Deutsche Bank
Markets Research

Global

Quantitative Strategy
Quantcraft

Date
10 November 2015

Delving Into New Territories

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

This *Quantcraft* explores new territory. Having already covered Trend Following, Carry and Value across asset classes, we now delve into more exotic signals: **Macro Factors**, **Sentiment** and **Monetary Policy**.

We construct a **Macroeconomic Factor** portfolio, which tactically allocates between asset classes based on our understanding of inflation and growth. In order to do so, we have built daily *nowcasting* indices for 26 countries and regions.

We also build a **Sentiment** portfolio using data from the options market. We use implied skew, slope and correlation to build buy and sell signals for spot market instruments.

Finally, we also introduce a **Monetary Policy** strategy for foreign exchange, based on information coming from the interest rate market. In essence, we use interest rate momentum to predict FX returns.

The task is challenging: to extract new signals that are both profitable and uncorrelated to pre-existing factor strategies. As you will see, we were not always successful. Some of our conclusions are also counter-intuitive. Further, you will find that many of our final strategies have low Sharpe ratios, though we were satisfied as long as the correlations were low.

Figure 1: Delving into new territories

Source: Corbis

Delving Into New Territories

*The authors of this report wish to acknowledge the contribution made, in alphabetical order, by **Abhishek Singhania, Brent Sporre, Caroline Grady, Cristian Fuenzalida-Nunez, Danelee Masia, Jerome Saragoussi, Parag Thatte, Robert Burgess,** and **Yaroslav Lissovolik,** all current or former colleagues at Deutsche Bank CB&S Research.*

1. Introduction and outline

This *Quantcraft* report explores new territory. Having already covered Trend Following, Carry and Value across asset classes, we now delve into more exotic signals: **Macro Factor Investing**, **Sentiment** and **Monetary Policy**.

These are not uncharted terrains, but our conclusions are often surprising and at times counter-intuitive. Our target is exceptionally challenging: to extract new signals that are both profitable and uncorrelated to what we already have.

Achieving such goal has often required careful processing of our signals. We applied transformations, timing, filtering and orthogonalisation - a powerful but somewhat invasive technique that modifies the weights according to factor dependencies.

We weren't necessarily successful; you will find our graveyards along the way. Even where we succeeded, the individual Sharpe ratios are not high. Low Sharpe ratios are fine as long as they help us diversify beyond the traditional investment factors.

Section 2 outlines our new *macro factor* portfolio. We tactically allocate between assets (and asset classes) based on our insights into inflation and growth across multiple countries. In order to do so, we apply *nowcasting* technology to create macroeconomic indices for 26 countries and regions across the globe. We apply cross-sectional weight orthogonalisations in this section.

Section 3 introduces *sentiment* as a new cross-asset investment strategy. While this abstract concept can be observed through many channels, we focus on one particular locus: the volatility surface. We build spot market signals based on implied skew, slope and correlation. In this section, we apply time series signal orthogonalisations in order to reduce factor correlations.

Section 4 introduces a cross-market, cross-factor strategy between interest rates and FX. In essence, we capture the effect of monetary policy on foreign exchange by applying interest rate momentum into currencies. This strategy required no orthogonalisation.

Section 5 brings all strategies together. It addresses signal decay, aggregation and portfolio construction. It also covers turnover and other operational aspects, such as cost and liquidity exposures.

Section 6 concludes.

Unless otherwise stated, our asset pool encompasses 60 markets: 21 equity futures, 9 bond futures, 18 USD/FX forwards and 12 commodity futures.[1] The original strategies are evaluated in "rough" form; hence we initially assume daily rebalancing and no cost. More realistic assumptions around portfolio turnover and transaction costs are addressed later. The final results will look worse, but not much worse: trading costs will lower returns, but lower turnover will lift them (as signal-to-noise improves).

2. Macroeconomic factor investing

Our first portfolio is about macroeconomic factor investing. It is based on the premise that all asset classes are affected by where we stand in the economic cycle. If we have a good idea of near-term conditions for growth and inflation, we should have a good idea of which assets will perform and which will not.

Macro factor investing complements dynamic factor investing[2]. It is purer, but also harder to implement. Some of the challenges, and our proposed solutions, are:

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[1] Equity futures: ASX (Australia), Bolsa (Mexico), Bovespa (Brazil), CAC (France), DAX (Germany), HSE (Hong Kong), IBX (Spain), ISE (Turkey), JSE (South Africa), Kospi (South Korea), Nasdaq (US), Nikkei (Japan), OMX (Sweden), RDX (Russia), SMI (Switzerland), S&P (US), TSE (Canada), TWE (Taiwan), FTSE (UK) and WIG (Poland). 10-year bond futures: Australia, Canada, Switzerland, Germany, UK, Japan, Mexico, New Zealand and US. FX forwards: USD/EUR, USD/AUD, USD/GBP, USD/NZD, USD/CAD, USD/CHF, USD/JPY, USD/NOK, USD/SEK, USD/KRW, USD/RUB, USD/SGD, USD/TWD, USD/MXN, USD/TRY, USD/ZAR, USD/BRL and USD/PLN. Commodity futures: Gold, Silver, Platinum, WTI, Brend, Heating Oil, Soybeans, Corn, Coffee, Copper, Aluminium and Zinc.

[2] The case for fundamental factor investing is laid out in Mesomeris et al. [2012].

- Which factors to choose from? *Growth* and *inflation* seem like obvious choices, but the list expands into more exotic themes. Ang [2014] also highlights *productivity risk*, *volatility*, *demographic risk* and *political risk* as examples, while other authors also include market-based variables such as the yield curve[3]. We opt for what is most commonly agreed - growth and inflation.
- How can these factors be observed? Macro factors are somewhat abstract, at least when compared to fundamental factors such as Carry and Momentum. We build a series of macroeconomic indices that track growth and inflation for 25 countries and 1 region, updated daily. We also built global macro indices, thereby grouping countries into one.
- How to address the non-linear relationship between macro factor behaviour and asset returns[4]? We look at the macro variables from multiple angles (level, pace, surprise) as shown in the coming section.
- How to build a macro investment portfolio based on these indices? We use predictive regressions to estimate expected asset returns, and then use those to build strategy weights. We also orthogonalise our exposures to dynamic factors.

2.1 Building macro indices: *Beat* and *Surprise*

Macro factors are not directly observable; we need to build proxies for growth and inflation. We also need our proxies to update fast – preferably daily.

As such, we delved into *nowcasting*. This field of research has grown significantly in recent years, and different schools of thought have emerged[5]. Our methodology was inspired by Beber et al [2014]: instead of trying to predict one economic tea leaf of interest (such as GDP or CPI), we extract the common information – the first principal component – from all tea leaves that fall into the same category. This gives us a broader idea of true activity conditions beyond GDP alone, and of inflation conditions beyond CPI alone.

We use both *hard* (ex-post) and *soft* (ex-ante or contemporaneous) economic data gathered from Bloomberg. While it varies by country, the hard data is mainly comprised of retail sales, industrial production, GDP, housing, trade and unemployment. Soft data includes consumer confidence, business confidence and other sentiment surveys provided by one or more agencies in the same country or region. Price data includes CPI, PPI and GDP deflator, and other variations depending on the country.

We create 2 types of indices: the *beat* indicators, which measure the pulse of an economy, and the *shock* indicators, which capture the unexpected difference between actual release and median analyst expectations as polled by Bloomberg. In total, we use 377 macroeconomic releases[6] for our *beat* indices and 317 for *shock*, chosen after a survey of our economists, the literature, and Bloomberg[7]. We use unrevised data

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[3] One of the most often quoted papers on macroeconomic factors is Chen, Roll and Ross [1986], which uses market-based variables in addition to economic variables.

[4] This question was nicely highlighted by Ang [2014]. Trahan et al [2011] also highlight some examples.

[5] The approaches most widely used in recent years are summarized into 4 blocks:

i. The traditional *Nowcasting* approach, which explicitly forecasts GDP at high frequency through the use of latent factors. Giannone et al [2007] is among the pioneers of this technology; the authors applied GDP-forecasting regressions using Kalman-smoothed principal components of a mixture of economic data. The approach was refined further in Banbura et al [2010], who introduced a system of equations that jointly updates factors (from a VAR model instead of PCs), ingredients (which become a function of the factors but whose residuals are models as AR(1)) and ultimately the GDP forecasts, all using the Expectation and Maximisation algorithm. This most "famous" approach is also arguably the most robust for predicting GDP.
ii. The *MIDAS* approach, which also forecasts high frequency GDP but through mixed data sampling regressions. This method aggregates higher frequency regressors (such as daily equity index levels) through a polynomial of choice, thereby maintaining a regression-style framework without adding too many parameters. While MIDAS regressions have been in the literature for years, Andreou et al [2012] have been widely referenced in association with this approach in recent years. Stringa et al [2015] also uses regressions to predict GDP, though applying a more rudimentary OLS approach instead of MIDAS; the authors then weight each ingredient according to its ability to predict GDP, eventually smoothing and grouping them.
iii. The economic conditions approach, aimed at capturing broader dynamics instead of focusing on a specific variable (such as GDP). In this vein of research, we highlight 2 studies: Arouba et al [2008] and Beber et al [2014]. The first introduces the "business conditions index", a latent variable that is forecasted using its own history and economic releases including GDP, and whose calibration applies a recursive two-step Kalman filter. The third creates "indices of economic activity" by extracting the PC1 of a mixture of economic variables, using a major innovation: they separate the data releases into 2 buckets: backward looking (hard) and forward looking (soft) data.
iv. Either of the 3 approaches above, but using *big data* sources instead of traditional ingredients to estimate macroeconomic factors. The literature on this topic is growing and promising, with successful applications for inflation (US), unemployment (Italy and Germany), and broad economic conditions (Israel) - see Bulut [2015] for a good overview and an application in foreign exchange.

Of all approaches evaluated, we ultimately favoured that of Beber et al [2014]. First, our interest in economic activity is broader than what can be captured by one variable alone – such as GDP. Second, their approach allows us to differentiate between hard data and soft data when predicting asset returns. Third, their approach is less computationally expensive than the ones involving recursive parameter calibration. Finally, its main shortcoming – less adaptivity in the ingredients compared to Nowcasting – turned out not to be a major issue. While we stuck to traditional economic indicators, future studies may include big data as outlined in (iv) above.

[6] Our list is too long to be put in the Appendix, but feel free to ask for more information. We chose not to include financial market data as we are ultimately interested in predicting asset returns; including it would have potentially made the process circular.

[7] In the case of Bloomberg, we focus on the most relevant releases according to quantity of alert subscriptions. This approach did not add value in the end.

and its respective announcement dates, as opposed to the period the data applies to[8].

In all, we cover 25 countries: Australia, Brazil, Canada, Switzerland, China, Czech Republic, UK, Hungary, Indonesia, Israel, India, Japan, South Korea, Mexico, Malaysia, Norway, New Zealand, Poland, Russia, Sweden, Singapore, Turkey, Taiwan, USA, South Africa. We also cover 1 region: Eurozone.

Our indices are run daily, though only change when there is new information introduced for the given indicator. The process, which is largely based on Beber et al [2014], is as follows:

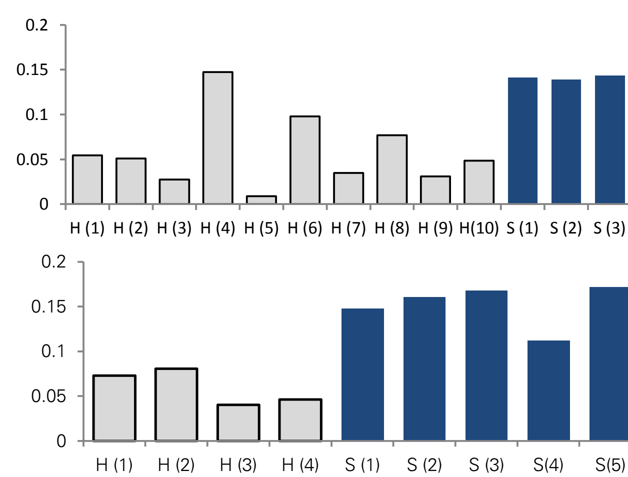
1. Take all data series from a given category (such as growth), make them stationary [9] and change direction if need be so as to ensure a positive correlation to others. Index the data according to business days, forward filling the missing points with what is previously available[10].
2. Build a matrix of Spearman ranked correlations using anchored windows, and apply correlation averaging [11] to address the infrequent and asynchronous nature of changes in each data release. Set negative correlations to zero[12].
3. Standardise each data series using a 5-year lookback window[13], and record the values from the most recent date.
4. Run principal component analysis with the correlation matrix estimated in (2), and transform the PC1 loadings into weights such that they sum to 1. Sum-multiply these weights by the values recorded in Step 3 to give us the current estimate of change in the dataset, ΔI_t. Estimate today's intermediate index level as $I_t = I_{t-1} + \Delta I_t$. If there has been no new release, $I_t = I_{t-1}$. This intermediate

   index removes the need to smooth either the data or the output, thereby making the process more adaptive.
5. Standardise the intermediate index using a 5-year lookback window as in Step 3. The current z-score is today's index level.

As we constructed our indices, a few characteristics were worth noting:

- When it comes to countries with a rich pool of economic releases, soft data often gets stronger weights than hard data in our correlation-based PC1 estimation. This has been especially the case in the Eurozone, Switzerland, Australia and the UK, and Japan to a smaller extent. Figure 2 shows our PC1 loadings for the Swiss and Australian *beat* indices as examples. The pattern is less clear in the US, where employment data also carries a heavy loading.

Figure 2: Growth *beat* indices for Australian and Switzerland – current factor loadings



Releases for Australia: H(1): Building Approvals, H(2): Company Profits, H(3) Current Account, H(4): GDP, H(5) Housing Finance, H(6) New Motor Vehicle Sales, H(7) Private Capital Expenditure, H(8) Private Sector Credit, H(9) Retail Sales, H(10) Unemployment Rate, S(1): NAB Business Conditions, S(2): PMI Manufacturing, S(3) NAB Business Confidence. Releases for Switzerland :H(1): GDP, H(2): Industrial Production, H(3): Unemployment Rate, H(4) Retail Sales, S(1) KOF Leading Indicator, S(2): SVME PMI, S(3) SECO Consumer Climate, S(4) ZEW Expectations, S(5) UBS Consumption Indicator. Source: Deutsche Bank

- Data concerns are more pertinent in EM, where there are fewer soft data releases and fewer analysts who publish forecasts. This occasionally required some indices to have a later start date, or to be removed altogether. Part of the issue has been handled through the construction of regional indices,

[8] Strictly speaking, unrevised data is not *vintage* data. Proper vintage data requires using the release value known at the date of analysis (as opposed to date of announcement), and therefore may include revisions. We assumed the marginal impact of proper vintage data (versus unrevised data) is not significant, although some authors may argue otherwise (see, for instance, Croushore et al [1999]).

[9] This part is tricky. For data expressed as year-on-year (i.e. CPI), or as levels (i.e. ISM), we use 3-month changes. For data expressed as surprise (actual minus expected), we use levels. This only applies to *beat* data; the *surprise* data (actual minus analyst expectations) is not manipulated as it's assumed to be stationary as is.

[10] We initially thought that forward-filling was simplistic, and tried a more adaptive approach using stepwise error correction models (a more computationally friendly version of vector ECMs). Instead of running a system of ECMs (as the VECM would), we ran individual ECMs one after the other using the residual of the previous regression as dependent for the next ECM.

[11] Correlation averaging was introduced by Ait-Sahalia et al [2005], as quoted in Beber et al [2014], and is generally applied in high frequency finance. It involves (1) sub-sampling the data in equal steps but with different starting indices (i.e. 1-65-130-..., 2-66-131-...), (2) calculating the correlation coefficient in each of these subsamples, and (3) averaging the correlation estimates. We want an anchored window to enhance the stability of our estimates. Hayashi et al [2005] introduced a potentially more robust estimator (the so-called Hayashi-Yoshida correlation), which we may use in future studies.

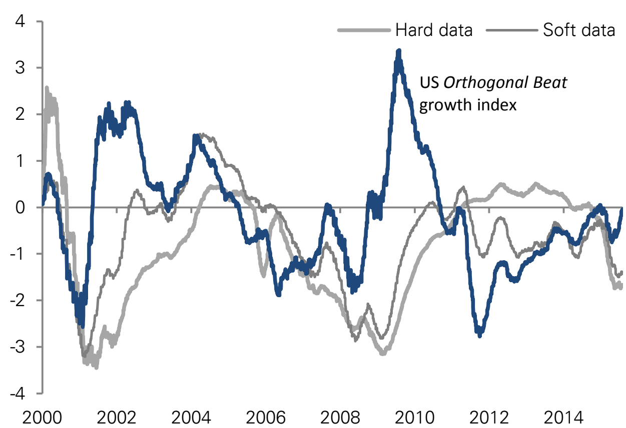
[12] This adjustment makes the correlation matrix positive semi-definite, thereby making the PC1 loadings more stable.

[13] We use rolling windows to make the recent estimates more adaptive, and choose 5 years as the typical business cycle length. Only unique datapoints are used in the standardisation (i.e. no repetitions).

or the Global *beat* and *shock* indices, where we aggregate country indices into one using GDP weights.

- There is value in orthogonalising soft data against hard data, and building an index based on the residual of that regression. The idea was introduced in Beber et al [2014] and leads to what we call *orthogonal beat* indices. We apply it primarily to US growth, as it was the most successful application. Figure 3 shows it in more detail.

Figure 3: *Orthogonal Beat* index for US growth and respective hard and soft data sub-indices

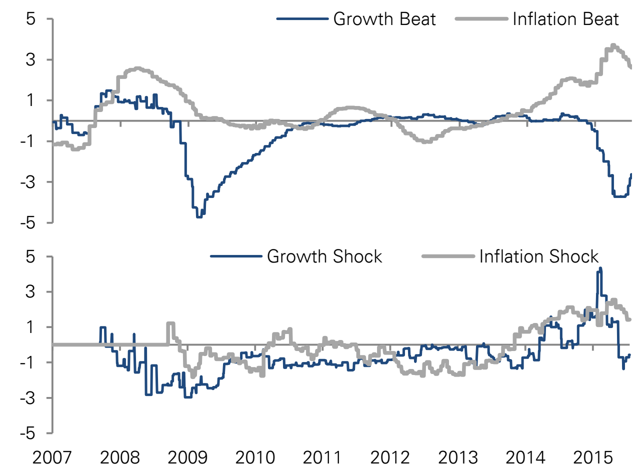


Source: Deutsche Bank

The charts below show some examples of our *beat* and *shock* indices:

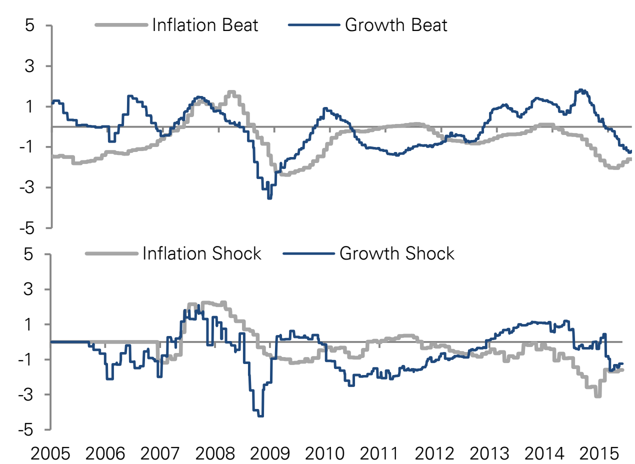
- Russia has felt stagflationary forces over the past year, with rising inflation and falling growth, as shown in Figure 4. At the same time, growth has taken longer to drop relative to analyst expectations, while inflation rose faster than they expected, which explains the surprise readings above zero for both in 2014.
- China, on the other hand, has seen a steady drop in both growth and inflation indicators since the middle of last year, with analysts being negatively surprised in both. This is seen in Figure 5.
- After a long period of negative momentum and surprises, Swedish inflation data has picked up. This has, in turn, prompted a less aggressively dovish stance by the Riksbank.

Figure 4: Russia *beat* and *shock* indices



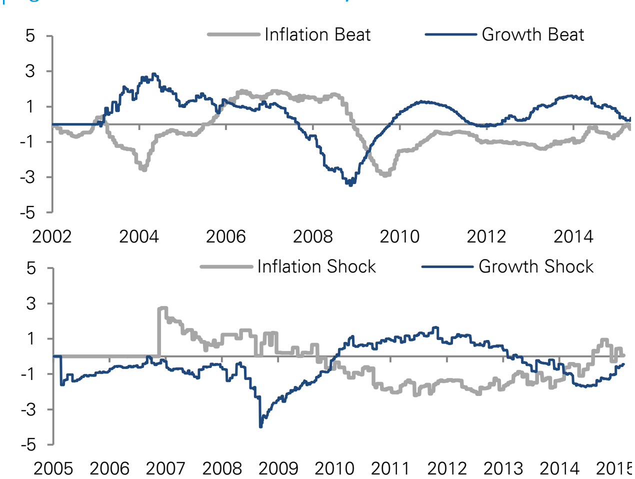
Source: Deutsche Bank

Figure 5: China *beat* and *surprise* indices



Source: Deutsche Bank

Figure 6: Sweden *beat* and *surprise* indices



Source: Deutsche Bank

2.2 From macro indices to tactical asset allocation

Building macro indices is necessary, but not sufficient. We need to understand the interaction between these inputs and asset returns, so that we can make better informed investment decisions.

Ideally we would treat growth and inflation as asset-embedded characteristics just as we treat, for instance, momentum (the size of past returns) and valuation (price deviation from fair value). If that was the case, we could have built long-short baskets that maximise exposure to these factors just as we do with Momentum and Value strategies.

But economic factors are different from dynamic factors, which presents us with challenges.

2.2.1 Global or local?

First, *the macro factor in that country may not be as relevant to local assets as the same factor coming from another country, or from a group of countries.* A simple solution - using country-specific indices alone - is not enough; Beber et al [2014] and our macro research colleagues argue that global dynamics are often more important. Another solution - using global indicators alone - would also be simplistic as it often fails to differentiate between countries.

We address this question by using *both* local and external factor indices and weighting between them. The weights are set according to a linear regression where the predicted variable is 1-month forward-looking asset returns, evaluated over the past 5 years. As we show below, both indicators matter but their relative influence changes over time. The only asset class where this was not needed is commodities; we used US indicators for energy and precious metals, as suggested by Adams et al [2008], and US and Chinese indicators for base metals, as per our commodity strategists.

2.2.2 Static premium, not dynamic premium

Second, macro factors are better at explaining the performance of static premia - bond, equity and currency risk premia - than they are in being dynamic factors in their own right. From this perspective, our indices are best employed for tactical asset (class) allocation instead of in traditional, dynamic factor strategies.

Growth and inflation are not the only drivers of asset class premia but they are a good start. Ang [2014] argues that economic growth explains around 60% of the variation in equity risk premium, and expected inflation explains 40% of the variation in real rates and 90% in nominal bonds. Rosenberg [2002] argues that both are also key drivers of exchange rates - with growth influencing medium-term currency moves through the capital account and inflation affecting long-term moves through purchasing power parity. Finally, Adams et al [2008] show how commodity sectors, particularly energy[14] and metals, are sensitive to growth and inflation - particularly in the US.

As such, our macro factor portfolio deliberately allows for directional exposure to all markets. Unlike in our correlation and monetary policy strategies, we do not force a number of longs and shorts inside an asset class. We accept that portfolio returns may be heavily correlated with broad market direction because *making a call on market direction is what economic factors are best at.*

2.2.3 Signal timing

Timing is the third issue we need to address. The more we allow for directional asset class exposure, the more it needs to be considered.

Put simply, *macro uncertainty - economic and financial - is a notable part of the risk whose premium is captured by static factor strategies*. Regardless of the asset class, assets perceived as "riskier" - typically those with higher carry and exposure to economic growth - weaken under macro uncertainty, and the converse applies to assets seen as "safe havens". As an example, Ang [2014] documents a clear, 25-year negative correlation between VIX changes and monthly equity returns, with the opposite being (partly) true for bond returns.[15] Furthermore, our *Volcano* research reports often show a positive link between the VIX and base metals, energy, and high yielding currencies.

As such, we time our static factor exposures based on our current understanding of market uncertainty - or its synonym, market risk appetite. We proxy appetite through our Global Sentiment Indicator (GSI), a variable first introduced in Natividade et al [2012] and which has been used extensively in our Carry and Trend Following portfolios.[16] The GSI is bounded between 0 and 1; higher levels point to higher risk conditions; lower levels suggest the opposite.

Initial portfolio positions are either inflated or deflated according to the level of the GSI, and whether asset returns are positively or negatively skewed. The deflator scales the original position size to keep us from being caught wrong-footed. In other words:

- <u>If asset returns are negatively skewed</u> (equities, commodities, high yield FX): if the GSI is above 0.5

[14] The energy sector, for instance, is widely seen as a good inflation hedge. While part of the argument appears circular to us, other studies confirm the same findings (see Kat et al [2007] and Erb et al [2006]).

[15] The author goes on to call volatility "an extremely important [macro] risk factor". He also raises the question of whether uncertainty risk is different from volatility risk. By using our Global Sentiment Indicator, which is partly built using implied volatilities, we assume they are the same.

[16] On Bloomberg: DBQSGSI Index.

and the strategy is long the asset, the size of the position is deflated. If the GSI is below 0.5 and the strategy is short the asset, the position is also deflated. The deflator in this case is:

$$D_t^{(1)} = 2 - GSI_t \times 2$$

- If asset returns are positively skewed (G10 bond futures, low yield FX): if the GSI is above 0.5 and the strategy is short the asset, the size of the position is deflated. If the GSI is below 0.5 and the strategy is long the asset, the position is also deflated. The deflator in this case is:

$$D_t^{(2)} = 2 \times GSI_t$$

The formulae above show that, while we change formulas depending on whether the GSI is above or below 0.5, the adjustment factor is linearly continuous. Put differently, we do not apply binary timing, thereby minimising *threshold risk*.[17]

Further, our overall portfolio leverage is untouched; in absolute terms, all positions are re-standardised so as to add up to 1. The timing adjustment only serves to re-distribute our positions and only works if (a) the position is of opposite direction to what would be desired in light of current risk appetite, and (b) the strategy has both longs and shorts.

2.2.4 Deep tissue orthogonalisation and strategy construction

The final challenge is to make our economic factor strategies sufficiently independent from other factor strategies. We accept being correlated to static premia, but should try to be uncorrelated to Trend Following and Carry because those factors are already captured elsewhere in our suite of cross-asset strategies - Natividade et al [2013b] and Anand et al [2014].

This is hard; growth and inflation risk are often embedded into the aforementioned factors. For example, economic momentum often translates into price momentum. Inflation differentials often translate into interest rate differentials, which - in the case of FX - are already exploited in the carry trade. We should focus on the element of uniqueness from our macro factor strategies, assuming that it exists. If we cannot find it, our strategies will not add value.

Therefore, we introduce orthogonalisation to our strategies. The idea is to reduce the effect of exogenous factors onto our Macro Factor strategies through regressions. We call it cross-sectional weight orthogonalisation, as described in Luo et al [2010] and Kassam et al [2010].

[17] It may look as if we only see 2 regimes of market risk appetite, which would not be true. We see at least 3 regimes – see Natividade et al [2012].

In each asset class, our macro factor strategies are built as follows:

1. We first transform our *beat* and *shock* indices from "levels" to their 1-year time series z-scores. This step would have been needed even if we ignored factor correlations. As highlighted by our macro strategists and by Ang [2014], the *level* is a persistent measure and already accounted for by the market; recent *changes*, however, are not. As a reassuring example, Bridgewater's "All Weather Strategy" is also based on changes rather than levels of growth and inflation (see Bridgewater [date not specified]).
2. These z-scores feed into a regression as predictors of future 1-month returns for each asset. The indices we use depend on the asset class, as we show in the sections below. The signal is today's estimate of future 1-month returns given the indices used.

   $$r_{t,t+1M} = a_i + b_i \times \sum_j z_{t-1Y,t}\left(I_{j,t}\right) + \varepsilon_{i,t}$$

   $$\hat{s}_{i,t} = \hat{r}_{i,t}$$

   where $r_{t,t+1M}$ is the 1M forward-looking return for asset i, $z_{t-1Y,t}\left(I_{j,t}\right)$ is the 1-year z-score of macro index j and $\hat{s}_{i,t}$ is the signal at time t.
3. We take the original signal $\hat{s}_{i,t}$ and transform it into a first strategy weight $w_{i,t}^{1st}$ for the current date. We apply *equal volatility weights* to all assets in the strategy, thereby removing the effect of signal intensity[18]. We do not pre-determine the number of longs or shorts, but all strategy weights add up to 1 in absolute terms. This allows us to accurately compare them to factor strategies we want to orthogonalise against.
4. We apply our timing filter, as per Section 4.2.3, to the first strategy weights, by multiplying them by the deflator. This gives us the second weights $w_{i,t}^{2nd}$.
5. We take the current portfolio, built using the current second weights $w_{i,t}^{2nd}$, and calculate its historical return assuming that those weights don't change.
6. Separately, we take the current asset weights $w_{i,t}^{f}$ for the factor we want to orthogonalise against

[18] Two assets with the same volatility, and whose signal direction is the same, will get the same weight in the macro strategy regardless of the size of the signal. We found little value in using signal intensity, as is the case with trend following - our other market-directional strategy. It also allows us to stick to one of the simplest machine learning algorithms, the OLS regression.

(factor f) – namely Carry and Trend. We build a portfolio with those weights and calculate its historical return, also assuming static weights.

7. We regress the historical returns from Step 5 against those in Step 6, and record the beta coefficient.

   Mathematically[19]:

$$R_t^{2nd} = a + \sum_f b_f \times R_t^f + \varepsilon_t$$

   where:

   R_t^{2nd} are the returns of a portfolio that implements today's second strategy weights as static.

   R_t^{fi} are the returns of a portfolio that implements today's factor strategy weights as static.

8. We set the revised strategy weight for a given asset in the target strategy $w_{i,t}^{rev}$ as equal to the original weight, defined in Step 4, minus the beta from Step 7 multiplied by the factor weight from Step 6. Mathematically:

$$w_{i,t}^{rev} = w_{i,t}^{2nd} - \sum_f w_{i,t}^f \times b_f$$

9. The final strategy weight for a given asset is equal to the revised weight set in Step 8, but standardised such that the absolute sum equals 1.

The next sections describe how we implemented our macro factor strategies in each asset class.

2.3 Our macro factor strategy in foreign exchange

We start with foreign exchange, an asset class where economic factors are particularly popular. The strategy is allowed to take on directional USD exposure; as outlined earlier, economic factors help explain the static (directional) premium of an asset class.

Much of the rationale behind our macro factor strategy is based on a flagship study by De Longis et al [2014]. In essence, De Longis and Tufekci found that:

- US data should not be used for signal generation, as its effect largely depends on where we stand in the economic cycle. The funding status of the USD further reaffirms this argument. Positive US data may either lead to USD appreciation - based on growth differentials - or to depreciation, if it encourages risk-seeking appetite into higher yielding currencies. Negative US data may weaken the dollar due to its dovish implications, or it may lead to USD strength if it prompts risk aversion. In summary, the effect of US data on FX is not clear cut.[20]
- Foreign growth data is particularly important for USD moves due to the shape of the US net investment position. The US is a net recipient of fixed income capital - particularly into US Treasuries - and a net exporter of other capital that goes mostly into international equities. As such, significant foreign economic growth encourages US capital outflows and leads to dollar depreciation. The converse is also true: weaker foreign growth leads to capital repatriation and USD strength.

Their argument sheds light on why signals based on the spread between non-US and US macro indices underperformed those that used non-US data alone. While we initially wanted to use the spread, since the USD/FX rate is the value of FX relative to the USD, the authors showed that such implementation would have been incorrect.

We only focus on growth, leaving inflation aside in FX. First, growth indicators better reflect the argument above, as capital flows are channeled into non-fixed income investments outside the US. Second, the effect of inflation on FX is already captured in other strategies - namely FX Carry (Anand et al [2014]) and rates-FX (Section 4). Finally, the relationship between inflation and FX is not always the same; it depends on *country risk premia*. In developed countries, downside inflation surprises are interpreted as dovish and therefore hurt the currency. In EM, however, falling inflation can improve perceptions of country risk, which is bullish FX.

Further, we need to decide which growth indices to use as regressors for signal generation. Unlike other markets, we used the *shock* instead of the *beat* indices for signal generation in foreign exchange. Our choice was chiefly based on the clear outperformance of one relative to the other, which is somewhat puzzling in that this is unique to FX. We can argue that markets are more interested in the "shock" component of data releases, which is what our *shock* indices capture, but it is not clear why the same argument does not apply to other asset classes as well.[21] The only explanation that comes to mind has to do with *speed of absorption*.

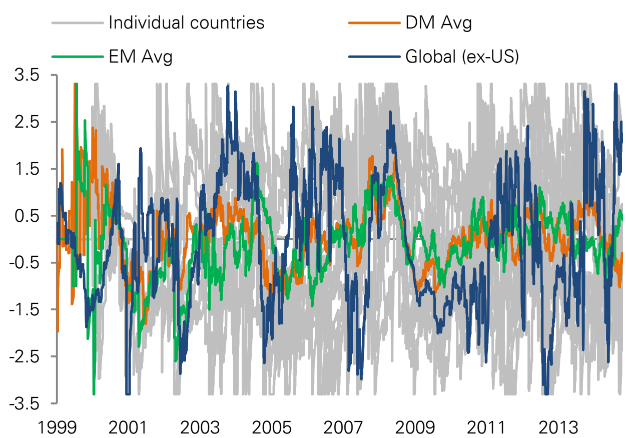
[19] We formulate the regression as multivariate OLS for simplicity. In reality, we apply 2 stepwise univariate OLS regressions (one for trend, one for carry), so as to address the potential collinearity between the two factors.

[20] This argument is also outlined in Edwards et al [2009], with particular reference to the Australian dollar.

[21] Three other arguments work against *shock* indices. First, the pool of analyst forecasts may not be sufficiently rich or of good quality, which is often the case in smaller countries. Also, the median forecast can be increasingly influenced by herd behaviour as we get closer to the release date. Finally, the median of all forecasts may not be the most informative statistic. As Brehon [2011] shows, there is valuable information in the higher moments of the distribution of analyst forecasts.

FX markets are faster than others at incorporating new information due to higher liquidity, and hence the (slower) information from our *beat* indices is arguably already "in the price" of FX[22].

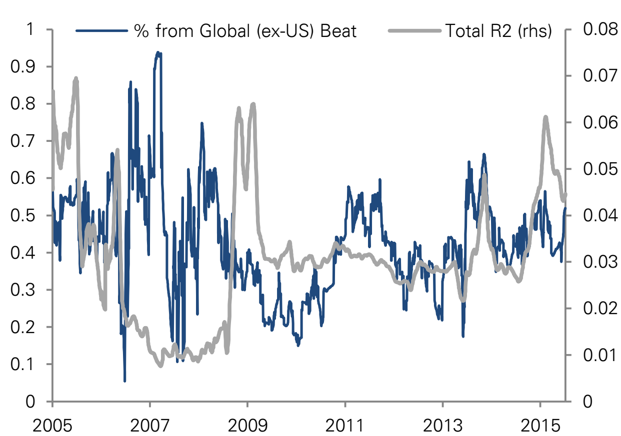
Figure 7: *Growth shock* indices, global (ex-US) and country-specific, transformed into 1-year z-scores



Source: Deutsche Bank

Last - but not least - is the question of which *growth shock* indices to include. As mentioned in Section 4.2.1, we use both local and global (ex-US) indices as regressors. Figure 8 shows that the contribution from each is similar over time, with country-specific indices being marginally more relevant after 2009. In aggregate, they explain circa 3% of the 1-month forward looking variations in our pool of USD/FX pairs.

Figure 8: Explanatory power and attribution of *growth shock* indices onto 1M forward looking FX returns

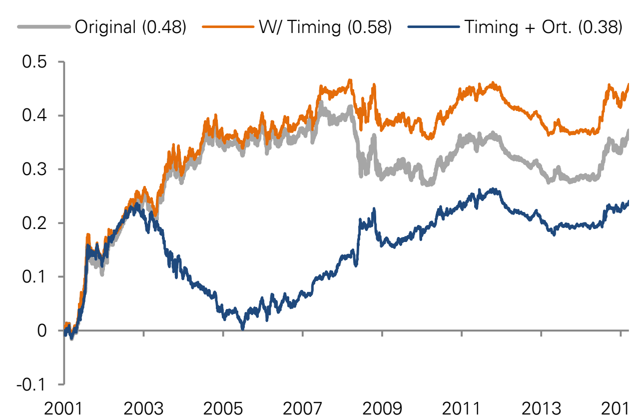


Source: Deutsche Bank

Figure 9 shows the returns of our macro factor strategy applied to foreign exchange, built using the steps described in Section 4.2.3. As before, we use 18 currency pairs: USD against G10 plus KRW, RUB, SGD, TWD, MXN, TRY, ZAR, BRL and PLN.

It shows an intuitive pattern for economic factor strategies: *the timing filter helps, but factor orthogonalisation hurts*. Timing according to market sentiment is beneficial because it curbs long exposures to high yielders during risk aversion, and short exposures during risk seeking environments, with the opposite applying to the low yielders. Orthogonalisation is detrimental because Carry and Trend-Following - the 2 factors we orthogonalise against - have some relationship to economic growth and have performed well over the past 15 years.

Figure 9: Strategy returns before cost (Sharpe ratios in parenthesis)

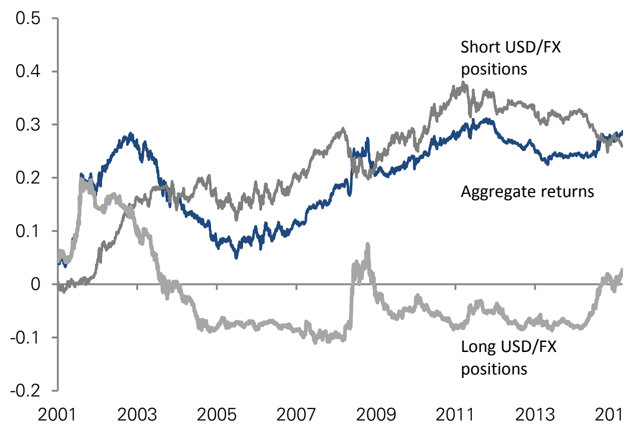


Source: Deutsche Bank

The final risk-adjusted returns look low (a Sharpe ratio of 0.38 in 14 years, before cost), but this is compensated by a significant drop in correlations. The strategy is now negatively correlated to FX Carry (-0.14 over the same period) and only moderately correlated to FX Trend (+0.22). The drop in returns was commensurate with the drop in correlations, and yet we managed to save some positive expectancy.

[22] Speed of absorption also helps explain why trend signals in FX tend to decay faster than those in, say, equities. We show some supporting results and quote related literature in Natividade et al [2013].

Figure 10: Economic factor strategy returns in FX according to long and short legs



Source: Deutsche Bank

Finally, Figure 10 shows how our returns are distributed between longs and shorts. USD/FX shorts dominate, as would be expected by the general dollar depreciation over the same period. That said, long USD/FX positions have helped in both 2008 and 2014.

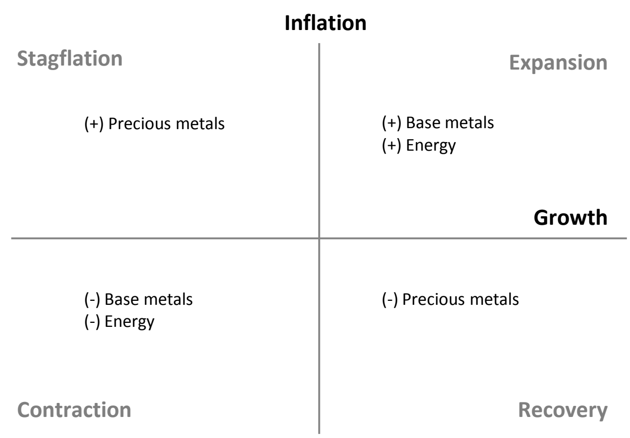
2.4 Our macro factor strategy in commodities

Our macro factor strategy in commodities is inspired by both Adams et al [2008] and our discussions with Deutsche Bank's commodities research team.

Commodities are unique in that it is the only asset class where we can use both growth and inflation *beat*[23] indices. The first is important because it has direct implications for the consumption of raw materials, and the second because (processed) commodities are often part of a country's CPI basket. As per Figure 11, different environments for growth and inflation should, in principle, relate intimately to commodity performance:

- Expansionary periods should be bullish for energy and base metals. The former is expected to outperform due to its inflation hedging properties, whereas industrial demand helps the latter.
- Recovery periods should be bearish for precious metals. As outlined in Adams et al [2008], precious metals tend to underperform under weak recovery periods.
- Economic contraction is bearish for energy and base metals. Opposite from the "expansion" quadrant, we should expect underperformance from the sectors most sensitive to the business cycle. This environment should be neutral for precious metals due to conflicting forces: lower physical demand is bearish, but their safe haven status is bullish.
- Stagflation is good for precious metals, as it's seen as one of the few outperformers (of all asset markets) in this scenario, at least according to the blogosphere[24]. Stagflation should be neutral for energy; falling growth is detrimental but the inflation hedge property helps, and moderately bearish base metals due to falling industrial demand.

Figure 11: Expected performance of commodity sectors according to growth and inflation



Source: Deutsche Bank

As for geographical regions, Adams et al [2008] show that growth and inflation in the US is still by far more relevant than that of other countries, and therefore we use it for signal generation in energy and precious metals[25]. That said, we use the *orthogonal beat* index for US growth, as described in Section 4.1, as it contains more valuable information on US growth than the standard growth *beat* index (which groups hard and soft data together).

23 As with other asset class other than FX, *beat* indices outperform *shock* indices when used as signal generators in commodities.

24 See, for instance, https://www.quora.com/What-are-the-best-asset-classes-to-be-invested-in-during-stagflation , http://www.mademan.com/mm/5-best-investments-stagflation.htmlj , http://www.usagold.com/cpmforum/2014/01/31/gold-as-a-stagflation-hedge/ and https://www.blanchardgold.com/investment-news/the-longview/gold-for-stagflation-recession-or-worse/ . Most analyses have a potential sample bias problem, as they typically focus on gold in the 1970s alone.

25 We exclude a few commodities from this strategy. First is agriculture. This is because the relationship between agricultural assets and the economic cycle is more often overshadowed by asset-specific dynamics. Agricultural price cycles tend to last circa 3 years, 2 years less than the average for other sectors and the economic cycle as a whole. We also exclude platinum and palladium from the precious metal sector. While technically these are precious metals, they resembles base metals in price action and aggregate demand; Sporre et al [2015a] estimate that <40% of platinum demand, and <50% of palladium demand in 2015 is coming from jewelery and investments, with the rest taken up by the automobile industry and other industrial sources.

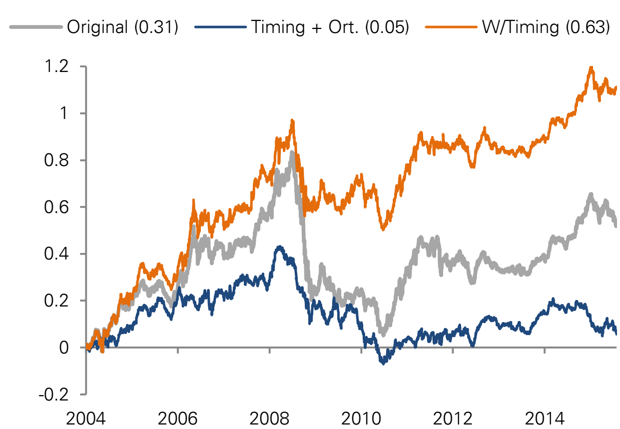
As for base metals, we also include China. Sporre et al [2015b], for instance, state that China accounts for nearly half of global refined copper consumption, and therefore it cannot be ignored. We include it in our US-China hybrid growth and inflation *beat* indices from 2007 onwards, weighted by GDP, which are used for signal generation in base metals alone.

Figure 12 shows our factor strategy results for commodities. The pattern already seen elsewhere is now magnified: the timing filter helps a lot, but orthogonalisation hurts even more.

Timing according to sentiment doubles our Sharpe ratio while keeping correlations to Carry and Trend the same: +0.16 and +0.37 over the past 11 years. The former is benign, but the latter is not.

But more importantly, orthogonalisation removes most of our economic returns. The technique is effective in cutting our correlations (now +0.1 in both Carry and Trend) but that seems to come at too high a cost.

Figure 12: Strategy returns in commodities before cost (Sharpe ratios in parenthesis)

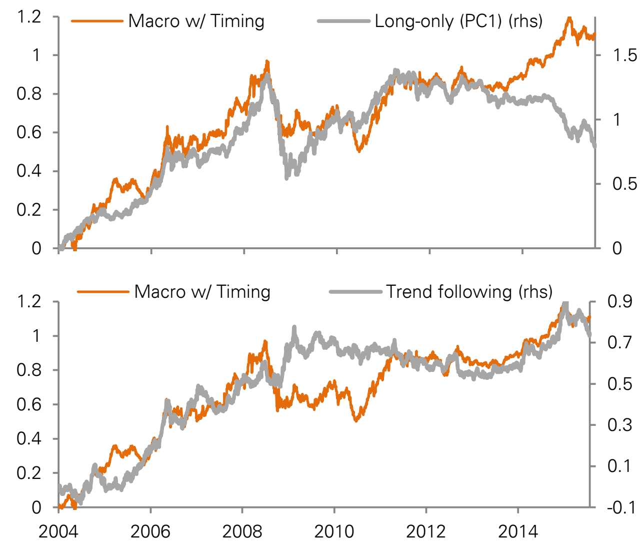


Source: Deutsche Bank

This raises an uncomfortable question: *are the macro forces affecting commodities already captured by trend following*? Figure 13 seems to point us in that direction. It shows that (a) macro factor investing adds value relative to a naive long-only, but also (b) that much of it is also captured by a trend following algorithm using the same pool of assets and similar construction.

As this warrants further research, we leave commodities out of our macro factor portfolio for now.

Figure 13: Comparison between macro factor investing, trend following and static long-only in commodities



Source: Deutsche Bank

2.5 Our macro factor strategy in fixed income

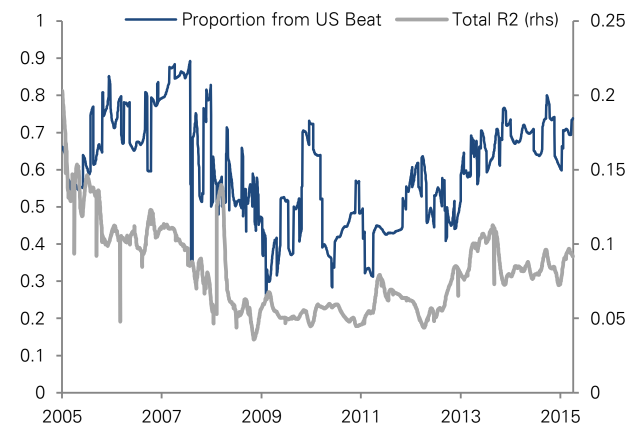
Bond futures are next. Whilst both growth and inflation are relevant, we focus on the latter[26] as the impact is unambiguous: rising inflation should be negative for Treasury bonds. As Ang [2014] puts it, bonds are instruments with fixed payments and therefore their *real* value falls when inflation rises.

As is the case in FX and equities, we load both local and external versions of our target macro factor. We focus on US inflation, as opposed to global inflation, as the former seems far more influential. When we regress future 1-month bond futures returns against local and US inflation *beat* indices, the average (adjusted) R-squared is circa 2.5x that of the same regression but using global inflation instead of the US. Further, as we decompose the R-squared into the contributing regressors, we find that US inflation explains an average of 58% of those variations. As Figure 14 shows, this explanatory power seems to increase at turning points of the US monetary policy cycle.

[26] Two arguments further support our choice. First, Ang et al [2003] highlight that, of the macro factors they considered in their study (including economic activity), inflation and "inflation risk" explained most yield movements.

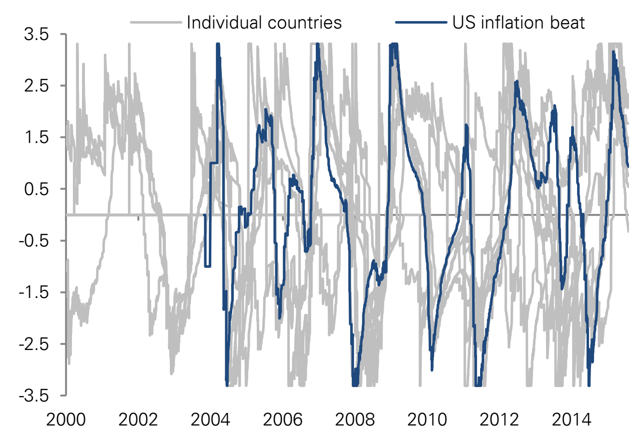
Second, explicitly including growth complicates the economic interpretation and would require adding the "level" dimension instead of just z-scores. While central banks almost unanimously combat inflation (or seek "price stability"), which simplifies our signal, their stance on growth depends on their statutory mandate and on where the economy is in the business cycle - the level effect. High and falling growth, for instance, is treated differently from low and falling growth.

Figure 14: Explanatory power and attribution of *inflation beat* indices onto 1M forward looking bond futures returns



Source: Deutsche Bank

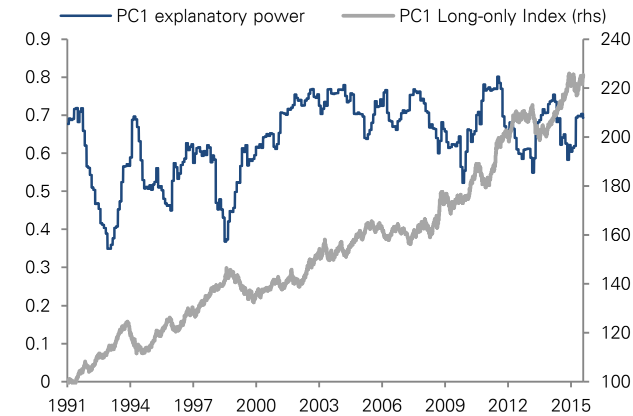
Figure 15: Inflation *beat* indices: country-specific and US, transformed into 1Y z-scores



Source: Deutsche Bank

The key challenge to our inflation strategy has been to achieve diversification and positive returns that are independent from Carry and Trend. Our pool of bond futures markets is mostly restricted to G10, where monetary and inflation cycles are similar across countries[27]; we use 10Y Treasury futures in Australia, Canada, Switzerland, Germany, UK, Japan, Mexico, New Zealand and the US. Further, the structural decline in policy rates and bond risk premia has made it difficult to harness positive returns from being short.

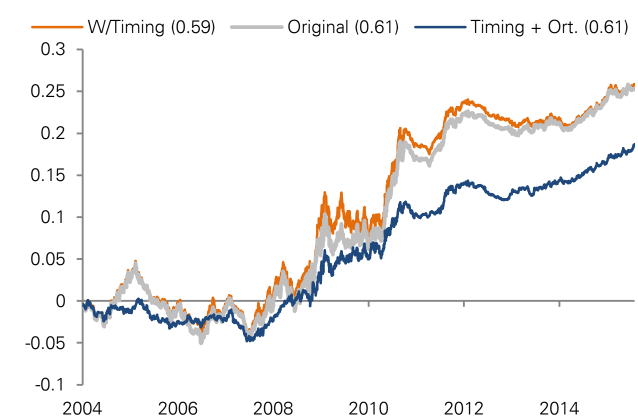
Figure 16: G-10 bond futures basket: PC1 explanatory power and long-only returns



Positions are weighted by the PC1 factor loadings. Source: Deutsche Bank

Figure 17 shows a pleasant surprise. Orthogonalising against Carry and Trend brought down our factor correlations, but not at the cost of lower (risk-adjusted) returns. 11-year correlations to Trend Following, Carry and the static (long-only) factor dropped by almost half[28], and yet our pre-cost Sharpe ratio stayed near +0.6. The 11-year backtested Sharpe ratio (before cost) in our macro strategy for bond futures is 0.61.

Figure 17: Strategy returns in bond futures before cost (Sharpe ratios in parenthesis)



Source: Deutsche Bank

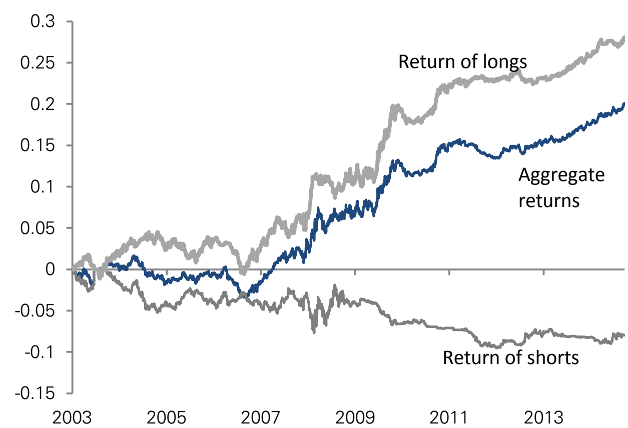
The attribution of returns is another important feature of our macro factor strategy in bond futures. As Figure 18 shows, most of our returns come from being long - no wonder given what we see in Figure 16. That said, the strategy was also short certain bond futures

[27] The first principal component explains over 60% of the variations in the mix of bond futures we use.

[28] The 11-year correlation of monthly returns between the macro strategy and the PC1 of bond futures returns went from +0.52 to +0.29, after applying factor orthogonalisation. The correlation to trend following fell from +0.40 to +0.20, and, in Carry, it went from +0.22 to +0.14.

markets throughout the backtest, with very few exceptions. The "shorts" were negatively correlated to the "longs"[29], but not enough to significantly curtail returns.

Figure 18: Macro strategy in bond futures – returns according to long and short positions



Source: Deutsche Bank

2.6 Our macro factor strategy in equity index futures

Finally, we also apply our macro factor strategy to equity index futures. We use 20 index futures: ASX (Australia), Bolsa (Mexico), Bovespa (Brazil), CAC (France), DAX (Germany), Eurostoxx (Eurozone), IBX (Spain), ISE (Turkey), JALSH (South Africa), Kospi (South Korea), Nasdaq (US), S&P 500 (US), Nikkei (Japan), OMX (Sweden), RDX (Russia), SMI (Switzerland), TSE (Canada), TWE (Taiwan), FTSE (UK) and WIG (Poland).

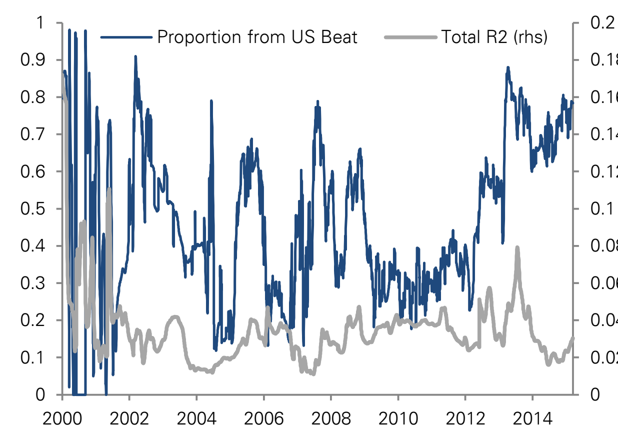
Macro factor investing is not as straight forward in equities; it can be complicated because the interaction between inflation and growth often has implications for sectors and for the market as a whole.

The link between economic growth and equity performance is clear. As highlighted earlier, Ang [2014] argues that it explains 60% of the equity risk premium. Further, while quoting the Gordon's growth (discount dividend) model for equity risk premium[30], Ilmanen [2011] also uses economic growth[31] as proxy for cash flow growth.

Inflation, on the other hand, seems more useful when used in conjunction with growth and applied to sector rotation, as opposed to being used on its own[32]. Trahan et al [2011] argue that a pick-up in inflation under subdued growth could imply an upcoming economic revival, thereby encouraging exposure to early cyclicals such as consumer discretionary stocks. At the same time, high inflation under falling growth suggests an upcoming contraction and therefore encourages rotation into late cyclicals such as energy and industrials.

But while inflation can be useful to detect turns in economic growth, we exclude it from our macro strategy. Not only are we not interested in sector rotation, but also worry about the parameter threshold risk[33] associated with fine-tuning an algorithm for all interactions between growth and inflation. Our *growth beat* indices are already transformed into short-term z-scores to capture potential economic turns.

Figure 19: Explanatory power and attribution of *growth beat* indices onto 1M forward looking equity index futures returns



Source: Deutsche Bank

Having decided to stick to growth *beat* indices, the next question is which regions to include. We use both country-specific indices and the US *orthogonalised beat* index. Beber et al [2014] found that equity indices are more responsive to US growth indicators than they are to global data or even growth indicators from their own countries (specifically, Europe, Japan and the UK). Our analysis partly concurs with that; in our larger asset

[29] The 11-year correlation of monthly returns between the long legs and the short legs is -0.60.

[30] $ERP = D/P + G - Y$, where ERP is the equity risk premium, D/P is cash flow yield, G is the cash flow growth rate and Y is the bond yield.

[31] To be exact, he uses "an average of a survey forecast of future output growth and several realised real growth rates (of GDP, corporate profits and earnings per share over the past decade).

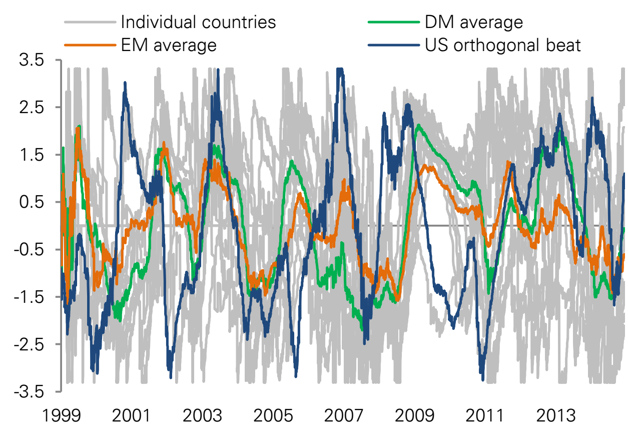
[32] There are two opposing arguments on how inflation relates to equities. The argument in favour is that equities are a claim on real assets, and therefore should perform well in inflationary periods just as real assets normally do. The argument against it is that inflation, as put by Trahan et al [2011], is a "growth depressant". In fact, the general academic evidence is that inflation is detrimental to equity performance.

[33] Bridgewater [date not specified] and Ang et al [2012] have achieved successful results on that front, and we encourage the reader to look into both.

pool, the US growth variable accounts for half of the explanatory power that our regressors have onto future 1M equity returns, but that number is stronger during recessions and turning points.

Figure 20 shows our regressors in more detail; the *growth beat* indices from individual countries are shown in the background, while the US *orthogonal beat* is shown in blue. All data is pre-processed into 1-year rolling z-scores so as to reflect what goes directly into the regression.

Figure 20: *Growth beat* (country-specific) indices and US *orthogonal beat*, transformed into 1-year z-scores



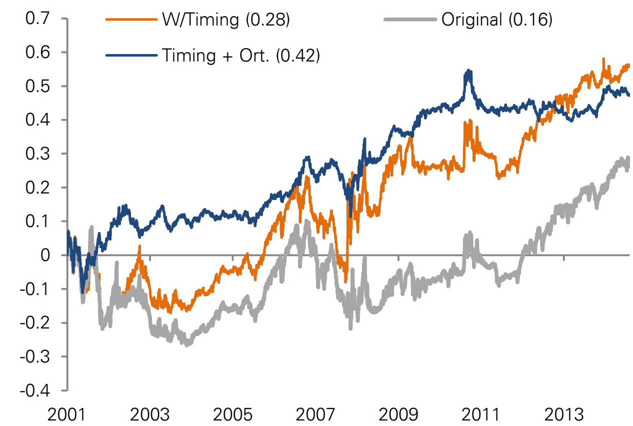
Source: Deutsche Bank

As we analyse the returns of our macro factor strategy in equity indices, the benefit of sentiment timing becomes clear. The strategy, in essence, accurately tilted towards the shorts in 2008 and longs in 2012-13, thus better capturing the external environment.

Orthogonalisation also contributed by reducing the volatility of returns and halving factor correlations.[34] Most returns are attributed to the long positions, as would be expected, but the short legs reduced the drawdown profile in the aggregate strategy, as per Figure 22. The 13-year backtested Sharpe ratio (before costs) is +0.42.

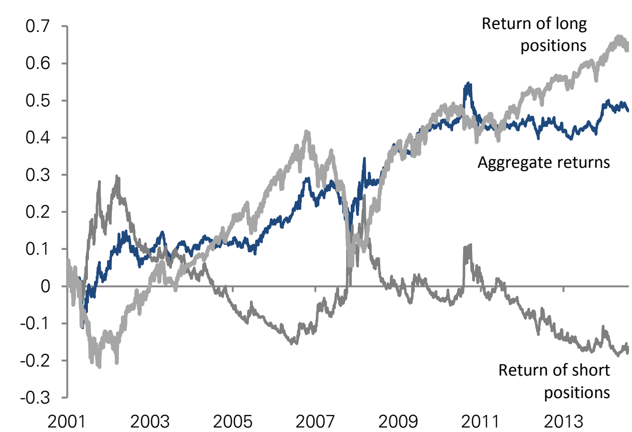
[34] The long-term correlation of monthly returns between the macro factor strategy and equity Trend Following fell from 0.74 to 0.18 after orthogonalisation. The correlation with carry stayed flat (from 0.01 to 0.05) while the correlation to equities long-only (PC1) stayed negative (from -0.26 to -0.27).

Figure 21: Strategy returns in equity futures before cost (Sharpe ratios in parenthesis)



Source: Deutsche Bank

Figure 22: Macro strategy in equity futures – returns according to long and short positions



Source: Deutsche Bank

2.7 Our macro factor portfolio summarised

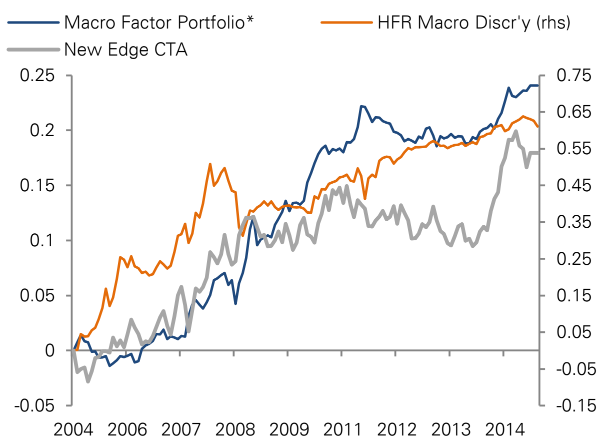
Our macro factor portfolio groups individual macro strategies into one:

- FX: capture the influence of surprises in economic growth across countries (ex-USA) on a range of 18 currency pairs.
- Bond futures: exploit the effect of inflation momentum on 9 bond futures markets.
- Equity futures: capture the influence of economic growth momentum on 18 equity indices.

As per Section 2.2.4, the influence is estimated via least square regressions in all instances. The positions are conditioned on market sentiment - arguably another macro factor. They are further orthogonalised against our Carry and Trend portfolios, so as to capture value in excess of what our dynamic factors already harness. As macro factors play a large role in explaining the static premium of each asset class, the number of longs and shorts is unconstrained.

Figure 23 compares the joint macro factor portfolio[35] with a potential benchmark - the HFR Macro Discretionary Index[36] - which shows a similar performance in recent years. Correlations to cross-asset trend following - proxied here by the New Edge Macro CTA Index[37] - are also contained, but not nullified[38] as we had hoped. Roughly speaking, macro factor investing and trend following outperformed and underperformed in similar periods. *This shows the challenge in disentangling economic momentum from price momentum.*

Figure 23: Macro factor portfolio as compared to potential benchmarks



** Macro factor portfolio: daily rebalancing, no cost. Source: Deutsche Bank*

As highlighted in Section 2.2.4, we evaluate positions on a daily basis. The results in Figure 23 also assume no cost. Both aspects - turnover and cost - will now be addressed in Section 5.

3. Constructing a sentiment portfolio

Market sentiment is probably one of the most commonly used expressions on a trading floor. It is an abstract concept, which is good and bad. It is good in that the more abstract it is, the more positive is the alpha harnessed by those who succeed in capturing it. The bad news is that the task of capturing it is exceptionally difficult. Newsflow, positioning, liquidity and the vol surface are all channels through which investors express how they "feel" about an asset, and each contains its own intricacies.

This section focuses on sentiment implied by the options market. The idea was first motivated in Natividade et al [2014], where we found that the volatility surface explained a notable variation of sub 3-month (contemporaneous) returns across asset classes.

Specifically, we evaluate 4 signals: volatility risk premium (and implied volatility), implied skew, volatility slope and implied correlations. If the signal is promising, it translates into a dynamic factor strategy that uses the template introduced in our last *Quantcraft*: long half and short half of the asset pool but applying non-linear weights based on signal rankings for each asset[39].

We treated all assets as equals wherever possible, thus ignoring overarching asset class distinctions. In other words, the Zinc skew signal is compared directly to the same signal in Bund futures. While still long-short, we build pure multi-asset strategies instead of asset class neutral strategies that are grouped into one later.[40] This approach is validated by 2 arguments:

- While the strategy will have net directional exposure to every asset class, its sensitivity to broad directional moves can be controlled through optimisation constraints and orthogonalisation.
- The signal is captured *more holistically.* It allows us to be overweight assets whose signals are stronger, and reduces the risk of executing a signal in the wrong direction[41]. This "privilege" is somewhat unusual; as illustrated in our last *Quantcraft*, signal sources are often constrained to an individual asset class.

3.1 The challenge: unique alpha

Ideally, any new signal must prove 2 things: that it is unique, and that it generates positive returns.

This raises the bar for sentiment signals, as they must show more than "risk-on, risk-off" information. To

[35] Grouped FX, equity and bond futures positions using inverse volatility weights. The volatility period used was 2004 alone. We show more accurate results in Section 5, after adding slippage and constraints.

[36] HFRXDT Index on Bloomberg.

[37] NEIXCTAT Index on Bloomberg.

[38] The 10-year correlation of monthly returns between our macro factor portfolio and the New Edge CTA Index is 0.17.

[39] In short, the weights are defined according to the inverse normal transform of each signal's relative rankings. See Natividade et al [2014] for details. The weights therefore reflect signal intensity, but in smoothed form.

[40] The curious reader may be interested in knowing that we also backtested long-short strategies inside each asset class and grouped them together later (using inverse vol weights) so as to check the differences. The results were worse in spite of the greater diversification potential.

[41] If the universe of assets is small, and the strategy is constrained as long-short, a small positive signal (which would've generated a small long weight) translates into a short weight if the signal size is smaller than that of all other assets. Such is often the case, for instance, in cross-sectional momentum strategies in USD/G10 FX.

qualify, we want our new strategies to be sufficiently independent from 4 factors: the static factor (purified asset class returns, which we proxied through the first principal component of each asset class[42]), and 3 dynamic factors: Carry, Trend Following and Cross Sectional Momentum.

We used 2 techniques to address this issue during signal construction: z-scoring and time series signal orthogonalisation:

- *Z-scoring* involves changing the signal from a raw "level" to a z-score relative to its own 1 year history. It is the same transformation that we applied to our Macro Factor signals. This allows our signal to be more adaptive to changing market dynamics, thereby increasing the turnover of positions and reducing time-homogenous exposures to regions and sectors. Ultimately, it weakens our strategies' correlations to factor strategies that are more static, such as long-only equities and rates.
- *Time series signal orthogonalisation* is a lighter version of the cross-sectional weight orthogonalisation applied earlier. We noticed the need for a lighter approach as factor correlations were already lower in this case, and cross-sectional weight orthogonalisation was leading to a significant drop in our transfer coefficients.[43] We conducted signal orthogonalisation by regressing the original signal (not the strategy weight) against the factor signal (not the factor strategy weight) and extracting the alpha and residual. Mathematically:

  $$s_{i,t}^{O} = a_i + b \times s_{i,t}^{Fc} + \varepsilon_{i,t}$$

  $$s_{i,t}^{F} = a_i + \varepsilon_{i,t}$$

  where $s_{i,t}^{O}$ is the original sentiment signal (i.e. the z-score) for asset i at time t, $s_{i,t}^{Fc}$ is either the factor signal for the same asset or PC1 (i.e. market) returns, and $s_{i,t}^{F}$ is the final, orthogonalised signal. It was particularly important when constructing our skew strategy.

We applied z-scoring in all cases. But if factor correlations dropped enough after the z-score transform, we did not further apply signal orthogonalisation – our goal had already been achieved. In instances where we compared different asset classes in the same strategy, we also divided the z-score by the volatility of asset returns.

On average, the return profile of our strategies dropped after the above treatment. In some cases the returns still looked attractive, but in others the drop proved fatal. We start with the latter.

3.2 Volatility risk premium (VRP) and implied volatility

The VRP is a good place to start. Implied volatility is the most important component of the vol surface, and its spread to realised vol is one of the most widely researched sentiment signals. Its existence has been rationalised by academics[44], and it has been seen as useful in predicting future spot returns (especially in equities). A typical conclusion is that this "fear" factor can be used for timing a long equities position: the higher today's VRP is, the higher that future equity returns are likely to be[45]. This highlights the *reversal* nature of the signal for equities, as it suggests buying when equity markets are falling[46].

We defined VRP as the ratio of 3M ATMF implied volatility to 1-year exponentially weighted realised volatility (1M half life). We apply it to our pool of 60 assets across FX, equities, commodities and bond futures. The signal was based on multiplying this ratio

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[42] For clarity, our PC1 series were built using correlation matrices of 1 year's worth of daily returns, rolled monthly. The indices were therefore rebalanced once a month. Our equities universe spanned 21 index futures: Australian ASX, Mexican Bolsa, Brazilian Bovespa, CAC 40, DAX, Eurostoxx 50, Hong Kong HSE, Spanish IBX, Turkish ISE, South African JSE, Korean KOSPI, NASDAQ, S&P 500, Nikkei, Swedish OMX, Russian RDX, Swiss SMI, Canadian TSE, Taiwanese TWE, UK FTSE and Polish WIG. Our FX universe spanned 18 currencies, all against the USD: G-10 FX + KRW, RUB, SGD, TWD, MXN, TRY, ZAR, BRL and PLN. Our rates universe spanned 10Y interest swaps in 20 markets: G-10 + BRL, HUF, ILS, KRW, MXN, PLN, SGD, TRY, TWD and ZAR. Finally, our commodities PC1 had weights on 12 constituents: gold, silver, platinum, crude oil, Brent, heating oil, soybeans, corn, coffee, copper, aluminium and zinc, all using the front futures contract.

[43] The transfer coefficient is the correlation between original strategy weights and final strategy weights.

[44] As outlined in Ilmanen [2011], the VRP is said to reflect compensation for systematic risk, price pressures from investor supply and demand, and biased forecasts of future empirical volatility. Other authors who defended similar arguments include Carr and Wu [2009], Benzoni et al [2010] and Broadie et al [2009].

[45] Luo et al [2011, 2012a, 2012b] describes US VRP as a "fear index", arguing that it has much stronger predictive power on future equity returns than either implied or realised volatility alone. Han and Zhou [2011] fine tune the argument by showing that US stocks with low beta to idiosyncratic volatility or US VRP have higher expected returns. Londono [2014] also argues that the US VRP influences a country's equity returns more than that country's own VRP, while Bollerslev et al [2012] introduce a global VRP variable which seems to provide even stronger predictive power. Interestingly, recent studies suggest the opposite in foreign exchange; Della Corte et al [2014] argue that currencies with high VRP depreciate relative to those with low VRP. More specifically, they argue that currencies whose past 1Y realised volatility is high (low) relative to the current 1Y implied vol tend to appreciate (depreciate), a phenomena partly explained by risk-averse hedgers becoming reluctant to hold currencies that are expensive to insure. Note that they define VRP as realised volatility minus implied, in contrast to the opposite (and more standard) convention. Further, using a smaller set, Londono and Zhou [2012] also find that equity VRP can influence short-term FX performance.

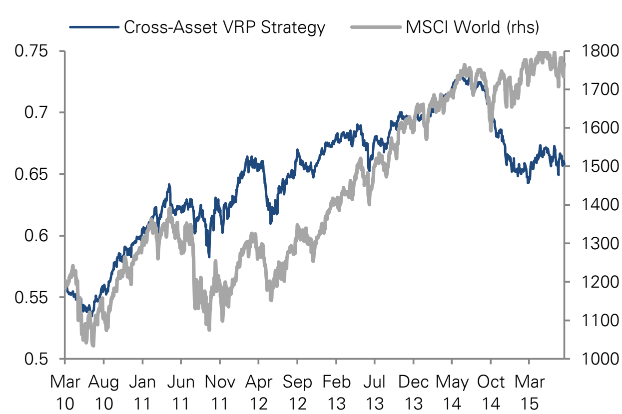
[46] The higher VRP reflects an options market that is worried, a situation more often linked to falling equities.

by an *empirical skew* variable[47], built in order to separate assets that are positively skewed from those that are negatively skewed. The adjustment was designed to extend the reversal principle from the equities literature into other asset classes, while accounting for different return profiles. If the asset falls faster than it rises, a high VRP means "buy"; if it rises faster than it falls, it means "sell".

We evaluated the VRP signal in terms of levels and z-scores, either as 4 separate asset class strategies or as one cross-asset strategy (long 30 assets and short 30 assets, with decaying weights). The results were disappointing:

- If we use levels, the strategy returns are highly correlated to generic proxies of risk, due largely to time-invariant positions. This is no surprise. The strategy was consistently long riskier assets (such as equities) and consistently short safe havens (such as the USD), even more so in recent years as more markets started fitting into such binary categorisation[48]. The returns may look attractive, but are largely subsumed by exposures to other, "easier" factors such as FX carry and equity risk premia.

Figure 24: VRP Strategy (levels) versus MSCI World



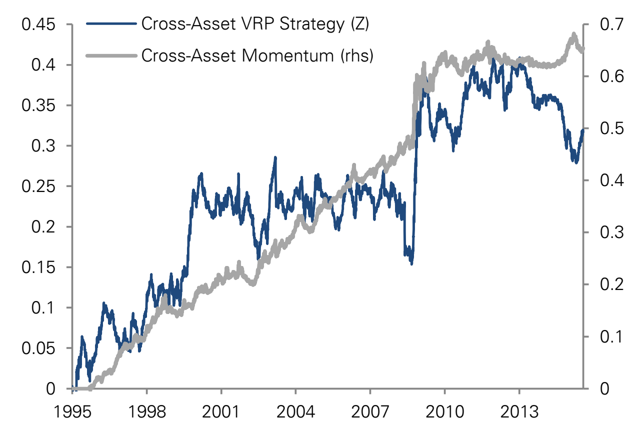
Source: Deutsche Bank

- If we use z-scores, strategy returns become less attractive and highly correlated to cross-asset momentum. As Figure 25 shows, not much is left if we further apply signal orthogonalisation.
- We also backtested the VRP through long-short strategies inside each asset class, with or without the skew variable. We also tested the implied volatility directly. *The findings were similar: promising but highly correlated returns, or orthogonal but weak returns.*

The few promising backtests were not consistent enough to mitigate the risk of hand-picking. We could have also considered testing the VRP solely for timing other strategies, as our colleagues in single stock equities do[49], but decided against it given the success of our pre-existing Global Sentiment Indicator (see Natividade et al [2012]).

As such, we did not pursue the VRP signal further.

Figure 25: VRP Strategy (z-scores) versus cross-asset momentum



Source: Deutsche Bank

3.3 Implied skew

Skew is next. The pricing of calls relative to puts is also a popular topic in academia, and reasonable effort has been spent trying to rationalise its existence, use it for timing future events[50] or - most importantly - predict future spot returns.

The findings suggest skew is *inversely* related to VRP, as the signal embeds *momentum*: if calls are appreciating relative to puts, one should buy - not sell. both Xing et al [2010] and Cahan et al [2010] advocate

[47] We took the difference between the volatility of negative asset returns and of positive returns, using an anchored window from the late 1990s onwards. If that difference is negative, which indicates a negatively-skewed asset, the skew variable reads 1, otherwise it reads -1. This adjustment may seem superfluous in equities, but it is useful in asset classes where some assets are positively skewed (such as agricultural commodities and funding currencies) while others are negatively skewed (i.e. base metals and investment currencies).

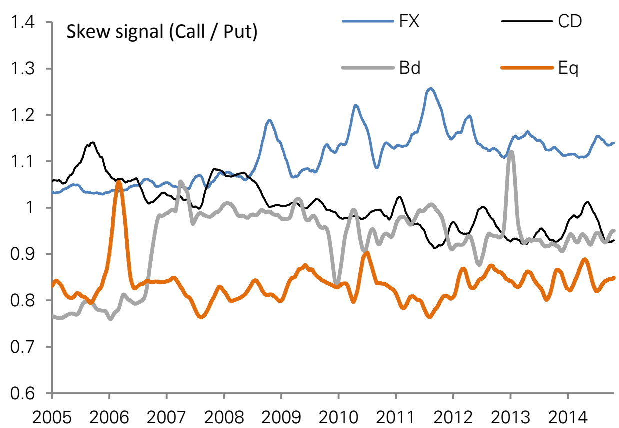
[48] We show the growing power of the first principal component in explaining the variations of each asset class in Natividade et al [2013b], also arguing that part of it is structural and unlikely to abade.

[49] See Luo et al [2014].

[50] Authors have typically focused on crisis periods. Doran et al [2006] found some timing power in S&P skew when it came to S&P crashes, though the magnitude of the predicted moves was statistically insignificant. Kurbanov [2010] quoted similar conclusions for foreign exchange: some predictive power ahead of currency crashes, but not during normal times and with crash magnitudes that were not statistically significant.

that stocks with a lower call-to-put volatility ratio underperform those with a higher ratio, and attribute the phenomena to a preference by informed traders to use OTM puts. Our findings concur with academia, but first we provide some background.

Figure 26: 1M 25D call-to-put vol ratios across asset classes



6-month rolling average. Source: Deutsche Bank

We define implied skew as the 25-delta 1M call volatility divided by the 25-delta 1M put[51]. As we plot this ratio across asset classes in Figure 26, clear differences arise. The call-to-put ratio – or "risk reversal"[52] – is arguably the most polluted of all signals coming from the vol surface, as it mostly reflects either options inventory or empirical skew - and not sentiment directly. For instance:

- In equities, the implied skew is consistently below that of other asset classes, which usually reflects inventory. *Investors are not consistently bearish equities relative to bonds, currencies or commodities*. As a traditional "long-only" asset class, equity markets observe a natural demand for put protection from investors, thus bidding up the price of puts relative to calls. Even relative to empirical skew, the implied skew in equities is also the most expensive[53].
- The FX implied skew is least affected by inventory issues, making it more comparable to the empirical skew, but the latter is often acute and time-invariant, which poses the same problem. As a funding currency, the USD has tended to appreciate faster than it depreciated over time, therefore leading to a consistently high call/put skew ratio. On average[54], the higher the carry in a particular USD cross, the higher the skew, regardless of market sentiment on that currency pair[55].
- Both inventory and empirical skew considerations have affected commodity risk reversals over the years, with the latter becoming more relevant recently due to the so-called *financialisation* phenomenon. As argued in Zaremba [2013], commodities have become increasingly equity-like: they fall faster than they rise, thereby justifying the multi-year drop in the call-to-put ratios in Figure 26. That said, inventory shocks still force a positive skew (empirical and implied) in many commodities, especially in agriculture, thereby still generating uncorrelated returns in the asset class. While commodity skew also reflects sentiment, risk reversal levels are mostly dictated by the 2 other factors above.
- The options skew in bond futures appears symmetric in Figure 26, but this masks two strong determinants of risk reversals. First, it has soft boundaries; markets naturally find it less likely that interest rates will be far below zero compared to far above zero. Second, the direction of the next move – and hence, skew – can be anticipated by where we stand in the interest rate cycle. Central banks are far less likely to cut in the middle of a hiking cycle, and to hike in the middle of an easing cycle. Both factors strongly affect the implied skew, as argued in Vahamaa [2004], thereby making it hard for us to capture market sentiment using call-to-put ratios alone.

All of these structural issues must be removed from our skew estimate in order for it to represent sentiment alone. Therefore, our signal is constructed by taking the ratio of 1M 25-delta vols and changing it to its 1-year time series z-score. We further orthogonalised our skew signal against the relevant asset class returns, using the recipe described in Section 3.1, thereby further reducing any structural exposure to each asset class. Finally, we divided the residual signal by the volatility of each asset for a more consistent comparison.

[51] We chose 1M due to data characteristics and some academic results showing better predictive power in shorter dated risk reversals. See Doran et al [2006].

[52] In some asset classes, the risk reversal is defined as the spread (not the ratio) between call and put vols.

[53] Equities fall faster than they rise, a phenomena validated by the so-called *leverage* effect (see Black [1976]). However, the relationship is not as acute as implied by risk reversals. Examples of that can be seen in our *Volcano* reports – see Anand et al [2015] for a recent example.

[54] "On average" because for other funding currencies with even lower interest rates, USD puts are more expensive than USD calls.

[55] This is partly highlighted in Della Corte et al [2014], where performance of their risk reversal strategy is linked to interest rate differentials.

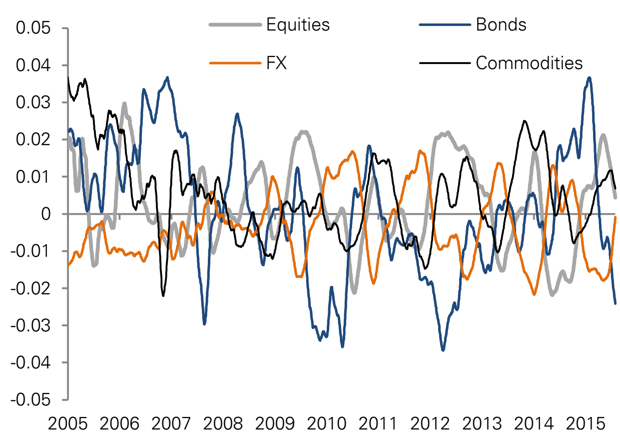
The signal is applied in *momentum* format: the higher it is, the stronger our buy signal, and vice-versa, therefore making the same assumptions as Xing et al [2010] and Cahan et al [2010]. From there, we build a long-short strategy using 48 assets[56] from all asset classes. We go long half of our asset pool and short the other half using non-linear decaying weights and rebalancing daily.

In essence, *we are capturing how much options traders favour an asset now relative to its past and relative to other assets.* This measure of relative "bullishness" is not (in many cases) immediately connected to the VRP, and therefore captures additional information from the volatility surface.

Figures 27, 28 and 29 show our results. Looking into the numbers in more detail, we find that:

- Asset class weights rotate heavily, but don't reach significant levels - residing within +/- 5% of the full strategy.

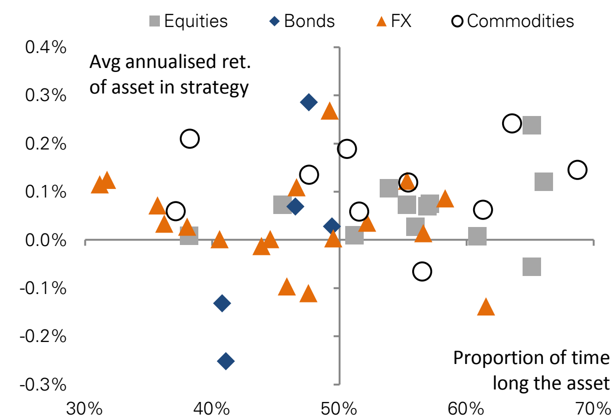
Figure 27: Skew strategy weights by asset class



Source: Deutsche Bank

- These (tame) directional exposures are rewarded. This format outperforms building 4 individual long-short strategies first (one in each asset class) and then combining them, which would have forced zero asset class exposure. It suggests there is valuable information in the *aggregate* sentiment observed in each asset class.
- A good portion of our returns come from the rally in commodities and equities post 2008, though the portfolio has seen positive contributions from other asset classes as well, as shown in Figure 28. Longs and shorts, on aggregate, seem to perform independently[57].

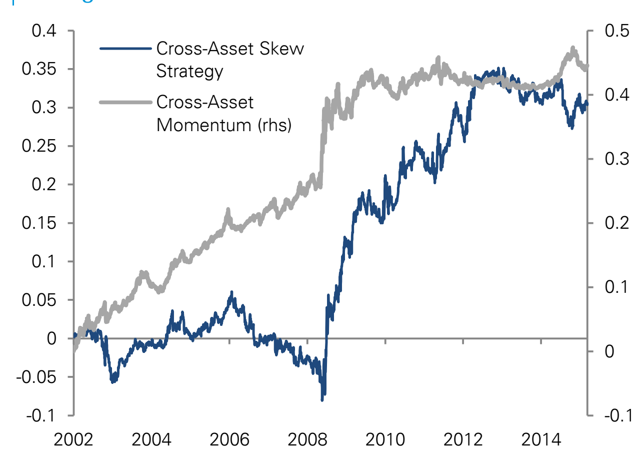
Figure 28: Skew strategy - attribution of backtested returns by asset and proportion of long positions



Source: Deutsche Bank

- The strategy is not correlated to cross-sectional momentum[58], even though the signal might suggest it should be. It seems the options market says more than just what has rallied recently. This confirms the findings of our earlier research into the accuracy of market makers when predicting future spot conditions through how they priced skew, at least in foreign exchange (see Natividade [2008]).

Figure 29: Skew and cross-sectional momentum strategies – backtested returns



Source: Deutsche Bank

[56] We only included 48 assets due to data constraints. Those missing include IBX, ISE, Kospi, RDX, TSE, Taiwan and WIG equity futures, Australian, NZ, Swiss and Mexican bond futures, and Coffee futures.

[57] The 10Y correlation of monthly returns is +0.13.

[58] The correlation of monthly returns is +0.11 over the past 10 years, and +0.04 over the past 5 years. 10--year correlations are also low versus cross-asset carry (+0.04), trend following (+0.08) and long-only positions in each asset class (rates: +0.2, equities: +0.03, commodities: -0.07, FX: -0.03).

The skew signal is the first to qualify for our composite sentiment portfolio. While the 13-year backtested Sharpe ratio is barely acceptable (+0.41 and without costs), the signal is unique enough to be included in our suite of sentiment signals.

3.4 The implied volatility slope

Our next surface-based sentiment signal comes from the implied volatility slope, a measure that reflects traders' expectations of the future path of volatility.

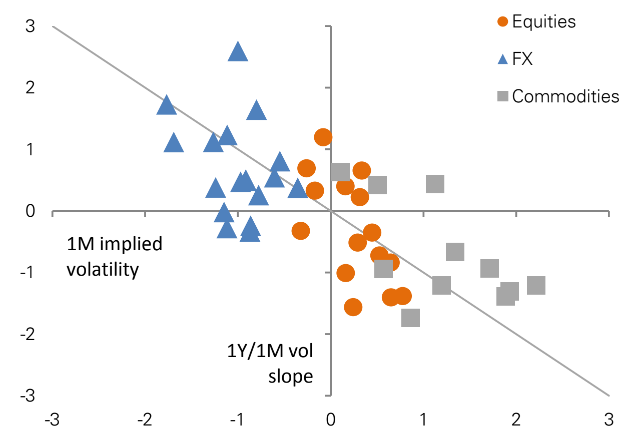
The academic literature on this topic is not directly applicable, but provides some useful clues: both Vasquez [2014] and Jones et al [2012] claim that the vol slope can predict future *straddle* returns in equity options, and harness it through cross-sectional long-short portfolios[59]. The steeper the vol slope, the more they buy equity straddles.

While we are not interested in trading straddles, these findings are relevant because they point to a cross-sectional[60] rise in asset volatility when the curve is cross-sectionally steep, and the opposite when the curve is inverted. If this rise in volatility has specific implications for spot direction, then we can use the signal to build spot portfolios. The authors suggest, at least in equities, that a steep slope is bearish spot: a steep slope predicts higher vols, which in turn is linked to falling spot markets.

Our term structure signal is built by taking the ratio of short-term (1M or 3M) to long-term (1Y) ATMF vols across 44 assets – we exclude bond futures due to a lack of long-term vol data[61]. Once again, we transform this ratio to its 1-year Z-score in order to remove exogenous correlations and then divide the outcome by the volatility of each asset.

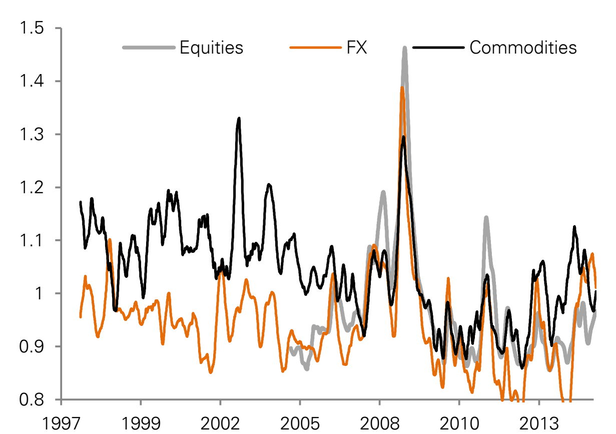
No other adjustment was required. The link to "unwanted" factors was sufficiently small[62] not to require signal orthogonalisation, which we believe is due to a lack of structurally persistent patterns in the vol slope of any asset class[63]. Figure 30 reinforces this view: relative to implied vols, most vol slopes are cross-sectionally comparable. Figure 31 further shows that most slopes have been similar over time, and especially over the past 10 years.

Figure 30: Vol slope against ATMF vol across asset classes, measured as cross-sectional z-scores



Average of cross-sectional, cross-asset z-scores for 1M vols (x-axis) and vol slope (y-axis) over the past 10 years. Source: Deutsche Bank

Figure 31: 1M/1Y ATMF vol slope – equities, FX and commodities



Source: Deutsche Bank

Our signal – the 1Y z-score of the volatility slope – encapsulates sentiment from a different angle: it captures the market view on how temporary the recent move in short term implied vols is likely to be.[64] The resulting strategy, put simply, is to buy assets where

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[59] Among the possible reasons mentioned for why this works, the one that makes most sense to us is the mispricing of short-term options by "noise" traders. There was no indication that the authors were using delta-hedged straddles, though the reasons should apply one way or the other.

[60] Jones et al [2012] argue that this is a cross-sectional phenomena - as in, applicable to one asset when ranked relative to other assets. They find the slope is not predictive of future returns when using univariate time series regressions alone.

[61] We also excluded IBX, ISE, KOSPI, RDX, TSE and WIG equity futures, and coffee futures. In total we had 15 equity indices, 18 USD/FX and 11 commodity futures.

[62] Backtested 20Y/5Y correlations are as follows: -0.1/+0.07 to the equities PC1, -0.02/-0.11 to the rates PC1, -0.16/-0.09 to the commodities PC1, +0.09/+0.06 to the FX PC1, +0.26/+0.27 to cross-asset momentum, +0.26/+0.3 to cross-asset trend following, and -0.05/+0.07 to cross-asset carry. We would've desired a lower correlation to momentum and trend, but this is sufficiently low for us not to want to further transform the signal.

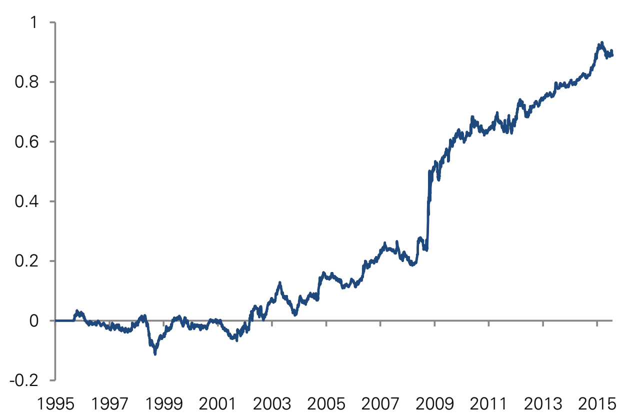
[63] This is only the case because we use 1Y ATMF vols as our long-dated tenor. Longer dated vols are largely driven by structured flows; for an overview in FX, see Natividade [2007a] and Natividade [2010].

[64] The vol slope reflects traders' expectations that short-term implied vols will eventually revert to some long-term level. The z-score, in turn, captures the pace and intensity of that reversal. It goes beyond what the VRP and skew capture. For more details, see Natividade [2007b].

vols are expected to fall back (and fast) to a lower long-term level, and sell those where the opposite is true.

Figure 32 plots the backtested cumulative returns of the strategy employing our slope signal described above, while Figure 33 describes the rotation between asset classes. The results are nice, but they're also puzzling. We did not apply the empirical skew adjustment as we had in the VRP signal, and hence this signal applies equally to positively and negatively skewed assets.[65] Academic research explains why it works in equities – buying when we expect volatilities to fall – but it works in other asset classes as well. Why?

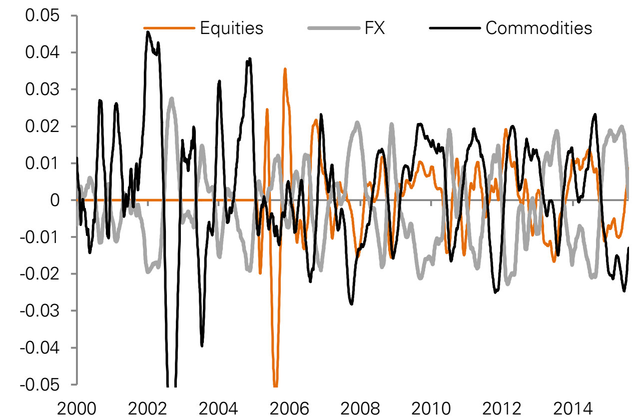
Figure 32: Backtested cumulative returns – long-term Sharpe ratio of +0.7 (before costs)



Source: Deutsche Bank

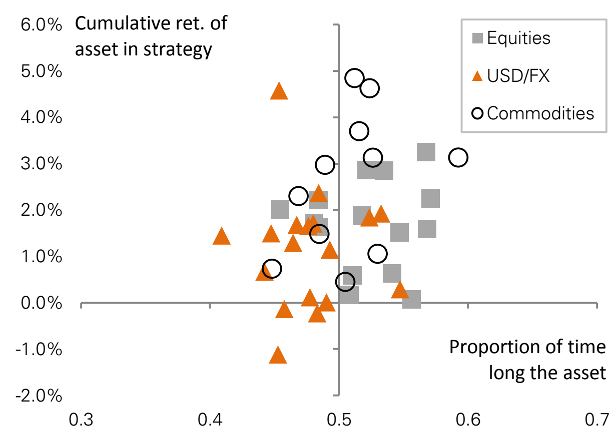
To answer that question, we need to look at the numbers more closely. And as we do so, we find that the signal works in distinctly different ways depending on the asset class. Figure 35 helps us visualise this in more detail, by showing the relationship between empirical skew and strategy returns for every asset. The X-axis has the volatility of positive asset returns divided by that of negative asset returns; a reading above 1 implies the asset is positively skewed. The Y-axis plots, for each asset, the returns from being long minus the returns from being short based on strategy weights.

Figure 33: Aggregate strategy weights by asset class



6M moving average of aggregate weights. Source: Deutsche Bank

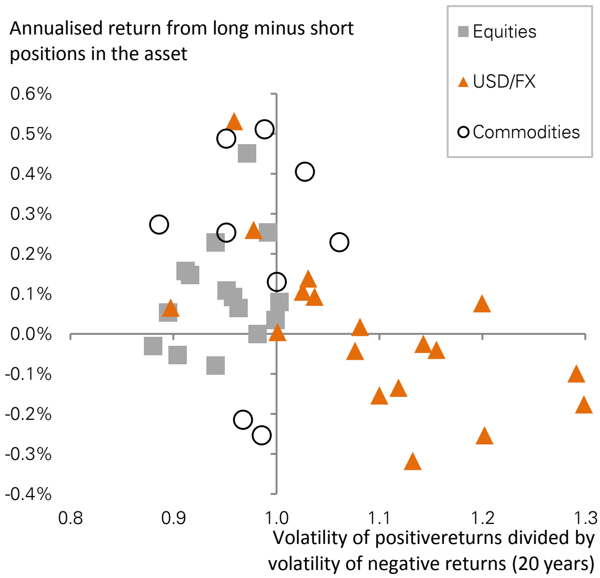
Figure 34: Slope strategy - attribution of backtested returns by asset and proportion of long positions



Source: Deutsche Bank

65 We tried variations of skew adjustments for the slope signal, as we wanted to identify a relationship between skew and vol slope that applied to all asset classes so as to get a "cleaner" signal. Alternatives tried included different measures of empirical skew, as well as the risk reversals, with no improvement. Eventually we found that the relationship between skew and the slope signal changes according to the asset class, as shown in Figure 35.

Figure 35: Slope strategy – relationship between empirical skew and direction of returns



Source: Deutsche Bank

In summary:

- In equity futures, most returns come from when the strategy was long. The vol slope works as a *reversal* signal: go long when the curve is most inverted, which is usually when equities are falling. Equity returns are negatively skewed; the assets are at the left half of Figure 35, which reiterates our point. That said, an inverted vol slope also suggests vols will fall in the future; if that happens, equities will likely rise. Therefore, the signal connects our findings with those of Vasquez [2014].

- In FX, most returns come from when the strategy was short US dollars. The vol slope works as a *momentum* signal: sell USD when the curve is steepest, which typically occurs when the dollar is falling, and buy USD when the slope is inverted - usually when the USD is appreciating[66]. If we consider the forward-looking aspect of the slope, however, the signal is at odds with Vasquez [2014]. If the vol curve is steep, it suggests vols will rise, which in turn should suggest the USD will appreciate as USD/FX returns are positively skewed. But our signal says we should sell dollars, not buy.

- The results in commodities are mixed, which reflects the distinct characteristics of each sector. Over the long run, asset returns have been more symmetric in agriculture, energy and base metals (the assets in the centre of Figure 35), but more negatively skewed in precious metals. At the same time, long positions outperformed the shorts everywhere other than base metals[67] over the long run, partly pointing to both reversal (for precious metals) and momentum (for agriculture). Empirical skew, and the attribution of returns to longs and shorts, have been different in the past 5 years and yet the signal has been effective. This is still somewhat puzzling to us.

The vol slope signal is the second to qualify in our composite sentiment portfolio. The 20-year backtested Sharpe ratio is a respectable +0.7 (before costs). It is also sufficiently independent from our skew signal.

3.5 The implied correlation signal

Our final sentiment signal is based on market-implied correlations, and applied to the two markets where data is most widely available: FX and equities.

In foreign exchange we define the (Black & Scholes) implied correlation as a function of USD/FX, EUR/FX and EUR/USD 3M delta neutral vols. This "triangle" has better quality data, and it also helps remove the effect of EUR/USD (the common cross-variance). The formula[68] is:

$$\rho_{\$/FX,E/FX} = \frac{\sigma^2_{\$/FX} + \sigma^2_{E/FX} - \sigma^2_{E/\$}}{2 \times \sigma_{\$/FX} \times \sigma_{E/FX}}.$$

In equities, the implied correlation of an index represents an estimate of the market capitalisation-weighted average implied correlation between the constituents. The formula[69] is:

[66] As a typical funding currency in the past 20 years, the USD has tended to appreciate faster than it depreciates. Currency pairs residing at the left of Figure 35 involve even lower yielders (i.e. USD/JPY, USD/CHF).

[67] The same would have been the case in base metals if it wasn't for gains by being heavily short in 2008. At the time, all vol curves were inverted, but base metals curves were not as inverted as most others.

[68] Note: if the USD is the quote currency in either - but not both - of the crosses, the correlation estimate is multiplied by -1.

[69] For details, see Mougeot [2007]. An equivalent formula shown in CBOE [2009] is: $\rho_{Index} = \dfrac{\sigma^2_{Index} - \sum_i^N w_i \sigma_i^2}{2\sum_{i=1}^{N-1}\sum_{j>i}^{N} w_i w_j \sigma_i \sigma_j}$

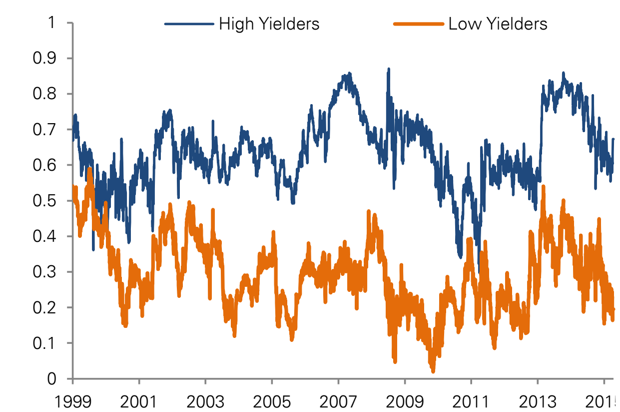
$$\rho_{Index} = \frac{\sigma_{Index}^2 - \sum_i^N w_i \sigma_i^2}{\left(\sum_i^N w_i \sigma_i\right)^2 - \sum_i^N w_i^2 \sigma_i^2}$$

where σ_i^2 is the implied variance of a given constituent (3M tenor in our case)

The academic literature on this topic is scarce but encouraging. The gist is that implied correlations - and correlation risk premia - reflect an *economic pricing of risk* that is directly tied to sentiment: investors require higher returns from assets that are more correlated at times of risk aversion, since these assets typically weaken in that environment.

The challenge is in disassociating this metric from others that already capture the same thing. In FX, for instance, some of the premia is already captured through interest rate differentials, as noted in Mueller et al [2013], and hence a correlation strategy is bound to be highly correlated to the carry trade. In equities, the closest "competitor" is variance risk premium, even though Valenzuela [2014] argues that implied correlations are a better measure.[70]

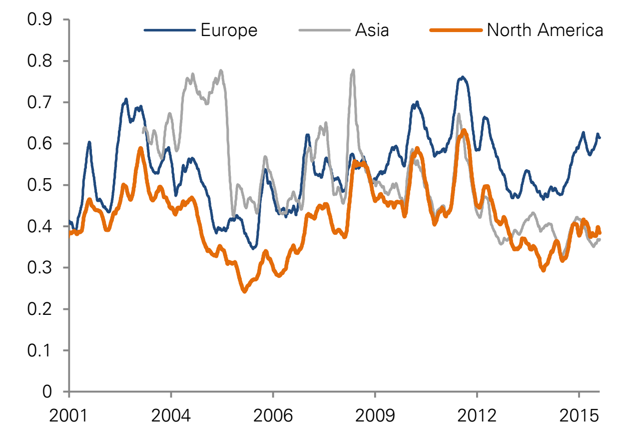
Figure 36: FX implied correlations by yield magnitude



Source: Deutsche Bank

Figures 36 and 37 illustrate this challenge. The 3-month USD/FX - EUR/FX implied correlations of high yield currencies are unanimously higher than those of low yield currencies[71]. The 17-year correlation between the FX Carry trade and a long-short strategy built using these implied correlation levels as signals, with no time series transformation, is in excess of +0.55[72]. In equities, the premium captured by implied correlation levels is marked by geography: European implied correlations are generally higher than those in North American indices[73]. Such time-invariant phenomenon also leads to unwanted exposures: the 15-year monthly correlations to Equity Carry and PC1 exceed +0.25, and the 5-year monthly correlation to the VIX is -0.3. Further, we saw no improvement in results from evaluating implied correlations as a spread to realised in either FX or equities[74].

Figure 37: Equity index implied correlations by region



Source: Deutsche Bank

Our implied correlation signal for each asset (17 USD/FX and 14 equity index futures[75]) is based on transforming the 3M implied correlation into a 1-year time series z-score, and further dividing it by the volatility of asset returns. While this is the same procedure used in our skew and slope signals, the correlation strategy differs in that we construct separate long-short portfolios in FX and in equities. It also differs from the skew strategy in that there was no need to orthogonalise the final signal against any exogenous factor. The factor correlations were already low.

[70] We agree with the author. The 10-year correlation of monthly changes between strategy returns using equity VRP and equity implied correlations is +0.04. The latter yields a robust Sharpe ratio while the former barely breaks even over the same historical window.

[71] Equally-weighted high yield currencies: MXN, TRY, ZAR, BRL, AUD, NZD. Equally-weighted low yield currencies: SGD, TWD, CHF, JPY.

[72] Correlation of 1-month changes, rolled daily. The FX Carry trade is proxied by DBHVBUSI (DB Balanced Harvest, a proxy for Global FX Carry). See Natividade et al [2005] for details.

[73] European indices: CAC, DAX, Eurostoxx, IBX (Spain), OMX, SMI and FTSE. North American indices: S&P 500, Nasdaq and TSE (Canada). Asian indices: ASX (Australia), Hang Seng, Kospi, Nikkei 225 and TWE (Taiwan).

[74] We used Pearson product-moment correlations in both FX and equities. In the former, we applied an exponentially decaying 1-year lookback window as in line with Brehon et al [2009], while in equities we used a 3-month equally-weighted lookback window. We found that the ranking of signals did not change much between implied correlations and correlation risk premium (CRP), and that the CRP signal was often noisier.

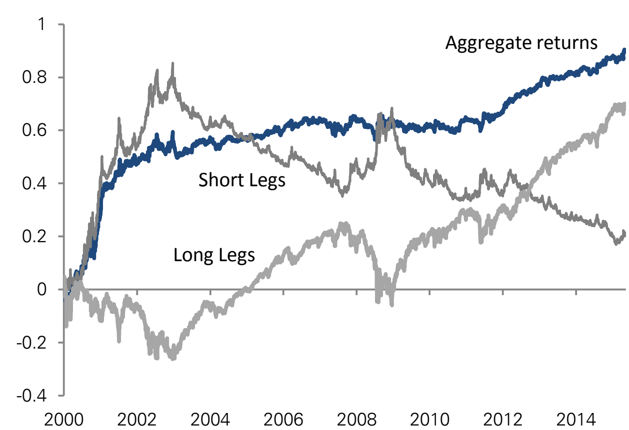
[75] In FX, we use our original pool of 18 currency pairs but exclude EUR/USD for obvious reasons (we cannot estimate USD/EUR vs EUR/EUR correlations). In equities, we take our original pool of 21 equity index futures and exclude, due to lack of data, the Mexican Bolsa, Brazilian Bovespa, Turkey's ISE, South Africa's JALSH, Russian RDX, Canada's TSE and Polish WIG.

The resulting strategy is simple. The more that correlations are expected to rise, the more that we should buy equity futures and the USD; the more they're expected to fall, the more that we should sell.

Figures 38 and 39 show the respective backtested returns of our correlation strategies in FX and equities. Our attention is mostly drawn to how the returns are distributed between longs and shorts, and how they relate to the prior theme of momentum in currencies and reversal in equities seen in the slope signal:

- As we argued in Natividade et al [2013b], the first principal component (PC1) is largely dominant in equities and increasingly dominant in FX, and thus it is no surprise that the returns in our long positions are negatively correlated to those of our shorts.

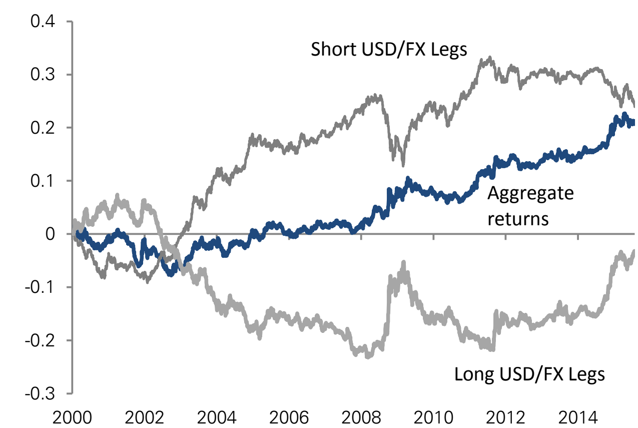
Figure 38: Equity index correlation strategy and contribution from longs and shorts (15-year backtested Sharpe ratio: 0.62 before costs)



Source: Deutsche Bank

- We find most returns come from being long equities and short USD/FX, which is commensurate with the rally in global equities and the USD sell-off over the backtest period. That said, the aggregate of longs and shorts produces returns that are more stable, and that are less influenced by directionality, than any of the individual legs, as well as relative to an unconstrained version of the strategy[76]. This is indicative that the strategy should also work when equities are falling and the dollar is rising – as has been the case recently.

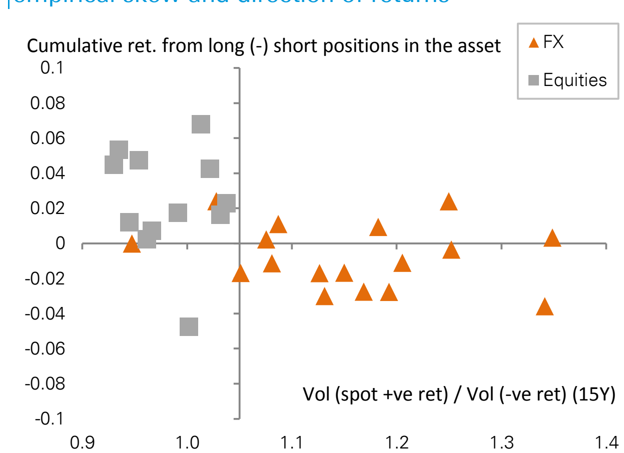
Figure 39: FX correlation strategy and contribution from longs and shorts (15-year backtested Sharpe ratio: 0.38 before costs)



Source: Deutsche Bank

- As was the case with our slope strategy, the equity correlation signal has a *reversal* nature because it emits buy signals when implied correlations are highest from both time series and peer index perspectives. Equities are negatively skewed, and therefore implied correlations tend to rise when the index is falling. This concurs with Valenzuela [2014], who published similar findings on the S&P 500.
- Also in line with the slope strategy, the FX correlation signal points towards *momentum*. The higher the implied correlation, the more likely the strategy will buy USD. USD returns are positively skewed against most other currencies, which implies that USD/FX is rallying when the strategy emits the buy signal.

Figure 40: Correlation strategy – relationship between empirical skew and direction of returns



Source: Deutsche Bank

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76 Unconstrained in the sense that we do not force half of the positions to be long and short the other half.

The implied correlation z-score-over-vol is therefore the third and final signal to qualify for our sentiment portfolio. The 15-year backtested Sharpe ratios (before cost) are not high (+0.38 in FX and +0.62 in equities) but they are sufficiently uncorrelated to the other signals and to exogenous factors[77] so as to deserve their place in our suite of sentiment strategies.

3.6 Our sentiment portfolio summarised

Our sentiment portfolio aggregates all 4 strategies, each capturing a specific aspect of the volatility surface. For a given asset, we are interested in how this aspect has evolved relative to its own history and to the history of the equivalent for other assets:

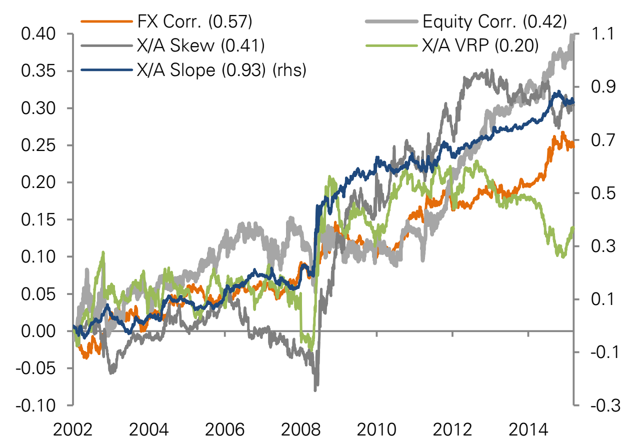
- Our skew signal captures the change in directional expectations. It is conceptionally linked to momentum in all asset classes, but uncorrelated in practice.
- The slope signal shows whether the market expects recent vol moves to be temporary, as it captures how quickly, and how strongly, short-term implied volatilities will revert to their long term average. It is conceptually linked to momentum in FX and reversals in equities; in practice, though, it is uncorrelated with both.
- The 2 correlation signals capture the change in market expectations of future correlation. As with the slope signal, they are linked in theory (but not in practice) to momentum in FX and reversals in equities.

All of these signals ultimately seek to capture the change in market risk appetite at the asset-specific level, as well as at the aggregate asset class level*.* The signals may be conceptually linked to vol risk premium but in practice they are not. Not only the correlations are low[78], but the economic value of these signals has been higher over time. They also complement one another given the low correlations.[79] By grouping them into one final portfolio, we try to harness all forward-looking information from the options market in the most efficient way possible.

Two important characteristics of our sentiment strategies are that (1) signal magnitude matters when it comes to allocating positions, and (2) that all assets with enough data are treated equally. This places our sentiment portfolio in equal footing with our cross-sectional Carry and Value portfolios introduced in previous *Quantcraft* reports, and makes it distinctly different from our trend following portfolio - where we harness value through signal independence and not signal intensity (see Natividade et al [2013b]).

Figure 41 shows the backtested returns of the qualifying strategies, in addition to the (non-qualifying) VRP strategy. We assume no cost and daily rebalancing; Section 5 addresses these and other operational considerations, such as how we group the signals together.

Figure 41: Backtested returns – sentiment strategies (long-term Sharpe ratios in parenthesis)



Source: Deutsche Bank

4. Building an interest rate strategy for foreign exchange

Our final strategy is unique to foreign exchange. It has cross-market, cross-factor characteristics in that it uses the momentum in interest rates to predict FX returns.

There's nothing new in stating that interest rates affect FX; they are the most widely agreed determinant of currency movements. That said, we tend to focus exclusively on interest rate levels – and FX carry trades – while ignoring additional information from the yield curve. If interest rates are such an important determinant of FX, then other yield curve dynamics – recent momentum, central bank expectations and term premium – may be relevant as well.

[77] The 15-year correlations of 1M returns involving our equity correlation strategy are: +0.12 (vs VIX), -0.2 (vs the equities PC1), +0.03 (vs trend following), -0.04 (vs cross-sectional momentum) and -0.04 (vs equity carry). The 14-year correlations of 1M returns involving our FX correlation strategy are: +0.13 (vs currency VIX), +0.09 (vs the FX PC1), +0.14 (vs trend following), +0.05 (vs cross-sectional momentum) and -0.11 (vs FX carry).

[78] The 13-year correlations of monthly returns versus our cross-asset VRP strategy are: -0.02 (FX Corr), +0.14 (Equity Corr), +0.24 (cross-asset Slope) and +0.21 (cross-asset Skew).

[79] The 15-year correlation of monthly returns between them is, on average, +0.08.

The academic coverage on this topic is abundant, but again, most focus on rate levels[80] alone. That said, three papers have caught our attention in that they explicitly evaluate the influence of yield curve determinants on FX: Chen et al [2009], Ang et al [2010] and Georges [2014]. Each study has complementary features: the first analyses yield curve levels, slope and curvature; the second adds changes in the parameters, and the third formulates a trading rule. They all have one argument in common: there's more information in the yield curve than what we currently use, and this extra information also generates meaningful economic returns.

As we looked closer into the yield curve, our initial tests[81] produced the following conclusions:

- Interest rate levels have the strongest effect on FX, as suspected, but this is already covered in our work on carry strategies – see Anand et al [2014].
- Rate changes also carry important information. It directly addresses perceived shifts in monetary policy and inflation target. This "rates momentum" factor was the most promising. In line with the findings from Ang et al [2010] and Georges [2014], buying and selling FX based on 1M rising and falling interest rates posted a 20-year backtested Sharpe ratio of +0.55 (before cost), with negligible correlation to Carry (+0.04) and Momentum (+0.05) using a 24-year history of monthly returns.
- The yield curve slope is less encouraging. In agreement with Ang et al [2010], we found that a currency portfolio based on this parameter exhibits a reasonable Sharpe ratio (+0.45), but is highly correlated with the FX carry strategy (+0.73). In other words, this signal does not seem independent enough.
- The term structure curvature also failed to emit meaningful information on future FX returns; a preliminary strategy using this as a signal posted an 18-year Sharpe ratio of -0.13. This is in agreement with Chen et al [2009].

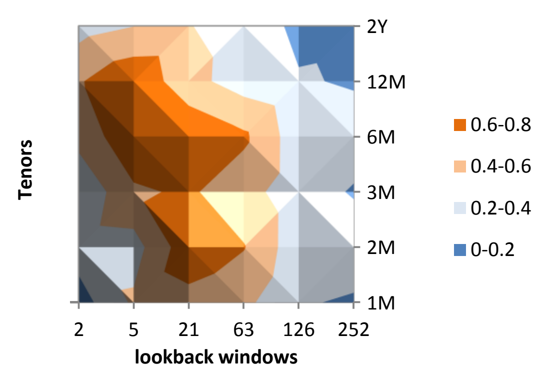
4.1 Fine tuning our rates-FX signal

These preliminary results allowed us to narrow our focus down to one variable: rates changes – or, in other words, the effect of rates momentum on FX returns. But while the search space is narrower, many parameters are yet to be specified. For instance, which tenor should we focus on? Which lookback window to estimate changes from? Should we use other methods to estimate rates momentum or is changes already enough? Do we need to adjust the signal for asset volatility or rates volatility? Should we apply a filter on the signal?

We start by addressing the first 2 questions. Our approach was purely empirical: we ran a trading strategy in USD/G10 through all pairwise combinations of tenor and lookback window and evaluated the in-sample Sharpe ratios. In all instances, the interest rate is the yield implied from the FX forward of a given tenor and the trading strategy bought currencies whose interest rates were rising, and sold those whose rates were (comparatively) falling. In summary:

- The 6M tenor produced the best results. Shorter tenors are "noisier", and more sensitive to technical money market dynamics. Longer tenors are also attractive, though less reactive. But as all money market tenors are generally correlated to each other, we felt that parameter fitting risks were low and therefore stuck to a single tenor – 6M implied yields.

Figure 42: Sharpe ratio heatmap



20-year in-sample backtest, no costs. Source: Deutsche Bank

- The 1M lookback window performed best, but our returns were highly sensitive to changes in this parameter. The lack of stability requires caution, and hence we chose a combination of lookbacks (1M, 2M, and 3M) instead of just one, thereby avoiding potential over-fitting risks.[82]

We next tried adding complexity to how we estimate rates momentum. We applied 2 other methods: a time

[80] Some selected papers include Eichenbaum et al [1995], who state that interest rate jumps lead to currency appreciation in G7, Calvo et al [2002], who find the relationship between the 2 variables to be weak in EM, and Drazen et al [2006], who focus on crisis periods (ERM 1992) and show that rate rises lead to short-term appreciation and long-term depreciation.

[81] All our preliminary tests are based on USD/G10. We looked at the following signals: (a) rates momentum - monthly changes on 6M implied yields, (b) yield curve slope – the spread between 2Y and 10Y rates, and (c) curvature – the difference between the 5Y rate and the average of 2Y and 10Y rates. To construct the portfolio, we ranked currencies based on the signal and bought the top 4 and sold the bottom 4 currencies from the pool, with non-linearly decreasing weights (same as our Sentiment portfolio).

[82] We refrained from adding very short term windows – such as intra-week - as the results were unstable due to noise in the signal, and didn't include lookback windows beyond 1 year because those signals were not adaptive enough.

trend (rates changes regressed against time units) and the Mann-Kendall test.[83] The former uses the sensitivity of 6M rates to the time units in the preceding 6 months while the latter is based on how sequentially strong the moves were over that period. Neither approach improved our results meaningfully; as such, we continued using the original format for rates momentum.[84]

Next, we adjusted for volatility. But contrary to elsewhere, we adjusted for the *volatility of interest rates* and not for the vol of asset returns. The latter can be polluted by central bank smoothing – particularly in EM – thereby distorting our estimate of currency risk and signal intensity. The former, in turn, is a more natural candidate.[85]

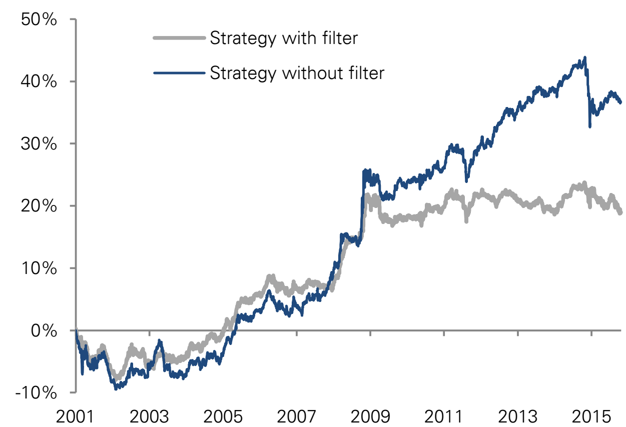
4.2 Signal filtering

Filtering was the next aspect of our strategy. It was motivated by the fact that rates momentum and FX returns do not relate uniformly across all markets. The sign of the relationship depends heavily on *country risk premium*. The higher is the country risk premium, the more that rising rates hurts the currency. As outlined in Kearns et al [2005], higher rates typically have 3 effects: (a) a rise in the government fiscal burden, (b) a drop in economic output due to the higher cost of working capital, and (c) foreign capital is channeled into domestic currency assets. The net effect from these 3 forces generates the final currency move. In cases where (a) and (b) are less of a concern – countries with lower risk premia – the third effect dominates and the currency strengthens. But when country risk premium is high, the first 2 forces take priority and lead to immediate currency depreciation, even though – in theory – these effects should not be felt as fast.

The need for filtering became clear as we added emerging currencies to the mix. We expected that adding USD/EM would help the strategy, as is usually the case since emerging currencies carry more "premium" – be it momentum, carry or sentiment premium. But contrary to our prior, the results degraded slightly, thereby reflecting the adverse effect that country risk premia has on our signal.

That said, we also believe the filter should be simple and intuitive; it just needs to identify adverse signal conditions. If a rise in rates leads to currency depreciation, the signal is not capturing what we want, and hence it should be removed. Therefore, if the 1-year correlation of (past) daily interest rate moves and (future) daily FX returns is negative, we remove exposure to the currency pair and redistribute its original weight to other assets.[86] Figure 43 shows our results after applying this filter. The clear outperformance since 2005 suggests that not only the filter has captured country risk premia, but also that *it has prepared the strategy for distortions in how rates related to FX after the onset of global quantitative easing.*

Figure 43: Strategy returns (without cost) – with and without the filter



Source: Deutsche Bank

Finally, the success of our simple filter encouraged us to try other, more complex filtering techniques. But as Figure 44 shows, those failed to achieve stronger results.

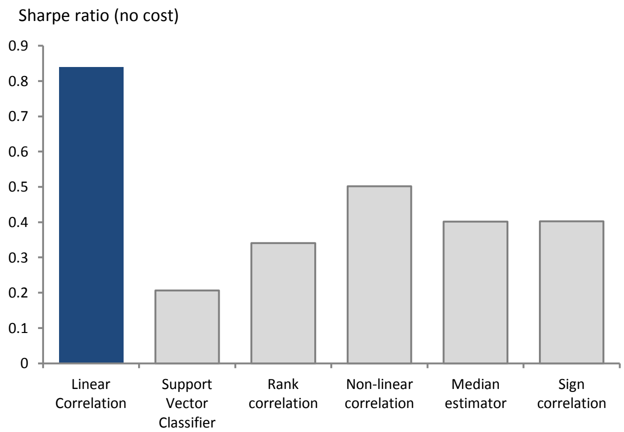
[83] See Natividade [2012b].

[84] Compared to the original format, the Sharpe ratios halved when using the MKT and time trend.

[85] Using the volatility of rates also makes sense in the framework of expectations. We are concerned with particularly strong unanticipated momentum in rates. As we checked the results using both vol estimates, and a third estimate that combines them, we found all to be highly correlated but the first (rates volatility) ultimately outperformed.

[86] After looking at other alternatives, we chose to correlate daily changes in FX carry against the next day's FX return. Longer periods for changes in carry (1W, 1M changes and beyond), and longer look-ahead periods for FX returns (1W, 1M and beyond) produced worse results. We believe this is due to a less adaptive estimation of country risk premium.

Figure 44: Backtested 20-year Sharpe ratio according to different filtering techniques



We used a Support Vector Classifier (SVC), Spearman rank correlation, and three robust correlation measures (nonlinear robust estimator, median estimator, and quadrant (sign) estimator). All filters are applied in the same way. As for the SVC, we used it to categorize the relationship between rates and FX in two states (+1 and -1). At each rebalancing date, the SVC is trained with 1 year of data of daily rate changes and next day's FX returns. The kernel used is the radial basis function with a default value of 1 for its parameters (box constraint and RBF sigma). Once the SVC is trained, the current state of the relationship between rates and FX is estimated by passing the values of the last rate change and FX return to the trained SVC. We use this value as a filter in our strategy, take no position in the currencies if the estimated value is less than 0, or keep the position otherwise. See Natividade [2013a] for a review of machine learning methods. We assumed no trading costs.
Source: Deutsche Bank

4.3 The final strategy

We use 3M FX forwards in 18 USD/FX: USD/G10 + BRL, KRW, MXN, PLN, RUB, SGD, TRY, TWD, and ZAR. The signal is estimated daily and so is our strategy rebalancing. For each currency pair, we estimate the signal in the following way:

1. Calculate the interest rate spread between the country and the US as per 6M FX forwards. Record the change over the past 21, 42 and 63 business days. Both spot and forward rates are snapped from Bloomberg at 17:00 NY time.
2. Calculate volatility of daily changes in 6M interest rate differentials, using the same lookback windows as in Step 1.
3. Calculate the ratio of changes (Step 1) over volatility (Step 2) for all 3 windows. The final signal is the average of these 3 ratios.

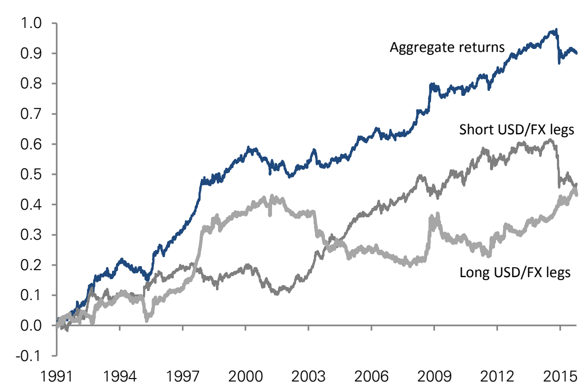
As for the strategy:

1. Rank all currency pairs on the basis of the signal, estimated earlier, in descending order.
2. Go long the top half and short the bottom half of the currency pool according to the rankings.
3. Weight all positions using the same procedure outlined in our sentiment strategies (non-linear decay).
4. Calculate the 1 year correlation between (past) 1-day interest rate spread moves and (future) 1-day FX returns for each currency. Assign a zero weight to the currency where the correlation is negative.
5. Re-distribute the weights such that the sum of longs equals the sum of shorts, the net capital exposure is 0 and the gross exposure is 1. Execute the trades 1 business day after the target positions are finalised.

Figure 45 plots the backtested cumulative returns of the strategy employing our slope signal described above, before costs, together with the attribution to long and short positions. As was the case in our other strategies, the short USD/FX positions contributed more than the USD/FX longs. The 24-year backtested Sharpe ratio of the strategy (before cost) is +0.84, and the returns are mostly uncorrelated to FX Carry and cross-sectional momentum.[87] The large drawdown in Q4 2014 was chiefly attributed to a long RUB exposure.[88]

Finally, Figure 46 shows the distribution of weights between USD/G10 and USD/EM. The weights rotate significantly between categories over time, highlighting the lack of structural exposures and – therefore – likely lack of correlation to FX Carry.

Figure 45: Rates-FX strategy and contribution from longs and shorts

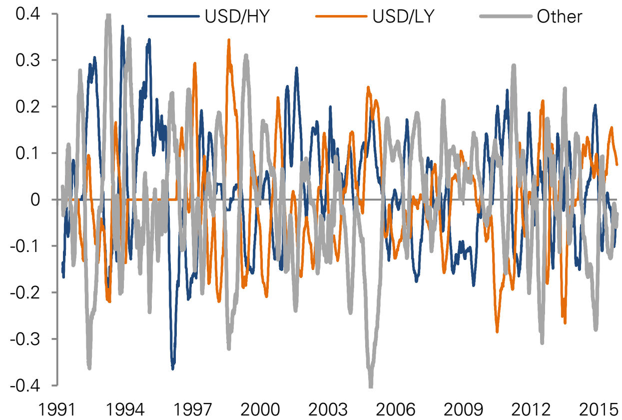


Source: Deutsche Bank

[87] The 25-year correlation of monthly returns between the rates-FX strategy and FX Carry is -0.06, and +0.06 versus FX cross-sectional momentum. Both FX Carry and Momentum were built using the same set of assets and weighting technique.

[88] The RUB was single-handedly responsible for a 0.06 drop in the 24-year Sharpe ratio of this strategy (from 0.90 to 0.84), solely due to the strategy being long in Q4 2014. As much as we were tempted to exclude it from our pool, we could not find a convincing reason to do so. One can argue that RUB NDF implied yields do not reflect CBR monetary policy, or that our filter needs to address Russian country risk premia differently. But then again, the same argument can be applied to Brazil (another high yielding NDF market) and, to some extent, Turkey. In fact, Russian NDFs have been among the most stable in EMFX after 2005 (see McCauley et al [2014]). RUB exposure should ultimately be controlled in portfolio construction, which we do in Section 5.

Figure 46: Allocation of weights between high yielders, low yielders and other USD/FX



6M moving averages. High yielders: AUD, NZD, BRL, ZAR, TRY. Low yielders: JPY, CHF, TWD. Others: remaining USD/G10 and USD/EM. Aggregate weights sum to 0. Source: Deutsche Bank

5. Signal aggregation and portfolio construction

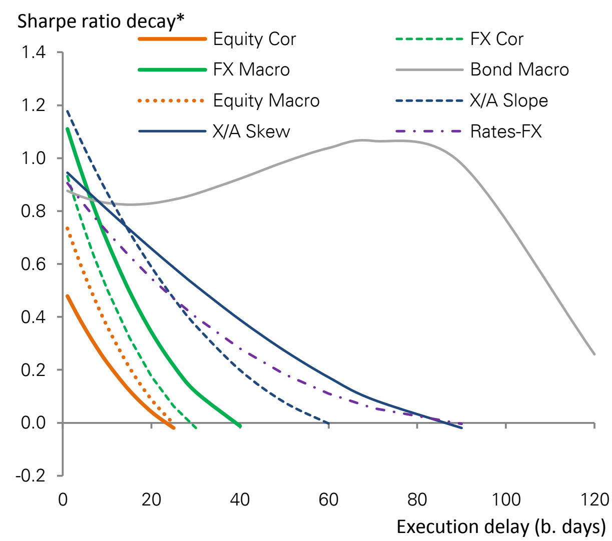
Having defined our underlying signals, it is now time to build 3 portfolios: sentiment, rates-FX and macro factors. In doing so, we must apply realistic assumptions and yet "respect" the characteristics of each signal. This involves 3 items: signal decay, signal aggregation, and portfolio turnover.

5.1 Signal decay

Signal decay evaluates for how long we can "trust" a signal. The faster it erodes, the faster the turnover required and the higher the expected cost. We measured decay speed by evaluating the effect on the Sharpe ratio of a delay in trading execution from 1 business day (our original assumption) to up to 6 months later[89]. As Figure 47 shows, the picture is mixed:

- Half of our signals are "fast". The FX and equity correlation signals, and the equity and FX macro signals, all lose half their value within 1-2 weeks and "die" within 1 month. This makes sense, as suggested by our prior research. These are either based on fast moving data or on analyst surprises. We were only surprised by the fast decay in our equity macro signal; it suggests markets are fast at incorporating innovations in relative growth.
- The slope and skew signals, and the rates-FX signal are slower. Half the value is still preserved after 1 month, but the signal "dies" shortly after 3 months.
- The bond macro signal is the slowest. The signal is well "alive" after 3 months, although it decays fast after that. This suggests markets are slower at incorporating new information on inflation than they are at incorporating growth innovations.

Figure 47: Signal decay profile



** Ratio of Sharpe ratio according to x-day execution delay divided by baseline scenario (1-day execution delay). Not that numbers often don't start at 1 as we are fitting a cubic polynomial to the data. Source: Deutsche Bank*

These results shed some light on how to go about aggregating our signals and deciding on the rate of turnover. Half of our signals are "fast", but the remaining are slow enough to give us enough diversity. This suggests that we do not need to be constrained by an explicit turnover target.

5.2 Signal aggregation

We aggregate our signals with 2 goals in mind: *independence* and *alpha maximization*. This approach was introduced in our cross-asset Value portfolio (see Natividade et al [2014]), and is now applied to both our Sentiment and Macro Factor portfolios. It works as follows:

1. We apply the maximum diversification (MD) algorithm to allocate weights between different strategies inside the same portfolio. The MD algorithm, introduced by Choueifaty et al [2008], allocates greater weight to strategies that are less correlated to other strategies. Its 2-step optimization process also addresses the volatility mismatch between individual strategies and asset classes.

[89] Our methodology is inspired by Grinold et al [1999]. The authors also highlight the equivalence between this method and that of using information coefficients for different forward horizons. We fit a 3rd order polynomial to the Sharpe ratio decay curve so as to smooth it.

2. For each asset, we take all applicable signals and group them together according to the strategy weights above. Simple grouping is possible because all individual signals have already been pre-processed into asset weights inside each strategy. This gives our preliminary aggregate asset weight.

3. We go from preliminary to final weight by applying an optimization function that maximizes signal intensity subject to turnover constraints – which we explain below – and liquidity constraints: portfolio exposure to each asset should not exceed 2% of the daily turnover in that market.[90] We opt for this alpha maximization approach to the final objective function[91] because our estimate of risk – the covariances - has already been accounted for in Step 1. Figure 48 shows our signal aggregation in more detail, as applied to the Sentiment portfolio. The same technique is applied to the Macro Factor portfolio, which groups the macro signals on FX, equity indices and bond futures together.

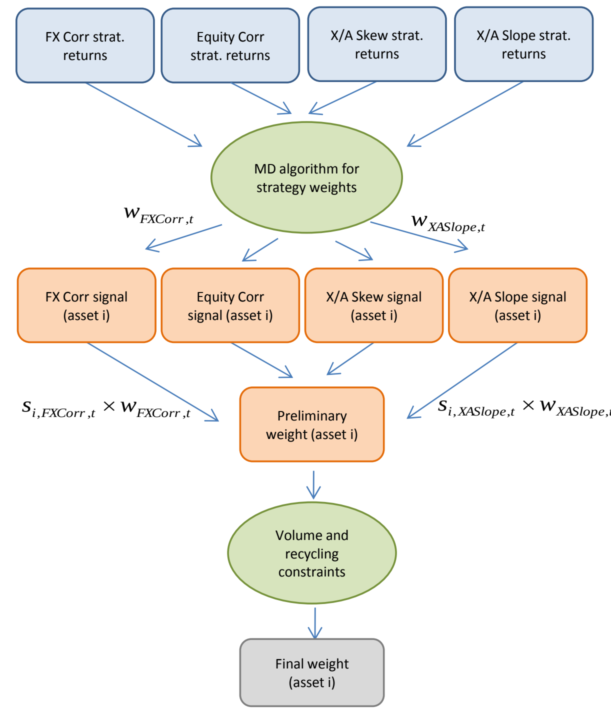
5.3 Portfolio turnover

Turnover constraints serve to strike a balance between portfolio adaptivity and cost control. They allow us to rebalance daily[92], thus adapting to ever evolving markets, while controlling for noise and costs through lower and upper recycling boundaries.

This is the "moment of truth" for our portfolios; we need to strike a balance between adaptivity, noise and transaction costs before we start paper trading.

Adaptivity encourages us to recycle the portfolio as often as possible, and by as much as possible. But trading costs preclude us from that. Noise control also argues against high turnover, as some of the changes in our signals simply reflect noisy data.

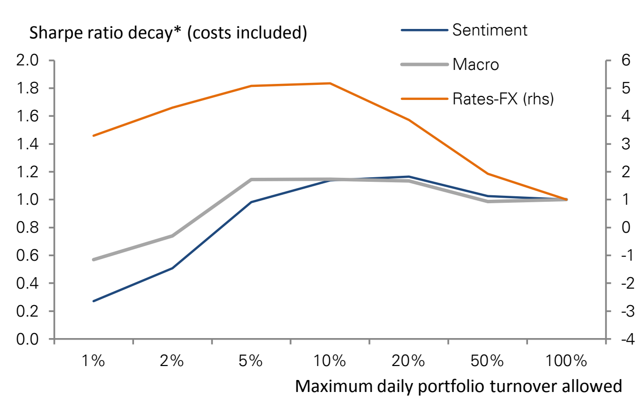
Figure 48: Signal aggregation at rebalancing date – sentiment portfolio



Source: Deutsche Bank

Figure 49 shows the sensitivity of our Sharpe ratios to changes in daily recycling boundaries. Transaction costs are now included and all trades are executed one business day after we know what to trade and by how much.

Figure 49: Sharpe ratios under different turnover constraints divided by Sharpe ratio with unconstrained turnover – costs always included



* Rates-FX: 24-year history. Macro Factor portfolio: 10-year history. Sentiment portfolio: 15-year history. Source: Deutsche Bank

The decay patterns show how the 3 forces are interacting. It provides us with the following conclusions:

[90] The upper and lower boundaries represent 1% of market daily volume. We highlight 2% above as we allow for the exposure to change from its upper boundary to the lower boundary in one day. The data on asset volumes is sourced from surveys and futures exchanges, and is updated annually since the 1990s; we assume zero volume prior to the first recorded figure.

[91] $\arg\min (x-s)'(x-s)$ where x is the final weights vector and s is the preliminary weights (signal) vector.

[92] Investors commonly claim that daily rebalancings are much costlier than, say, rebalancing once a month. We disagree. One can rebalance every day and yet strictly control the maximum turnover so that slippage is minimised. Rebalancing a maximum of 5% of the portfolio every day, for instance, should be more cost-efficient than rebalancing 100% of the portfolio once a month as it implies a much smaller market impact. It also makes the portfolio more adaptive to changing market conditions.

- *None of the portfolios should be allowed to recycle up to 100% every day.* Not only that costs too much, but we would end up trading a lot of noise as well. One can see that by noticing that none of the curves peak at 100%.
- *None of the portfolios should be too slow either*; that is not adaptive enough. All Sharpe ratio curves rise as we allow for more than 1% in daily turnover.
- Optimal daily turnover boundaries seem to be 20% for the Sentiment portfolio and 5% for Macro Factor and Rates-FX.

5.4 The results

Figure 50 shows our final Sharpe ratios, without leverage, having accounted for all construction aspects. It also shows the sensitivity of our risk-adjusted returns to transaction costs and asset-specific constraints. One can see that costs hurt the Sentiment portfolio significantly, as it turns over the most (up to 20% every day). Asset liquidity constraints hurt our Macro Factor portfolio the most, as it restricts our exposure to profitable but smaller markets. That said, liquidity constraints actually help the rates-FX strategy - it made it less exposed to the RUB last year.

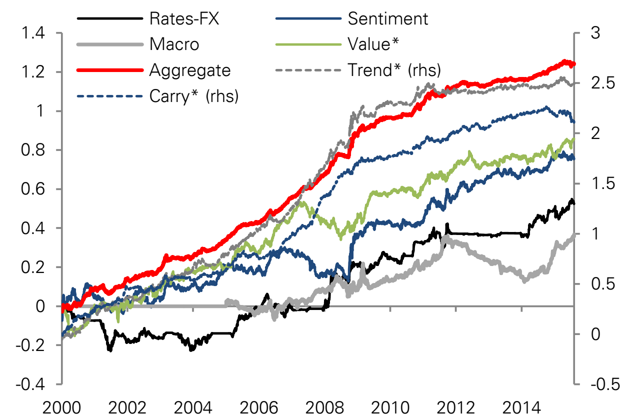
Figure 50: Sharpe ratio sensitivity (strategies without leverage)

	Sharpe ratios		
Cost?	True	True	False
Volume constraints?	True	False	True
Macro Factor	0.47	0.74	0.58
Sentiment	0.59	0.56	0.87
Rates-FX	0.44	0.36	0.52

Macro Factor: 10Y backtested Sharpe ratios. Sentiment: 15Y Sharpe ratio. Rates-FX: 25Y Sharpe ratios. Source: Deutsche Bank

Finally, we aggregate the Macro Factor and Sentiment portfolios, and the Rates-FX strategy, with our pre-existing low frequency factor strategies: Trend (published in 2013 and paper trading since 2014 as MArTA), Carry (published in 2014 and paper trading this year as Carrie) and Value (published in 2014 and paper trading this year as Valentina). They are aggregated using equal capital weights, given the comparable volatility profile. The results in Figures 51, 52, 53 and 54 all apply leverage, as we target 10% volatility.

Figure 51: Backtested cumulative returns (costs included, 10% vol target)



** Trend includes paper trading since 2014. Value and Carry include paper trading since April 2015. Source: Deutsche Bank*

Figure 52: Backtested performance profile (costs and leverage included)

	Rates-FX	Sentiment	Macro	Value	Trend	Carry	Aggregate
Ann.Ret. (%)	3.3	4.7	3.3	5.3	15.5	13.0	7.7
Ann.Vol. (%)	6.7	8.1	6.4	7.9	9.9	8.1	3.9
Sharpe Ratio*	0.48	0.58	0.52	0.67	1.56	1.61	1.98
Sortino Ratio	0.65	0.83	0.75	0.93	2.14	2.23	2.68
Max Drawdown (DD) (%)	-22.9	-17.3	-23.8	-19.4	-12.7	-17.6	-4.7
Max DD Length (yrs)	6.3	2.1	4.0	2.0	0.1	0.9	0.6
Avg Top 5 DDs (%)	-12.0	-11.1	-12.5	-12.2	-11.2	-9.0	-3.6
Length Top 5 DDs (yrs)	2.4	1.0	1.8	1.3	1.0	0.7	0.4
DD / Ann. Ret.	3.7	2.4	3.8	2.3	0.7	0.7	0.5
Transfer Coefficient	0.91	0.98	0.83	0.82	0.88	0.85	

** The Sharpe ratios are different from those of Figure 50 because these apply leverage. Source: Deutsche Bank*

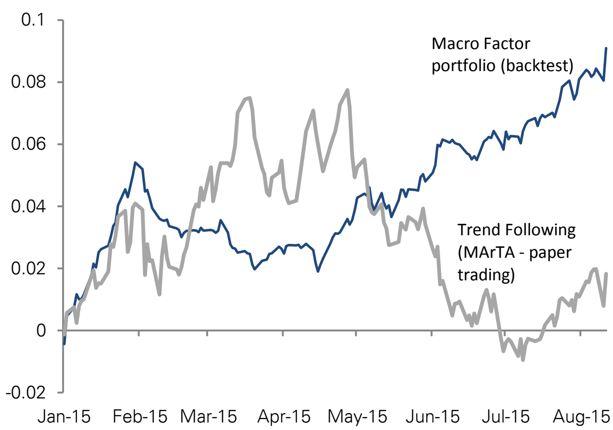
As we compare portfolio dependencies, we notice that none of the 15-year monthly correlations exceeds 0.3 in absolute terms. That said, both Sentiment and Macro portfolios have been partly correlated to Trend Following. The Macro portfolio has also been negatively correlated to Value. Correlations have been generally stronger over the past year, though not in all instances; the Macro portfolio has decoupled from Trend Following this year.

Figure 53: 15-year correlations of monthly returns (lower triangle) and 1-year correlations of weekly returns (upper triangle)

	Rates-FX	Sentiment	Macro	Value	Trend	Carry
Rates-FX		-0.10	-0.18	-0.07	-0.14	-0.02
Sentiment	0.15		0.15	0.02	0.32	-0.10
Macro	0.07	0.06		-0.28	0.10	-0.23
Value	-0.01	-0.10	-0.29		0.06	0.24
Trend	0.13	0.28	0.24	-0.24		0.33
Carry	-0.05	0.01	0.01	-0.09	0.21	

Source: Deutsche Bank

Figure 54: Macro Factor vs Trend Following portfolios year-to-date



Source: Deutsche Bank

6. Conclusions

Delving into new factors is challenging, but rewarding. Our study concludes the following:

- *The more exotic we go, the more we need to bring in new techniques*. Transforms, timing, filtering and orthogonalisation are all a part of that.
- *There is no guarantee of success*. Our graveyards include the Volatility Risk Premium and Macro Factor investing in commodities. Even after applying our techniques, the Macro Factor portfolio is still moderately correlated to Trend Following.
- *Do not expect high risk-adjusted returns.* Once we grouped signals into new portfolios, and accounted for implementation issues, none of our long-term Sharpe ratios exceeded +0.6.
- *Diversification is key.* As long as we can continue bringing unique signals into our suite of cross-asset systematic strategies, our aggregate performance should improve.

References

Adams, Z., Fuss, R. and Kaiser, D. [2008], "Macroeconomic Determinants of Commodity Futures Returns", The Handbook of Commodity Investing, The Frank J. Fabozzi Series, John Wiley & Sons, 1st edition.

Ait-Sahalia, Y., Mykland, P.A. and Zhang, L. [2005], "How often to sample a continuous-time process in the presence of market microstructure noise", Review of Financial Studies 18, 351-416.

Anand, V., Natividade, C., Mesomeris, S., Davies, C., Jian, S., and Capra, J. [2014], "Riding Carry", Deutsche Bank Quantcraft, 03 September 2014.

Anand, V., Natividade, C., Thakkar, K., Feddeler, P., Kocic, A. and Mesomeris, S. [2015], "Nothing has changed from the way it wasn't", Deutsche Bank Volcano, 24 September 2015.

Andreou, E., Ghysels, E. and Kourtellos, A. [2012], "Should macroeconomic forecasters use daily financial data and how?", Working Paper, available at SSRN.

Ang, A. and Piazzesi, M. [2003], "A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variable", Journal of Monetary Economics 50 (2003) 745–787.

Ang, A., Chen. S. J. [2010], "Yield curve predictors of foreign exchange returns", Working Paper, Columbia University.

Ang, A. and Ulrich, M. [2012], "Nominal Bonds, Real Bonds, and Equity", Working Paper, available at SSRN.

Ang, A. [2014], Asset Management: A Systematic Approach to Factor Investing, Oxford University Press, 1st Edition.

Arouba, S., Diebold, F. and Scotti, C. [2008], "Real-Time Measurement of Business Conditions", Working Paper, available at SSRN.

Banbura, M., Giannone, D. and Reichlin, L. [2010], "Nowcasting", ECARES working paper 2010-021.

Beber, A., Brandt, M. and Luisi, M. [2014], "Realized and Anticipated Macroeconomic Conditions Forecast Stock Returns", Working Paper, available at SSRN.

Benzoni, L., Collin-Dufresne, P. and Goldstein, R. [2010], "Explaining asset pricing puzzles associated with the 1987 marketk crash", Working Paper, available at SSRN.

Black, F. [1980], "Studies of stock price volatility changes", Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economical Statistics Section, American Statistical Association, p.117-181.

Bollerslev, T., Marrone, J., Xu, L. and Zhou, H. [2012], "Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence", Working Paper, available at SSRN.

Brehon, D. and Natividade, C. [2009], "Correlation Swap Shop", Deutsche Bank FX Derivatives Focus, 14 July 2009.

Brehon, D. [2011], "Using Analyst Skill to Forecast Data Releases", Deutsche Bank Quantcraft, 22 November 2011.

Bridgewater [date not specified], "The All Weather Story", available at http://www.bwater.com/Uploads/FileManager/research/All-Weather/All-Weather-Story.pdf

Broadie, M., Chernov, M. and Johannes, M. [2009], "Understanding index option returns", Review of Financial Studies 22(11), 4493-4529.

Bulut, L. [2015], "Google Trends and Forecasting Performance of Exchange Rate Models", Ipek University Department of Economics - Working Paper Series, No: 15-05 August 2015.

Cahan, R., Luo, Y., Alvarez, M., Jussa, J. and Weiner, S. [2010], "The Options Issue", Deutsche Bank Quantitative Research, 12 May 2010.

Calvo, G. and Reinhart, C. [2002], "Fear of Floating," Quarterly Journal of Economics 117, 379-408.

Carr, P. and Wu, L. [2009], "Variance Risk Premia", Review of Financial Studies 22, 1311-1341.

Chen, N.-F., Roll, R., and Ross, S. [1986], "Economic Forces and the stock market", Journal of Business, 59, 383-403.

Chen, Y. C., and Tsang, K. P. [2009], "What does the yield curve tell us about exchange rate predictability?", Working Paper, University of Washington.

Choueifaty, Y., and Coignard, Y. [2008], "Toward Maximum Diversification", The Journal of Portfolio Management, Fall 2008, Vol. 35, No. 1: pp. 40-51.

Croushore, D. and Start, T. [1999], "A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter?", Federal Reserve Bank of Philadelphia Working Paper No. 99-21, December 1999.

De Longis, A. and Tufekci, E. [2014], "Economic Data Surprises and Currency Alpha", *The Role of Currency in Institutional Portfolios*, Risk Books, 1st Edition.

Della Corte, P., Ramadorai, T. and Sarno, L. [2014], "Volatility Risk Premia and Exchange Rate Predictability", Working Paper, available at SSRN.

Doran, J., Peterson, D., and Tarrant, B. [2006], "Is there Information in the Volatility Skew?", Working Paper, available at SSRN.

Drazen, A. and Hubrich, S. [2006], "A Simple Test of the Effect of Interest Rate Defense", NBER Working Paper W12616.

Edwards, K. and Plumb, M. [2009], "US Economic Data and the Australian Dollar", Reserve Bank of Australia Bulletin, July, pp 9–16.

Eichenbaum, M. and C. Evans [1995], "Some Empirical Evidence on the Effects of Shocks to Monetary Policy on Exchange Rates," Quarterly Journal of Economics 110 (4), 975-1009.

Erb, C. and Harvey, C. [2006], "The Tactical and Strategic Value of Commodity Futures", Financial Analysts Journal, vol. 62, no. 2 pp. 69-97.

Georges, N. [2014], "ANANTA: A systematic quantitative FX trading strategy", Working Paper, available at SSRN.

Giannone, D., Reichlin, L. and Small, D. [2007], "Nowcasting: The Real-Time Informational Content of Macroeconomic Data", Working Paper, available at SSRN.

Grinold, R. and Kahn, R. [1999], *Active Portfolio Management*, McGraw Hill, 2nd edition.

Han, B. and Zhou, Y. [2011], "Variance Risk Premium and Cross-Section of Stock Returns", Working Paper.

Hayashi, T. and Yoshida, N. [2005], "On covariance estimation of non-synchronously observed diffusion processes", Bernoulli 11(2), 2005, p.359-379.

Ilmanen, A. [2011], Expected Returns: An Investor's Guide to Harvesting Market Rewards, John Wiley & Sons, 1st Edition.

Kassam, A., Mesomeris, S. and Salvini, M. [2010], "Factor Neutralization and Beyond", Deutsche Bank Portfolios Under Construction, 21 September 2010.

Kat H. and Oomen R., [2007], "What Every Investor Should Know about Commodities, Part I: Univariate Return Analysis", Journal of Investment Management, vol. 5, no. 3, s.1-25.

Kearns, J., Manners, P. [2005], "The impact of monetary policy on the exchange rate: A study using intraday data", Research Discussion Paper, Economic Research Department, Reserve Bank of Australia 2005-02.

Kurbanov, A. [2010], "Predictability of currency returns: The evidence from over-the-counter options market.", Master's Thesis, Copenhagen Business School, October 2010.

Jones, C. and Wang, T. [2012], "The term structure of equity option implied volatility", Working Paper, available at SSRN.

Londono, J. [2014], "The Variance Risk Premium around the World", Working Paper, available at SSRN.

Londono, J. and Zhou, H. [2012], "Variance Risk Premiums and the Forward Premium Puzzle", Board of Governors of the Federal Reserve System: International Finance Discussion Paper, Number 1068 December 2012.

Luo, Y., Cahan, R., Jussa, J. and Alvarez, M. [2010], "Volatility = 1/N", Deutsche Bank Portfolios Under Construction, 16 June 2010.

Luo, Y., Cahan, R., Alvarez, M., Jussa, J., and Chen, Z. [2011]. "Quant Tactical Asset Allocation (QTAA)", Deutsche Bank Quantitative Research, September 19, 2011

Luo, Y., Wang, S., Alvarez, M., Cahan, R., Jussa, J., and Chen, Z. [2012a]. "New Insights in Country Rotation", Deutsche Bank Quantitative Research, February 9, 2012.

Luo, Y., Cahan, R., Alvarez, M., Jussa, J., Chen, Z., and Wang, S., [2012b]. "From Macro to Micro", Deutsche Bank Quantitative Research, May 2, 2012.

Luo, Y., Wang, S., Alvarez, M., Jussa, J., Wang, A. and Rohal, G. [2014], "Macro Uncertainty, Investor Sentiment, and Asset Returns", Deutsche Bank Quantitative Research, 15 September 2014.

McCauley, R., Shu, C. and Ma, G. [2014], "Non-Deliverable Forwards: 2013 and Beyond", BIS Quarterly Review March 2014.

Mesomeris, S., Wang, Y., and Avettand-Fenoel, J. [2012], "Thematic Report – A New Asset Allocation Paradigm", Deutsche Bank Quantitative Strategy, 5 July 2012.

Mougeot, N. [2007], "Hidden Assets Investing Series: Trading Dispersion", Deutsche Bank Equity Derivatives Technical Report, 14 May 2007.

Mueller, P., Vedolin, A., and Yen, Y. [2011], "Bond Variance Risk Premia", Working Paper, available at SSRN.

Mueller, P., Stathopoulos, A. and Vedolin, A. [2013], "International Correlation Risk", Financial Markets Group Discussion Paper 716, January 2013.

Natividade, C., Nystedt, J. and Hafeez, B. [2005], "FX Forward-Rate Bias Goes Global", Deutsche Bank Global Markets Research, 27 September 2005.

Natividade, C. [2007a], "Exploring The World Of Long Dated JPY Volatility", Deutsche Bank FX Derivatives Focus, 20 September 2007.

Natividade, C. [2007b], "Profiting From The Bias in Forward Volatility", Deutsche Bank FX Derivatives Focus, 7 December 2007.

Natividade, C. [2008], "Global FX Gamma Report Review", Deutsche Bank Global Markets Research, 28 October 2008.

Natividade, C. [2010], "Long-dated volatility: issues and opportunities", Deutsche Bank FX Derivatives Focus, 19 August 2010.

Natividade, C. and Chen, K. [2012], “Switching Styles”, Deutsche Bank Quantcraft, March 2012.

Natividade, C. [2012b], “Catching Trends”, Deutsche Bank Quantcraft, 25 October 2012.

Natividade, C. [2013a], “Machine (un)learning?”, Deutsche Bank Quantcraft, 6 March 2013.

Natividade, C., Mesomeris, S., Alvarez, M., Beceren, M. and Davis, C [2013b], “Colours of Trend”, Deutsche Bank Quantcraft, 17 September 2013.

Natividade, C., Mesomeris, S., Davies, C., Jiang, C., Capra, J., Anand, V. and Qu, S. [2014], "Value Investing: Tricky But Worthy", Deutsche Bank Quantcraft, 3 December 2014.

Rosenberg, M. [2002], "The Deutsche Bank Guide to Exchange-Rate Determination: A Survey of Exchange-Rate Forecasting Models and Strategies", Deutsche Bank Global Markets Research, May 2002.

Sporre, G., Mann, P., Mulholland, A., and De Monchy, R. [2015a], “PGM Market Outlook”, Deutsche Bank Markets Research, 3 July 2015.

Sporre, G., Clifford, R., Kan, J. and Ding, S. [2015b], “Copper Market Update”, Deutsche Bank Markets Research, 24 August 2015.

Stringa, M. and Weng, N. [2015], "SIREN: A new tool for tracking euro-area macro news", Deutsche Bank Economics Research, 17 April 2015.

Trahan, F., Krantz K. [2011], The Era of Uncertainty: Global Investment Strategies for Inflation, Deflation and the Middle Ground, John Wiley & Sons, Inc., 1st Edition.

Vahamaa, S. [2004], "Option-Implied Asymmetries in Bond Market Expectations Around Monetary Policy Actions of the ECB", European Central Bank Working Paper Series, No. 315 - March 2004.

Valenzuela, M. [2014], "Implied Correlation and Expected Returns", Working Paper, available at SSRN.

Vasquez, A. [2014], "Equity Volatility Term Structures and the Cross-Section of Option Returns", Working Paper, available at SSRN.

Xing, Y., Zhang, X. and Zhao, R. [2010], "What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns?", Journal of Financial and Quantitative Analysis, Vol. 45, Issue 03, June 2010.

Zaremba, A. [2013], “Implications of financialization for commodity investors: the case of roll yields”, Working Paper.

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