asset | 0.71 | 1.41 | 0.73 | | 1.59 | 1.06 | 1.33 | | 1.61 |

| *Panel B: Maximum Drawdowns divided by Volatility* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Asset Class | V | C | M | Avg | V+C | V+M | C+M | Avg | V+C+M |
| FX | -3.8 | -3.6 | -2.5 | -3.3 | -2.8 | -1.7 | -2.7 | -2.4 | -2.3 |
| EQ | -5.0 | -5.3 | -2.5 | -4.3 | -0.7 | -3.3 | -3.8 | -2.6 | -5.0 |
| Commo | -3.7 | -1.8 | -2.2 | -2.6 | -1.6 | -2.7 | -1.9 | -2.1 | -2.0 |
| IR | -2.1 | -2.4 | -4.4 | -3.0 | -2.5 | -2.8 | -1.7 | -2.4 | -1.7 |
| Avg | -3.6 | -3.3 | -2.9 | | -1.9 | -2.6 | -2.5 | | |
| All Asset | -2.8 | -3.0 | -2.3 | | -1.7 | -1.7 | -2.4 | | -1.7 |

| *Panel C: Monthly Returns Skew* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Asset Class | V | C | M | Avg | V+C | V+M | C+M | Avg | V+C+M |
| FX | 0.77 | -1.19 | 0.28 | -0.04 | 0.23 | 0.95 | -0.23 | 0.32 | 0.30 |
| EQ | 0.00 | 0.32 | 0.68 | 0.33 | 0.62 | 0.80 | 1.03 | 0.82 | 1.06 |
| Commo | -0.21 | 0.16 | 0.28 | 0.08 | 0.16 | 0.00 | 0.41 | 0.19 | 0.36 |
| IR | -0.08 | -0.17 | -0.25 | -0.17 | -0.13 | -0.09 | -0.21 | -0.15 | -0.06 |
| Avg | 0.12 | -0.22 | 0.25 | | 0.22 | 0.41 | 0.25 | | |
| All Asset | 0.13 | -0.32 | 0.09 | | -0.19 | 0.51 | -0.05 | | 0.19 |

**Table 11**: Correlation of Cross Sectional and Time Series Strategies

| *Panel A: Overall* | | | | | | |
|---|---|---|---|---|---|---|
| | Cross Section | | | Time Serie | | |
| | Value | Carry | Mom. | Value | Carry | Mom. |
| Value | 1 | | | | | |
| Carry | -9% | 1 | | | | |
| Mom. | -9% | 15% | 1 | | | |
| Value | 39% | -20% | -1% | 1 | | |
| Carry | -10% | 49% | 19% | -3% | 1 | |
| Mom. | -6% | 9% | 51% | -10% | 24% | 1 |

**Table 12**: Assessing the Market Risk of Cross Sectional Combined with Time Series

| *Panel A: Beta Coefficients and T-Statistics in Parenthesis* | | | | |
|---|---|---|---|---|
| Asset Class | Value | Carry | Mom. | Avg |
| FX | -10%(-9.2) | 39%(34.1) | -10%(-9.2) | 6% |
| EQ | -25%(-21.0) | -25%(-23.0) | -9%(-8.3) | -20% |
| Commo | 0%(-0.1) | -7%(-6.4) | -6%(-4.9) | -4% |
| IR | 5%(4.3) | -12%(10.1) | -7%(-5.9) | -5% |
| Avg | -8% | -1% | -8% | |
| All Asset | -7%(-13.2) | -1%(-2.0) | -8%(-12.4) | |

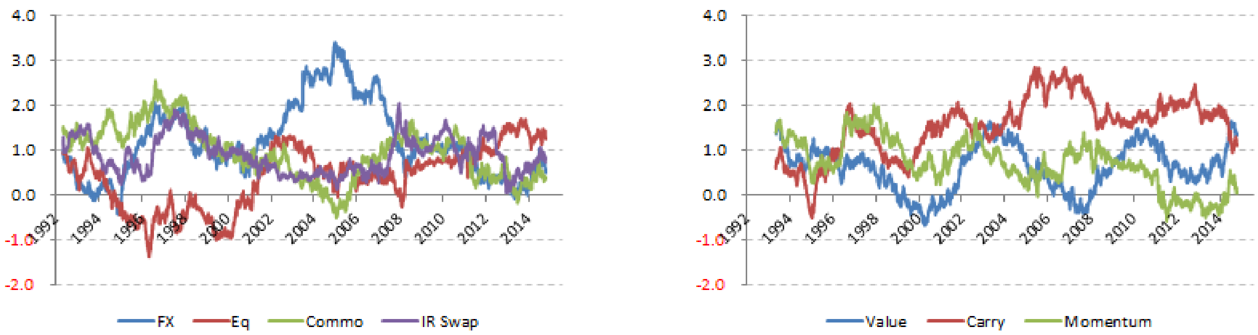



Figure 9. CS+TS: 3Y Rolling Sharpe per Asset Class (left) and per Investment Style (right)

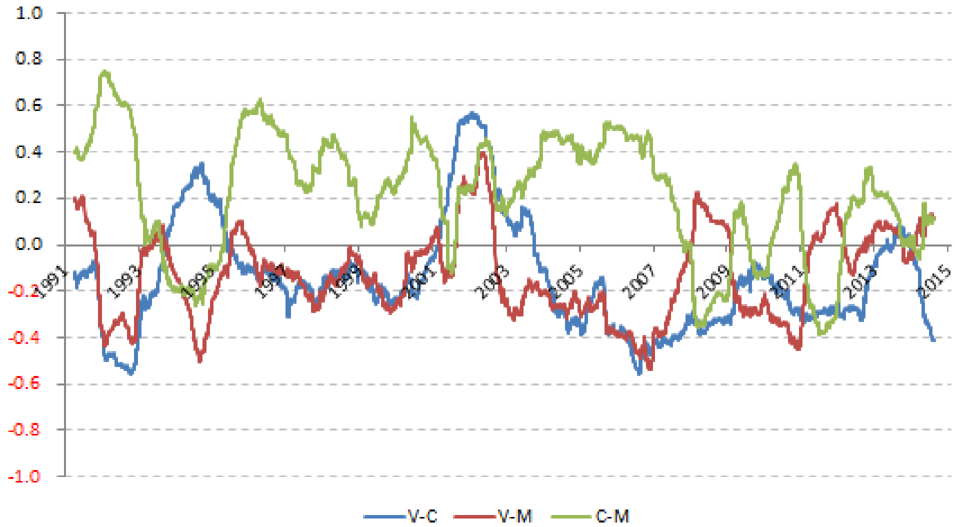



Figure 10. CS+TS: 1Y Rolling Correlations

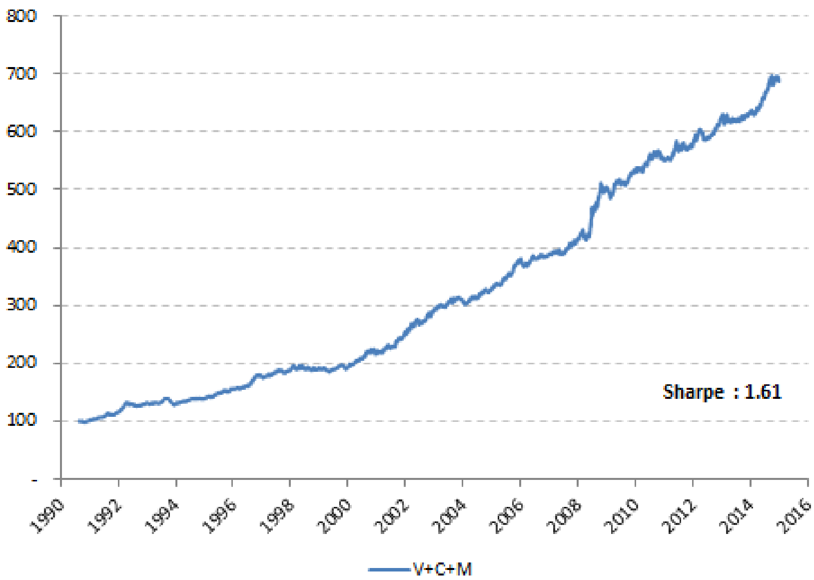
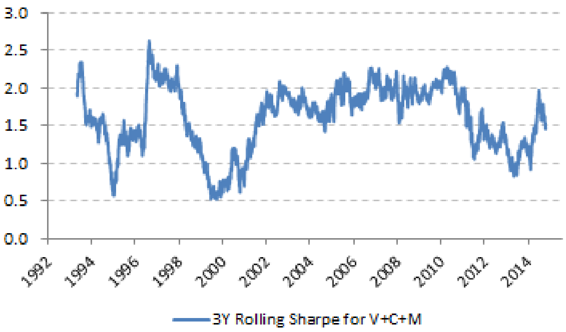



Figure 11. CS+TS: Value+Carry+Momentum Compounded P&L



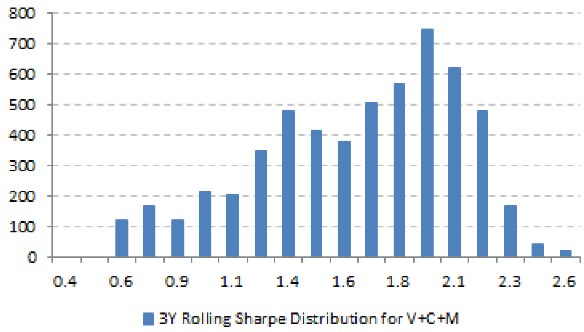




Figure 12. CS+TS: 3Y Rolling Sharpe (left) and Monthly Return Distribution (right) for Value+Carry+Momentum

# 5 Is it too good to be true?

By combining simple signals in carry, momentum and value across less than 100 liquid futures, forwards and swap markets we are able to achieve a remarkably stable strategy over 25 years with a Sharpe ratio of close to 2, returning an approximately eight-fold increase on a hypothetical 15% volatility investment. This can be considered a genuine return, as the strategy has very low funding costs. Is this too good to be true? Why is not every investor trading these styles in combination? We tried our hand at six possible explanations.

Selection bias is a partial answer. Why did we choose these styles and not others? Because, by and large, they have worked consistently over time and across asset classes. However, in defense of our results, not many styles make sense across such diverse asset classes; so the selection pool is not large.

What about potential over-fitting? There was no fitting in this exercise, although some potentially creeps in from experience. Why do our value predictors look back much further than the momentum predictor? Because momentum has worked better at medium frequencies, whereas value is clearly a long-term game. How obvious would this have been 25 years ago?

Survivorship and selection bias of assets is also a problem. Toxic emerging markets may be excluded. This study excluded Argentina but included the likes of Russia, Greece, Indonesia. This kind of bias will likely favor value and carry through the removal of markets where turmoil has caused major assets to exit.

Momentum suffers from another potential bias. Back in 1990, many markets we would include now were much smaller. The ones that make it into our study have likely grown over this time, often via a strong long-term up-trend. By adding data for markets which are now big, but were once small, we likely give a positive bias to momentum predictors.

Another, perhaps more appealing explanation for the performance is simply that few firms have the appetite and patience to trade something so simple. It is easy to forget the arguments in 1999 that value had been replaced by growth, in 2008 that carry was toxic, and in 2011-13 that momentum was finished. These are long-term signals whose performance oscillates over time (figures 1, 5 and

9), with each style experiencing negative performances for at least three years. It is difficult to stick with underperforming strategies this long.

# 6 Conclusion

There are many studies that examine carry, value and momentum strategies, either individually or in combination. However, some of these studies look at the directional or time-series versions of these strategies while others look across assets usually with long-short portfolios. Our paper explores the differences in the performance of any strategy depending on the implementation: directional vs. cross-asset.

Our empirical work examines a large number of assets: equity, fixed income, foreign currency as well as commodities. While the average performance of the strategies is impressive - and is particularly striking if the strategies are combined - we argue that caution should be exercised. There is a reason that carry, value and momentum are popular. They have worked well in the past. Hence, it is no surprise that average returns for these strategies are positive. However, the focus of our paper is not to find the most profitable strategy. Our research provides information about the conditions whereby a particular strategy is best implemented in the cross-section or in the time-series.

Our results are suggestive of a framework that may help identify, ex ante, the likelihood that a directional will outperform a cross-asset implementation of any particular strategy. The underlying ingredients are linked to the correlation of the asset returns as well as the correlation of the trading signals. Such a framework is the subject of on-going research.

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# 8 Appendix

## 8.1 Data Collection

1. FX

   We considered 31 currencies, all expressed versus the USD, to avoid information redundancies. Here is the complete list:

   - G10: AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, USD
   - EM Asia: HKD, INR, IDR, KRW, MYR, PHP, SGD, TWD, THB
   - EM Latam: BRL, CLP, COP, PEN, MXN
   - CEEMEA: CZK, HUF, ILS, PLN, RUB, TRY
   - Africa: ZAR

FX: Signal and Total Return Time Series Start Dates

| Currency Pair | Value TS | Carry TS | Momentum TS | P&L TS |
|---|---|---|---|---|
| AUDUSD | 05-Nov-74 | 13-Dec-83 | 27-Oct-87 | 27-Jun-86 |
| BRLUSD | 16-Nov-95 | 03-Feb-99 | 02-May-00 | 01-Jan-99 |
| CADUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| CHFUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| CLPUSD | 04-Dec-12 | 22-Oct-97 | 02-May-00 | 01-Jan-99 |
| COPUSD | 02-Dec-97 | 03-Feb-99 | 02-May-00 | 01-Jan-99 |
| CZKUSD | 10-Apr-97 | 11-Dec-96 | 02-May-00 | 01-Jan-99 |
| EURUSD | 03-Nov-78 | 14-Dec-98 | 02-May-90 | 02-Jan-89 |
| GBPUSD | 04-Dec-78 | 02-Jan-87 | 09-May-88 | 08-Jan-87 |
| HKDUSD | 03-Sep-84 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| HUFUSD | 18-Apr-97 | 22-Jul-98 | 02-May-00 | 01-Jan-99 |
| IDRUSD | 06-Sep-95 | 04-Feb-04 | 02-May-00 | 01-Jan-99 |
| ILSUSD | 12-Feb-85 | 20-Jul-98 | 11-Aug-82 | 21-Jul-98 |
| INRUSD | 04-May-92 | 11-Dec-98 | 02-May-00 | 01-Jan-99 |
| JPYUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| KRWUSD | 12-Feb-85 | 11-Dec-98 | 02-May-00 | 01-Jan-99 |
| MXNUSD | 02-Dec-76 | 03-Nov-97 | 02-May-00 | 01-Jan-99 |
| MYRUSD | 02-Dec-08 | 20-Apr-05 | 03-May-72 | 22-Jul-05 |
| NOKUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| NZDUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| PENUSD | 02-Dec-97 | 21-Jul-00 | 02-May-00 | 01-Jan-99 |
| PHPUSD | 06-Sep-95 | 09-Dec-98 | 02-May-00 | 01-Jan-99 |
| PLNUSD | 21-Apr-97 | 21-Jul-98 | 02-May-00 | 01-Jan-99 |
| RUBUSD | 12-May-97 | 09-Aug-01 | 08-Nov-94 | 02-Jan-01 |
| SEKUSD | 05-Nov-74 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| SGDUSD | 06-Nov-84 | 29-Dec-88 | 02-May-00 | 01-Jan-99 |
| THBUSD | 02-Dec-97 | 20-Sep-95 | 02-May-00 | 01-Jan-99 |
| TRYUSD | 31-Dec-87 | 11-Dec-96 | 02-May-00 | 01-Jan-99 |
| TWDUSD | 06-Aug-87 | 11-Dec-98 | 02-May-00 | 01-Jan-99 |
| ZARUSD | 02-Dec-83 | 29-Dec-88 | 02-May-90 | 02-Jan-89 |
| USD | 04-Nov-74 | 01-Jan-71 | 02-May-72 | 01-Jan-71 |

2. Equity

The equity sample covers 26 indices across several geographic regions. Here is the complete list:

- US : S&P, DowJones, Nasdaq, MidCap, Russell2000
- EUROPE : Eurostoxx50, Germany-DAX, Germany-Tech, Germany-MidCap, France-CAC40, Spain-IBEX, Italy-FTSEMIB, Sweden-OMX, Norway-OBX, Greece-FTASE, Finland-HEX25, Belgium-BEL20, Austria-ATX, Netherlands-AEX
- Japan : NIKKEI, TOPIX
- UK : FTSE100
- SWITZERLAND : SMI
- EM Latam : Brazil-IBOV, Mexico-MEXBOL
- EM Asia : Hong Kong-HIS, Korea-KOSPI2, Taiwan-TWSE, India-NIFTY, India-SENSEX
- CEEMEA : Russia-RTSI$, South Africa-TOP40, Poland-WIG20, Hungary-BUX
- AUSTRALIA : AS51

| Equity: Signal and Total Return Time Series Start Dates | | | | |
|---|---|---|---|---|
| Indices | Value TS | Carry TS | Momentum TS | P&L TS |
| US - S&P | 30-Nov-00 | 14-Apr-83 | 06-Sep-83 | 22-Apr-82 |
| US - Dow | 10-Jan-20 | 15-May-03 | 23-Feb-99 | 07-Oct-97 |
| US - Nasdaq | 30-Sep-90 | 04-Apr-97 | 25-Aug-97 | 11-Apr-96 |
| US - MidCap | 05-May-93 | 09-Feb-93 | 30-Jun-93 | 14-Feb-92 |
| EUROPE | 31-Dec-25 | 17-Jun-99 | 03-Nov-99 | 23-Jun-98 |
| GERMANY | 30-Nov-00 | 16-Mar-92 | 30-Apr-92 | 26-Nov-90 |
| FRANCE | 30-Nov-00 | 12-Dec-89 | 07-May-90 | 08-Dec-88 |
| SWITZERLAND | 31-Dec-18 | 15-Sep-99 | 02-Apr-93 | 29-Oct-91 |
| SPAIN | 31-Dec-00 | 29-Jul-93 | 20-Dec-93 | 21-Jul-92 |
| HUNGARY | 01-Sep-97 | 19-Nov-98 | 13-Apr-99 | 11-Nov-97 |
| NORWAY | 31-Jul-69 | 07-May-98 | 06-Jan-97 | 17-Jun-93 |
| SOUTH AFRICA | 31-Jan-54 | 17-Aug-95 | 19-Oct-95 | 16-May-94 |
| GREECE | 31-Jan-77 | 01-Sep-00 | 24-Jan-01 | 02-Sep-99 |
| JAPAN-Nikkey | 31-Dec-00 | 25-Oct-89 | 05-Feb-90 | 05-Sep-88 |
| JAPAN-Topix | 06-May-93 | 06-Aug-91 | 11-Oct-91 | 17-May-90 |
| AUSTRALIA | 31-Dec-00 | 24-Apr-01 | 05-Sep-01 | 03-May-00 |
| HONG KONG | 31-Dec-72 | 01-Apr-93 | 23-Aug-93 | 02-Apr-92 |
| KOREA | 31-Jan-63 | 11-Mar-97 | 10-Jul-97 | 04-May-96 |
| TAIWAN | 31-Jan-88 | 02-Aug-99 | 10-Nov-99 | 22-Jul-98 |
| BRAZIL | 31-Jan-88 | 03-Apr-98 | 23-Dec-96 | 21-Jul-95 |
| MEXICO | 31-Jan-88 | 11-May-00 | 14-Sep-00 | 04-May-99 |
| INDIA-Nifty | 31-Jan-88 | 08-Jun-01 | 30-Oct-01 | 13-Jun-00 |
| UK | 31-Dec-23 | 11-Apr-89 | 25-Jul-89 | 29-Feb-88 |
| NETHERLAND | 31-Jul-69 | 17-Jan-90 | 17-May-90 | 03-Jan-89 |
| FINLAND | 31-Jan-62 | 12-Sep-00 | 14-May-99 | 31-Oct-95 |
| BELGIUM | 31-Dec-27 | 05-Jan-95 | 24-Mar-95 | 02-Nov-93 |

3. Commodities

   We used a mix of commodity futures (16 in total). Here is the complete list:

   - Precious Metals: Gold, Silver, Platinum, Palladium
   - Industrial Metals: Copper, Nickel, Aluminum
   - Energy: Crude Oil, Natural Gas
   - Agriculture: Corn, Wheat, Soybean
   - Soft Commodities: Coffee, Cocoa, Sugar, Cotton

Commodities: Signal and Total Return Time Series Start Dates

| Commodities | Value TS | Carry TS | Momentum TS | P&L TS |
|---|---|---|---|---|
| Golds | 04-Nov-74 | 02-Jan-75 | 25-May-76 | 03-Jan-75 |
| Platinum | 07-Nov-90 | 29-Jan-87 | 20-Aug-87 | 02-Apr-86 |
| Palladium | 01-Sep-97 | 06-Dec-88 | 23-Oct-87 | 02-Apr-86 |
| Copper | 07-Oct-92 | 06-Dec-88 | 30-Apr-90 | 07-Dec-88 |
| Nickel | 24-May-01 | 23-Jul-97 | 23-Dec-98 | 24-Jul-97 |
| Silver | 04-Nov-74 | 02-Jan-75 | 25-May-76 | 03-Jan-75 |
| Aluminium | 24-May-01 | 23-Jul-97 | 11-Dec-98 | 24-Jul-97 |
| Crude | 29-Jan-87 | 01-Oct-84 | 31-Aug-84 | 31-Mar-83 |
| NatGas | 02-Feb-94 | 27-Jan-92 | 19-Aug-91 | 04-Apr-90 |
| Corn | 04-Nov-74 | 14-Feb-68 | 15-Nov-60 | 02-Jul-59 |
| Wheat | 04-Nov-74 | 01-Jul-59 | 17-Nov-60 | 02-Jul-59 |
| Soybean | 04-Nov-74 | 04-Dec-68 | 15-Nov-60 | 02-Jul-59 |
| Coffee | 17-Jun-76 | 09-Jul-73 | 09-Jan-74 | 17-Aug-72 |
| Cocoa | 04-Nov-74 | 26-Jan-60 | 23-Nov-60 | 02-Jul-59 |
| Sugar | 04-Nov-74 | 16-Jan-63 | 31-May-62 | 04-Jan-61 |
| Cotton | 04-Nov-74 | 05-Feb-62 | 22-Nov-60 | 02-Jul-59 |

4. Rates

   We used swap data (14 in total). Here is the complete list:

   - G10: Europe, UK, Japan, US, New-Zealand, Australia, Switzerland, Canada, Norway, Sweden
   - EM: Hungary, Poland, South Africa, Philippines

Rates: Signal and Total Return Time Series Start Dates

| Currency | Ticker Bloomberg | Value TS | Carry TS | Momentum TS | P&L TS |
|---|---|---|---|---|---|
| EUR | EUSA10 Comdty | 01-Jan-99 | 04-Jan-99 | 08-May-00 | 29-Jan-99 |
| GBP | BPSW10 Comdty | 16-Nov-90 | 16-Nov-90 | 20-Mar-92 | 30-Nov-90 |
| JPY | JYSWAP10 Comdty | 30-Jun-94 | 01-Nov-88 | 19-Mar-90 | 30-Nov-88 |
| USD | USSWAP10 Comdty | 01-Nov-88 | 01-Nov-88 | 24-Apr-90 | 30-Nov-88 |
| NZD | NDSWAP10 Comdty | 25-Mar-96 | 25-Mar-96 | 12-Aug-97 | 29-Mar-96 |
| AUD | ADSWAP10 Comdty | 01-Jun-88 | 03-May-89 | 24-Jan-91 | 31-May-89 |
| CHF | SFSW10 Comdty | 16-Nov-90 | 16-Nov-90 | 20-Mar-92 | 30-Nov-90 |
| CAD | CDSW10 Comdty | 02-Feb-98 | 09-Dec-91 | 29-Aug-90 | 31-Dec-91 |
| NOK | NKSW10 Comdty | 29-Oct-93 | 29-Oct-93 | 03-Nov-95 | 29-Oct-93 |
| SEK | SKSW10 Comdty | 31-Mar-94 | 08-Feb-91 | 29-Jun-92 | 28-Feb-91 |
| HUF | HFSW10 Comdty | 27-Nov-01 | 27-Nov-01 | 22-Apr-03 | 30-Nov-01 |
| PLN | PZSW10 Comdty | 12-Jun-00 | 12-Jun-00 | 07-Feb-02 | 30-Jun-00 |
| ZAR | SASW10 Comdty | 03-Oct-95 | 01-Feb-99 | 25-Feb-97 | 26-Feb-99 |
| PHP | PPSWN10 Comdty | 31-Mar-99 | 04-Apr-01 | 14-Aug-00 | 30-Apr-01 |