An agent-based financial market model with information sharing

Michał Kaftanowicz, M.Sc.Eng.

positif.ly

2018-03-12

positif.ly

positif.ly is an insight elicitation platform designed to perfect human-machine interaction that poses probing questions to relevant respondents, rewards those who share their knowledge honestly, and delivers rated insights back to clients.

Information elicitation process done on behalf of a client on the positif.ly platform is called **pulsing**.

Problem statement

- How much can an access to elicited information about other market participants' beliefs and anticipated behavior improve your trading margins?
- How does this positif.ly premium depend on environment, model's structural assumptions and agents' behavioral parameters?

Success conditions

- Simplicity
- Ease of visualization and interpretation
- Face validity
- Ability to translate at least some of the model parameters into product operating parameters (e.g. pulse group sizes and target market penetration where premium is maximized for specific markets)

Chosen tools

- Agent-based model of a financial market
- Python 3
- Mesa framework

Agent-based models of financial markets

Westerhoff (2004):
"(...) Day and Huang (1990) derive complex dynamics from nonlinear fundamental trading rules, whereas in the models of Chiarella (1992), Chiarella et al. (2002), and Farmer and Joshi (2002) the agents apply nonlinear technical trading rules. The switching process developed by Kirman (1991) depends on social interactions. In Brock and Hommes (1998), the traders tend to select predictors that have been profitable in the recent past. Lux and Marchesi (2000) combine social interactions and profit considerations."

Agent-based models of financial markets

Westerhoff (2004):
"On the one hand, these models are remarkably successful in replicating the stylized facts of financial markets. On the other hand, these models have clearly improved our knowledge about what is going on in the markets. A main insight is that asset prices are at least partially driven by an endogenous nonlinear law of motion."

Model assumptions

- Single asset
- Explicit fundamental value process
- Two types of traders: chartists and fundamentalists
- No long-term strategy – traders are Markovian
- No double auction – demand influences price via price impact function

Model parameters

- Number of traders
- Proportion of fundamentalists
- Ratio of agents using positif.ly
- positif.ly pulse group sizes
- Fundamental value time series
- Market maker coefficient

Agents parameters

- Demand coefficient
- Confidence coefficient
- Pulse group size (fundamentalists)
- Learning coefficient (fundamentalists)
- Trend following strength and trend reversal strength coefficients (chartists)
- Starting wealth
- Period wage
- Number of starting shares

Chartists

Each chartist tries to predict the asset price in the next step using its current and previous price:

$$E_t^i(P_{t+1}) = \begin{cases} P_t + (P_t - P_{t-1})c_{tfs}^i & \text{with prob. } pr_{tf}^i \\ P_t - (P_t - P_{t-1})c_{tfs}^i c_{trs}^i & \text{with prob. } (1 - pr_{tf}^i) \end{cases} \quad (1)$$

where:

- $P_t = \log(p_t)$
- c_{tfs}^i is trend following strength coefficient
- c_{trs}^i is (relative) trend reversal strength coefficient
- pr_{tf}^i is trend following probability

Hence, chartist traders randomly choose between two simple technical analysis rules: trend following or trend reversal.

Fundamentalists

Each fundamentalist tries to assess the fundamental value of the asset:

$$E_t^i(FV_t) = (1 - c_{la}^i)(E_{t-1}^i(FV_{t-1}) + (FV_t - FV_{t-1}) + \varepsilon_t^i) + c_{la}^i FV_t \quad (2)$$

where:

- c_{la}^i is agent's learning ability coefficient
- ε_t^i is random perception error term

Hence, in each step fundamentalist traders update their previous FV assessment by a FV change perceived with a random error and correct towards the true FV proportionally to their learning ability.

Information sharing

- Some fundamentalist traders have access to get additional signals from pulsing of their peers
- Pulsing groups are formed randomly
- Their FV assessments become averages of assessments of responders from pulsing group (and their own)
- Their confidence increases:

$$c^i_{conf} = (1 + \log_{10}(n^i_{pulse})) \tag{3}$$

where n^i_{pulse} is the number of of respondents in fundamentalist i's pulse group, if they are using positif.ly

Agents' demand

Both chartist and fundamentalist traders place orders according to the demand function:

$$d_t^i = (\log(v_t^i + 1) - \log(p_t + 1)) c_d^i c_{conf}^i \tag{4}$$

where:

- p_t is asset price at time t
- v_t^i is $E_t^i(P_{t+1})$ for chartists and $E_t^i(FV_t)$ for fundamentalists
- c_d^i is agent's demand coefficient
- c_{conf}^i is agent's confidence coefficient

Chartists buy if they expect the price to go up.

Fundamentalists buy if they perceive the price to be below the fundamental value.

Technical constrains on demand

Positive demand means buying, negative demand means selling.

- Can't buy more shares than you can afford
- Can't buy more shares than there are on the market
- Can't short-sell more shares than you could afford to buy back

Price impact function

Aggregated demand drives the market price up and down according to the formula:

$$p_t = p_{t-1}(1 + \mathrm{sgn}(d_t) c_{mm} |d_t|^{\phi}) \tag{5}$$

where:

- $d_t = \sum d_t^i$ is net demand
- c_{mm} is market maker coefficient
- ϕ is price impact exponent
- Source: Lillo et al. (2003)

Caveat: consequences of price impact function as opposed to double auction

Model dynamics

At each step:

- Fundamental value changes
- Agents get their wages
- Agents try to predict future price (chartists) and assess new fundamental value of the asset (fundamentalists)
- Agents using positif.ly pulse their respondents and update their assessments
- Agents compute their demand and buy or sell shares
- Price changes as a function of aggregate demand
- Agents' wealth, net worth and profits get updated

Trading results metrics

- **Wealth** is the amount of money agent owns. Gets increased with each step by periodic wage.
- **Net worth** is agent's wealth plus number of shares they own times current price.
- **Profit** is agent's net worth minus starting wealth minus sum of all periodic wages.
- **Mean positif.ly premium** is the relative difference of mean profit of agents with positif.ly access and mean profit of agents without it at a particular moment in time (step in simulation run)
- **Mean positif.ly premium integral** is the sum of mean positif.ly premium values across the whole simulation run

Visualization

Mesa framework for Python 3 allows simple visualization in the browser.

Experiments - questions and setup

How does the mean positif.ly premium integral for fundamentalists depend on:

- fundamentalists proportion?
- fundamentalists intel ratio?
- fundamentalists intel sources number?
- fundamentalists learning ability?

Let's assume 300 steps for each run and the fundamental value time series of bitcoin price in 2015-2016, smoothed out using moving average with $n = 20$.

Experiments - fundamental value process

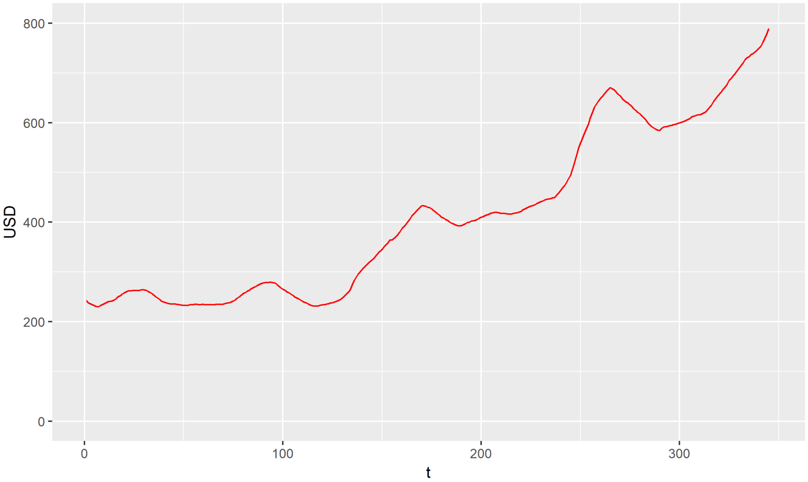

Figure 1: BTC price 2015-2016, smoothed out

Results

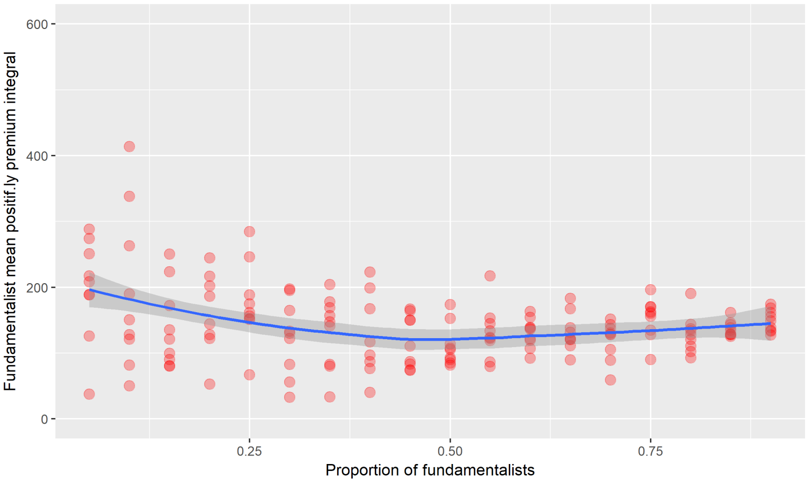

Figure 2: Relation between the proportion of fundamentalists and fundamentalist mean positif.ly premium integral

Results

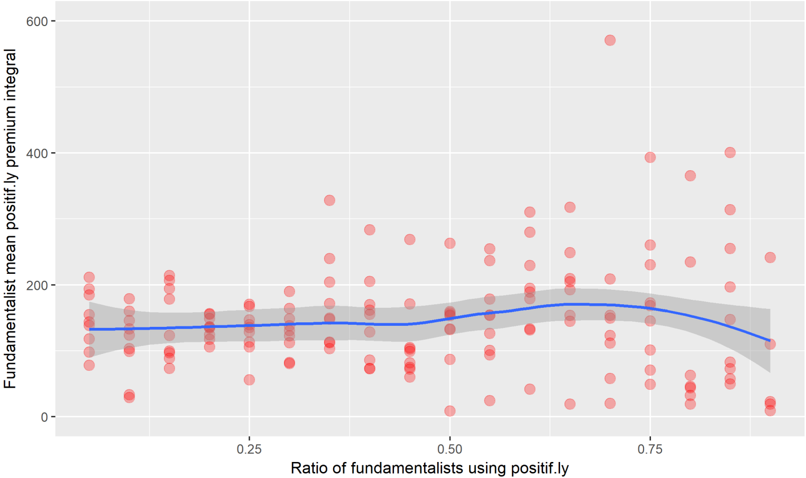

Figure 3: Relation between the ratio of fundamentalists using positif.ly and fundamentalist mean positif.ly premium integral

Results

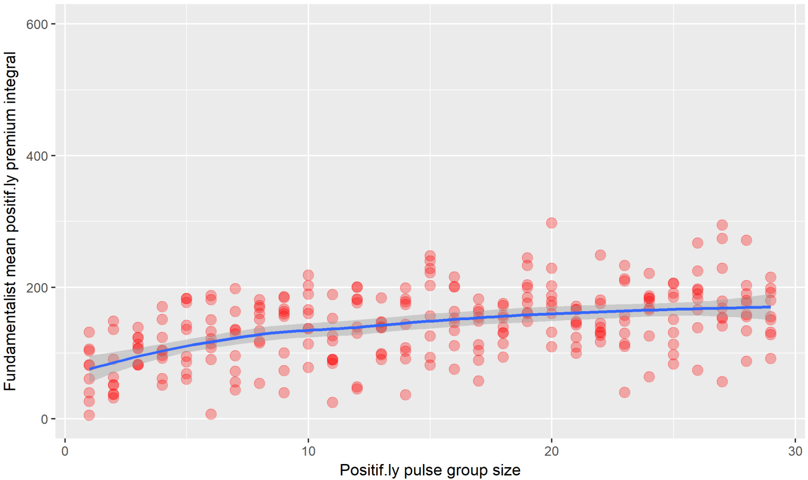

Figure 4: Relation between the positif.ly pulse group size and fundamentalist mean positif.ly premium integral

Results

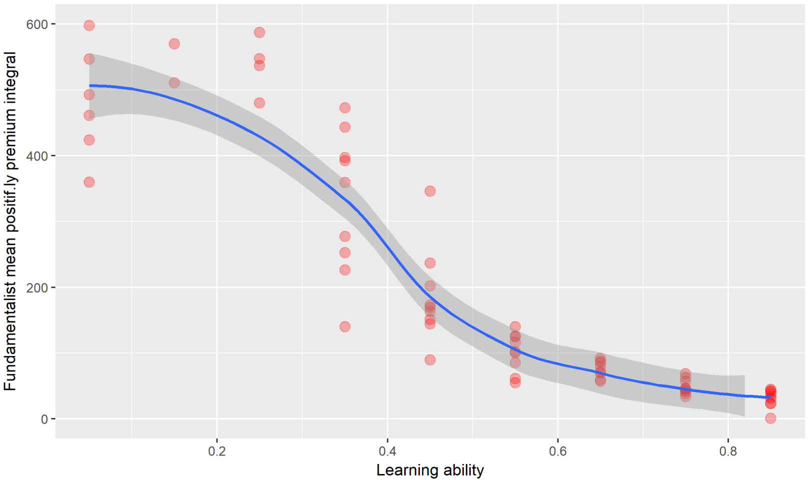

Figure 5: Relation between the learning ability and fundamentalist mean positif.ly premium integral

Conclusions

- It is possible to recreate realistically looking asset price movements using a simple agent-based model with nonlinear, stochastic trading rules
- Mean positif.ly premium integral is positive for the majority of simulated cases
- Mean positif.ly premium integral for fundamentalists becomes less variable when the proportion of fundamentalists among traders increases
- Mean positif.ly premium integral for fundamentalists becomes more variable when the ratio of them using positif.ly increases
- Mean positif.ly premium integral for fundamentalists increases when the pulse group size increases
- Mean positif.ly premium integral for fundamentalists decreases when agents' learning ability increases

Future directions

Extensions of the model

- Price discovery through double auction instead of demand price impact function
- Costly access to pulse results
- Exploring the relationship between pulse results access and pulse participation
- Strategic behavior of participants with regard to pulse:
  - How much noise might they purposefully add to their results?
  - Would they be willing to participate at all?
  - Pulse entering and exiting
- Reward mechanism design: how to maximize signal strength and pulse group retention?

Future directions

Calibration of the model

- Based on results of actual pulses with actual people
- Single global calibration? Per market? Per respondent group?

References

Day, R. H.; Huang, W. (1990). Bulls, bears and market sheep. Journal of Economic Behavior & Organization, 14(3), 299-329.

Lillo, Fabrizio; Farmer, Doyne J; Mantegna, Rosario N. (2003). Master Curve for Price-Impact Function. Nature. 421. 129-30. 10.1038/421129a.

Westerhoff, F. Multiasset market dynamics. Macroeconomic Dynamics, 2004, 8, 596-616

Thank you for your attention

Simulation code will be available at
`https://github.com/positifly/Value-simulation`.