(Un)Realistic Simulations of Financial Markets

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Abstract – *Communication on the state of (un)realistic microscopic simulations of financial markets.*

Keywords: Rational Expectations, General Equilibrium Theory [AD54, Mut61, McK02], Modern Portfolio Theory [Mar52, Sha64, BS73], Complexity and the Economy [Art99, Sol99], Synchronous simulations surveys [LLS00a, LLS00b],
Asynchronous simulations [SMLS00, MS03, Cap03, JLM04, BPBK04],
Markets Microstructure [DS99, O'H00]

1 State of the art

1.1 Different questions for different research fields

The literature on financial markets[1] is huge, and spans across various research fields: Finance, Quantitative Finance, Economics, Econometrics, EconoPhysics, Behavioural Economics, Behavioural Finance, Markets Microstructure, Agent-Based Computational Finance, etc. While the interests at stake reflect dramatically on the basic questions those different research communities are trying to answer, the most striking discrepancy is probably between Economists, who build elegant theories on the way markets (should) work, and financial practitioners, who struggle to maximise their gains on the floor, day after day. Traditionally, Economists make use of stylised and analytically tractable models of markets, assuming a rational behaviour from homogeneous participants in order to solve otherwise unsolvable equations, and come up with a theoretically sound price formation mechanism resulting from a constant equilibrium between the forces of supply and demand [AD54, Mut61, McK02]. As far as those models can be from the real world of hands-on trading floors, each with its specific microstructure properties and market mechanisms, they gave birth forty years ago to the Modern Portfolio Theory [Mar52, Sha64] and Black-Scholes option pricing formula [BS73], both of which reshaped completely the financial industry, leading to an even wider role played by financial markets in the modern economy.

[1] The term *financial markets* usually refers to securities exchanges, foreign exchanges or fixed-income.

1.2 The mainstream Economics viewpoint

The major benefit of this approach is to provide a consistent framework into which prices vary from one equilibrium to another, depending on precise variations of macroeconomic parameters such as interest rates or news concerning the economy. In this context, the Economist is able, by picking the appropriate model, to advise the Prince on how best to conduct affairs, and can apply his expertise to policy making. Unfortunately, those models usually bear highly stylised and unrealistic assumptions purely for convenient reasons, and Econometricians have a hard time calibrating them to real data. An important example and open question concerns the efficiency of the markets [Fam65b, Fam65a, $F^{+}69$], a great hypothesis both theoretically pleasant and mathematically vital in terms of models simplifications, but which can be tested only indirectly by adding a price formation mechanism and many other components to the model; in the end, the absence of good fit to empirical data does not tell us much about the true efficiency of the market [Fam91].

Another major area of concern is the price formation mechanism itself: while traditional models usually consider a simple Walrasian auction in which an omnipotent market maker aggregates supply and demand, defines the equilibrium price and clears the market, real markets rely on different mechanisms to confront and match offer and demand, such as: floor markets where traders engage in bilateral deals (e.g. NYSE), decentralised dealer markets where customers submit their orders to dealers who re-balance their inventory by trading with each other (e.g. NASDAQ), and electronic limit order books where limit orders are submitted directly to an open book that follows strict price / timing priorities (used by NYSE and NASDAQ). In fact, it is quite common for financial markets competing against each other to use two or three of those mechanisms simultaneously, to provide a greater degree of freedom and efficiency to their customers in terms of trading cost, anonymity, liquidity, etc. See [Has] for an overview of the market mechanisms implemented by the New-York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotation (NASDAQ), the Chicago Mercantile Exchange (CME) and EURONEXT. All those details, that make the bread and butter of practitioners, have largely been eluded so far by mainstream Economics[2].

1.3 The agent-based approach

About fifteen years ago, following the early works and techniques applied by Economists such as Bachelier [Bac00], Mandelbrot [Man63], Stigler [Sti64] or Markowitch [KM89], more and more Physicists entered the long term quest of bringing those theoretically sound but unfalsifiable models closer to reality, under the banner of the so-called EconoPhysics research field. The idea is to replace the static framework of the Rational Expectations and General Equilibrium Theories by a bottom-up approach consisting of heterogeneous, learning agents with bounded rationality competing and evolving inductively in a complex system usually out-of-equilibrium. In this new paradigm, price variations are due not only to exogenous factors, such as news about the economy and macroeconomic parameters, but are also generated endogenously by the multiple interactions between participants; the price emerges from those complex interactions. While some empirical evidence supports the idea that most large price fluctuations cannot be linked to economic news [CPS89], the agent-based, complex approach can be seductive for different reasons:

- Questions concerning the market efficiency and the actors rationality are still unresolved and some statistical peculiarities universally observed in financial time series across different markets are left unexplained;
- This bottom-up approach is constructive, and allows any type of non-linearity in the models;
- The wide availability of data makes financial markets a perfect laboratory for such agent-based models;
- Some practical experiments can be conducted, both with artificial agents and human subjects.

A more general discussion on the role of agent-based models in Social Sciences can be found in [Axt99, Tes03]. The approach taken when building such agent-based market models can be summarised as follows:

1. Find some stylised facts exhibited by the market you are trying to model (e.g. fat-tailed log-returns distribution, clustered volatility, persistence in volumes, etc.);
2. Design your agents (their cognitive capacity, their strategies, the way they learn and eventually evolve, etc.);
3. Design your market microstructure (the interactions between agents, the price formation mechanism, etc.);
4. Run some simulations to calibrate your model to the stylised facts you are trying to reproduce;
5. Explain the dynamics of your model (the eventual phase transitions, the forces pushing your agents to self-organise, etc.) and assess its robustness.

[2] Nevertheless, an immediate question comes to mind: how far should we go in the level of granularity? Given that stylised facts seem to appear equally on various markets that obey completely different market mechanisms (e.g. NYSE with its limit order book and specialist on a floor market VS NASDAQ as a dealer market), one has to wonder to which level of granularity we should go (and where to stop) while modeling those markets.

1.4 Perils of the approach

This field is rather new, and suffers from various issues, namely the interpretation of the results (how to analyse the dynamics linking inputs to outputs in our artificial simulations), the estimation of parameters (how to calibrate the parameters of our model to real data) and the generalisation power (how to be sure that the model can be used on unseen data) [Ric04].

For all those reasons, fifteen years after the first agent-based models of financial markets [Man91, TMHH92], mainstream Economists remain sceptical about this entire approach, and consider that simulations, inductive by construction, cannot tell us anything about the way markets operate, as opposed to traditional deductive, analytical models.

In this context, a first step for Agent-Based Computational Finance models could be to test the robustness of existing analytical models by relaxing some assumptions about the agents or the market microstructure. This is closer to the orthodox viewpoint adopted by Economists, and was at the origin of many toy-models, extremely stylised and simplified compared with real markets, and intended to explain one particular property of markets [Art94, CZ97, Zha98, CGGS99, JHHZ00, CMZ01, AS03, LM99, AWL03, CB00, GB03]. For instance, most models incorporate only two assets, a riskless and a risky one and consider only a simple price formation mechanism, the Walrasian auction. Focusing on those toy-models is usually justified by the assumption that as long as we do not master their dynamics, there is no point in increasing their complexity; in addition, simpler models might be more easily accepted by the Economists community.

A more challenging approach is to go beyond those models (and further away from mainstream Economics) and plunge into the world of analytical intractability.

1.5 Artificial financial markets

To populate the gap between toy-models and empirical markets, another stream of research was devoted to artificial financial markets, with the aim of reproducing a more realistic market microstructure (See [LLS00a, LeB04] for a review). These platforms are designed to accommodate any type of trader behaviour, and are moving slowly towards real-like trading mechanisms. Obviously, the price to pay is the loss of analytical tractability; in particular, we are getting closer to the Markets Microstructure research field, in which the following price formation mechanisms are investigated:

- floor trading (open outcry) vs electronic trading (screen-based);
- single-price clearing (such as a batch auction) vs continuous auctions (limit order book);
- auction markets vs competitive dealer markets;
- order-driven (quantities provided, not price) vs quote-driven (price provided, not quantities);
- open vs closed order book;

In this quest towards more realistic features, artificial financial markets are getting richer. In particular, they are now moving towards asynchronous simulations [MS03, Cap03, JLM04, BPBK04] in which no constraints are imposed in terms of time scale, as in traditional synchronous models [PAH+94, MCFR00, LeB02, Sol99].

2 Possible research paths

There are different directions we could push forward.

From a Behavioural Economics viewpoint, we could use our artificial market platform as a computational *and* experimental laboratory to study how people behave in a market environment, how they design their strategies and depart from rational expectations, how they update them through an iterative process driven by competition between agents, etc. What we offer to Behavioural Economists is a highly rigorous and documented framework to conduct experiments with human beings, in real-time [Cap03] or off-line [MS03] – see [Duf04] for a review of computational vs experimental laboratories, and [PLLC99, BO99, The00] for examples of experimental laboratories.

Secondly, an important literature exists in Markets Microstructure that poses the question of best microstructure, or market mechanisms, in terms of liquidity, transparency, transaction costs and market efficiency [DS99, O'H00]. For instance, empirical studies as well as ad-hoc models analyse the advantages of different existing market mechanisms, such as the call auction (or batch auction, often used to set the opening price), the continuous auction (usually implemented as a limit order book) and the dealership market (usually preferred for markets with few participants but large orders, where anonymity is the key). This stream of research seems to be a natural way to go for the Agent-Based Computational Finance community. An example of a result in this field, that could be a starting point, is that the optimal trading structure highly depends on the type of order flow the market receives; the batch auction is preferred to an open order book when actors do not want to reveal any information to the market, for instance while executing large orders. When such an auction is not available, our platform constitutes an ideal tool to conduct experiments on how such orders should be sliced and entered in the order book separately to keep the liquidity impact low, while exposing oneself to a limited base-price move [Sof04]. This trade-off could explain the 20 minutes serial correlation exhibited by price returns on stock markets.

Finally, from a more Econophysics-oriented point of view, this simulation platform, in between real markets and Econophysics-like toy-models in terms of realism, is perfectly placed to test the hypotheses those models formulate, by placing them into the best market-like environment we know. The hedge we have is that this has never been done before, and every result will potentially be new and useful. By that, we mean that we could test simple models in highly realistic conditions.

In terms of expertise, this ambitious approach can be conducted by attracting not only physicists, but also psychologists to run experiments on people's behaviour, computer scientists to canonise this behaviour (or the ideal ones proposed by existing Econophysicists models) into artificial agents, practitioners to relate those experiments to real markets and provide us with useful knowledge about market mechanisms, and economists to eventually assess the consequences of our results in terms of policy making.

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