FX-Trading: Challenging Intelligence

Marc Wildi
marc.wildi@zhaw.ch

Institute of data analysis and process design
Zurich University of Applied Sciences

September 6, 2018
AI in Finance 2018, ZHAW Winterthur

Introduction

- In the abstract to this presentation: "...We here sweep through this methodological range by proposing a series of novel and less novel, linear and non-linear, intelligent and less so approaches, either in isolation or in combination..."
- Instead of sweeping through a multitude of decorrelated pieces let me emphasize just **one** most **simple** performance **booster** in some more detail.

Are FX-Markets Efficient?

- DB (2018): "With trillions in currencies exchanging hands every day, **foreign exchange** is indisputably the world's largest and most liquid financial market. Yet in spite of its size, this report argues that it is also likely to be the **least "efficient"** compared to other asset classes."
- "We review the latest data from a wide range of sources and conclude that only 45%-60% of FX market participants are likely to be profit-seeking. The presence of a **large portion of non-profit maximizing** participants explains why the **efficient market hypothesis fails** to hold in currencies and why FX moves can be both predictable and profitable. The rising share of **passive investors** as well as the increasing importance of **regulation** suggests that the FX market may be becoming **less**, rather than more efficient over time."

Momentum

- The authors of the above report rely on simple momentum, value and carry strategies
- In this presentation we also rely on a **deliberately simple** filter strategy
  - The filter is **not** supposed to be the star of this presentation
  - It is used for illustration purposes, mainly

A System Based on All Pairwise Combinations (APC)

- Trading systems are often based on a **home** currency (for example USD)
  - Foreign currencies are bought by selling ('short') the home currency
  - DB 2018: USD against G9
  - **Common risk** factor: home currency
- Instead, we here consider **all pairwise combinations** of n currencies, APCn:
  - $\frac{n(n-1)}{2}$ pairs
  - **Diversification**: smaller risk (see below)

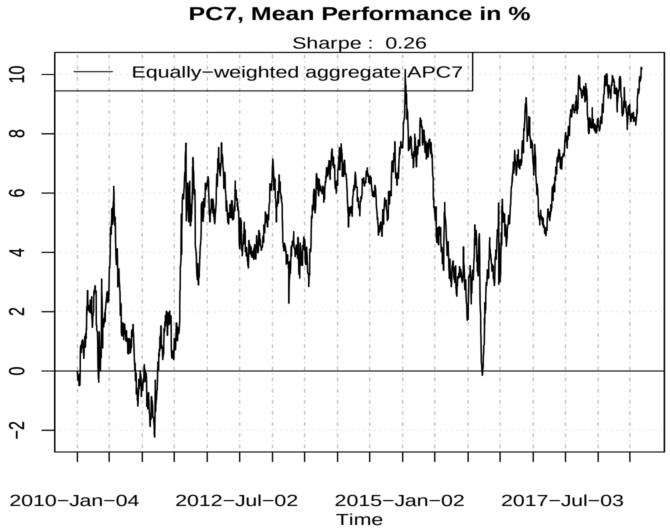
Simplifying Assumptions of APCn-Concept

- Assumptions:
  - All pairs are traded **simultaneously**
  - **Equally-weighted** portfolio: resources are split evenly across APCn

Empirical Design

- Daily log-returns from $2008-09-19$ to $2018-09-04$
- Consider most liquid (low costs) currencies **EUR,USD,GBP,JPY,CHF,CAD,AUD**: APC7
  - Mix of **majors**, **crosses** and **commodity** pairs
  - All pairwise combinations amount to **21 pairs**
- Long/short depending on **filter sign**
  - Plain vanilla weekly filter (which is not outstanding)
- We account for **trading costs**
  - Bid-ask spread

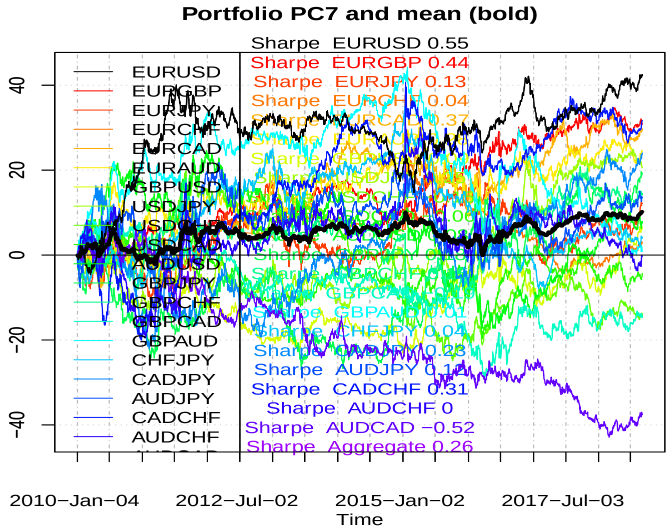
Cumulated Return APC7 in %: Weekly Filter



Equally-Weighted APC7

- The mean annual return is 1.14% (as my Bank's...) with an annualized Sharpe of 0.26
- Let's have a look at the individual performances in the next slide

Portfolio and individual FX-performances



Supremum

- The **maximal** mean annual return of **4.7**% is obtained by *EURUSD* with an annualized Sharpe of 0.55
  - **Supremum** is a **benchmark** for testing our ideas
- Let's have a look at the trading **signals** (for illustration we show all pairs having **EUR** as base currency)

Signals in Portfolio (All Pairs with EUR)

	2018-08-31	2018-09-03	2018-09-04
EURUSD	-1	-1	-1
EURGBP	-1	1	1
EURJPY	-1	-1	1
EURCHF	-1	-1	1
EURCAD	1	1	1
EURAUD	1	1	-1

Table: Trading signals of pairs with EUR

- On $2018-09-04$ (last column) we observe that the EUR is sold 2-times and bought 4-times: it receives a weight of $4-2=2$
- Similarly, we observe weights of 0 and -2 for the previous two days (columns on the left)
- Let's summarize these weights for all currencies in the next table

Weights of Currencies in APC7

	EUR	USD	GBP	JPY	CHF	CAD	AUD
2018-08-22	6	-4	4	-6	2	0	-2
2018-08-23	2	4	-2	-4	6	0	-6
2018-08-24	6	4	-6	-4	0	2	-2
2018-08-27	4	-6	-2	-4	0	2	6
2018-08-28	6	-6	-2	-4	4	2	0
2018-08-29	0	-2	6	-6	4	2	-4
2018-08-30	-4	2	6	0	4	-2	-6
2018-08-31	-2	4	0	6	2	-4	-6
2018-09-03	0	2	-6	6	4	-4	-2
2018-09-04	2	4	-4	0	-2	-6	6

Table: Weight of currencies in equally-weighted portfolio

- Let's summarize further the above findings in the next table

Activated Pairs of APC7

- At each time point we report the traded (activated) pairs only: the columns are arranged from left to right according to the (absolute) weight of the pairs reported above

	Weight 6	Weight 4	Weight 2
2018-08-28	EURUSD	CHFJPY	GBPCAD
2018-08-29	GBPJPY	AUDCHF	USDCAD
2018-08-30	GBPAUD	EURCHF	USDCAD
2018-08-31	AUDJPY	USDCAD	EURCHF
2018-09-03	GBPJPY	CADCHF	AUDUSD
2018-09-04	AUDCAD	GBPUSD	EURCHF

Table: Activated pairs of equally-weighted portfolio

Factors of APC7

- At each time point we report the daily returns obtained by applying the filter to the correspondingly (activated) pairs: the columns are arranged from left to right according to the (absolute) weight of the pairs reported above

	Factor 1	Factor 2	Factor 3
2018-08-28	0.003	0.005	0.004
2018-08-29	0.015	0.009	-0.000
2018-08-30	0.005	0.005	-0.005
2018-08-31	0.012	0.006	0.006
2018-09-03	0.006	0.004	-0.003
2018-09-04	0.002	0.002	-0.002

Table: Daily returns of filter-strategy for the activated pairs

- On $2018 - 09 - 04$ (last row) the daily returns $0.002, 0.002, -0.002$ correspond to the filter-strategy applied to $AUDCAD, GBPUSD, EURCHF$

Factors of APC7

- The series in the above table are called **factors**
- Factors are non-linear time-dependent constructs which are **dependent** on the trading strategy (filter or other)
- Two different factors **do not share** a common currency (orthogonality, diversification)
- The **first factor** F_{1t} (left column) is the most important one because
  - it receives the **largest weight** $w_1 = 6$ (which is relevant for portfolio-replication)
  - and other properties to be discussed below
- Straightforward extensions to arbitrary set of currencies and/or to arbitrary trading strategies (filters or others): **generic framework**

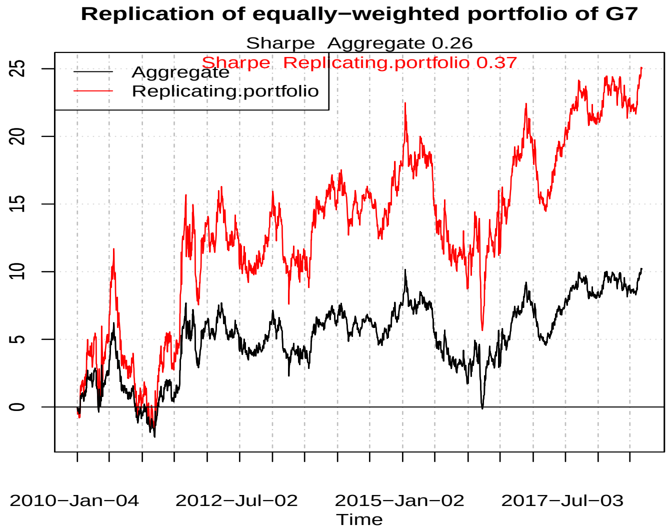
Minimal Replicating Portfolio

- In the absence of tradings costs, the **payout** (profit/loss) of the entire portfolio $APC7$ can be replicated by

$$RP_t(3) = 6F_{1t} + 4F_{2t} + 2F_{3t}$$

  where $RP(3)$ is a minimal **replicating portfolio** (minimal in terms of traded pairs and/or costs)
- Cumulated returns of $RP(3)$ and of APC7 are shown in the next figure

Cumulated Returns

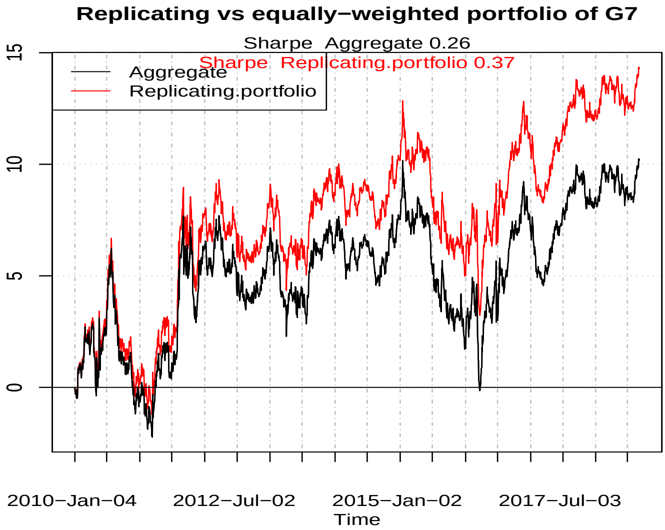


Leverage

- The **payouts** of both strategies are **identical** (in the absence of trading costs).
- But the **return** of $RP(3)$ is **leveraged**
  - APC7 splits the capital evenly into **21** parts
  - $RP(3)$ splits the capital unevenly into $6+4+2=\mathbf{12}$ parts
  - For the same payout, $RP(3)$ requires $12/21*100\%=\mathbf{57}\%$ of the capital (no waste of capital in cancelling trades)
  - $RP(3)$'s return is inherently **leveraged** by the factor $21/12=\mathbf{1.75}$
  - The Sharpe ratio is not affected by leveraging (but by lesser trading costs by $RP(3)$)
- For large n (number of currencies) the leverage term converges to 2

- In the next figure we artificially scale-down the return of $RP(3)$ by its inverse leverage 0.57
  - Any differences illustrate the effect of **trading costs** (less trades by $RP(3)$)
  - Which affect the Sharpe ratio

Replication: Aligned Returns



$RP(3)$: Added-Value

- The added-value of $RP(3)$ is **twofold**:
  - **Leverage** (1.75 in our example) : does not affect Sharpe
  - **Smaller costs**: improve return and Sharpe
- After these 'trivial bits' let us look more thoroughly at the above factors

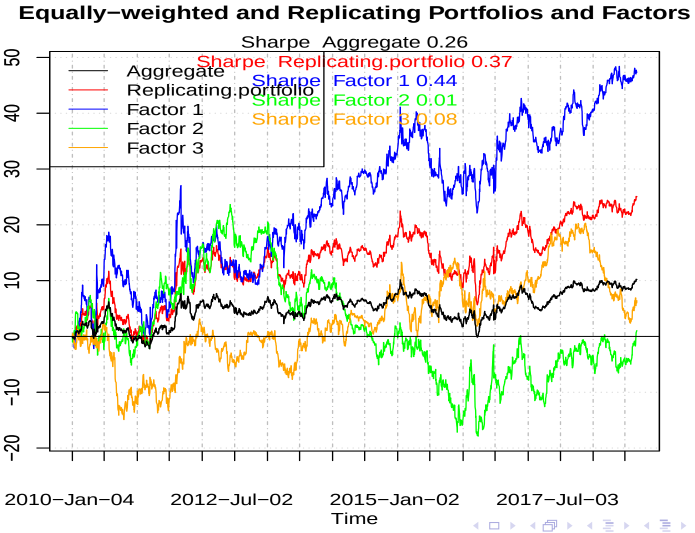
Correlations

- The first factor F_{1t} of $RP(3)$ receives the largest weight $w_1 = 6$ and therefore the **correlation** between $APC7_t$ and F_{1t} is generally 'large'
  - The correlation between the **cumulated** performances of F_{1t} and APC7 is **0.94**
  - The correlation between the **daily returns** is **0.89**
  - **Diversification?** Yes, see below...

Factor-Based Strategies

- Let F_{it}, $i = 1, 2, 3$ be considered as **separate** trading-strategies (rather than unequally aggregated in RP3)
- Intuition:
  - F_{1t} should track $APC7_t$ more or less closely in terms of payouts
    - Largest weight, highest correlation
  - Therefore, the single-pair factor F_{1t} should **boost the return** through additional leveraging
  - And some more goodies, see below
- The cumulated returns of the factors are displayed on the next slide, together with $APC7$ and $RP(3)$

Factor Performances: Distinguishing First Factor (blue line)



Analysis

- We observe improved performances of F_{1t} (blue line) in terms of **absolute return** as well as of **Sharpe ratio**
  - Surprising because F_{1t} is a **single-pair** return series (admittedly composite over time, see below)
- Leverage:
  - Assume that the performances of F_{2t} and F_{3t} are **'small'** when compared to F_{1t} (as is the case here)
  - Using the replicating portfolio formula we then obtain

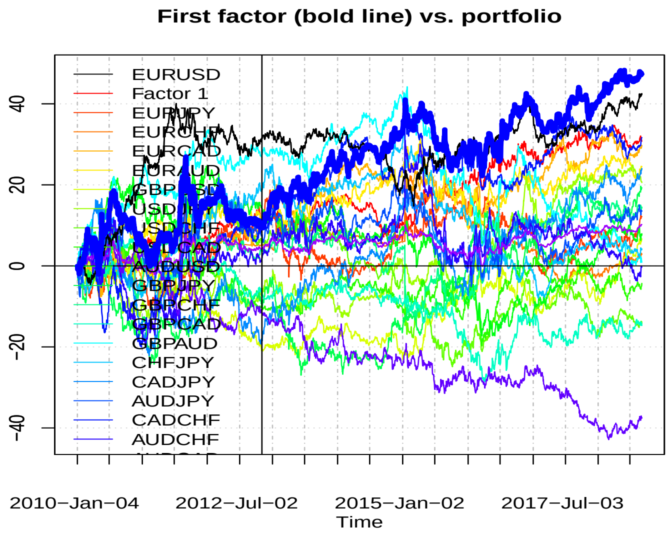
$$APC7_t = 6F_{1t} + 4F_{2t} + 2F_{3t} \approx 6F_{1t}$$

  - We then infer that it would require $6/21 * 100\% = \mathbf{30}\%$ of the capital only for replicating the **payout** of the portfolio
    - Leverage term of $21/6 = \mathbf{3.5}$ (approaches 4 by increasing the number of currencies n in APCn)
    - The above figure suggests even stronger outperformance, see next slide

The Distinguishing First Factor

- In the above explanation we assumed that performances of F_{2t} and F_{3t} were 'small' when compared to F_{1t}
- Justification:
  - F_{1t} selects pairs by combining the **strongest** currency (the filter is long 6-times) with the **weakest** currency (the filter is short 6-times) at each time point t
  - If the filter delivers **'pertinent'** signals then F_{1t} should outperform the other factors, as assumed
- We expect the first factor to perform **exceedingly** well because of
  1. the **improved leverage** effect: this affects the return but not Sharpe
  2. **smaller costs** (less trades): affects both return and Sharpe
  3. distinguishing feature: a **strengthening of the filter inference** by identification of the **max-min pair** (strongest/weakest currencies): affects both return and Sharpe. The **better the filter**, the **stronger the effect**!

First Factor (bold blue line) vs. (Supremum of) Portfolio



The Distinguishing First Factor

- The first factor dominates the **supremum** of the portfolio on the 'long run'
- The extent of the dominance depends on the quality of the **signals** (which is not outstanding but 'sufficient' in the case of our plain-vanilla filter)
  - More research would be needed for elucidating the relation between F_{1t} and the supremum of the portfolio as a function of filter performances (would fit nicely into a phd-topic)

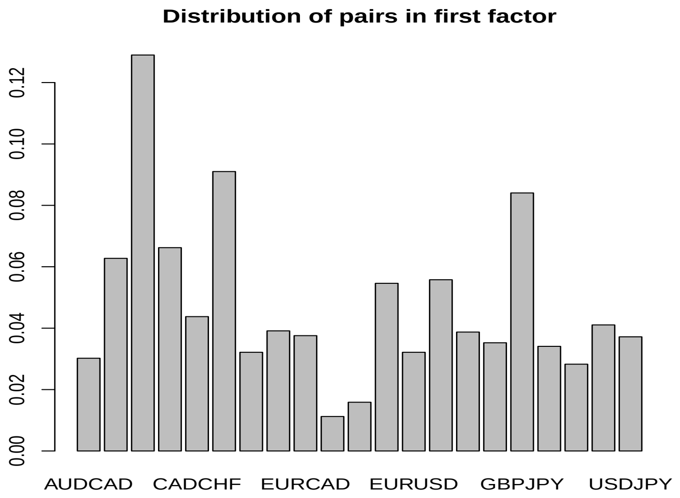
Diversification by Factors

- Let's talk a bit about 'diversification'...

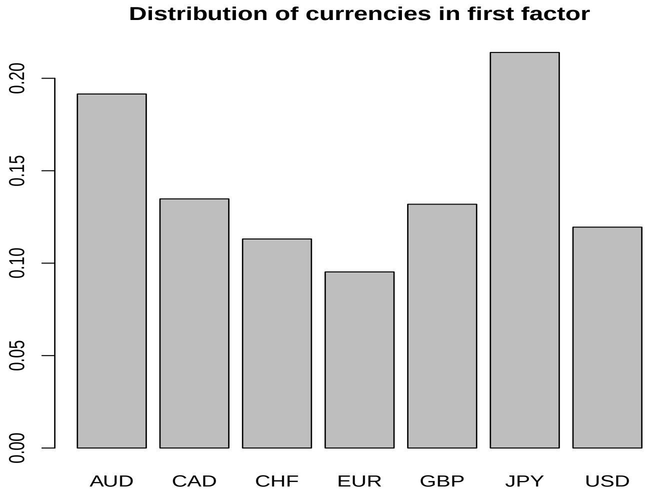
	Max-min pairs activated by first factor
2018-08-22	EURJPY
2018-08-23	AUDCHF
2018-08-24	EURGBP
2018-08-27	AUDUSD
2018-08-28	EURUSD
2018-08-29	GBPJPY
2018-08-30	GBPAUD
2018-08-31	AUDJPY
2018-09-03	GBPJPY
2018-09-04	AUDCAD

Table: Selected pairs in first factor

Distribution of Pairs in First Factor



Distribution of Currencies in First Factor



Longitudinal Diversification

- The first factor substitutes a **longitudinal diversification** for the ordinary **cross-sectional** diversification
- In contrast to the **undiscriminating** cross-sectional smoothing by the equally-weighted scheme, the novel longitudinal diversification reflects **filter inferences**
- In summary: we have a **diversification** but it's **along the time** axis and it's a bit **smarter** under the assumption that the filter is able to extract relevant information

Factor-Based Trading Subsystems

- Given our above system APC7 of **all** pairwise combinations
- Select a **subset** of FX-pairs from this set
  - For example select all pairs with USD (home-currency)
- **Subsystem** based on F_{1t}:
  - Pick-out only those trading episodes of F_{1t} corresponding to the selected pairs (otherwise stay out of the market)
- Illustration: next slide

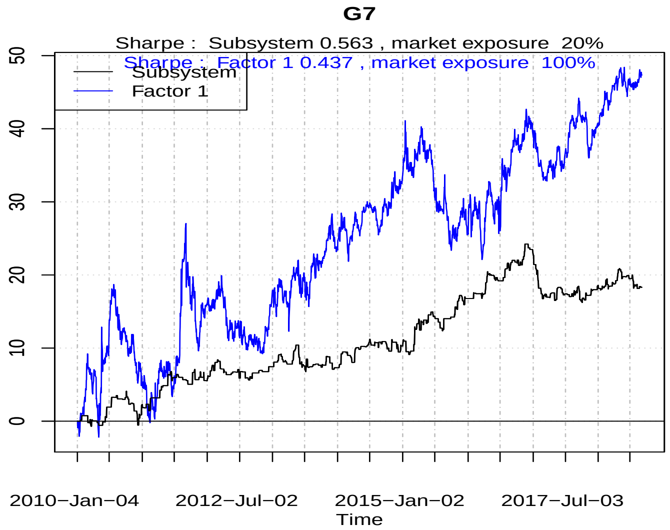
Subsystem Based on USD (Major G7 Pairs)

	Returns first factor	Subsystem USD
2018-08-22: EURUSD	0.0033	0.0033
2018-08-23: EURJPY	0.0103	0.0000
2018-08-24: AUDCHF	0.0032	0.0000
2018-08-27: EURGBP	-0.0037	0.0000
2018-08-28: AUDUSD	0.0025	0.0025
2018-08-29: EURUSD	0.0150	0.0150
2018-08-30: GBPJPY	0.0052	0.0000
2018-08-31: GBPAUD	0.0124	0.0000
2018-09-03: AUDJPY	0.0058	0.0000
2018-09-04: GBPJPY	0.0020	0.0000

Table: Trading signals of pairs with EUR

- Subsystem (second column): pick-out all performances when USD is selected by F_{1t} and stay out of the market otherwise

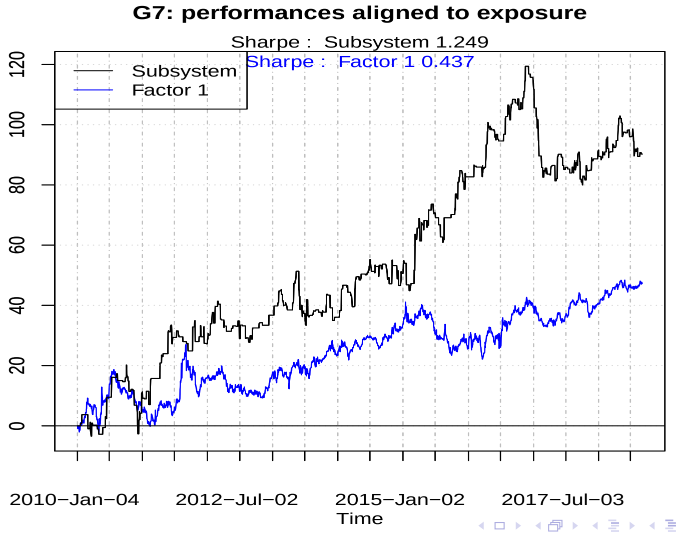
Trading Subsystem based on USD (G7, black line)



- The **return** of the subsystem based on USD (G7) (black line) is smaller because its market **exposure** of **20**.3% is smaller
- The annualized **Sharpe** ratio is underrating the performance because it does not account for the smaller exposure
- We now scale performances according to
  - inverse exposure (for the returns)
  - square root of inverse exposure (for Sharpe)

  see the following figure.

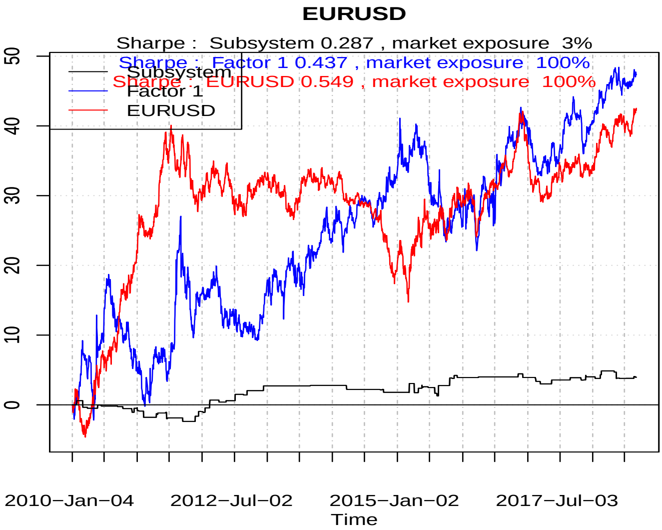
Subsystem based on USD (G2): Performances Aligned for Exposure



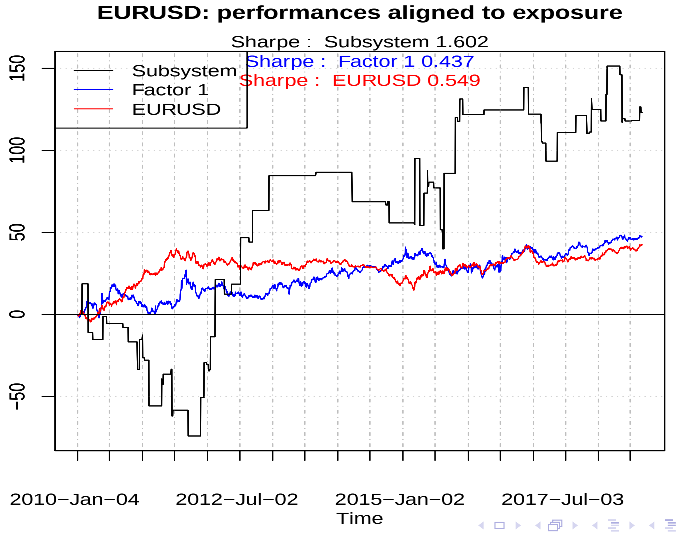
Remarks

- Instead of assigning full/zero weight (depending on whether a pair is activated by the factor) one could think about a **more elaborated weighting** scheme...
- The subsystem could be based on a single pair, only
  - Example: EURUSD
  - The figure in the next slide compares F_{1t} (blue line), *EURUSD* based on weekly filter (red) and the subsystem of *EURUSD* based on picking out selected returns of F_{1t} (black line).
  - Once more the annualized Sharpe ratio of the subsystem is underrating performances because of the (much) smaller market exposure of 3.2%

Trading Subsystem based on *EURUSD*



Subsystem based on *EURUSD*: Performances Aligned for Exposure



Revert the Above Framework: Embedding System

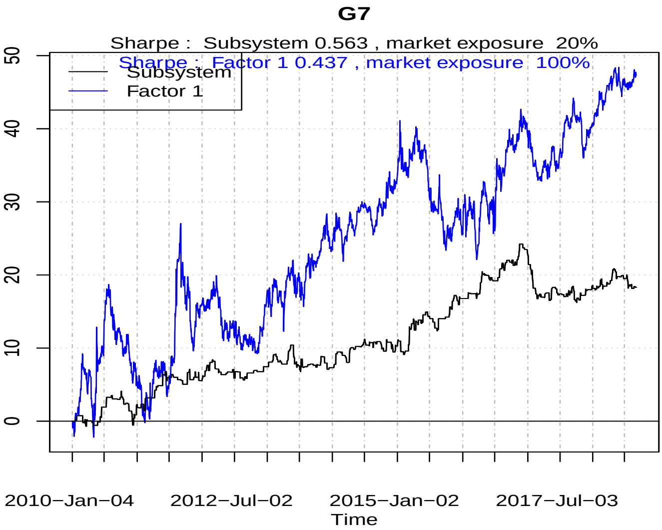
- Given a **real** trading system $FX(n)$ of pairs based on n different currencies $c_1, c_2, ..., c_n$
  - Not necessarily all pairwise combinations of currencies
  - For example the above major G7
- And given a trading strategy applied to the pairs of $FX(n)$
  - For example the plain vanilla weekly filter
- Derive a **fictive** embedding system APC$n+j$ of **all** pairwise combinations of $c_1, ..., c_n, c_{n+1}, ..., c_{n+j}$ where $c_{n+1}, ..., c_{n+j}$ are possibly additional currencies of interest
  - If $j = 0$ then we just consider APCn i.e. all pairwise combinations of currencies of the real system

Embedding of Real System into Fictive Factor-Based Strategy

- Assume that the following hold in the fictive APC$n+j$
  - equal-weighting
  - trade synchronization

  These assumptions need not hold for the real system $FX(n)$
- **Embedding**: at each trading time point t of the **real** system $FX(n)$
  - compute F_{1t} from the fictive APC$n+j$
  - assign 'more' weight to the pair in the real system $FX(n)$ conforming with the fictive pair activated by F_{1t}

Trading Subsystem based on USD (G7, black line)



To Conclude: a Caveat and a Back Door

- A Caveat: the pertinence of the proposed factor-based strategy depends on the quality of the filter
  - the filter fuels the factor-based engine
  - the factors leverage the filter
- A back door to filters
  - McElroy and Wildi (JTSE 2016), Wildi (Handbook on Seasonal Adjustment, Eurostat 2018), McElroy and Wildi (IJOF 2018), McElroy and Wildi (submitted 2018)

References/Links

- DB (2018) Alive and Kicking: A Guide to FX as an Asset Class, Deutsche Bank Research
- Wildi (2018): Eurostat Handbook on Seasonal Adjustment
- McElroy and Wildi (2016): Optimal Real-Time Filters for Linear Prediction Problems (JTSE)
- McElroy and Wildi (2018): The Trilemma Between Accuracy, Timeliness and Smoothness in Real-Time Signal Extraction, IJOF (2018)
- McElroy and Wildi (2018): The Multivariate Linear Prediction Problem: Model-Based and Direct Filtering Solutions
- SEF Blog: Blog on Signal Extraction and Forecasting