Order book model with herd behavior and long-range memory

Aleksejus Kononovicius, Julius Ruseckas

Institute of Theoretical Physics and Astronomy, Vilnius University

aleksejus.kononovicius@tfai.vu.lt
http://kononovicius.lt/, http://rf.moklasplius.lt/
This talk based on an article

Order book model with herd behavior exhibiting long–range memory

Aleksejus Kononovicius, Julius Ruseckas
Institute of Theoretical Physics and Astronomy, Vilnius University

Abstract

In this work, we propose an order book model with herd behavior. The proposed model is built upon two distinct approaches: a recent empirical study of the detailed order book records by Kanazawa et al. [Phys. Rev. Lett. 120, 138301] and financial herd behavior model. Combining these approaches allows us to create a more plausible financial market model, which is also capable to replicate the long-range memory phenomenon of the absolute return and the trading activity. We compare the statistical properties of the model against the empirical statistical properties of the Bitcoin exchange rates and New York stock exchange tickers. We also show that the fracture in the spectral density of the high–frequency absolute return time series might be related to the mechanism of convergence towards the equilibrium price.

The article will appear in Physica A (DOI: 10.1016/j.physa.2019.03.059)
If spectrum of a time series takes power-law form:

\[ S(f) \sim \frac{1}{f^\beta}, \quad 0.5 < \beta < 2, \]

then we say that the time series exhibits long-range memory. In the ideal case \( \beta \approx 1 \) as \( f \to 0 \).
Long–range memory in the Bitcoin time series

(a) $p(r)$ vs $r$

(b) $S_r(f)$ vs $f$

(c) $p(n)$ vs $n$

(d) $S_n(f)$ vs $f$
Simple stochastic model of long–range memory

It is known that solutions, \( y(t) \), of the SDE in Ito sense,

\[
\text{d}y = \left( \eta - \frac{\lambda}{2} \right) y^{2\eta-1} \text{d}t + y^\eta \text{d}W,
\]

with \( \eta > 1 \), have power–law spectrum:

\[
S(f) \sim f^{-\beta}, \quad \beta = 1 + \frac{\lambda - 3}{2(\eta - 1)},
\]

and also that the stationary distribution of \( y \) is also a power–law (exponent \( \lambda \)).

e.g.: [Ruseckas and Kaulakys, PRE 81: 031105 (2010)]

financial market application: [Gontis et al., Physica A 389: 100–106 (2010)]
Imitative behavior model

Suppose we have $N$ agents, which choose between two states. Let $X$ be the number of agents choosing the first state. Let each agent change his opinion either independently ($\sigma_i$) or due to imitation ($h$).

Then system-wide transition rates given by:

$$\lambda(X \to X + 1) = (N - X)(\sigma_1 + hX),$$
$$\lambda(X \to X - 1) = X(\sigma_2 + h[N - X]).$$

It is straightforward to show that $\frac{X}{N} \sim \text{Be} \left( \frac{\sigma_1}{h}, \frac{\sigma_2}{h} \right)$ when $N \to \infty$.


equivalent to Voter model [Clifford and Sudbury, Biometrika 60: 581–588 (1973)]
Suppose that two states correspond to chartist and fundamentalist trading strategies.

Suppose that chartists trade based on the mood:

\[ D_c = r_0 X_c \xi, \quad \xi = \frac{X_o - X_p}{X_c}. \]

Suppose that fundamentalists trade based on the fundamental information.

\[ D_f = X_f \ln \frac{P_f}{P}. \]

From Walras equilibrium condition we can define return:

\[ D_c + D_f = 0, \quad \Rightarrow \quad r = r_0 \frac{X_c}{X_f} \Delta \xi = r_0 \frac{X}{N - X} \Delta \xi. \]

Properties of $y = \frac{X}{N-X}$

Corresponding SDE for $y = \frac{X}{N-X}$ is:

$$dy = \left(\sigma_1 + \frac{2h - \sigma_2}{\tau(y)}y\right)(1+y)dt + \sqrt{2h\frac{y}{\tau(y)}}(1+y)dW,$$

with feedback scenario $\tau(y) = y^{-\alpha}$. 

![Graphs showing probability density and power spectra](image_url)
Imitative behavior matching to the empirical data

If we describe $\xi$ dynamics using the same imitative behavior model and include “exogenous” noise, we were able to replicate the empirical data from various stock markets.

Model with $y$ and $\xi$ dynamics and “exogenous” noise (red curve) against NYSE 1 minute return (blue curve).

What is the nature of the “exogenous” noise?

Similarly as in ARCH family models, we have assumed that $y$ and $\xi$ dynamics drive the unobserved volatility of the market, while some exogenous randomness affects what the observed return:

$$r_t \sim \mathcal{N}(0, \sigma), \quad \sigma = f(y, \xi).$$

- The nature of the exogenous noise is dubious.
- The model implies certain things about trading activity which do not relate to the observed reality.
Order book dynamics?! 

- There is no market marker – prices are “negotiated”
- **Bid** = Buy
- **Ask** = Sell
- **Limit orders** – to buy/sell at specified price (time?)
- **Market order** – to buy/sell now (price?)
Behavior of agents in order-book terms

- Chartists place limit orders to the both sides of the order book at quotes (=desired prices) $Q_i = V \pm S_i$.
- $V$ is updated instantaneously after each transaction.
- Chartists submit market orders based on the current market mood.
- Fundamentalists submit market orders (only) based on the market fundamentals.

[Kanazawa et al., PRL 120: 138301 (2018)]
Possible events within our model and their reasonable time scales

- Chartists adjust their valuation, cancel and deposit limit orders (instantaneous).
- Chartists submit market orders, $p_{bid} = \frac{1+\xi(t)}{2}$ (seconds).
- Fundamentalists submit market orders, bid if $P_f > P(t)$, ask if $P_f < P(t)$ (seconds).
- Chartists flip their mood, $\xi(t + \Delta t) = -\xi(t)$ (tenths of minutes).
- Agents switch between chartist and fundamentalist trading strategies (multiple hours).
Trade submission must be faster than switching dynamics

Order book model
Then $y$ and return are correlated.
Matching the Bitcoin time series

(a) $p(r)$ vs. $r$ with a log-log scale.
(b) $S_r(f)$ vs. $f$ with a log-log scale.
(c) $p(n)$ vs. $n$ with a log-log scale.
(d) $S_n(f)$ vs. $f$ with a log-log scale.
Conclusions

- We have combined stochastic (phenomenological), herd behavior (abstract) and order book (realistic) models.
- The new model replicates return and trading activity statistics.
- It touches upon the topic of efficient markets and price convergence. It seems that the markets catch up with “equilibrium” in a trading day or two.
- Opens up a path for Bayesian inference – the model provides a physical meaning for the size of order book and its sides.

Based on [A. Kononovicius, J. Ruseckas, accepted to PhysA, doi: 10.1016/j.physa.2019.03.059]

Similar Bayesian approaches are already in development [T. Lux, J Eco Dyn Con 91: 391–408 (2018)].
Thank you!

email: aleksejus.kononovicius@tfai.vu.lt