

Inventory prediction in foreign exchange markets

Damien Challet

CentraleSupélec and Encelade Capital

with

Mehdi Lallouache, Rémy Chicheportiche, Serge Kassibrakis

Mosaic Finance, Capital Fund Management, Swissquote Bank

May 12, 2017

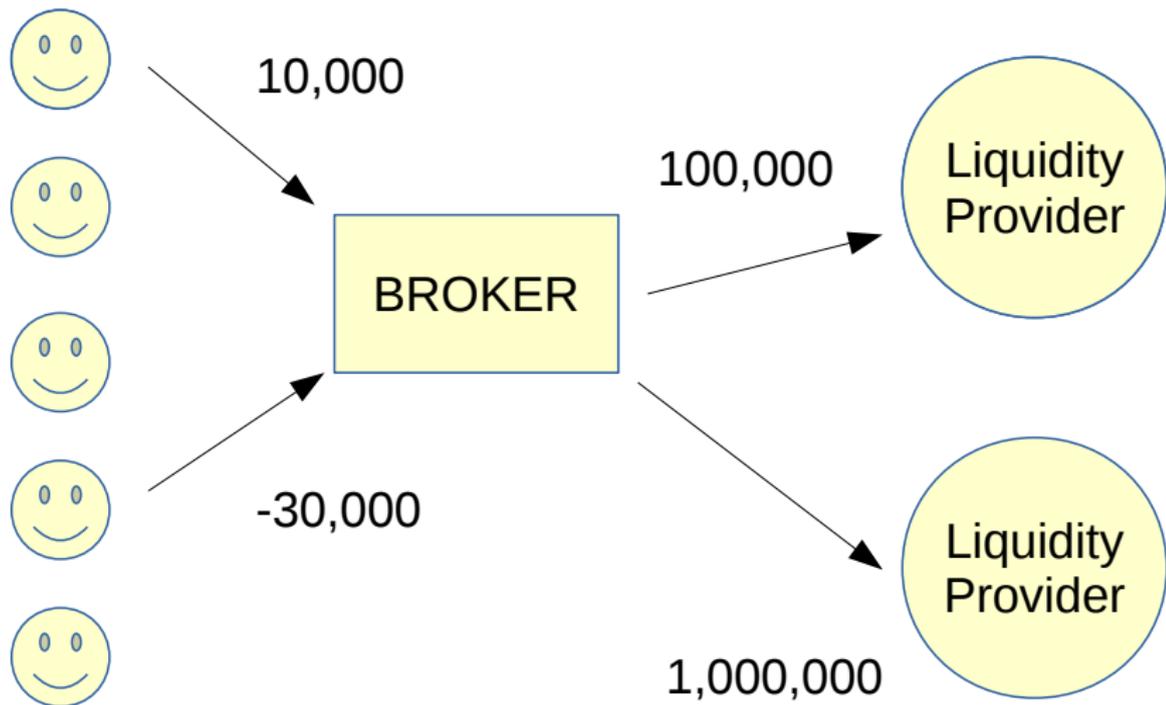
Public data: price nearly unpredictable

Proprietary data: nearly inaccessible, underexploited

Machine learning: nearly useless, too much noise

Foreign exchange market structure

Exchange EUR \rightarrow USD

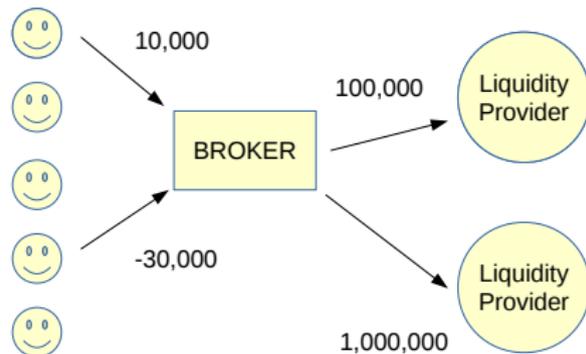


Broker inventory

- Minimum amount to Liquidity Provider
- Broker aggregates small amounts

→ *inventory*

- Order matching: save exchange fees



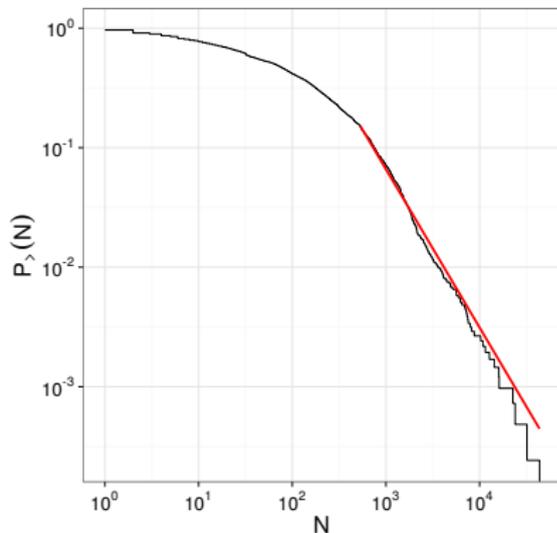
Inventory management

- Set maximum inventory $\Phi_{MAX} \in [100,000, 10,000,000]$
- Random client order flow $\phi_t \sim P(\phi)$
- Keep orders in inventory $\Phi_t = \sum_{t' \leq t} \phi_{t'}$
- Flush inventory to liquidity provider if $|\Phi_t| > \Phi_{MAX}$
- Random price changes $\frac{dP_t}{P_t} = trend + noise_t$
- Mathematical Finance: optimise risk as a function of Φ_{MAX} and time horizon T

Big data approach to inventory management

- $O(10^4)$ clients
- $O(10^7)$ transactions

Number of transactions per client



Financial markets *are* predictable with client IDs

Prediction problems = Science + Engineering

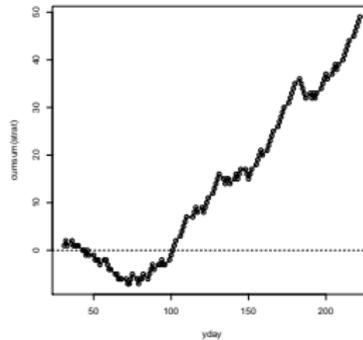
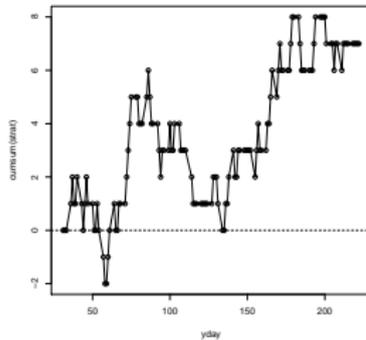
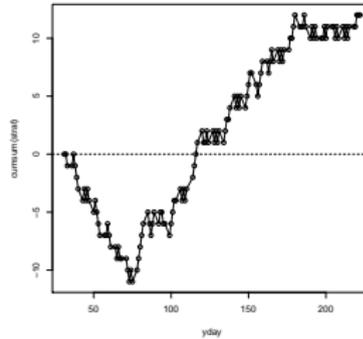
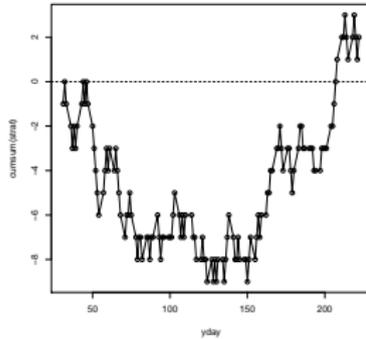
Science: flux

- 1 cluster clients
- 2 lead-lag networks
- 3 machine learning
- 4 ENJOY!

Engineering

- 1 Predict price returns
- 2 Inventory constraints
- 3 PROFIT!

Cluster traders



Tumminello et al. (2011a)

- 1 Agent i , $state_i(t) \in \{1, \dots, S\}$

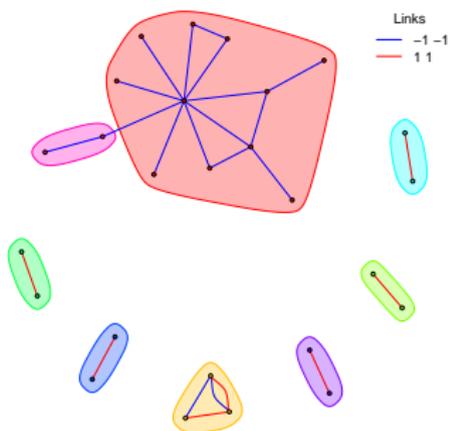
$$s_i(t) = \text{sign} \frac{Buy(t) - Sell(t)}{Buy(t) + Sell(t)} \in \{-1, 0, 1, 2 = \emptyset\}$$

- H_0 : states of agents i and j are Poisson processes
- $O(N^2)$ pairs
 - multiple hypothesis correction
 - NETWORK

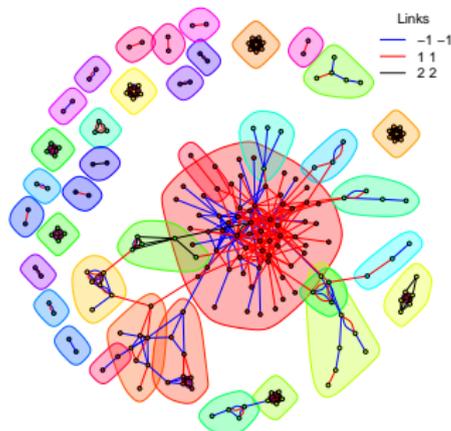
Synchronized traders

Challet et al. (2017) EUR.USD SQ

daily



hourly



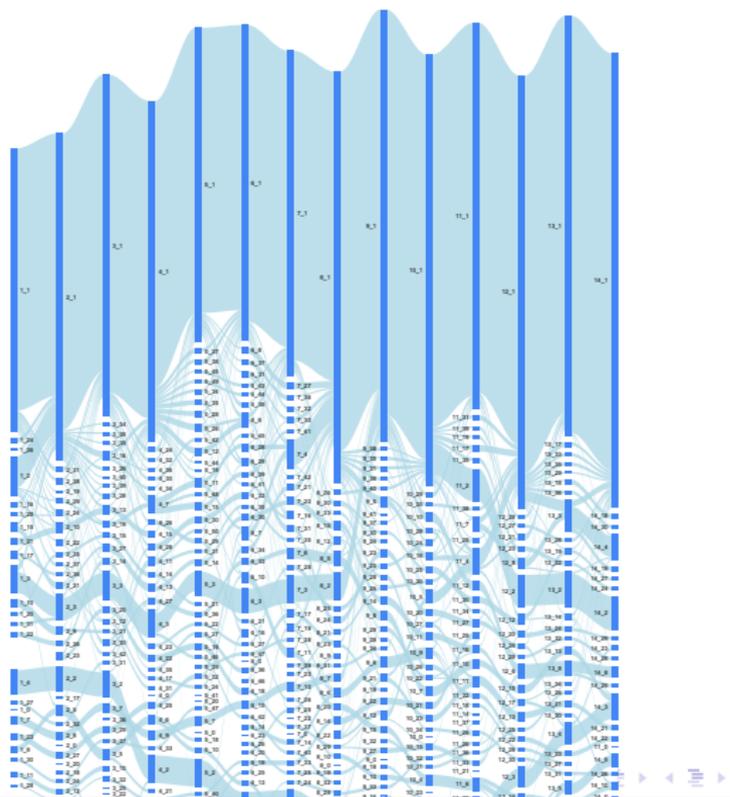
Conditions:

① Clusters of agents are stable

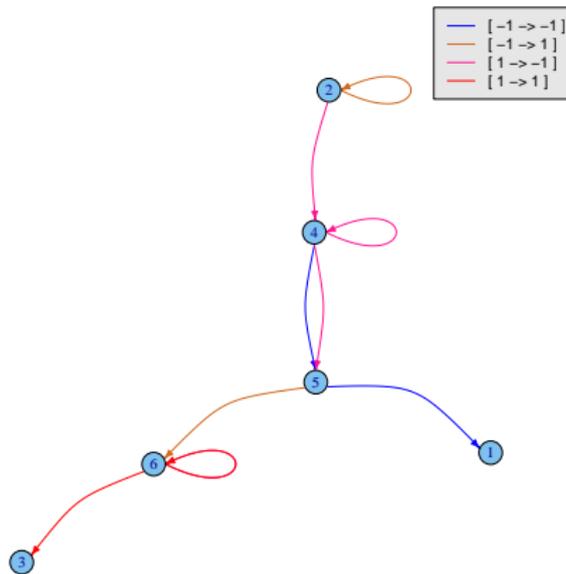
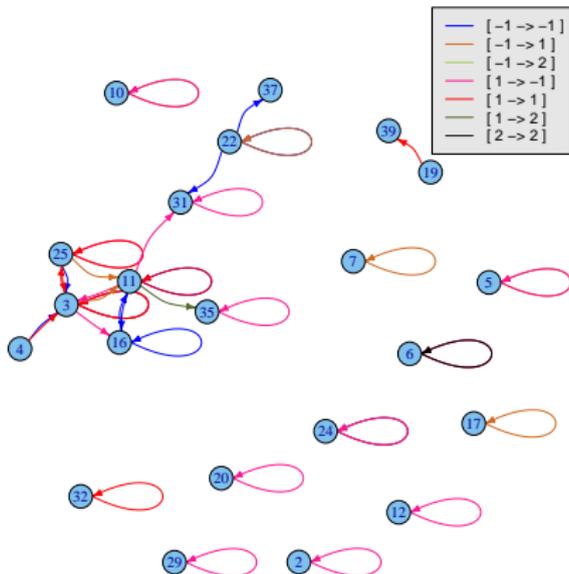
② Cluster activity is predictable

≡ persistent lead-lag cluster networks

Cluster stability



Compute p-value of $\{s_g(t), s_{g'}(t+1)\}$



Explicit/implicit communication

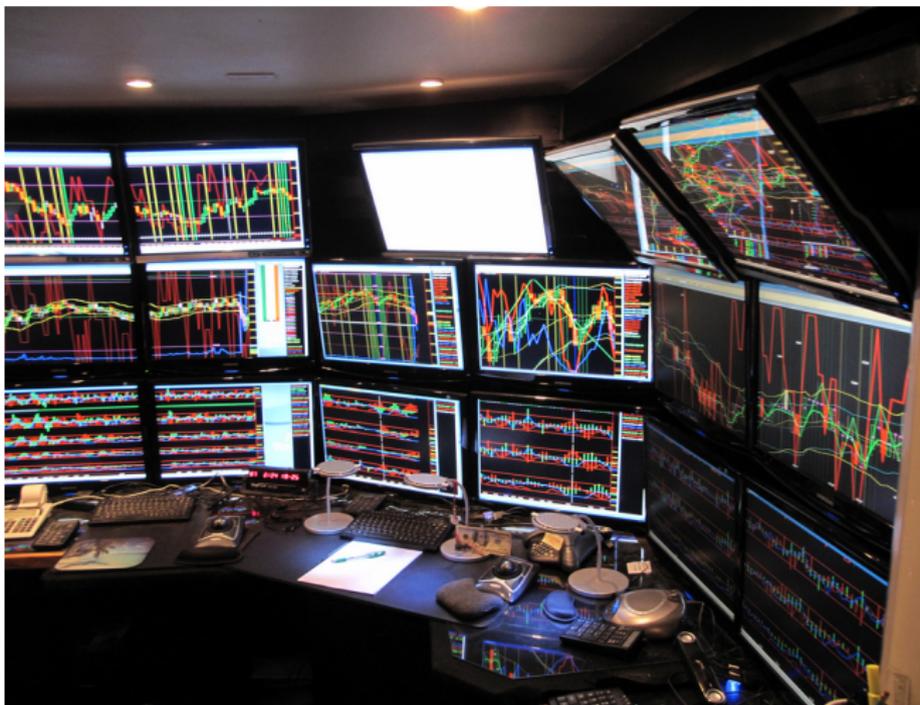
Delayed reaction

- 1 faster news
- 2 same strategy, faster parameters
MA(CD) 12, 26, 5 \rightarrow 10, 25, 4:
- 3 Master in Finance

Trader-trader: explicit communication



Implicit communication: prices



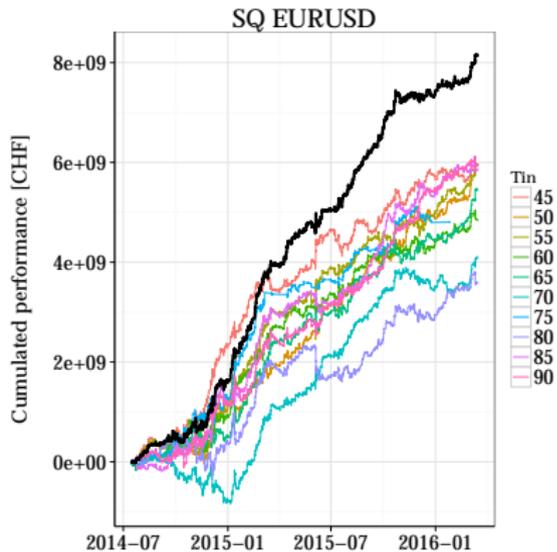
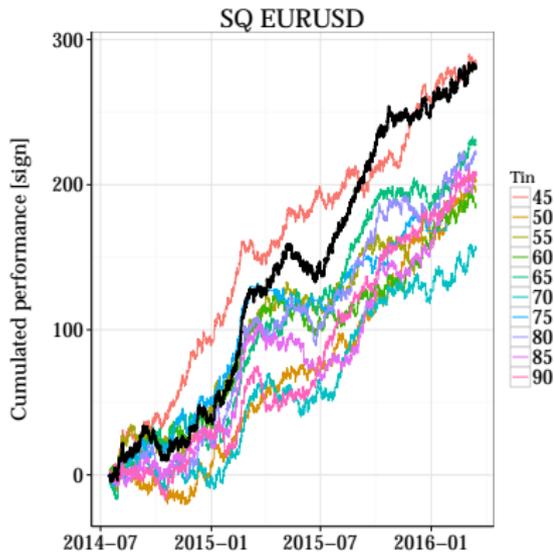
How to predict order flow

- 1 Determine groups
- 2 Determine group state $\sigma_{g,t}$
- 3 Learn on-line sign of next global order flow

$$P_{t_0,t_1} = \begin{pmatrix} \sigma_{1,t_0} & \sigma_{2,t_0} & \sigma_{1,t_0-1} & \sigma_{2,t_0-1} & h(t_0) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sigma_{1,t_1} & \sigma_{2,t_1} & \sigma_{1,t_1-1} & \sigma_{2,t_1-1} & h(t_1) \end{pmatrix} \sim \begin{pmatrix} \hat{s}_s(t_0 + 1) \\ \vdots \\ \hat{s}_s(t_1 + 1) \end{pmatrix}$$

- 4 \sim : vanilla Random Forest (15 seconds / day)

Results



How to predict VWAP

VWAP= Value-Weighted Average Price *of next orders*

- 1 Determine groups
- 2 Determine group state $\sigma_{g,t}$
- 3 Learn on-line sign of next VWAP difference

$$P_{t_0,t_1} = \begin{pmatrix} \sigma_{1,t_0} & \sigma_{2,t_0} & \sigma_{1,t_0-1} & \sigma_{2,t_0-1} & h(t_0) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sigma_{1,t_1} & \sigma_{2,t_1} & \sigma_{1,t_1-1} & \sigma_{2,t_1-1} & h(t_1) \end{pmatrix} \sim \begin{pmatrix} \hat{s}_s(t_0 + 1) \\ \vdots \\ \hat{s}_s(t_1 + 1) \end{pmatrix}$$

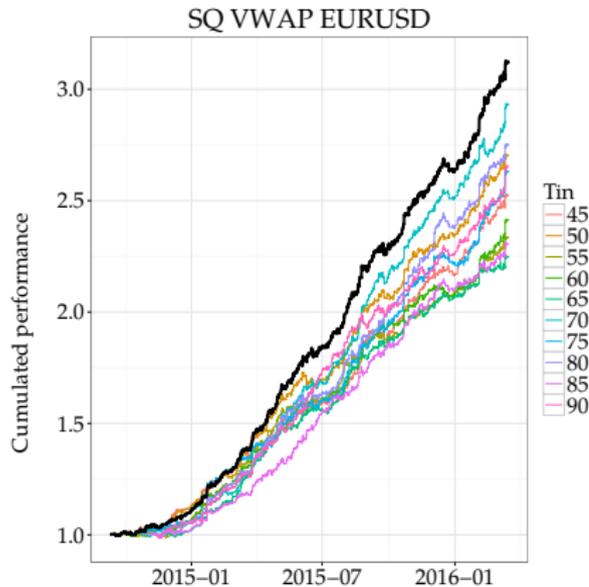
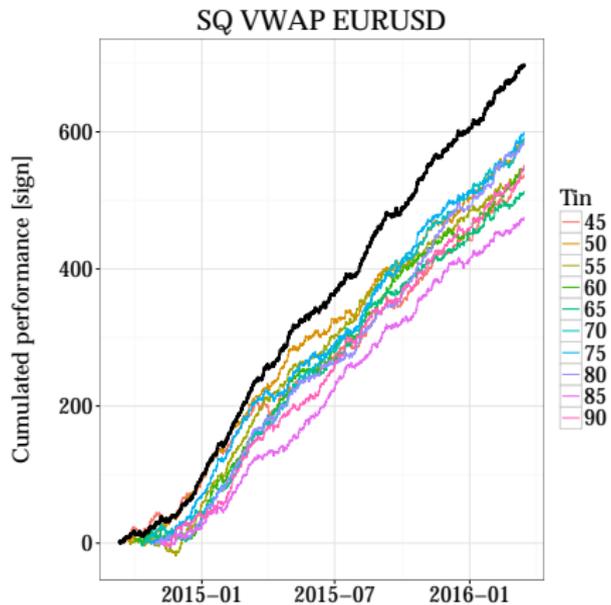
- 4 \sim : vanilla Random Forest

Conditions of success

- 1 VWAP predictable if order flow is predictable
- 2 Order flow depends on past prices
- 3 FX traders: systematic strategies



Result: VWAP



- ① Order flux OK
- ② VWAP OK
- ③ Trader's activity is triggered by that of other traders

Todo

- Reverse engineer strategy of groups
- Other fields
- Other time horizons
- ...