Economics
The Open-Access, Open-Assessment E-Journal

Discussion Paper
No. 2017-63 | September 25, 2017 | http://www.economics-ejournal.org/economics/discussionpapers/2017-63

Fundamentals unknown: momentum, mean-reversion and price-to-earnings trading in an artificial stock market

Joeri Schasfoort and Christopher Stockermans

Abstract
The use of fundamentalist traders in the stock market models is problematic since fundamental values in the real world are unknown. Yet, in the literature to date, fundamentalists are often required to replicate key stylized facts. The authors present an agent-based model of the stock market in which the fundamental value of the asset is unknown. They start with a zero intelligence stock market model with a limit-order-book. Then, the authors add technical traders which switch between a simple momentum and mean reversion strategy depending on its relative profitability. Technical traders use the price to earnings ratio as a proxy for fundamentals. If price to earnings are either too high or too low, they sell or buy, respectively.

(Published in Special Issue Agent-based modelling and complexity economics)

JEL C63 D53 D84 G12 G17
Keywords Agent-based modelling; financial markets; technical and fundamental analysis; asset pricing

Authors
Joeri Schasfoort, ✉ University of Groningen, Groningen, The Netherlands, joerischasfoort@gmail.com
Christopher Stockermans, University of Groningen, Groningen, The Netherlands

The authors thank Julian Peters, Mark van der Broek, Vincent Velthuizen, Niels Gouda, Nick Szirbik,and Saina Abeshzadeh from the LcFP for their contributions to the model code and or process. Furthermore, the authors thank Dirk Bezemer for useful comments and feedback.

Citation Joeri Schasfoort and Christopher Stockermans (2017). Fundamentals unknown: momentum, mean-reversion and price-to-earnings trading in an artificial stock market. Economics Discussion Papers, No 2017-63, Kiel Institute for the World Economy. http://www.economics-ejournal.org/economics/discussionpapers/2017-63

Received September 12, 2017 **Accepted as Economics Discussion Paper** September 18, 2017
Published September 25, 2017

1 Introduction

Stock market modellers often assume that there is a fundamental value for stocks. This value is known by, at least, a subsection of the traders, also known as fundamentalists. The rest of the agent population is made up of price following, chartists, and random noise traders. Fundamentalists profit from selling stocks which are above their fundamental value and vice versa. Their activity drives the stock price back to underlying fundamental value. Recent examples include: Franke and Westerhoff (2012); Fischer and Riedler (2014); Leal and Napoletano (2017); Chiarella et al. (2017); Zhou and Li (2017).

This approach has been very successful in replicating some of the most well-known stylized facts about stock market returns: the absence of significant auto correlation (Samuelson, 1965; Cont, 2005; Stanley et al., 2008), fat tails (Gu et al., 2008), and volatility clustering (Gigerenzer and Selten, 2002). In these frameworks, the lack of auto correlation can largely be explained by fundamentalists trading on a noisy fundamental (Gaunersdorfer and Hommes, 2007), or by noise traders (Chiarella et al., 2009); chartist activity explains the fat tails (Cont and Bouchaud, 2000); and switching between the two explains volatility clustering (Lux and Marchesi, 2000).

There is evidence of both types of behaviour in actual markets (Balvers and Wu, 2006). However, Bouchaud et al. (2008) argue that the inclusion of traders which know the underlying fundamental value of a stock is somewhat of a heroic assumption. In reality the number factors influencing the fundamental value of a stock are so large that there should be, at the very least, an irreducible intrinsic error.

In this paper, we set out to develop an agent-based framework in which agents do not know the fundamental value. As fundamentals cannot be fully observed, traders use the price-to-earnings ratio as a proxy. If the price to earnings ratio is too high (too low), traders will try to sell (buy) stocks.

Our model consists of two types of traders, technical traders and zero-intelligence traders. Technical traders use a moving average trading strategy. Brock et al. (1992) identify moving average technical trading as profitable and widely used. In its simplest form this strategy means buying or selling when the short period moving average deviates from the long period moving average. Two contrary variants of this strategy, momentum (Hong and Stein, 1999) and mean-reversion (Balvers et al., 2000), can both be profitable. Balvers et al. (2000) even find that combination momentum-contrarian strategies outperform both pure momentum and pure contrarian strategies. Momentum traders estimate a price trend and assume that it will extrapolate. On the other hand, momentum traders calculate price deviations from the average price and assume that prices will revert to the trend.

We calibrate our model parameters to S&P500 data. Despite its weaker assumptions about fundamentals, our model is generally able to replicate the main observed stylized facts: no auto correlation, fat tails, and long memory in returns, along with volume correlations with price volatility and occasionally volatility clustering.

2 The Model

We model a stock market in which heterogeneous agents trade with each other following either mean-reversion or momentum strategies with a fundamental component or a zero-intelligence rule. The model was implemented using Python 3[1].

2.1 Agents

The model contains three types of agents: traders x, a firm f, and the stock market limit-order book which matches orders c. All agents are boundedly rational (Gigerenzer and Selten, 2002). They can observe their own state variables, the values of their state variables in previous periods, and some state variables of other agents.

Trader x, records the following state variables: an amount of deposits d_x and the number of stocks h_x it holds. Each individual trader has a time-frame over which it calculates moving averages: the short moving average q_x^1, and the long moving average q_x^2. In addition, each trader will have a currently preferred strategy: mean reversion s^u, momentum s^y, or zero-intelligence s^z.

Firm f records its stochastic profits or losses r. The firm has a fixed amount of stocks n_f which are distributed at the beginning of the simulation.

The stock market is implemented using a limit order book c. The limit-order book is made up of a bids-book, b_c, which holds all active bid-type orders and an asks-book a_c, which holds all active ask-type orders. At any time, the stock market keeps track of the best bid $o_{t,i}^{b*}$ and ask $o_{t,i}^{a*}$ type orders. Each limit order o contains information about the limit price p_o volume v_o and the agent x_o which issued it.

Table 1 provides an overview of the state variables and their domains. In the notation of variables, subscripts mark the agent and the time step t of the variable. Superscripts indicate indicate other parameter attributes: low (l), high (h), bid (b), ask (a) or if the variable or parameter refers to another variable or action.

[1] The code is available online at: https://github.com/LCfP/abm

Symbol	Description	Possible values
id	identifier	0-∞
r_f	Firm profits	0-∞
h_f	Firm amount of stocks outstanding	0-∞
d_x	Trader deposits i	0-∞
h_x	Trader stocks in portfolio i	0-∞
ba_x	Trader bid ask spread (measured in basis points)	[l, u]
r_x	Trader returns	0-∞
pe^h_x	Trader price-to-earnings upper threshold	24 - 28
pe^l_x	Trader price-to-earnings lower threshold	11 - 13
vr_x	Trader-volume-risk-aversion	fixed
η	Propensity-to-switch	fixed
q^1_x	Trader short moving average memory	50 - 60
q^2_x	Trader long moving average memory	65 - 93
s_x	Trader strategy	$\{u, y, z\}$
b_c	Bids book	list of bid orders
a_c	Asks book	list of ask orders
$o^b_{t,i}$	Best active bid order	bid order
$o^a_{t,i}$	Best active ask order	ask order
p_o	Limit-order price	0-∞
v_o	Limit-order volume	0-∞
x_o	Limit-order owner	0-∞

Table 1: State Variables

2.2 Simulation sequence

In this section we describe the simulation algorithm. We simulate agent actions and interactions over t periods. As a consequence of these actions and interactions, the state variables of the agents are updated every period. Unless stated otherwise, agents act in a random order. Each period represents a day in which the following sequence takes place.

Firm profits

At the beginning of certain working days n, firms release their updated profits r_f. We follow Bottazzi and Secchi (2003) and represent firm sectoral growth with a Geometric Brownian Motion:

$$r_t = r_{t-1} W(\mu, \sigma, \delta) \tag{1}$$

Where $W(\mu, \sigma, \delta)$ is a process which follows a Geometric Brownian motion.

Trading

Then, traders enter the market. Random noise traders determine whether to buy or sell with equal probability. Noise traders supply liquidity in the market by buying and selling randomly. Noise traders x^o buy and sell randomly given probabilities to buy p_t^b and to sell p_t^s that are assigned every period.

If a trader is using a momentum or mean reversion strategy, it first determines if the stock is currently under or overpriced based on the price to earnings ratio, pe_t. If this is the case it will immediately submit an order to the order book which can either be a buy or a sell order,

$$o_t = \begin{cases} o_t^b & \text{if} \quad pe_t < pe_t^l, \\ o_t^s & \text{if} \quad pe_t > pe_t^h, \end{cases} , \tag{2}$$

If neither condition holds the trader will determine whether it wants to buy or sell using its trading strategy. The agent, following either x^u or x^y, decides to buy or sell by relying on the long and short moving average of the price. It calculates the momentum of the price series, m, by dividing the long term moving average, MA^l, by the short term moving average, MA^s,

$$m_t = \frac{MA^s}{MA^l}, \tag{3}$$

where momentum and mean reversion traders calculate momentum over a different time window. When prices gain momentum and vary from a calculated trend, mean reversion traders will buy and sell believing that the price will return to the original trend. On the other hand, momentum traders buy when the prices gain momentum and sell when it drops (Hong and Stein, 1999).

Thus, if the trader uses a momentum strategy it will try to buy if momentum is sufficiently high and vice verse,

$$o_t = \begin{cases} o_t^b & \text{if} \quad m > u, \\ o_t^s & \text{if} \quad m < l, \\ o_t^h & \text{if} \quad l < m < u, \end{cases} . \tag{4}$$

If the trader uses a mean reversion strategy it will try to sell high momentum stocks and buy negative momentum stocks,

$$o_t = \begin{cases} o_t^b & \text{if} \quad m < l, \\ o_t^s & \text{if} \quad m > u, \\ o_t^h & \text{if} \quad l < m < u, \end{cases} , \tag{5}$$

where, u and l are the upper and lower threshold the trader wants to buy/sell respectively. Then, the trader will decide at which volume and price it want to submit the limit order.

The trader submit an order price, o_t^p, close to the best (highest price) bid, o_t^{b*}, and best (lowest price) ask price , o_t^{a*}, present in the limit order book. The price is then a random variable with normal distribution with standard deviation θ set around o_t^{a*} and o_t^{b*} depending on if the trader wants to buy or sell, respectively.

$$o_t^p = \begin{cases} X \sim N(o_i^{p,s}, \theta) & \text{if} \quad o_t = o_t^b, \\ X \sim N(o_j^{p,b}, \theta) & \text{if} \quad o_t = o_t^s, \end{cases} . \tag{6}$$

Regarding volume, each trader has a volume risk parameter vr_x which accounts for its appetite for selling all its stock or depleting its money when taking selling or buying. The trader decides on the traded volume o_t^v as follows:

$$o_t^v = \begin{cases} \frac{d_{x,t}}{o_t^v} vr_x & \text{if} \quad o_t^b, \\ h_x vr_x & \text{if} \quad o_t^s, \end{cases} . \tag{7}$$

This offer is then sent to the limit-order book. As it enters the limit-order book, the stock market will redetermine the the best (highest price) bid, o_t^b, and best (lowest price) ask price and match them at the best ask price if the bid price is higher than the ask price,

$$o_t^{*,p} = o_t^{a*,p} \quad \text{if} \quad o_t^{b*,p} > o_t^{a*,p}. \tag{8}$$

The two orders are matched at the volume of the lowest volume order.

$$o_t^{*,v} = min(o_t^{a*,v}, o_t^{b*,v}) \tag{9}$$

Then, a transaction takes place. The bid holder j transfers an amount of money Δd_i to the ask holder i. Simultaneously the ask holder transfers a number of stocks Δh_j to the bid holder.

$$\Delta d_i = o_t^{*,p} o_t^{*,v}. \tag{10}$$

$$\Delta d_j = -\Delta d_i \tag{11}$$

$$\Delta h_j = o_t^{*,v}, \tag{12}$$

$$\Delta h_i = -\Delta h_j \tag{13}$$

The empty bids are then deleted from the order book. If there is volume left on the incoming order, the continuous double auction repeats itself until remaining volume is depleted or there are no more available matching orders.

As each agent exits the market, the age of the offers that are in the limit order book increases by 1. When an order reaches the expiration time c_ζ, it is removed from the order book. The next trader then proceeds to enter the market and the same process is repeated.

Strategy switching

After trading, momentum and mean reversion traders evaluate the performance of their strategy after a set number of days, n. Over this period, they compare their average returns, $\bar{r}_{x,n}$, to the average market return over this period, $\bar{r}_n$. The probability that the trader will keep its current strategy, pr, is determined by the amount of missed returns and the agent propensity to switch, η ,

$$pr_t = 1 - \eta(\bar{r}_n - \bar{r}_{x,n}) \tag{14}$$

Where the missed returns of trader k_x, is the difference between the volume adjusted average price at which the stock was traded and the price which the agent traded for in the previous period. η is the propensity to switch strategy.

2.3 Calibration

We calibrated the initial values of state variables and parameters so that the model matches the stylized facts from the S&P500. Table 2 presents an overview of the model parameters. To restrict the parameter space for the calibration somewhat, we set the simulation time to 200 days, the number of agents at 1000, and the time for profit updates / strategy evaluation to be 20 (working) days.

Then to calibrate the total amount of money, initial firm profit and the discount rate, we built a benchmark stochastic model filled with zero-intelligence traders which would result in a price-to-earnings ratio pe close to the average, $\bar{pe}_{sp500}$, and above the first quartile $q1$, pe^1_{sp500}, and below the second quartile $q2$, pe^2_{sp500}, S&P500 price-to-earnings ratios. For this, we retrieved monthly price-to-earnings ratios for the S&P500 from Quandl. We determined ranges, (start, end, step), for initial total money, (26000, 33000, 2000), initial firm profit, (1000, 10000, 2000), and the discount rate, (0.01, 0.25, 0.02). Then, we calculated all possible combinations of these parameters using full factorial sampling, see (Thiele et al., 2014), and simulated zero-intelligence model for each combination. Following Thiele et al. (2014),for every combination, we calculated the costs for deviations from the observed price-to-earnings ratio as,

$$c_{pe}(x) = \begin{cases} (\frac{\bar{x}_{sp500} - x_{sim}}{\bar{x}_{sp500}})^2 & \text{if} \quad x^1_{sp500} < x_{sim} < x^2_{sp500} \\ \infty & \text{otherwise} \quad . \end{cases} , \tag{15}$$

This led us to the values for these parameters which can be found in Table 2. Figure 1 shows the price to earnings dynamics in the model after the initial calibration exercise. This stable benchmark model serves as a starting point to calibrate the model with technical traders.

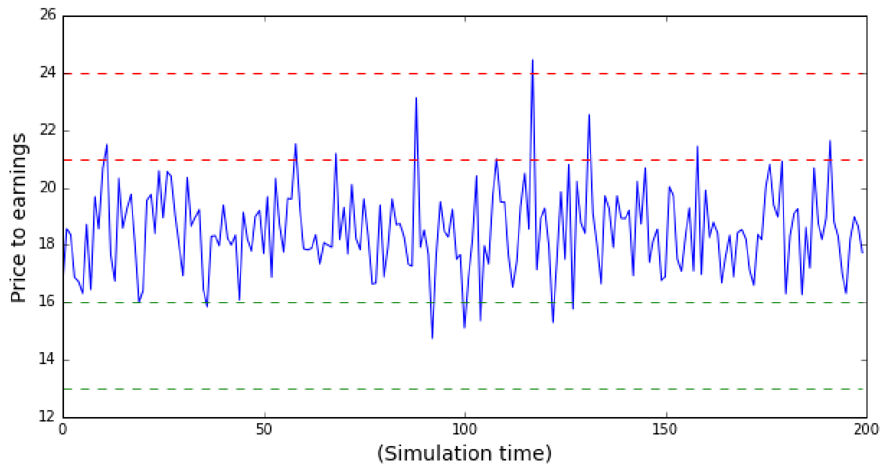

Figure 1: Price-to-earnings-ratio in the zero-intelligence model

Then, to determine the parameters needed to support momentum and mean-reversion trading, we calibrate the percentage technical traders versus noise traders, initial percentage mean-reversion traders versus momentum traders, price-to-earnings preferences, order expiration time, order-price-variability, order-variability, short and long moving average, hold threshold, and the propensity to switch strategy. For the second calibration, we sampled the parameter space using Latin Hypercube sampling. Then using Equation 15, we minimize the costs to match four stylized facts for returns: no autocorrelation ($c_a(w)$), fat tails ($c_f(x)$), volatility clustering ($c_v(y)$), and long-memory ($c_m(z)$). Our benchmark for this calibration was closing price and volume data for the S&P500 retrieved from Google Finance.

We calculate the total costs of each simulation as,

$$c(w,x,y,z) = c_a(w) + c_f(x) + c_v(y) + c_m(z). \tag{16}$$

After 500 simulations, we ended up with four parameter sets and picked the one with the lowest costs to end up with the remaining values in Table 2.

Symbol	Description[2]	Values (start, end, step)
ρ	Simulation time	1761, -, -
ι	Number of agents	1000, -, -
l	Number of periods between each firm profit update	20
μ	Firm percentage drift	0.058
δ	Brownian motion delta	0.00396825396
σ	Daily volatility expected in firm profits	0.125
d_0	Initial total amount of money*	[26000, 26000$*$1.1]
e_0	Initial profit*	1000
υ	Discount rate*	0.17
β	Share of mean reversion traders**	0, 1, 0.01
α	Share of momentum traders**	0, 1, 0.01
γ	Share of noise traders**	6
pe_0	Price to earnings window**	[(13, 16),(21, 24)]
ζ	Order expiration time**	(100, 10000)
ϕ	Agent order price variability**	1,1
χ	Agent order variability**	1.5
MA_0^s	Initial MA^s**	[20, 40]
MA_0^l	Initial MA^l**	[120, 150]
ω	Agent hold threshold**	[0.9995, 1.0005]
vr_x	Agent volume risk parameter**	0.1
η	Propensity to switch strategy**	1.1

Table 2: Parameters

[2] * Determined in the initial calibration, ** Determined in the second calibration.

3 Simulation Results

In this section, we explore the dynamics of the model. First, we review the stylized facts which the model is able to reproduce. Then, we discuss the model dynamics of a typical simulation exercise.

3.1 Model dynamics

In this section, we explore the typical dynamics of the model. At the very start of the model there is a small learning phase in which the model adjusts and the price settles in the upper are of the price-to-earnings window. The momentum traders push the price up, while technical traders with lower price-to-earnings ratios create downward price pressure. This period is characterized by relatively stable returns and volumes. Then, as the momentum traders start forgetting the upward momentum, prices start moving down. This means that the momentum changes, creating downward price pressure. As the price-to-earnings ratio approaches the threshold for most agents, they start to buy stocks, driving the price back up again. This can be seen in Figure 2.

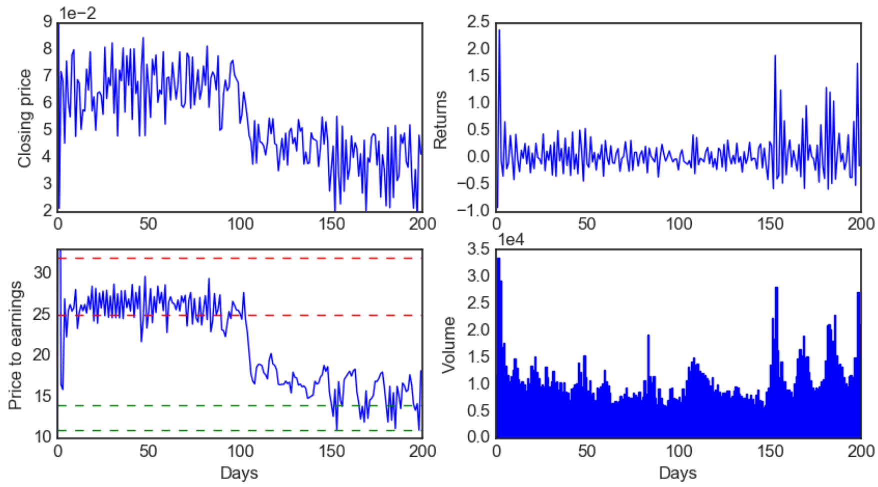

Figure 2: Typical closing price (top-left), Returns (top-right), Price-to-earnings ratios (bottom-left), and volume (bottom-right).

Over time, the momentum strategy proves to be marginally less profitable then the mean reversion strategy. This leads to some switching behaviour appreciated in Figure 3.

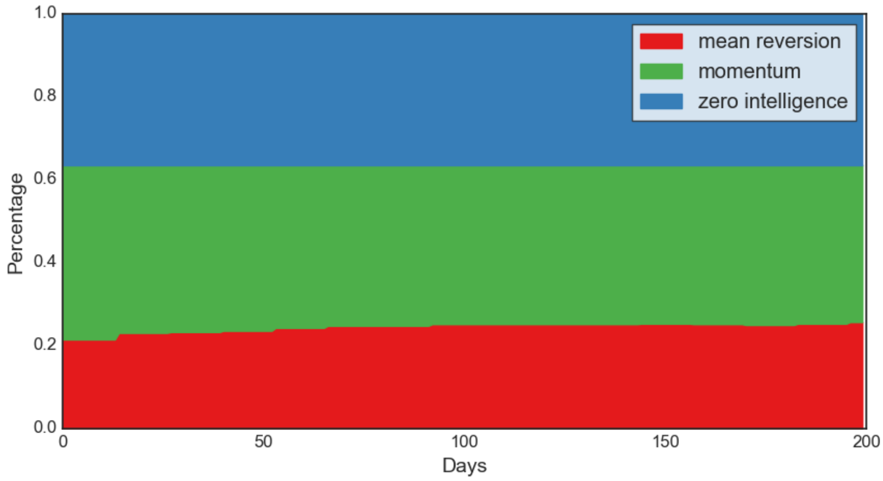

Figure 3: Share of trading strategies

3.2 Stylized facts

Stylized facts are statistical regularities that are reproduced in a wide range of different markets Buchanan (2012). Stock markets stylized facts are well documented, both on a micro and a macro level. For an extensive overview, we refer to Cont (2001); Gould et al. (2013). The capacity of a model to reproduce a list of these stylized facts acts as an initial metric of its validity.

Our model, like other contemporary models, is able to replicate five well established stylized facts at the same time. These stylized facts are: no auto correlations, fat tails, clustered volatility, and long-memory, although we note that clustered volatility only shows up in a minority of simulations.

Empirical results show that linear autocorrelations of asset returns are in most cases close to zero. Cont (2001) argues that if returns were autocorrelated, rational agents could more easily predict future returns. Arbitrage eliminates autocorrelation. Figure 4 show that, in our model, there is an absence of autocorrelation in returns. This is generated by both the noise traders and the contrarian interactions between momentum and mean-reversion traders.

In our model fat tails are generated by regimes in which the trend following agents are omni-present. Heavy tails can be observed if the (unconditional) distribution of returns displays a heavy tail with positive excess kurtosis Cont (2005). Fat tails, also known as heavy tailed distributions, empirical evidence displays heavier tails than what one would expect in a normal distributions Cont (2001). This means that extreme events occur more often than if returns followed normal distributions.

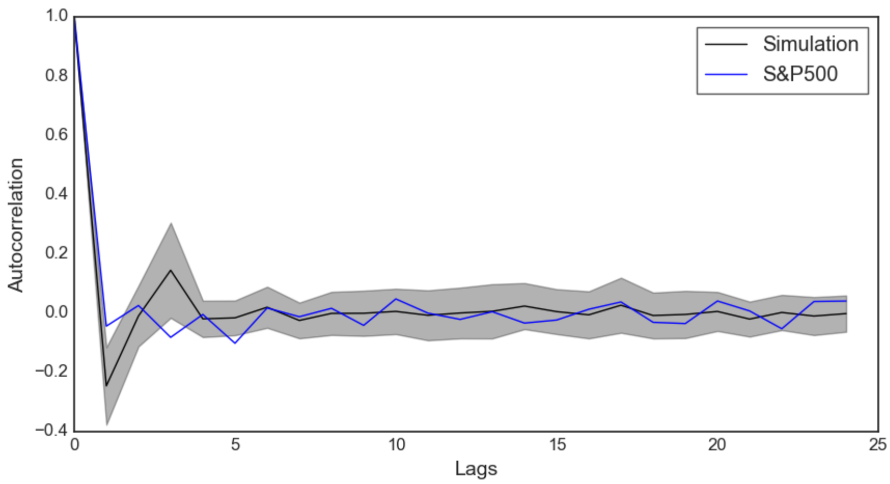

Figure 4: Autocorrelation in returns, Simulation average and standard deviations

Returns display irregular volatility at different time intervals (Gigerenzer and Selten, 2002). In the calibrated version of our model, absolute autocorrelations are positive and close the the observed values in the S&P500. However, this effect weakens over multiple runs. Figure 5 shows how for our calibrated model the autocorrelation in absolute returns approximates the S&P500 benchmark. However, as the grey band shows, this result does not hold up over multiple runs. In the baseline, volatility clustering is generated by a switch from one market regime to another, as the momentum disappears from memory. Similar to Guillaume et al. (1997) where differences in trader memories are also suggested to be the source of volatility clustering

Empirical returns have been shown to display long memory (Ferreira and DionÃsio, 2016; Arouri et al., 2012). The hurst component in our model also deviates from the 0.5 which characterizes a random walk. Table 3 summarizes the statistics associated with the stylized facts for both the S&P500 and the average of 50 simulation runs with different random seeds.

Stylized fact	S&P500	Model
Autocorrelation	-0.0079	-0.0055
Kurtosis	4.1262	94.3714
Autocorrelation abs	0.1602	0.0255
Hurst	-0.0024	0.0118
Correlation volume-price volatility	0.4671	0.2067

Table 3: Stylized facts model average over 50 runs

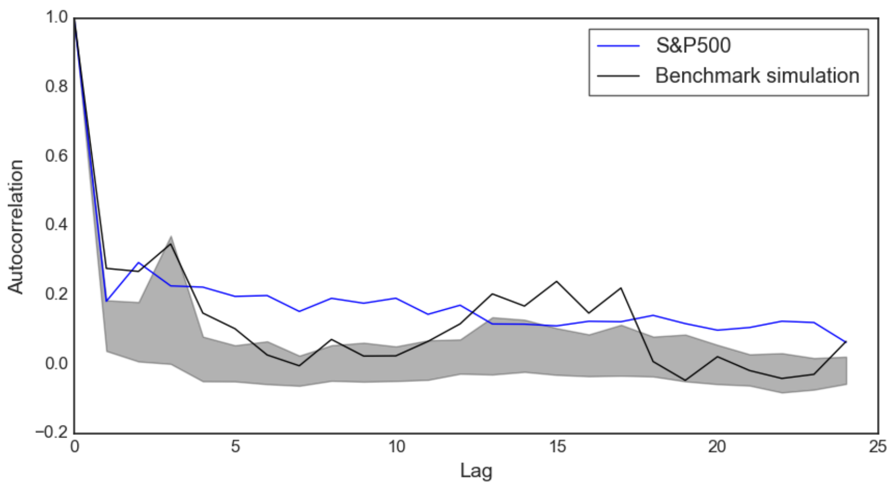

Figure 5: Autocorrelation in absolute returns, Simulation seed = 0 and standard deviations around the average

4 Summary and discussion

In this paper, we presented an agent-based framework in which agents do not know the fundamental value. Using a combination of momentum, mean reversion and noise traders and the price-to-earnings ratio, as a proxy for deviations from fundamentals, we where able to replicate the main observed stylized facts: no auto correlation, fat tails, and long memory in returns, along with volume correlations with price volatility and (occasionally) volatility clustering.

In future research, we would like to amend the model somewhat to replicate volatility clustering more consistently. Also, we would like to extend the analysis of this model by performing a sensitivity analysis on the parameters. This would help us explore exactly what flavours of this model can reproduce the stylized facts and why. We believe that our framework is flexible enough to replicate more stylized facts simultaneously. Ideally, both at the micro (order-book) and macro level.

Finally, we would like to make the model more realistic. We feel that the zero-intelligence traders are somewhat ad-hoc as such behaviour is not actually observed in real stock markets. In our model, these traders capture a host of different types of trading motivations such as market making and portfolio re-balancing. Therefore, in future works, we want to replace the noise traders by traders which follow market maker strategies and by traders which rebalance a portfolio of stocks. For the latter, we aim to extend our model with multiple firms and multiple stocks.

References

Arouri, M. E. H., Hammoudeh, S., Lahiani, A., and Nguyen, D. K. (2012). Long memory and structural breaks in modeling the return and volatility dynamics of precious metals. *The Quarterly Review of Economics and Finance*, 52(2): 207 – 218. ISSN 1062-9769. DOI http://dx.doi.org/10.1016/j.qref.2012.04.004. URL http://www.sciencedirect.com/science/article/pii/S1062976912000270.

Balvers, R., Wu, Y., and Gilliland, E. (2000). Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies. *The Journal of Finance*, 55(2): 745–772. ISSN 1540-6261. DOI 10.1111/0022-1082.00225. URL http://dx.doi.org/10.1111/0022-1082.00225.

Balvers, R. J., and Wu, Y. (2006). Momentum and mean reversion across national equity markets. *Journal of Empirical Finance*, 13(1): 24–48. DOI https://doi.org/10.1016/j.jempfin.2005.05.001. URL http://www.sciencedirect.com/science/article/pii/S0927539805000708.

Bottazzi, G., and Secchi, A. (2003). Common Properties and Sectoral Specificities in the Dynamics of U.S. Manufacturing Companies. *Review of Industrial Organization*, 23(3): 217–232. ISSN 1573-7160. DOI 10.1023/B:REIO.0000031366.28559.c1. URL https://doi.org/10.1023/B:REIO.0000031366.28559.c1.

Bouchaud, J., Farmer, J. D., and Lillo, F. (2008). How markets slowly digest changes in supply and demand. DOI https://ssrn.com/abstract=1266681. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1266681.

Brock, W., Lakonishok, J., and LeBaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance*, 47(5): 1731–1764. ISSN 1540-6261. DOI 10.1111/j.1540-6261.1992.tb04681.x. URL http://dx.doi.org/10.1111/j.1540-6261.1992.tb04681.x.

Buchanan, M. (2012). *It's a (stylized) fact!* Ph.D. thesis, Nature Research. DOI http://dx.doi.org/10.1038/nphys2191.

Chiarella, C., He, X.-Z., Shi, L., and Wei, L. (2017). A behavioural model of investor sentiment in limit order markets. *Quantitative Finance*, 17(1): 71–86. DOI 10.1080/14697688.2016.1184756. URL http://dx.doi.org/10.1080/14697688.2016.1184756.

Chiarella, C., Iori, G., and Perellò, J. (2009). The impact of heterogeneous trading rules on the limit order book and order flows. *Journal of Economic Dynamics and Control*, 33(3): 525 – 537. ISSN 0165-1889. DOI http://dx.doi.org/10.

1016/j.jedc.2008.08.001. URL http://www.sciencedirect.com/science/article/pii/S0165188908001437.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, 1(2): 223–236. DOI 10.1080/713665670. URL http://dx.doi.org/10.1080/713665670.

Cont, R. (2005). *Long range dependence in financial markets*, pages 159–179. London: Springer London. ISBN 978-1-84628-048-1. DOI 10.1007/1-84628-048-6_11. URL https://doi.org/10.1007/1-84628-048-6_11.

Cont, R., and Bouchaud, J. (2000). Herd behavior and aggregate fluctuations in financial markets. *Macroeconomic Dynamics*, 4(2): 170–196. URL https://www.cambridge.org/core/journals/macroeconomic-dynamics/article/herd-behavior-and-aggregate-fluctuations-in-financial-markets/51990E3780C6EBDA07A1753FC08E8453.

Ferreira, P., and DionÃsio, A. (2016). How long is the memory of the US stock market? *Physica A: Statistical Mechanics and its Applications*, 451: 502 – 506. ISSN 0378-4371. DOI http://dx.doi.org/10.1016/j.physa.2016.01.080. URL http://www.sciencedirect.com/science/article/pii/S0378437116001448.

Fischer, T., and Riedler, J. (2014). Prices, debt and market structure in an agent based model of the financial market. *Journal of Economic Dynamics and Control*, 48: 95–120. DOI https://doi.org/10.1016/j.jedc.2014.08.013. URL http://www.sciencedirect.com/science/article/pii/S0165188914002024?via%3Dihub.

Franke, R., and Westerhoff, F. (2012). Structural stochastic volatility in asset pricing dynamics: Estimation and model contest. *Journal of Economic Dynamics and Control*, 36(8): 1193–1211. DOI https://doi.org/10.1016/j.jedc.2011.10.004. URL http://www.sciencedirect.com/science/article/pii/S0165188912000802.

Gaunersdorfer, A., and Hommes, C. (2007). A nonlinear structural model for volatility clustering. *Long memory in economics*, pages 265–288. URL https://link.springer.com/book/10.1007/978-3-540-34625-8#page=272.

Gigerenzer, G., and Selten, R. (2002). *Bounded rationality: The adaptive toolbox*. MIT press.

Gould, M. D., Porter, M. A., Williams, S., McDonald, M., Fenn, D. J., and Howison, S. D. (2013). Limit order books. *Quantitative Finance*, 13(11): 1709–1742. URL http://www.tandfonline.com/doi/abs/10.1080/14697688.2013.803148.

Gu, G.-F., Chen, W., and Zhou, W.-X. (2008). Empirical distributions of Chinese stock returns at different microscopic timescales. *Physica A: Statistical Mechanics and its Applications*, 387(2): 495 – 502. ISSN 0378-4371. DOI http://dx.doi.org/10.1016/j.physa.2007.10.012. URL http://www.sciencedirect.com/science/article/pii/S0378437107010588.

Guillaume, D. M., Dacorogna, M. M., Davé, R. R., Müller, U. A., Olsen, R. B., and Pictet, O. V. (1997). From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets. *Finance and Stochastics*, 1(2): 95–129. ISSN 0949-2984. DOI 10.1007/s007800050018. URL https://doi.org/10.1007/s007800050018.

Hong, H., and Stein, J. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(2143-2184). URL http://www.economics-ejournal.org/economics/journalarticles/2007-13.

Leal, S. J., and Napoletano, M. (2017). Market stability vs. market resilience: Regulatory policies experiments in an agent based model with low-and high-frequency trading. *Journal of Economic Behavior & Organization*. DOI https://doi.org/10.1016/j.jebo.2017.04.013. URL http://www.sciencedirect.com/science/article/pii/S0167268117301142.

Lux, T., and Marchesi, M. (2000). Volatility clustering in financial markets: a microsimulation of interacting agents. *International Journal of Theoretical and Applied Finance*, 03(04): 675–702. DOI 10.1142/S0219024900000826. URL http://www.worldscientific.com/doi/abs/10.1142/S0219024900000826.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Managment Review*. URL https://search.proquest.com/openview/961f912f64105810cbc41db4da0497cb/1?pq-origsite=gscholar&cbl=35192.

Stanley, H. E., Plerou, V., and Gabaix, X. (2008). A statistical physics view of financial fluctuations: Evidence for scaling and universality. *Physica A: Statistical Mechanics and its Applications*, 387(15): 3967 – 3981. ISSN 0378-4371. DOI http://dx.doi.org/10.1016/j.physa.2008.01.093. URL http://www.sciencedirect.com/science/article/pii/S0378437108000903. Applications of Physics in Financial Analysis.

Thiele, J. C., Kurth, W., and Grimm, V. (2014). Facilitating Parameter Estimation and Sensitivity Analysis of Agent-Based Models: A Cookbook Using NetLogo and 'R'. *Journal of Artificial Societies and Social Simulation*, 17(3): 11. ISSN 1460-7425. DOI 10.18564/jasss.2503. URL http://jasss.soc.surrey.ac.uk/17/3/11.html.

Zhou, X., and Li, H. (2017). Buying on Margin and Short Selling in an Artificial Double Auction Market. *Computational Economics*. ISSN 1572-9974. DOI 10.1007/s10614-017-9722-4. URL https://doi.org/10.1007/s10614-017-9722-4.