

Learning to forecast, risk aversion, and microstructural aspects of financial stability

Alessio Emanuele Biondo

Abstract

This paper presents a simulative model of a financial market, based on a fully operating order book with limit and market orders. The heterogeneity of traders is characterized not only with regards to their trading rules, but also by introducing a behavioral individual risk aversion and a learning ability influencing the process of expectations formation. Results show that individual learning may play a role in stabilizing the aggregate market dynamics, whereas risk aversion can, counterintuitively, have perverse consequences on it.

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1 Introduction

Macroeconomics reveals to be an expression of complexity [53, 55]. Although several definitions of complex systems are available, it can be synthetically said that a complex system is characterized by the notion of *emergence*, i.e., the spontaneous formation of self-organized structures at a different layers of a hierarchical configuration, [40]. In a complex system, then, the interaction among several individual parts generates aggregate outcomes which qualitatively differ from the features of its constituents. One of the most dramatic consequence of this, as Prigogine explained, [69], is that any prediction about the timing of such emergent properties is only a waste of time. The theoretical consequences of complexity in macroeconomics are substantial, both in terms of research perspectives and of modeling tools, as discussed in relevant literature, [34, 50, 51, 78].

From a policy perspective, the recognition of such a complex nature of *aggregate Economics* should induce to ground the policy design very differently. Indeed, important suggestions may arise from the analysis of the effects produced by different individual characteristics on the global dynamics. An example of such an approach can be found in [14] where a study on some microstructural properties of the order book mechanism provided intuitions on possible policies for market stabilization.

The motivation of this paper is to check the effects due to heterogenous risk aversion and adaptive learning ability of traders on the stability of a financial market that operates through a realistic order book. Thus, the main result is the provision of the macro effects of micro features, which cannot act directly on the aggregate outcome but have a role in influencing the interactions among individuals. As Mitchell suggests, [65], the order book is a valid example of a complex system because its dynamics emerges as a global result of local individual interactions among traders. Thus, this paper makes a step forward in the direction of investigating how global extreme events, which characterize the behavior of actual markets, are possibly determined by individual characteristics of market participants determining how their orders are eventually managed and negotiated.

A vast literature on financial order book modeling exists. Crucial surveys can be found in [18, 68, 75]. Some existing models can be labelled as *trader-centric*, because they have been mainly based on frameworks aiming to derive fully rational optimal trading strategies, as in [19, 38, 48, 49, 67, 71, 72]; some other contributions can be named *facts-centric*, because they tended to study more the statistical features of the market as a dynamic process than the individual characterization of investors, as in [4, 15, 30, 32, 37, 64].

This paper is methodologically linked to a third stream of literature, which is inspired by the computational approach of agent-based models (ABMs) in economics. Such models, developed since the Nineties, have shown to be able to describe many aspects neglected by the orthodox modeling, as explained in [78]. Examples are, among others, [16, 17, 20, 21, 33, 39, 50, 58–60]. The heterogeneity of individuals and the global properties emerging from their interaction can be analyzed by means of specific statistical tools [63] and assume a determinant descriptive role in models of financial markets, as in [51, 56], and in models of order books, as in [22, 23, 27, 41, 70, 77].

In some recent works, the individual risk aversion has been considered in agent-based models to differentiate individual behavior. In particular, [74] adopts a model in which the probability of default of countries is explained by means of a modified version of [79], in which the risk aversion is negatively correlated with both default probability and income, whereas [35] describes different evolution of civil violence among citizens with different risk perceptions, and [46] show implications on flood risk analysis of different individual risk aversion of households. Focused on the description of financial markets, [36] discuss the effects of convex incentives on trading behavior of agents in a naive rational-investors-vs-noise-traders model, by showing that the risk aversion (through the incentives) may affect market dynamics. A broader approach is used by [3], who show how agents' behavior varies according to the combined effect of individual risk attributes and to learning abilities to account for errors done in past predictions. Other recent contributions show the impact

of self-correcting behavior. In [24, 25] an experiment is shown to report that agents use adaptive expectations instead of rational ones and that this may lead to a form of collective rationality (despite the absence of communication among participants), which consists in a robust divergence of predictions from the fundamental value. In particular, as in [26], traders systematically end up with an underestimation of the fundamental price. In [5] the origin of bubbles and crashes is questioned in terms of prediction errors: presented results of experiments in which non-optimal trend-following behaviors synchronize and reinforce the positive feedbacks between expectations and realised prices, even in presence of high trading heterogeneity. This exacerbates price oscillations and let optimism and pessimism arise even in presence of a stable fundamental value. In [52] it is shown that by fitting a genetic algorithms model of learning to laboratory experiments it is possible to get fruitful intuitions on market features for suitable policies.

The agent-based model here presented enriches the existing literature on the topic with regards to several aspects: first of all, heterogeneity is modeled not only in terms of behavioral attitude (as usually happens between *fundamentalists* and *chartists*) and with respect to individual informative sets (also within groups), but also in terms of risk aversion (by means of individual risk profiles) and adaptive learning ability (by means of the personal capability to remember past forecasting errors); secondly, orders (which can have variable quantity) have a time validity and they can be canceled before execution; third, the double auction mechanism governing the order-book results in a true contracts-driven price formation, in such a way that the simulated price series is entirely generated by the model and never added by any fictitious data, differently from [22, 23], among others; fourth, the quantity management system, designed for market orders.

The paper is organized as follows: section two contains the model description and validates the proposed framework by showing its compliance with the most acknowledged stylized facts of true financial data; section three is dedicated to simulations addressing the role played by individual features on market stability; section four will conclude.

2 The Market

Consider a fully connected network of heterogeneous agents as in [14]. In analogy with a wide body of existing literature, traders are distinguished by their informative endowment, as in [31, 42, 43, 54], among others. The present model embeds two usual and opposite attitudes to market participation. However, a variable accuracy of the owned information is added here. The two groups are named, as usual, *fundamentalists* and *chartists*: the former form their opinions by looking at information regarding the economic activity of the issuer and presume to know the “correct” value for the asset, i.e., the fundamental value; the latter, refer to the past performance of the asset price and estimate a reference value in order to infer the future trend.

2.1 Model Description

The heterogeneity of traders is detailed by giving each market participant a personal coefficient of risk aversion, and an individual possibility to learn from the past. Such features should be read in terms of informative qualifications of agents. Indeed, both are designed in order to differentiate the consciousness of investors with regards to both the past and the future. The execution of orders depends on a double auction mechanism, which relies on an order book where investors posts their orders (both market and limit orders), according to their heterogenous expectations. The effective registration of orders and the accountancy of negotiations are operated by a realistic order book without transaction costs. The series of simulative steps, from the expectations formation to the final execution of transactions, is marked by a sequence of phases within each cycle-run of the model. Such a sequence is preceded just by the order-validity management routine, which

identifies those traders who will actively participate to the successive steps and let the others (with active orders still pending in the order book) inactive for the current round. The steps are: 1) the expectations setting; 2) the strategy setting; 3) the order setting; 4) the order book management; 5) the trading. After each transaction, the price used for the negotiation is registered and a new cycle-run starts.

2.1.1 Expectations setting

In this model, traders are heterogenous. The individual expectation on the price dynamics of a fundamentalists is based on the fundamental value that she personally considers as the long-run appropriate value of the asset, at each time step, FV_t . In the model, the fundamental value is an exogenous variable, whose dynamics is set by:

$$FV_t = FV_{t-1} \pm \Theta_t \quad (1)$$

where Θ_t is a bounded random variable, drawn with uniform distribution within the interval $[-\sigma_\Theta, \sigma_\Theta]$ and FV_0 is set at the beginning of simulations. Each fundamentalist have her individual perception, possibly imperfect, of FV_t . Eventually, the price expectation of the fundamentalist i at time t is computed as:

$${}^i_F p_t^{exp} = FV_t \pm \Phi_t \quad (2)$$

where Φ_t is a bounded random variable, with uniform distribution in $[-\sigma_F, \sigma_F]$.

The individual price forecast of a chartist is, instead, built upon the inspection of past prices. Similarly to the approach adopted in [?], each chartist chooses a time window of a certain length and looks back to that portion of the past market prices series in order to define her personal reference value, which is computed as:

$${}^i_RV_t = \sum_{j=(t-\tau)}^t p_j / \tau \quad (3)$$

By eq.3 the average of last $\tau = (\tau_0 + \tau_i)$ prices, included in the chosen observational time window (ranging between $t - \tau$ and t), is computed. Further, $\tau_0 = 200$ and τ_i is an individual random variable with uniform distribution, in $(0, \delta)$. Then, the individual expected price of chartist i is:

$${}^i_C p_t^{exp} = p_t + \frac{p_t - RV_t}{\tau - 1} \pm \Lambda_t \quad (4)$$

where p_t is the current market price, Λ_t is a random variable with uniform distribution in $[-\sigma_C, \sigma_C]$ so that two traders with same time-window length may still have different expectations.

Eqs.(2) and (4) are widely acknowledged in related literature. Similar approaches can be found in [1, 2, 60, 76]. In terms of the composition of the community of agents, this configuration is conceptually different from the one used in other contributions, [22, 23], where each trader was designed as a weighted average of three components - fundamentalist, chartist, and noisy, with weights drawn from Gaussian distributions.

2.1.2 Strategy setting

The strategy to choose the trading behavior is set according to the following simple rule:

- if trader i expects a future price greater than the current one, i.e. ${}^i_j p_t^{exp} > p_t + \varsigma$, she will post a bid order and she will be a *bidder*, B_i ;
- if trader i expects a future price smaller than the current one, i.e. ${}^i_j p_t^{exp} < p_t - \varsigma$, she will post an ask order and she will be an *asker*, A_i ;

- in case of stationary expectations, i.e. $p_t - \varsigma \leq_j^i p_t^{exp} \leq p_t + \varsigma$, the trader will be a *holder*, and the trading strategy will be neither buy, nor sell.

where $j = F, C$ and ς is the *indolence* threshold, which measures the market nervousness: if the price forecast is not “sufficiently” different from the current market price, the investor will decide to wait without buying/selling.

2.1.3 Order setting

Orders details are price and quantity. They are decided without a utility function. The price setting rule for bid orders is based on the willingness to pay of the agent bidder, computed as a function of her expectations:

$${}^i_B w_t = {}^i p_t^{exp} - {}^i_A w_t^{exp} \quad (5)$$

The term ${}^i p_t^{exp}$ is i 's asset price expectation and ${}^i_A w_t^{exp}$ is i 's individual opinion about the askers' willingness to accept. Such an opinion is computed by weighting the reverted individual price expectation ${}^i p_t^{rev} = p_t - ({}^i p_t^{exp} - p_t) = 2p_t - {}^i p_t^{exp}$ (i.e., by letting the bidder form her hypothetical willingness to accept that she would have expressed in the case she were an asker):

$${}^i_A w_t^{exp} = {}^i \mu_\alpha {}^i p_t^{rev}$$

where ${}^i \mu_\alpha$ is an individual random variable, with uniform distribution, in $(0, \sigma_{\mu_\alpha})$.

Further, in analogy with [60,61], traders are able to perceive the market pressure deriving from demand/supply mismatch, $\Delta n = f(n_A, n_B)$, with n_A and n_B being, respectively, the number of askers and the number of bidders. Then, a bidder i computes the price of the order as:

$${}^i_B p_t = {}^i_B w_t + {}^i \mu_\beta [z_1 \Delta n + z_2 \Delta p] \quad (6)$$

where: Δp is the difference between the best quotes of the order book, which are computed as explained below, and are visible to all traders, as in true markets; ${}^i \mu_\beta \in (0, \sigma_{\mu_\beta})$, $z_1 \in (0, \sigma_{z_1})$, and $z_2 \in (0, \sigma_{z_2})$ are random variables with uniform distribution, which measure the influential weight of the market environment perceived by trader i . More details on Δn and Δp will be provided later.

The price setting rule for ask orders is symmetrically based on the willingness to accept of the agent asker, computed as a function of her expectations:

$${}^i_A w_t = {}^i p_t^{exp} + {}^i_B w_t^{exp} \quad (7)$$

In this case, i 's individual opinion about the bidders' willingness to pay, ${}^i_B w_t^{exp}$, is computed in analogy with the previously described rationale, by weighting the reverted individual price expectation ${}^i p_t^{rev} = p_t + (p_t - {}^i p_t^{exp}) = 2p_t - {}^i p_t^{exp}$ (i.e. by letting the asker form her hypothetical willingness to pay that she would have expressed in the case she were a bidder):

$${}^i_B w_t^{exp} = {}^i \mu_\alpha {}^i p_t^{rev}$$

Then, an asker i computes the price of the order as:

$${}^i_A p_t = {}^i_A w_t + {}^i \mu_\beta [z_1 \Delta n + z_2 \Delta p] \quad (8)$$

Once the price of the order has been decided, the quantity to be ordered is chosen according to the endowment of each trader i . Initially, the same endowment, ${}^i W$, is distributed to all agents, consisting in an amount of money ${}^i m$ and a quantity of shares ${}^i a$. Such an endowment changes in time according to the negotiated transactions, but short selling is not permitted. Thus, each investor trades a quantity drawn randomly from a feasible interval. For bid (${}^i q_t^B$) and ask (${}^i q_t^A$) orders, quantities will be set as:

$${}^i q_t^B = \omega \quad \text{and} \quad {}^i q_t^A = \eta \quad (9)$$

where ω and η are uniformly distributed random variables with values drawn, respectively, from the intervals $[1, m_t/p_t]$ and $[1, a_t]$. It is easy to see that a bidder can decide to buy, at most, the highest number of shares she can pay, and an asker can decide to sell, at most, all shares she has.

2.1.4 Order book management

When an agent has completely decided her strategy and desired price and quantity, she submit the order for it to be registered in the order book. As in true markets, two sections of the book have been designed: one for bid orders (posted by bidders) and another for ask orders (posted by askers). Each section is then ranked with respect to price of orders, as depicted in Fig.(1):



Figure 1: Both sections of the order book are ranked by prices. The ask side is ordered increasingly, so that the best ask is the first of the list; the bid side is ordered decreasingly, so that the best bid is the first of the list.

- bid orders decreasingly,
in such a way that the highest bid price, named *best bid* ($_B p_t^{best}$), is the first of the list, and the trader who posted it, i.e. the *best bidder*, with the highest willingness to pay, has the priority;
- ask orders increasingly,
in such a way that the lowest ask price, i.e. *best ask* ($_A p_t^{best}$), is the first of the list, and the trader who posted it, i.e. *best asker*, with the lowest willingness to accept, has the priority.

In analogy with [23], the taxonomy of orders is restricted to just market and limit orders. The distinction between such types of orders derives from the comparison between their prices ($_A p_t$ and $_B p_t$) and the current counter-side best quotes:

A- An ask order, posted by a trader i , will be:

- a limit order, if $^i_A p_t > _B p_t^{best}$
- a market order, if $^i_A p_t \leq _B p_t^{best}$

B- A bid order, posted by a trader i , will be:

- a limit order, if $^i_B p_t < _A p_t^{best}$
- a market order, if $^i_B p_t \geq _A p_t^{best}$

Limit orders have a finite time validity, chosen by the trader who posts it in the book. Once that period is expired, it is automatically cancelled. However, each investor may always decide to cancel her active order at any time during its validity. Agents cannot have simultaneous active limit orders. Similarly to the approach of [60, 61], it is assumed that limit orders standing in the book implicitly express a signal on the “market sentiment”. This induces the dynamic adjustment of the price settings rules, as above explained, by means of Δn and Δp . In particular, the market pressure term, Δn , is computed as:

$$\Delta n = \begin{cases} (n_A/n_B) - 1 & \text{if } n_A > n_B \\ (n_B/n_A) - 1 & \text{if } n_B > n_A \end{cases}$$

The price pressure term is computed as the absolute value of the difference between the two best quotes in the book, i.e. $\Delta p = |{}_A p_t^{best} - {}_B p_t^{best}|$. Both terms concur in the dynamical adjustment of individual price setting rules, as read in eqs.(6) and (8), at each iteration, by means of $[z_1 \Delta n + z_2 \Delta p]$.

Market orders are immediately executed at the best price of the counter side of the book. The following quantity-matching mechanism operates:

- a) if $q_t^B = q_t^A$, the negotiation regulation is done by assigning to the bidder (respectively to the asker) the corresponding increase (respectively decrease) in the owned asset quantity, and the related decrease (respectively increase) in the quantity of money;
- b) if $q_t^B \neq q_t^A$, the traded quantity of the transaction will be the “shortest side of the market” (i.e. the smallest ordered quantity between best ask and best bid). Money and stocks owned by traders are correspondingly updated. However, the trader who has remained partly unsatisfied, with the unmatched residual quantity, remains queueing in the order book, waiting for a new counterpart. Instead, the trader who has entirely negotiated her order is erased, and her side of the order book is updated. The successive trader becomes the new best trader in the former one’s place (with a new best price and order). The partially unsatisfied trader continues the transaction with such a new counterpart, at the new best price. This process can be repeated until either the unmatched quantity has been entirely negotiated, or the allowed order book length (regulated by a parameter) is reached. The order book length is defined as the maximum number of new counterparts that a trader is allowed to match in a single turn of transactions. In Fig.2, the role of the order book length parameter is shown.

2.1.5 Trading

Orders are finally negotiated according to their priority and validity. All the prices used in transactions, in order of execution, are registered and constitute the simulated time series. Thus, the order book registers all prices used to negotiate transactions of matching orders between a bidder and an asker. In all cases when a counterpart is not found, the order book does not register any transaction and the price list is not updated, as it would happen in true markets.

2.2 Stylized Facts of Order Book Statistics

This section is devoted to the preliminary check of the model for its compliance to some of the most known stylized facts, [29], regularly observed in financial markets and comprehensively reviewed in [18]. In particular, the simulated data will exhibit: 1- fat tails of returns distribution, 2- lack of autocorrelation of returns, 3- volatility clustering.

All simulated series are made of 15000 entries, net of a transient of 2000 entries, which has always been drop out. Returns have been obtained from the price series generated by the model, according to the canonical definition: $r_t = (p_t - p_{t-1})/p_{t-1}$. Parameters settings can be read in the following table:

PARAMETER	VALUE	INTERVAL LIMITS FOR:
σ_Θ	1	fundamental value variability
σ_F	1	fundamentalists’ heterogeneity
σ_τ	1	chartists’ time window length
σ_C	1	chartists’ heterogeneity
σ_{μ_α}	1	weight of WTA/WTP estimates:
σ_{μ_β}	1	weight of market pressure
σ_{z_1}	0.9	weight of Δn
σ_{z_2}	0.7	weight of Δp

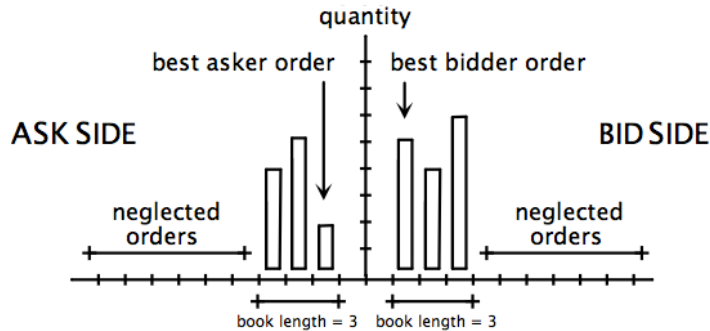


Figure 2: Market orders negotiations.

In the depicted example, the best bidder is demanding 5 shares and the best ask is offering 2 shares. Only the first 3 orders per side will be taken in account: the first transaction will be matched between the best bidder and the best ask and executed for 2 units at the best ask. Then, the best ask is erased. The matching for the remaining unsatisfied demanded quantity will be executed with the next ask, who becomes the new best ask, with her order of 5 shares and her ask price, which is the new best ask now (and it is higher than the previous one). The second transaction is executed and the best bidder is completely satisfied. The mechanism does not, of course, bounce back to the next bidder in order to satisfy the latter ask (whose order has remained partially unmatched). Further counterparts are scheduled only to substitute the first shortest side of the market. Notice, finally, that no more than 3 counterparts would have been matched in any case.

The initial setting for the fundamental value is $FV_0 = 50$; the indolence parameter is set as $\zeta = 0$ (but it will be later modified).

The Fig.3 shows prices and returns series generated by the model in comparison with those of four true financial assets (namely, BMW, Colgate, General Electric, and Uni-credit), ranging from Jan 1st, 1973 to June 30th, 2016.

The first stylized fact of financial data is the *fat tails of the returns probability density functions*. It has been firstly presented by Mandelbrot in [62], and more recently tested in [44], among others. It shows that the probability to find values which are distant from the average is greater than it would be in the Gaussian case. This is a strong regularity in financial series, whose theoretical stochastic generator process would manifest infinite variance [63]. One of the most relevant implications of this, is that no predictions can be effectively done since errors in forecasts are not bounded in any standard deviation known *a priori*. In Fig.4, returns distributions of, respectively, the true asset returns series and the artificial price series generated by the model, are shown in log-linear plots. Simulated data exhibit a fat tailed leptokurtic PDF of returns, which resemble true data very closely.

The second stylized fact is the *lack of autocorrelation in the returns time series*: this naturally confirms the impossibility of any predictive exercise on data dynamics, as shown in [28, 66]. The autocorrelation function has been computed, as shown in the top panel of Fig.5, by reporting lag-time variation of the theoretical autocorrelation index $\rho(k)$ for up to 60 lags, in order to investigate the significance of past data in explaining the series dynamics, as:

$$\rho(k) = \text{corr}(r_t, r_{t-k}) = \frac{\sigma_{r_t r_{t-k}}}{\sigma_{r_t} \sigma_{r_{t-k}}} \quad (10)$$

The presented comparison shows that returns generated by the model behave well with respect to this point.

The third stylized fact is the *volatility clustering*, firstly defined in [62]: periods with high volatility are followed by periods with high volatility, whereas periods with low volatility are followed by periods with low volatility. Thus, the absence of autocorrelation does not imply *per se* that a time series is identically distributed. The existence of autocorrelation in absolute values of returns, shows that a correlation is present, but that it is not linear. The autocorrelation function of absolute values of returns has been computed,

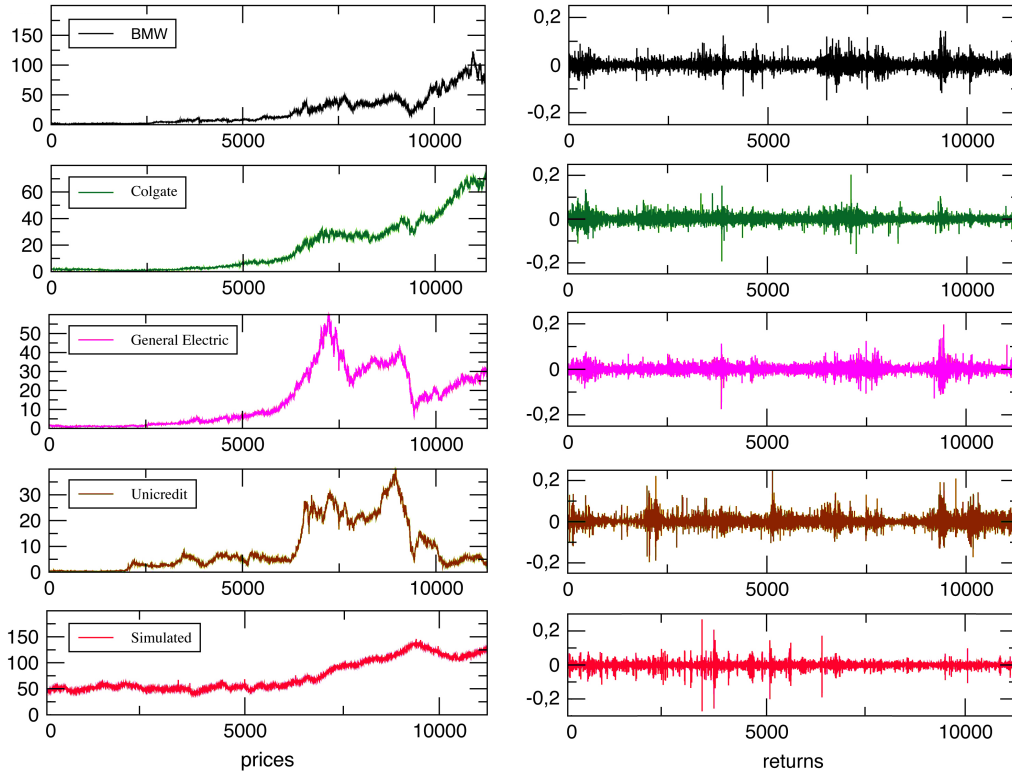


Figure 3: Prices and Returns Comparison

as shown in the bottom panel of Fig.5, in order to show that all series exhibit a positive and decreasing ACF. Among all series, simulated data show a slightly steeper slope. Power-law regressions for all series, $\rho_{|r|}(k) = \text{corr}(|r_t|, |r_{t-k}|) \simeq \rho_0 k^{-\alpha}$, give estimates of exponents $0 < |\alpha| < 0.5$ for all cases, giving evidence of long range dependence, [?], as reported below:

SERIES	SLOPE
BMW	-0.16
COLGATE	-0.12
GE	-0.11
Unicredit	-0.19
Simulated	-0.21

Part of the literature refers also to a fourth recurrent characteristic: the direct proportionality between the number of transactions and the volatility of returns. For example, in [73] it is shown that the variance of log-returns after a period of N trades in trade time, is proportional to N . Other part of literature, as in [57], refers instead to the long memory property of the traded volume. From a similar perspective, the analysis in [45], dealing with transactions data of the largest 1000 stocks in three US stock markets, explains that the distribution of the number of traded shares displayed a power law decay.

As it has been discussed earlier, such aspects cannot be tested with simulations of the present model release, because the quantity of shares that traders decide to order, though variable, is not a behavioral choice. Therefore, the model cannot give evidence of those empirical regularities derived from individual decisions.

3 Micro Features and Macro Effects

Financial volatility affects the “efficient” allocation of capitals and can become harmful for all market participants. Power law configurations of density functions of financial time

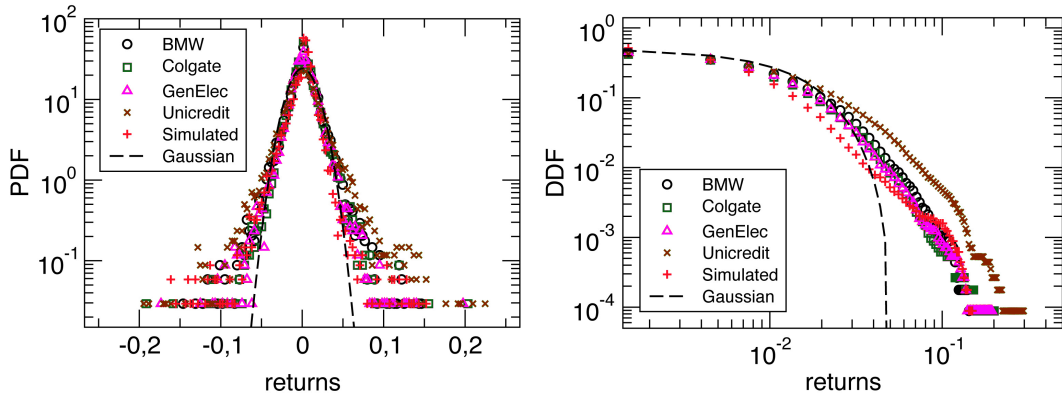


Figure 4: Density functions of Returns Series of four true assets and of the simulated data. Left Panel: comparison of fat tails in density functions; Right Panel: Decumulative Distribution Function, defined as the probability to have a return higher of a certain value. Both panels show that simulated data closely replicate the behavior of real financial data.

series show that the unpredictability of asset prices dynamics can be hardly managed. This section presents a discussion of the effects caused by individual characteristics of agents – namely, the risk aversion and the ability to learn from past prediction errors – on the aggregate market dynamics.

3.1 Risk aversion and market dynamics

The first feature being tested is the risk aversion of traders. The above-shown baseline model has been augmented with an individual behavioral attribute representing the risk aversion. Given that traders have not been endowed with a utility function, such a personal feature has not been treated as it usually does in related literature on the topic (see, for example, [?]). Here, agents are defined either “risk-lover/neutral” or “risk-averse”, by means of a binary parameter, randomly distributed at the beginning of simulations.

In particular, in comparison with the baseline model, each agent forms two expectations, one referred to the short run, and one to the long run. The short-run expectation, p_{SR}^{exp} , is calculated as the expected price defined in eqs.(2) and (4). Instead, the long-run expectation, p_{LR}^{exp} , is, respectively, the fundamental value for fundamentalists, and the reference value for chartists, as defined in eqs.(1) and (3).

In this model a behavioral representation of the risk aversion is advanced. In fact, traders have not a utility function. Thus, their perception of risk does not affect the value of their happiness, nor the value of their portfolios. The point is, instead, that the individual risk attitude matters on how investors decide about the future, provided that they form expectations on the market dynamics for both a short-run and a long-run perspective. Each trader sets the strategy according to her risk aversion, by means of a cautionary cross-check on expectations referred to different temporal horizons. Table 1 shows the correspondence between personal attitudes and trading decision rules:

3.1.1 Simulation Results

Results show that the individual risk aversion can affect the market dynamics and, more specifically, causes more instability. Such a result is surprising to a certain extent, because one could quite naturally expect that if agent are “more scared” to invest, this should dampen price variability and, in turn, returns volatility. This is as to say that fat tails are expected to be reduced. Instead, results of simulations confirms the opposite view: risk aversion slightly increases market instability and fat tails of the returns PDFs results to be fatter. Fig.6 shows the increasing impact on market volatility of the percentage of risk-averse traders. In the left panel, the log-linear plot of the density function of simulated

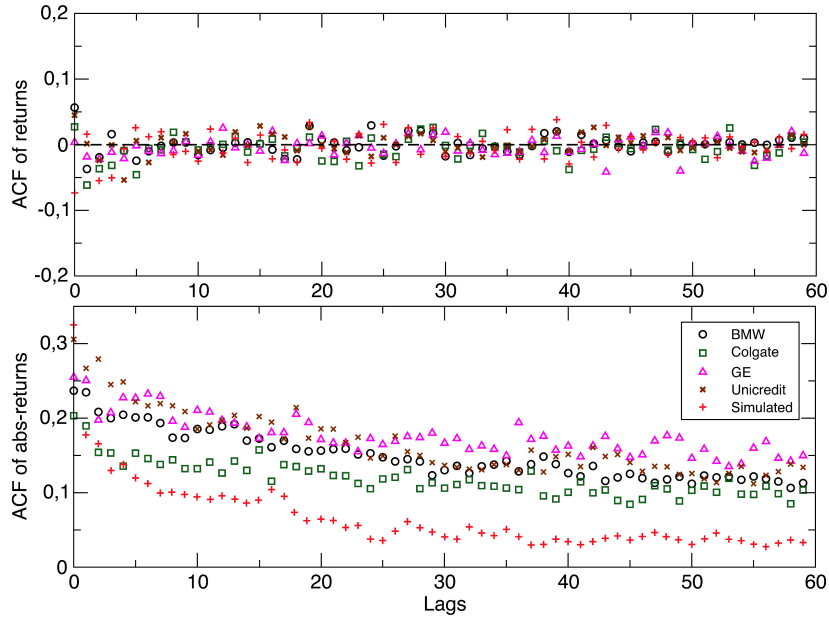


Figure 5: Autocorrelation and Volatility Clustering. In the top panel, all series appear to be uncorrelated with themselves. In the bottom panel, the positive decaying autocorrelation of absolute values of returns, shows the volatility clustering phenomenon: high volatility is followed by high volatility; low volatility is followed by low volatility.

returns is depicted and it shows the leptokurtic fat-tailed distribution of returns; in the right panel, instead, the decumulative distribution function (i.e., the probability to have a return higher of a certain value) of returns has been reported. In both panels fat tails become fatter as the percentage of risk-averse traders increases.

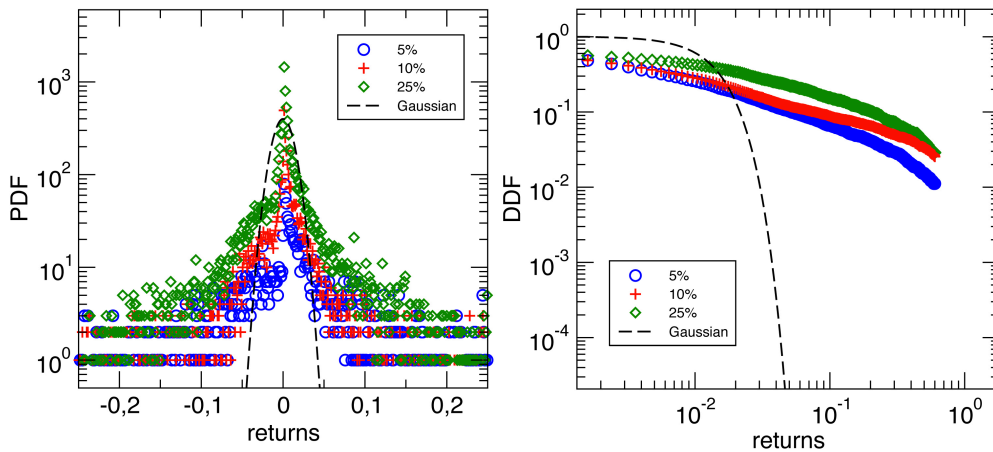


Figure 6: Risk-aversion and market volatility

The rationale of such an evidence is not strange: the behavioral risk aversion here introduced, i.e. the attitude of being particularly cautious, eventually induces a trader to follow the market in just a half of the cases. In all other situations, the risk-averse agent either trades against the market or simply holds on. Therefore, compared with the baseline model, the market overreacts to trend reversion and volatility increases. Further, the double-check mechanism used to validate expectations causes a sort of fragmentation in the flexibility of market dynamics. It operates similarly to putting thresholds in decision rules and implicitly creates “classes” of traders, whose strategies are eventually triggered by common (or very similar) trading rules. This result confirms that any form of behavioral homogeneity, specially in cases when it is a widespread opinion, generates

Table 1: Two-steps validation process for trading strategy setting

Short-Term	Long-Term	Cross-Check	Risk Aversion	Chosen Strategy	
$p_{SR}^{exp} > p_t$	$p_{LR}^{exp} \geq p_{SR}^{exp}$	-	ALL	BUY	
	$p_{LR}^{exp} < p_{SR}^{exp}$	$p_{LR}^{exp} > p_t$	ALL	BUY	
		$p_{LR}^{exp} = p_t$	LOVER/NEUTRAL	BUY	
		$p_{LR}^{exp} < p_t$	AVERSE	HOLD	
$p_{SR}^{exp} = p_t$	$p_{LR}^{exp} > p_{SR}^{exp}$	-	LOVER/NEUTRAL	BUY	
	$p_{LR}^{exp} < p_{SR}^{exp}$	-	AVERSE	HOLD	
		$p_{LR}^{exp} = p_{SR}^{exp}$	-	ALL	HOLD
		-	LOVER/NEUTRAL	HOLD	
$p_{SR}^{exp} < p_t$	$p_{LR}^{exp} > p_{SR}^{exp}$	-	AVERSE	SELL	
		$p_{LR}^{exp} > p_t$	LOVER/NEUTRAL	BUY	
		$p_{LR}^{exp} = p_t$	LOVER/NEUTRAL	HOLD	
		$p_{LR}^{exp} < p_t$	AVERSE	SELL	
	$p_{LR}^{exp} \leq p_{SR}^{exp}$	-	ALL	SELL	

instability and fatter tails of returns PDFs, as confirmed by tests done in [14].

3.2 Individual learning

The second feature being tested is the learning ability of agents with respect to the misalignments of their past predictions with respect to occurred values. The learning to forecast hypothesis stands for the fact that people observe realized prices and, individually, know their errors in forecasting while ignoring the history of other individuals' predictions. Thus, each trader may adopt an adjusting mechanism that considers, time after time, past errors in creating the new expectations. Here, similarly to [24, 25], agents are designed to settle their expectations by means of a simplified version of the rule presented in [47]. Specifically, each trader i forms her expected price as:

$${}_j^i p_t^{exp^{LtF}} = {}_j^i p_t^{exp} + \alpha(p_t - {}_j^i p_{t-1}^{exp}) + \beta(p_{t-1} - {}_j^i p_{t-2}^{exp}) \quad (11)$$

where; ${}_j^i p_t^{exp}$ is the expectation computed in t , according to the agent type $j = F, C$, as in eqs.(2) and (4); $LPE = (p_t - {}_j^i p_{t-1}^{exp})$ and $PPE = (p_{t-1} - {}_j^i p_{t-2}^{exp})$ are the *last* and the *past* prediction errors (i.e., the misalignments between the trader's expectations and the occurred values, respectively, in $t-1$ and in $t-2$), and coefficients α and β represent the weights of each error on future expectations.

In order to compare the efficacy of the correction mechanism, α and β are defined following two different hypotheses in averaging past misalignments:

- 1) fixed, by considering the relevance of either a short, or a long, or both kind of memories, as shown in the following table
- 2) variable, in such a way that each error counts for its relative weight with respect to a sort of measure of the total prediction errors, updated at each time step, i.e.,

$$\alpha = \frac{|LPE|}{|LPE| + |PPE|} \quad \beta = \frac{|PPE|}{|LPE| + |PPE|} \quad (12)$$

Table 2: Memory length and weights of prediction errors

	SHORT		LONG		BOTH	
	α	β	α	β	α	β
Scenario 1	0.1	0	0	0.1	0.3	0.5
Scenario 2	0.3	0	0	0.3	0.5	0.3
Scenario 3	0.5	0	0	0.5	0.5	0.5

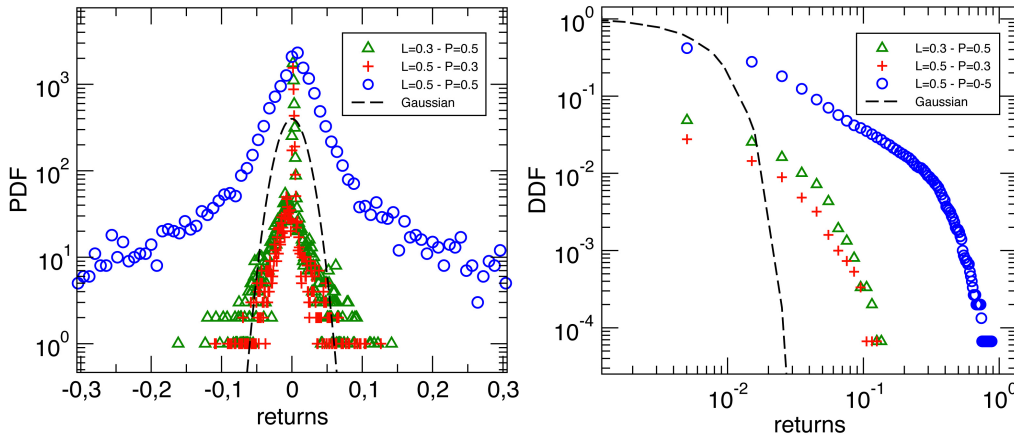


Figure 7: Learning-to-Forecast and market stability

3.2.1 Simulation Results

Results show that the learning plays a role in stabilizing the market dynamics. If traders account for their errors done in past predictions when setting new expectations, the final outcome is that the market variability is dampened.

The model adopted a two-periods-based learning, in order to put an emphasis on the combined synergy of both correction mechanisms. Simulations showed that when correcting with respect both periods, best results are obtained when weights are different from each other and, in particular, when the most recent prediction errors counts more. Both panels of Fig.7 shows exactly that when both errors are weighted the same, a cumulate and perverse destabilizing effect emerges. In the left panel, fat tails are effectively dampened when weights are asymmetric. The right panel shows that the probability to incur in more volatile fluctuations increases when both weights are set to 0.5.

Consistently, Fig.8 reports results of simulations in which only one prediction error has been used to set expectations.

In both cases, if the used weight is too high, the use of the correction reveals to be harmful, with respect to the overall market dynamics. There is a small, though recognizable, difference in results obtained with weights set to 0.1 and 0.3. Instead, fat tails unambiguously increase when half of the error is considered in setting new expectations. The rationale is that if agents assign too weight to past errors, they risk to amplify past dynamics as in a dangerous loop which exacerbates market instability, which resembles what happens when a microphone is put too close to a speaker.

Finally, simulation results show that the configuration with variable weights, updated at each time step, is less effective in reducing fat tails than with fixed ones. This means that the weights calculated as a relative proportion of the overall predictive inability act more dramatically on price variability, as reported in Fig.9. The left panel clearly puts in evidence that bad effect of the combined action of both corrections acts even worse than in the fixed weights case. When weights are variable, their computation reflects the relative magnitude of each error with respect to the overall misalignment, computed as

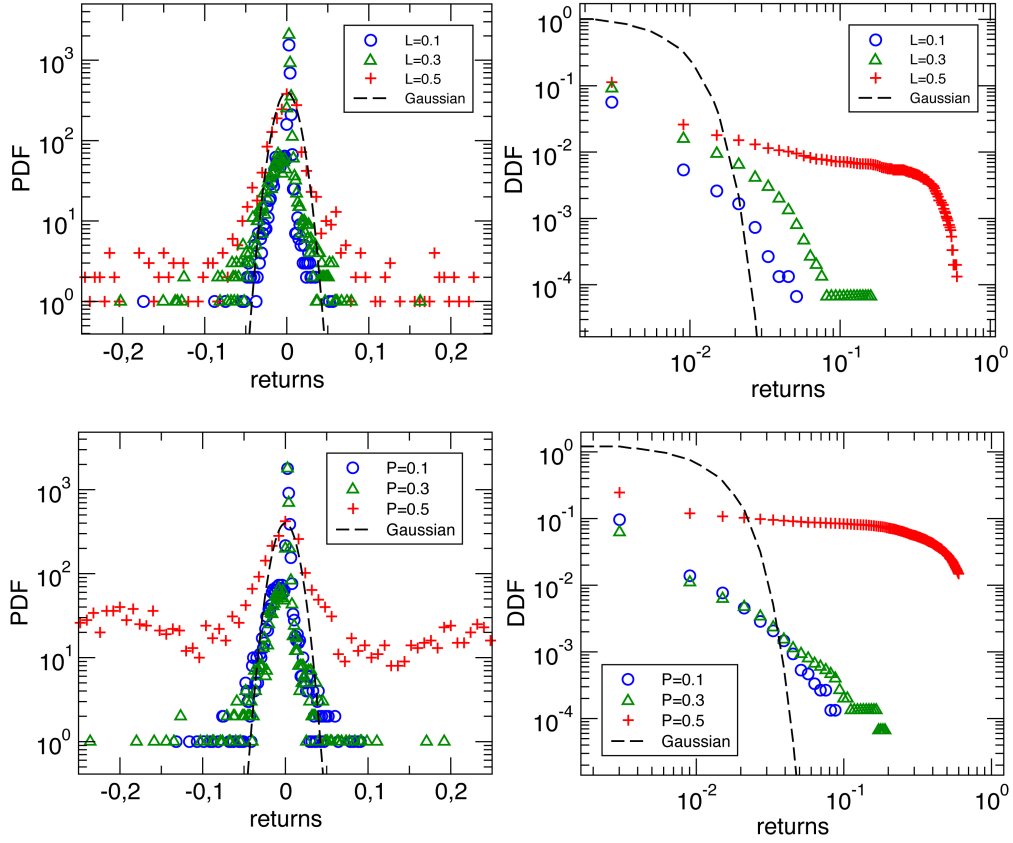


Figure 8: Learning-to-Forecast: last vs past prediction error.

in eq.(12). Such a result is consistent with above-shown Fig.7: indeed, in the variable setting, both weights can frequently be greater than 0.3, and this ends up in fatter tails.

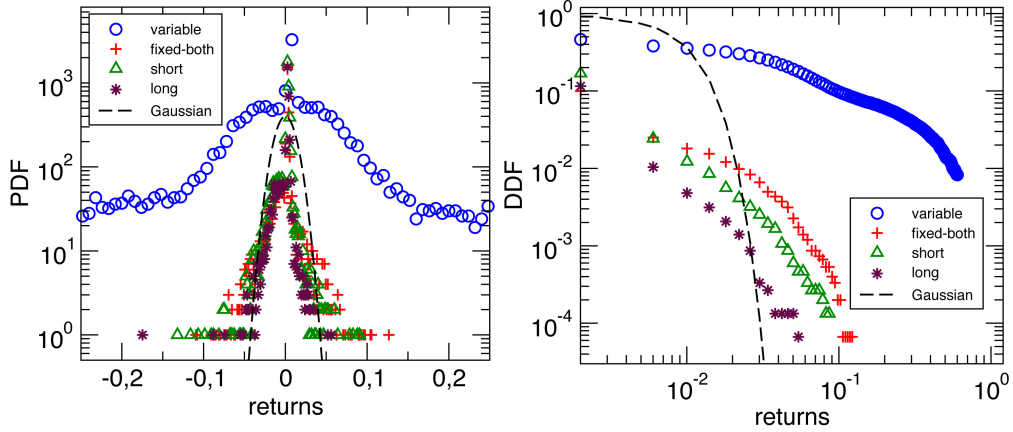


Figure 9: Learning-to-Forecast: variable vs fixed weights.

Moreover, since Fig.9 has been drawn by comparing the most effective results of each test done for learning, it shows the overall effects on market dynamics of different hypotheses. Consistently with what has been previously illustrated, when considering just one correction, LPE performs better than PPE. To consider both is better, but it reveals to be important to set a greater weight to LPE and a lower one to PPE.

4 Conclusive Remarks

In this paper, a new model of financial order book has been presented. A peculiar advantage of this model, compared to notorious existing models, is that simulated data is exclusively generated by transactions among traders. In order to assess the reliability of the model, its compliance with some of the most relevant stylized facts of true financial time series has been shown.

The main discussion has been oriented to underline the role played by individual features – namely the risk aversion of investors and the learning capacity from past prediction errors – on the aggregate dynamics of the market. Results of simulations showed that such features cause two opposite effects.

In particular, when risk aversion is considered as a behavioral ingredient of trading decisions, it exhibited a counterintuitive effect, by exacerbating fat tails of density functions of returns. The rationale for such a surprising outcome is that the double-check mechanism adopted to simulate a more cautionary approach to trading, causes a sort of fragmentation in the flexibility of market dynamics. It operates similarly to thresholds in decision rules and implicitly creates “classes” of traders, whose strategies are triggered by common rules. This result confirms that any form of behavioral homogeneity, specially in cases when it is a widespread opinion, generates instability and fatter tails of returns PDFs, as confirmed by tests done in [14].

Learning attitude showed, instead, a stabilizing effect, provided that some conditions are met. When agents learn from their past errors, and adopt correction mechanisms to account for past deviations of their forecasts from correct values, market oscillations can be dampened, i.e., fat tails of returns PDFs can be reduced. The rationale of such an evidence is that, apart from the purely theoretical hypothesis of always-perfectly informed agents, an adaptive correction scheme reveals to be very useful from the aggregate point of view, as confirmed by experiments done in related literature (see [?, ?] among others).

The policy implications emerging from obtained results are oriented to favor a climate where investors can develop differentiated perceptions of risk, i.e., to reduce the credibility of informative sources about presumed levels of risk and volatility and to encourage the individual understanding of the market activity. In other words, a higher level of financial awareness of traders can be helpful in reducing waves of optimism and pessimism, which induce wide price fluctuations.

Expectations and risk perceptions must be different enough, which is as to say that herding effects in information must be fought very strongly, in order to allow a sufficiently differentiated behavior of traders and a fluid market dynamics.

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