

Statistical Arbitrage Using Limit-Order Book Imbalance

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Modelling Imbalance

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Incorporating Price Change

Next, consider a two-dimensional CTMC $Z(t)$ that jointly models imbalance bin $\rho(t)$ and price change $\Delta S(t)$, where

$$\rho(t) \in \{1, 2, \dots, \#_{bins}\}$$

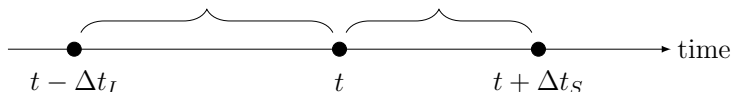
is the bin corresponding to imbalance averaged over the interval $[t - \Delta t_I, t]$, and

$$\Delta S(t) = \text{sgn}(S(t + \Delta t_S) - S(t)) \in \{-1, 0, 1\}$$

is the *sign* of the change in midprice of the *future* time interval Δt_S .

$\rho(t)$ is the imbalance bin of the time-weighted average of $I(t)$ over this past interval.

$\Delta S(t)$ is the sign of the mid-price change over this future interval.



Using MLE, we obtain a generator matrix \mathbf{G} for the CTMC. The transition matrix over a step of size Δt_I is given by

$$\mathbf{P}(\Delta t_I) = [p_{ij}(\Delta t_I)] = e^{\mathbf{G}\Delta t_I}$$

called our *one-step transition probability matrix*. Matrix entries give the probability of transition from one (imbalance, price change) pair to another over the time interval Δt_I . This can be written semantically as

$$p_{ij} = \mathbb{P}[\varphi(\rho_{\text{curr}}, \Delta S_{\text{future}}) = j \mid \varphi(\rho_{\text{prev}}, \Delta S_{\text{curr}}) = i]$$

Using Bayes' Rule, we can transform the \mathbf{P} matrix to

$$\mathbb{P}[\Delta S_{\text{future}} = j \mid B, \rho_{\text{curr}} = i] = \frac{\mathbb{P}[\rho_{\text{curr}} = i, \Delta S_{\text{future}} = j \mid B]}{\mathbb{P}[\rho_{\text{curr}} = i \mid B]}$$

This allows us to predict future price moves. We'll call the collection of these probabilities the \mathbf{Q} matrix.

Predicting Future Price Change

Sample Q matrix.

	$\Delta S_{\text{curr}} < 0$			$\Delta S_{\text{curr}} = 0$			$\Delta S_{\text{curr}} > 0$		
	$\rho_{\text{curr}} = 1$	2	3	1	2	3	1	2	3
$\Delta S_{\text{future}} < 0$									
$\rho_{\text{prev}} = 1$	0.53	0.15	0.12	0.05	0.10	0.14	0.08	0.13	0.14
$\rho_{\text{prev}} = 2$	0.10	0.58	0.14	0.07	0.04	0.10	0.13	0.06	0.12
$\rho_{\text{prev}} = 3$	0.08	0.12	0.52	0.09	0.06	0.03	0.11	0.10	0.05
$\Delta S_{\text{future}} = 0$									
$\rho_{\text{prev}} = 1$	0.41	0.75	0.78	0.91	0.84	0.79	0.42	0.79	0.77
$\rho_{\text{prev}} = 2$	0.79	0.36	0.71	0.83	0.92	0.82	0.75	0.37	0.78
$\rho_{\text{prev}} = 3$	0.79	0.74	0.40	0.81	0.83	0.91	0.70	0.76	0.39
$\Delta S_{\text{future}} > 0$									
$\rho_{\text{prev}} = 1$	0.06	0.10	0.09	0.04	0.06	0.07	0.50	0.09	0.09
$\rho_{\text{prev}} = 2$	0.10	0.06	0.15	0.10	0.04	0.08	0.12	0.57	0.10
$\rho_{\text{prev}} = 3$	0.13	0.14	0.08	0.10	0.11	0.05	0.19	0.14	0.56

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Trading Strategies Informed by the Q Matrix

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- Naive** Use market orders to buy (sell) if price is predicted to move up (down).
- Naive+** Post at-the-touch limit orders when zero price change is predicted.
- Naive++** Post a limit order to buy (sell) if price is predicted to move up (down).

Need to select:

- ▶ price change observation period Δt_S
- ▶ imbalance averaging period Δt_I
- ▶ number of imbalance bins $\#_{bins}$

Calibration done on the first day of the trading year, same parameters used for all days.

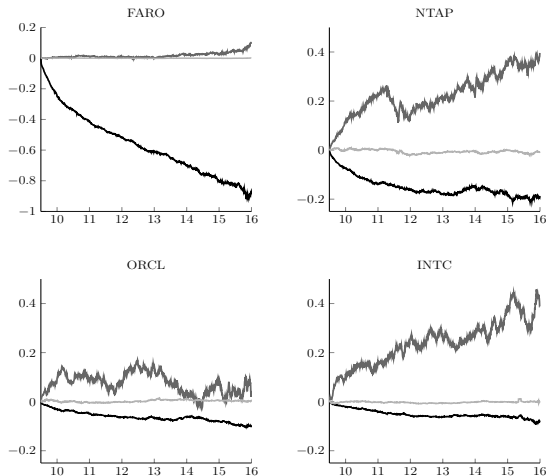
Brute-force search of parameter space, using max Sharpe ratio criterion, found that $\Delta t_S = \Delta t_I = 1\text{sec}$, and $\#_{bins} = 4$

Results of Naive Trading Strategies

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Normalized Profit and Loss (P&L)



Time (h)

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Why is the Naive strategy producing, on average, normalized losses?

- ▶ Backtest is out-of-sample; evidence to reject time-homogeneity
- ▶ Calibration is done on first trading day; likely nonrepresentative of trading activity
- ▶ Price change probability matrix \mathbf{Q} obtained using midprices, ignoring bid-ask spread; $\text{sgn}(\Delta S)$ may be insufficient for create profit, especially on FARO

Why do the Naive+ and Naive++ strategies outperform the Naive strategy?

- ▶ LOs vs MOs means different transaction price is being used (only MO loses value)
- ▶ Naive only executes when predicting non-zero price change
 - ▶ Only sign, not magnitude
 - ▶ Only *if one was already seen*

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- ▶ Imbalance Averaging Time Δt_I
A constant, specifying the time window over which the imbalance ratio $I(t)$ will be averaged.
- ▶ Price Change Time Δt_S
A constant, specifying the time window over which price changes will be computed.
- ▶ Number of Imbalance Bins $\#_{bins}$
A constant, specifying the number of bins (spaced by percentiles, symmetric around zero) into which $I(t)$ will be sorted.
- ▶ Imbalance ρ_t
The finite, discrete stochastic process that results from sorting $I(t)$ into the imbalance bins $\{1, \dots, \#_{bins}\}$, and which evolves in accordance with the CTMC \mathbf{Z} .

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- ▶ Midprice S_t
Stochastic process, evolves according to CTMC \mathbf{Z} .
- ▶ Midprice Change $\Delta S_t = \text{sgn}(S_t - S_{t-\Delta t_S})$
- ▶ Imbalance & Midprice Change $\mathbf{Z}_t = (\rho_t, \Delta S_t)$
Continuous-time Markov chain with generator \mathbf{G} .
- ▶ Bid-Ask Half-Spread ξ
Assumed constant. 2ξ is equal to the bid-ask spread.
- ▶ Midprice Change $\{\eta_{0,z}, \eta_{1,z}, \dots\} \sim F_z$
i.i.d. RVs, with distribution dependent on the Markov chain state.

- ▶ Other Agent Market Orders K_t^\pm
Poisson processes with rate $\mu^\pm(\mathbf{Z}_t)$. K^+ represents the arrival of another agent's buy market order.
- ▶ Our Limit Order Posting Depth δ_t^\pm
One of our controlled \mathcal{F} -predictable processes. δ^+ dictates how deep on the buy side we will post our buy limit order; $\delta^+ = 0$ implies at-the-touch.
- ▶ Our Limit Order Fill Count L_t^\pm
Counting processes (not Poisson), satisfying

$$\mathbb{P}[dL_t^\pm = 1 \mid dK_t^\mp = 1] = e^{-\kappa \delta_t^\pm}$$

- ▶ Fill Probability Constant κ
Fitted to satisfy the above relation, by considering the avg vol available at the first few depths relative to distribution of volumes of incoming market orders
- ▶ Our Market Orders M_t^\pm
 M^+ represents our buy market order. Assume we achieve the best bid/ask price.
- ▶ Our Market Order Execution Times
 $\tau^\pm = \{\tau_k^\pm : k = 1, \dots\}$
An increasing sequence of \mathcal{F} -stopping times.

► Cash $X_t^{\tau,\delta}$

A stochastic variable representing our cash, initially zero, that evolves according to

$$\begin{aligned} dX_t^{\tau,\delta} = & \underbrace{(S_t + \xi + \delta_t^-) dL_t^-}_{\text{sell limit order}} - \underbrace{(S_t - \xi - \delta_t^+) dL_t^+}_{\text{buy limit order}} \\ & + \underbrace{(S_t - \xi) dM_t^-}_{\text{sell market order}} - \underbrace{(S_t + \xi) dM_t^+}_{\text{buy market order}} \end{aligned}$$

► Inventory $Q_t^{\tau,\delta}$

A stochastic process representing our assets, initially zero, that satisfies

$$Q_0^{\tau,\delta} = 0, \quad Q_t^{\tau,\delta} = L_t^+ + M_t^+ - L_t^- - M_t^-$$

Call $W_t^{\tau,\delta}$ our net present value (NPV) at time t . Hence $W_T^{\tau,\delta}$ at terminal time T is our 'terminal wealth.'

At T , we:

- ▶ finish each trading day with zero inventory (avoid overnight positional risk)
- ▶ submit a market order (of a possibly large volume) to liquidate remaining stock
- ▶ price achieved will be $S - \xi \operatorname{sgn} Q - \alpha Q$
 - ▶ $\xi \operatorname{sgn} Q$ represents crossing the spread
 - ▶ α is a penalty constant
 - ▶ αQ represents receiving a worse price linearly in Q due to walking the book

Hence, $W_t^{\tau,\delta}$ satisfies:

$$W_t^{\tau,\delta} = \underbrace{X_t^{\tau,\delta}}_{\text{cash}} + \underbrace{Q_t^{\tau,\delta} \left(S_t - \xi \operatorname{sgn}(Q_t^{\tau,\delta}) \right)}_{\text{book value of assets}} - \underbrace{\alpha \left(Q_t^{\tau,\delta} \right)^2}_{\text{liquidation penalty}}$$

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Our performance criterion will be to maximize terminal wealth:

$$H^{\tau, \delta}(t, x, s, z, q) = \mathbb{E}_{t, x, s, z, q} \left[W_T^{\tau, \delta} \right]$$

The *value function* is given by

$$H(t, x, s, z, q) = \sup_{\tau \in \mathcal{T}_{[t, T]}} \sup_{\delta \in \mathcal{A}_{[t, T]}} H^{\tau, \delta}(t, x, s, z, q)$$

Admissible trading strategies is the product of the set \mathcal{T} of all \mathcal{F} -stopping times, with the set \mathcal{A} of all \mathcal{F} -predictable, bounded-from-below depths $\delta \geq 0$.

- ▶ recognizing τ does not require knowledge of the future
- ▶ δ cannot 'see into the future'; measurable with respect to information at an earlier time

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