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From thesis to trading: a trend detection strategy

DB Quantitative Strategy – FX & Commodities

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Deutsche Bank AG/London

Agenda

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Introduction (1)

- Quantitative strategy is about applying mathematical techniques to understand and predict financial market dynamics.
- Less macroeconomics, more statistics. Understanding the patterns in the information. Major focus on speed and dependency, not just direction.
- Once we feel comfortable in our understanding, and in the stability of these patterns, we employ them in building systematic trading strategies in spot and derivatives accross different asset classes.

Introduction (2)

- Most of the work is about building and implementing systematic trading models.
- The clientelle is divided into 2 constituencies:
  - Internal: implement models at given proprietary books, supervised by trading desks
  - External: educational roadshows with a variety of the bank's clients
- We run an annual internship programme, and the models often result from the work of our interns.
- When the intern is an MSc or PhD student, we try to link the topic with the intern's thesis.
- Florent Robert: intern since July 2010. Idea: employ innovative techniques to identify regime switches in the data. Eventually settled for techniques that can be implemented in data other than just volatility. The work culminated in a fully-implementable momentum strategy.

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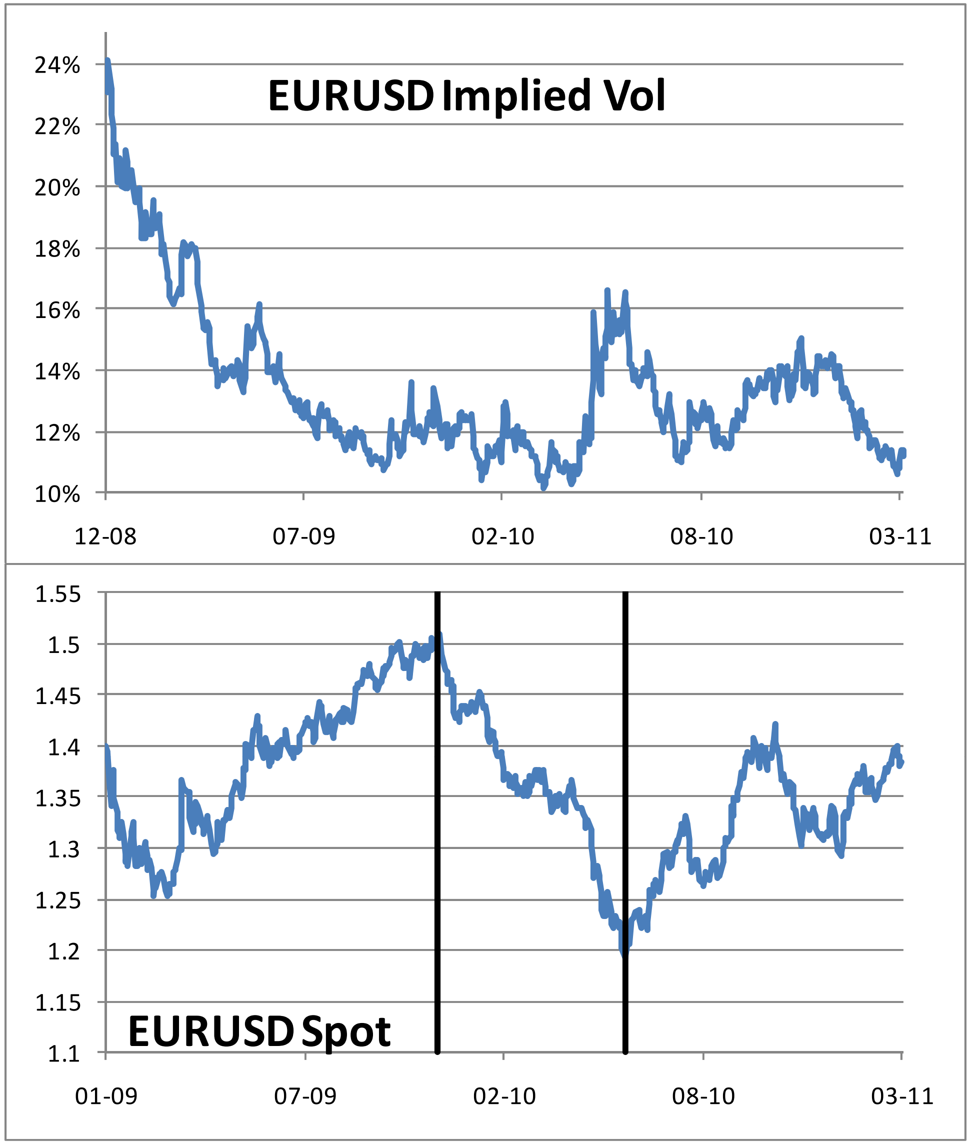
The theory (1)
Motivation

- Markovian regime switching to model
  - Switches in volatility
  - Credit defaults
- Bayesian disorder detection to model regime switches in prices
  - More straightforward, no transition matrix
  - Fair assumption: FX prices can be modelled locally as Brownian motions



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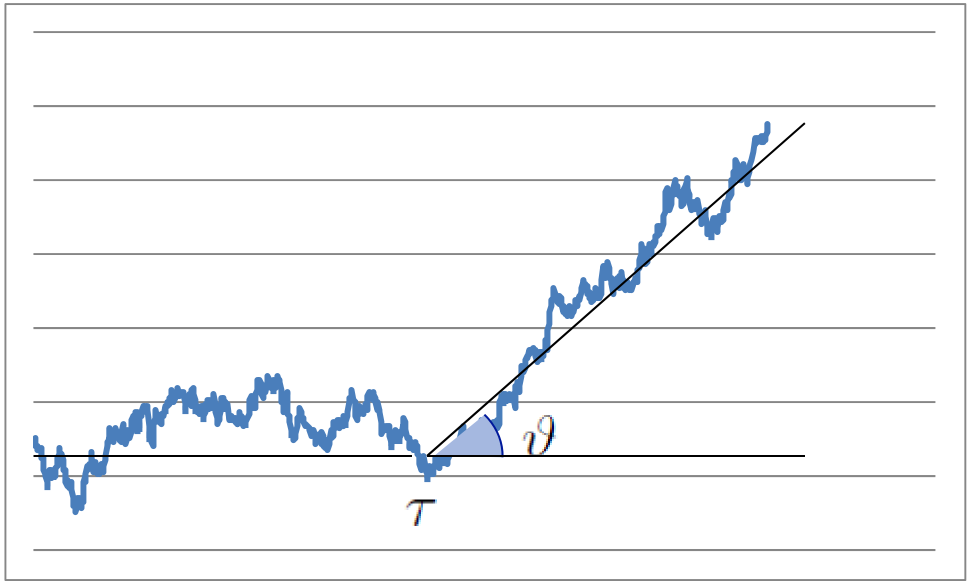
The theory (2)

Thesis



- $$dX_t = \begin{cases} \sigma dW_t, & t < \tau \\ \vartheta dt + \sigma dW_t, & t \leq \tau \end{cases}$$
- $\mathbb{P}[\tau > t] = (1-p)\, e^{(-\lambda t)}$
- $\mathcal{R}(T) = \mathbb{E}|T - \tau|$
- $\Pi_t := \mathbb{P}[\tau \leq t | \mathcal{F}_t]$

where $\mathcal{F}_t := \sigma(X_s, 0 \leq s \leq t)$

$$\mathcal{R}(T) = \mathbb{E}(\tau) + 2 \cdot \mathbb{E} \int_0^T \left(\Pi_t - \frac{1}{2} \right) dt$$

- Detect as quickly as possible a change in the observable system's behaviour. Time at which the change occurs: τ, the change-point.
- Here change in the system behaviour = change in the drift: from 0 to ϑ at τ
- T is the stopping rule, the time of the alarm. We want to minimize the expected miss
- Introducing, the a posteriori probability process Π_t : probability that regime change has already occurred by time t, given the observations available up to that time

The theory (3)
Thesis

- Approach using Girsanov: from new measure to actual measure
  - New measure $(\Omega, \mathcal{F}, \mathbb{P}_0)$:
    - X_t is a Brownian motion independent from τ
    - Larger filtration $\mathcal{G}_t := \sigma(\tau, \hat{X}_s; 0 \leq s \leq t)$
  - Change using $Y_t = \frac{\vartheta}{\sigma} \mathbf{1}_{\{\tau \leq t\}}$
    - $$\left.\frac{d\mathbb{P}}{d\mathbb{P}_0}\right|_{\mathcal{G}_t} = \exp\left(\int_0^T Y_s d\hat{X}_s - \frac{1}{2}\int_0^T |Y_s|^2 ds\right)$$
      $$= \frac{L_t}{L_\tau} \cdot \mathbf{1}_{\{\tau \leq t\}} + \mathbf{1}_{\{\tau > t\}} := Z_t$$
    - Exponential likelihood ratio process $L_t := \exp\left(\frac{\vartheta}{\sigma}\hat{X}_t - \frac{\vartheta^2}{2\sigma^2} t\right)$
  - In the newly defined measure $(\Omega, \mathcal{F}, \mathbb{P})$, we have exactly the problem that we originally posited

The theory (4)
Thesis

- Bayes rule: $\Pi_t := \mathbb{P}[\tau \leq t|\mathcal{F}_t] = \dfrac{\mathbb{E}_0\left[Z_t \mathbf{1}_{\{\tau \leq s\}}|\mathcal{F}_t\right]}{\mathbb{E}_0\left[Z_t|\mathcal{F}_t\right]}$

$$\Pi_t = \frac{p\,L_t + (1-p)\,\int_0^t \left({}^{L_t}/{}_{L_s}\right)\cdot \lambda e^{-\lambda s} ds}{p\,L_t + (1-p)\,\int_0^t \left({}^{L_t}/{}_{L_s}\right)\cdot \lambda e^{-\lambda s} ds + (1-p)\,e^{-\lambda t}}$$

- More interested in the dynamics of Π_t. Innovations process
  - Using Levy theorem, B is a Brownian motion in $(\Omega, \mathcal{F}, \mathbb{P})$

$$B_t = \frac{1}{\sigma} X_t - \frac{\vartheta}{\sigma}\int_0^t \Pi_s ds$$

  - Ito's theorem, $\Phi_t = \dfrac{\Pi_t}{1-\Pi_t}$

$$d\Pi_t = \lambda\,(1-\Pi_t)\,dt + \frac{\vartheta}{\sigma}\Pi_t\,(1-\Pi_t)\,dB_t$$

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The theory (5)

Thesis

$$\begin{aligned}
\lambda(1-x)Q'(x)+\frac{1}{2}\left(\frac{\vartheta}{\sigma}\right)^2 x^2(1-x)^2Q''(x) &= \frac{1}{2}-x;\ \text{for } 0<x<p_*\\
\lambda(1-x)Q'(x)+\frac{1}{2}\left(\frac{\vartheta}{\sigma}\right)^2 x^2(1-x)^2Q''(x) &\geq \frac{1}{2}-x;\ \text{for } p_*<x<1\\
Q(x) &\leq 0;\quad \text{for } 0\leq x<p_*\\
Q(x) &= 0:\quad \text{for } p_*\leq x\leq 1.
\end{aligned}$$

Finding the optimal stopping rule

- If you can find such a function Q , then applying Ito to $Q(\Pi)$, you can show that

$$\mathbb{E}\left[\int_0^T\left(\Pi_t-\frac{1}{2}\right)dt\right]\geq Q(p)-\mathbb{E}\left[Q(\Pi_t)\right]\geq Q(p)$$

- Remember that $\mathcal{R}(T)=\mathbb{E}(\tau)+2\cdot\mathbb{E}\int^T\left(\Pi_t-\frac{1}{2}\right)dt$. Is there a stopping rule T_* such that

$$\mathbb{E}\left[\int_0^{T_*}\left(\Pi_t-\frac{1}{2}\right)dt\right]=Q(p)$$

We can achieve this by taking $T_*=\inf\{t\geq 0|\Pi_t\geq p_*\}$

- Showing that Q exists, we get p_* and then

$$T_* = \inf\left\{t\geq 0|\frac{p}{1-p}+\lambda\int_0^t e^{-\frac{\vartheta}{\sigma^2}X_s+\left(\frac{\vartheta^2}{2\sigma^2}-\lambda\right)s}ds\geq\frac{p_*}{1-p_*}e^{-\frac{\vartheta}{\sigma^2}X_t+\left(\frac{\vartheta^2}{2\sigma^2}-\lambda\right)t}\right\}$$

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From thesis to trading model (1)
How can it be implemented?

- The idea is novel: it employs unusual but powerful techniques to detect switches between 3 market states, a clear improvement from traditional price action models (which focus on 2 market states)
- The clearest application is to a momentum strategy: to be long in an up-trend, short in a down-trend, and neutral in a sideways state
- In adapting to a trading model, a few assumptions must be made:
  - Exchange rate price changes can be *locally* normally distributed
  - The structure of the model does not alter much when evaluated in discrete time

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From thesis to trading model (2)

Estimating parameters: a modified validation approach

- What needs to be optimised?
  - The template distributions: first and second moments according to the slope (gradient) of the trend, and the variability around that slope through time. This underpins our assumption of local normality.
  - The switch mechanism: trend length, and thus the way that a trend switch becomes more likely through time. We assume the length of each trend follows a geometric distribution with an individual parameter. In other words, the likelihood of a trend switch rises with time in non-linear fashion.

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From thesis to trading model (3)

Estimating parameters: a modified validation approach

Figure 2: Identifying price action states

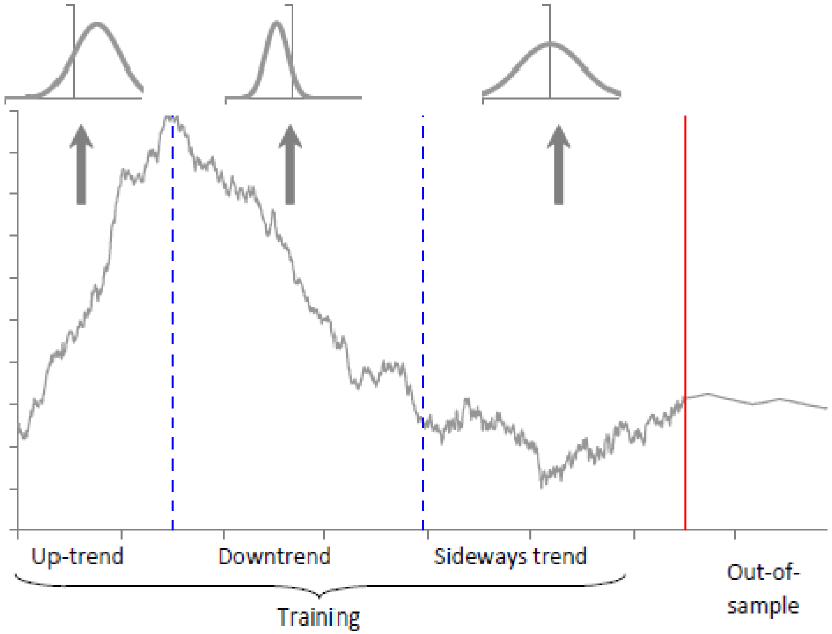
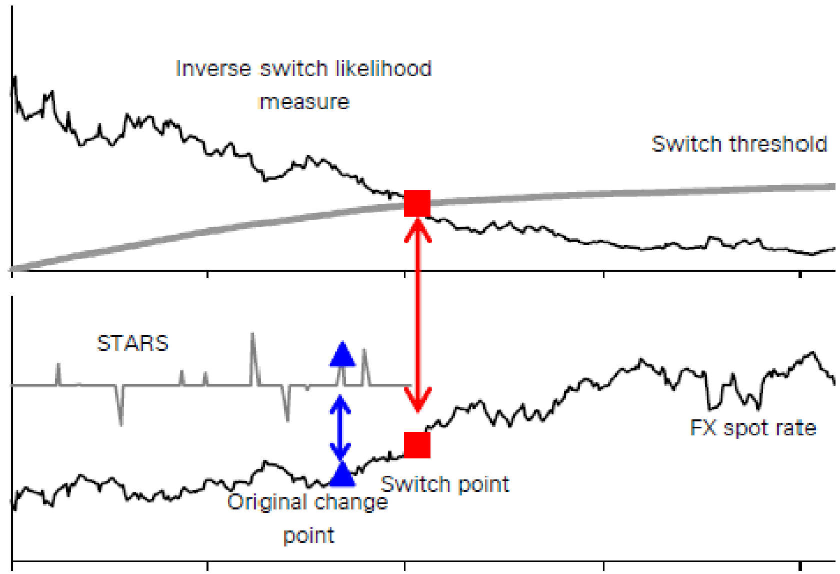


Figure 3: Detecting switch-points and original change-points for a given price action state



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From thesis to trading model (4)
Validation: a sequence of training vs out-of-sample windows

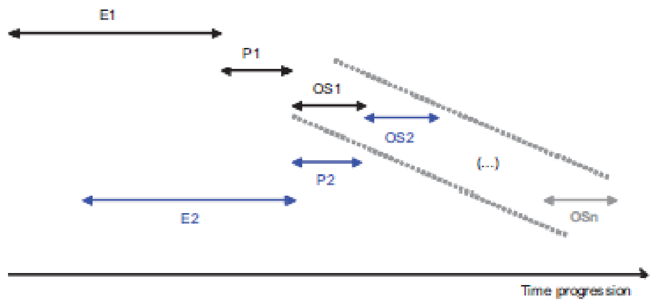
- Backtest, not simulation
  - Simulation: estimate the future based on today. Popular among pricing models. Forward-looking information (option prices) is used in calibrating the parameters of a process under a pricing measure. These are then applied to simulate the likely paths of the process in the future and thus to calculate the present value of an exotic payoff.
  - Backtest: evaluate the historical performance. The procedure will fit the required parameters to historical data to identify what best fits the purpose.
  - Simulation uses forward-looking data to estimate value: likely trajectory, then current price. Backtests use past information to estimate value: patterns, stability and then trading decisions. Backtests evaluate goodness of fit, a key component of trading strategies based on statistical convergence.In most of our models, we calibrate parameters based on backtests.

From thesis to trading model (5)

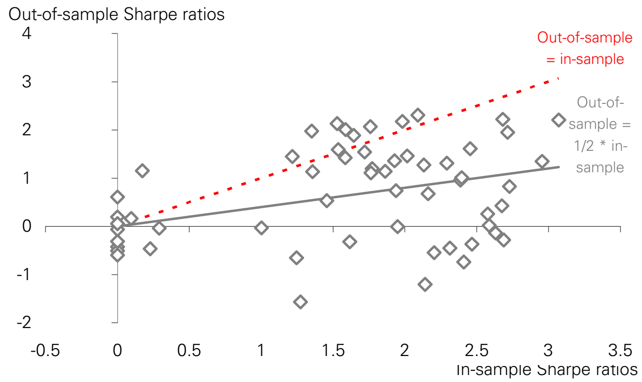
Validation: a sequence of training vs out-of-sample windows

- Overfitting: dangers of backtesting
  - In-sample vs out-of-sample treatment
- Modified K-fold cross-validation: cut the data into smaller in-sample and out-of-sample windows, and use data to train and test.
- Optimise parameters in-sample according to risk-adjusted performance.
- Evaluate performance out-of-sample; in a good model, the in-sample performance is generally a good predictor of out-of-sample returns.

Figure 4: Our parameter selection and trading process



Note: the dotted channel represents the actual (out-of-sample) trading period. The strategy's cumulative P&L results from the sum of the OS segments. Source: Deutsche Bank



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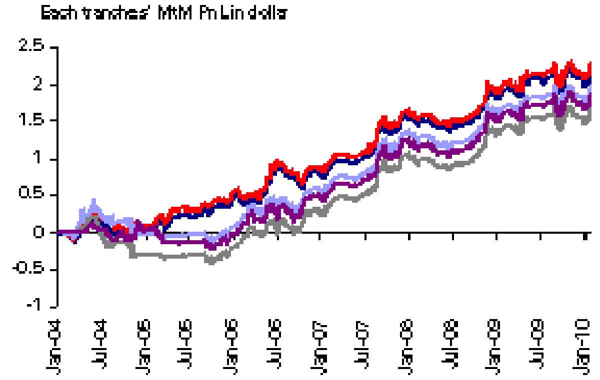
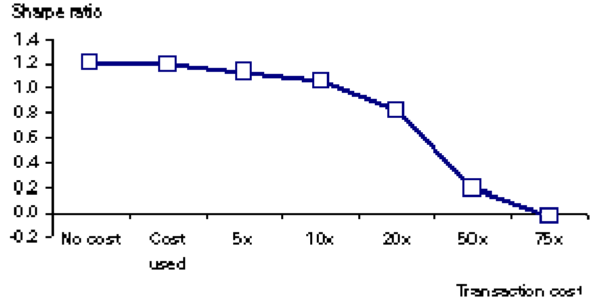
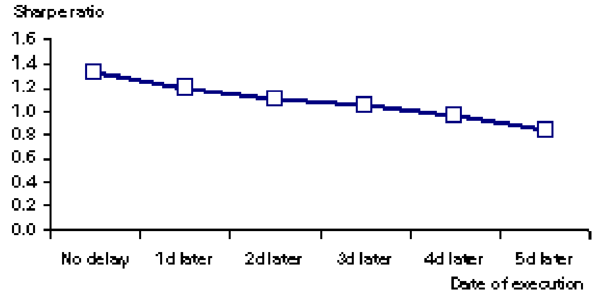
From thesis to trading model (6)

Stability and operational risks

- K-fold window choice: robustness vs adaptability
- Stability: what happens to your equity curve if you bump the data?
- Operational reality: what happens to your equity curve if you bump transaction costs and execution time?







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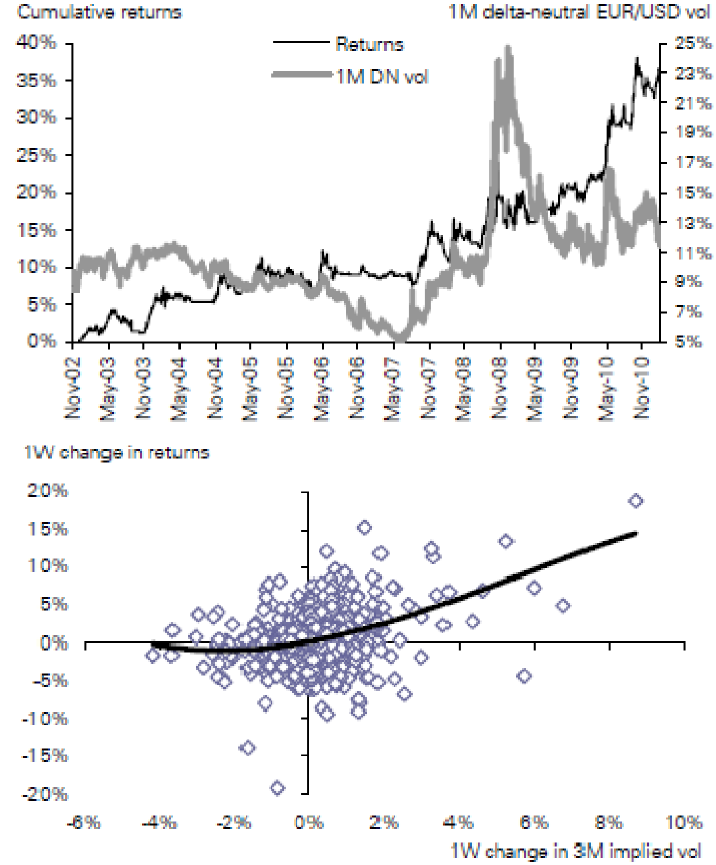
Results (1)
Positive aspects

- The results for EUR/USD are positive and linear.
- Intra-hour frequencies are noisier, and produce less trends; lower frequencies do better.
- Individual returns are somewhat similar to traditional momentum: low hit ratios (~50%) but high positive-to-negative trade returns ratio.
- More linearly consistent returns compared to a standard technical analysis strategy.
- Combining individual frequencies gives better returns. The model addresses shorter and longer trends.
- Positive and asymmetric correlation to EUR/USD implied volatility.



Data since 2002. Source: Deutsche Bank

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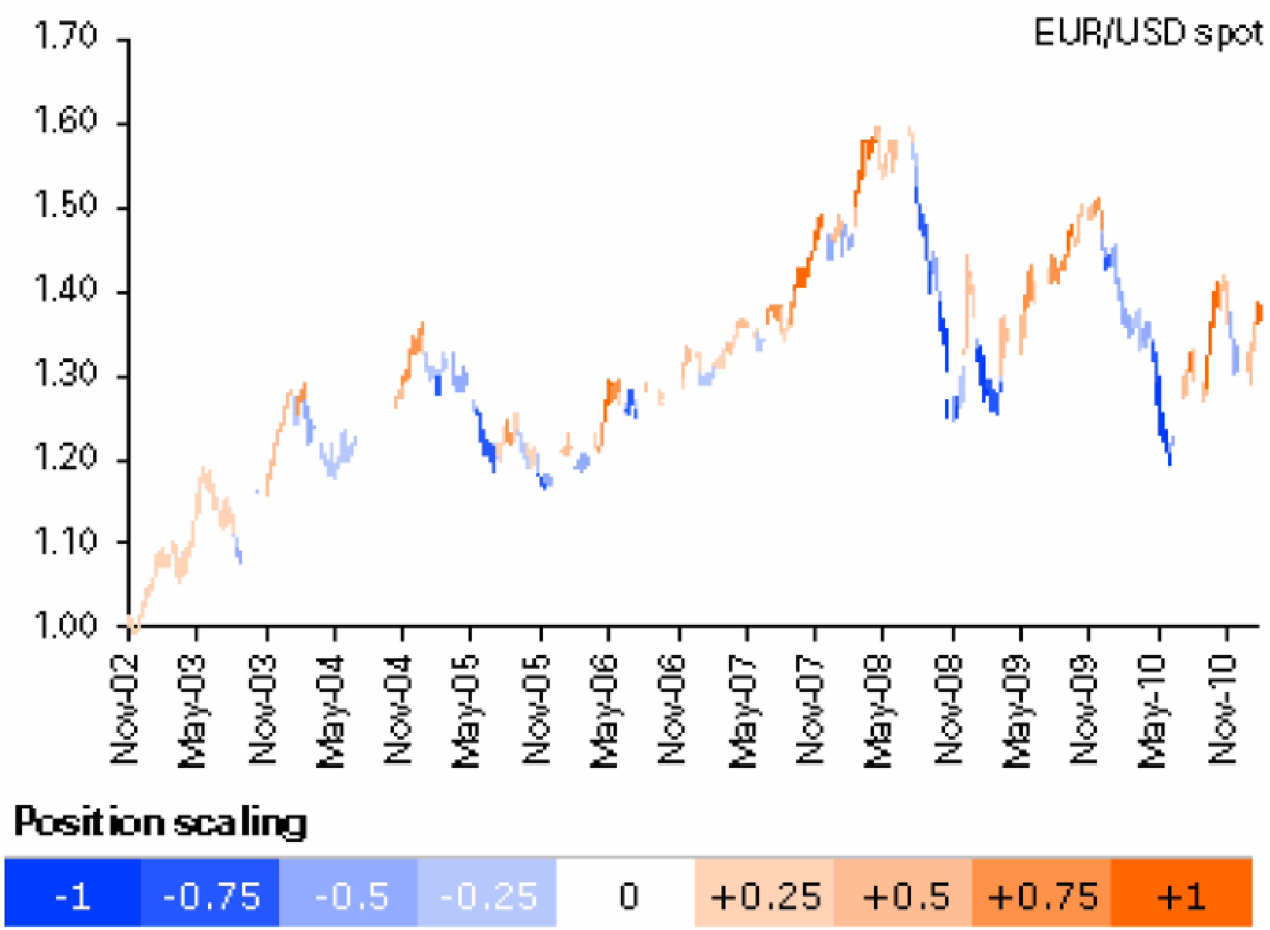
Results (2)
Positive aspects



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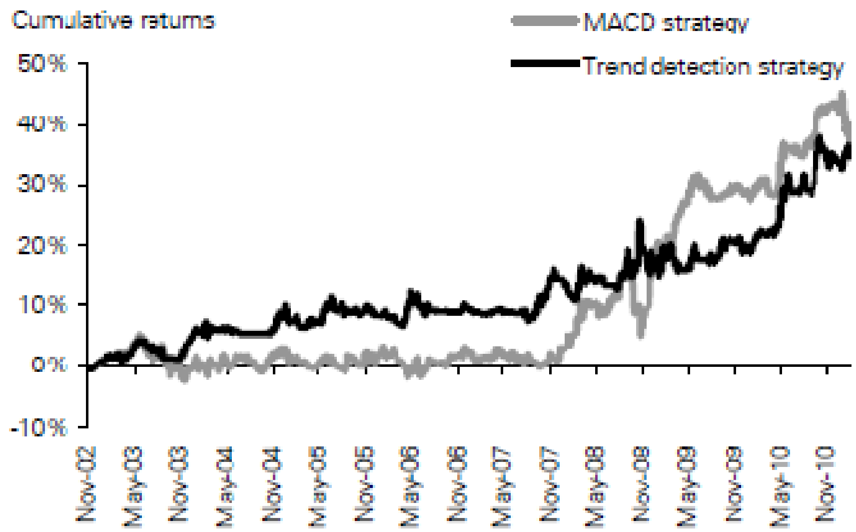
Results (3)
Risks and future work

- Are we capturing enough information by fitting a state into 2 parameters?
- The model assumes trades can be executed at any time of the day. Is that realistic? What are the implications of execution delay?
- Does it really perform better than a simpler MACD strategy?
- Is this the best way to implement a price action switch model?



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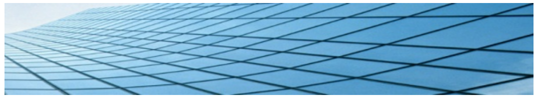
What next?

- Internal implementation
- Follow-up research notes
- Educational roadshows
- What model will come next?

Macro

Global Markets Research



Global

14 February 2011

FX Special Reports

Gaining Momentum

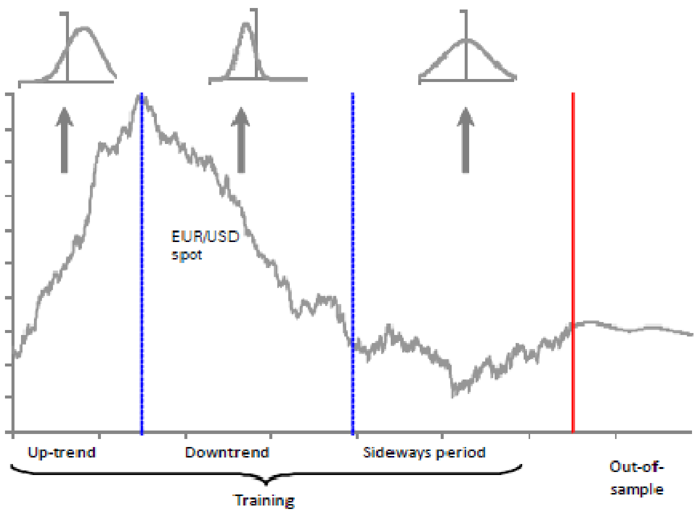
Modelling price action

This report introduces a model that "learns" about different price action states, and uses that information to identify trends and detect switches in the future. The results of a momentum strategy based on the model outperform a standard technical analysis strategy, and imply an asymmetric correlation to vol.

Learning, detecting and switching between price action states

- Price action strategies are very popular in foreign exchange, and typically divided into the momentum and mean-reversion styles.
- We introduce a model that addresses both styles. Our model "learns" about the characteristics of an uptrend, a down-trend and sideways price action for an underlying asset.
- We use this knowledge to identify the current price action state, and apply specific algorithms to detect changes from one regime to another. The algorithms utilise Bayesian disorder detection, and a sequential regime-switching tool.
- We create a simple momentum strategy based on the model, highlighting its performance when applied to EUR/USD. The backtest shows strong returns over time, outperforming a standard technical analysis strategy and implying an asymmetric correlation to volatility.

Figure 1: "Learning" the characteristics of each price action state



Source: Deutsche Bank

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Internships in FX & Commodity Quant Strategy

- Opportunity to join a team ranked as:
  - #1 in FX Quantitative Strategy by the Euromoney Survey (2009, 2010)
  - #1 in Derivatives Research by the Risk Awards Survey (2011)
  - Top 3 Commodities Research team by Energy Risk (2011)
- Opportunity to join a bank ranked as:
  - #1 in Foreign Exchange by the Euromoney Survey (past 6 years)
  - #1 in Commodity Derivatives by IFR (2011)
- Looking to hire 1-2 interns
- Preference for 1-year internships, but flexible duration and flexible start date
- Looking for candidates with strong quantitative and computing skills
- caio.natividade@db.com

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