

614 LECTURE NOTES IN ECONOMICS
AND MATHEMATICAL SYSTEMS



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Florian Hauser
(Editors)

Complexity and Artificial Markets

 Springer

Lecture Notes in Economics and Mathematical Systems

614

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Complexity and Artificial Markets

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ISBN 978-3-540-70553-6

e-ISBN 978-3-540-70556-7

DOI 10.1007/978-3-540-70556-7

Lecture Notes in Economics and Mathematical Systems ISSN 0075-8442

Library of Congress Control Number: 2008930214

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Production: le-tex Jelonek, Schmidt & Vöckler GbR, Leipzig

Cover design: WMX Design GmbH, Heidelberg

Printed on acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

Preface

In 2000, when Levy, Levy, and Solomon published their book *Microscopic Simulation of Financial Markets*, Harry Markowitz noted in the blurb that numerical simulations point “us towards the future of financial economics. If we restrict ourselves to models which can be solved analytically, we will be modeling for our mutual entertainment, not to maximize explanatory or predictive power.” At that time most economists were quite sceptical about the new techniques and thus a statement like this was encouraging for the Artificial Economics community. Since 2000, things have changed tremendously. Agent-based modeling, computer simulations, and artificial economics have become broadly accepted tools in social sciences by now. For a large number of problems they are the only reliable techniques to arrive at nontrivial results.

Neoclassical economics is usually split up into a micro and a macro analysis, the first dealing with the individual decision-maker (consumer, firm, investor etc.), and the second with economic aggregates such as aggregate demand and aggregate supply (labor, consumption, capital, etc.). The link, if there is any, between both levels is the representative agent, that is the assumption that either all agents are of the same type or that they act in such a way that the sum of their choices is mathematically equivalent to the decisions of identical, prototypical individuals. In such a world neither the problem of imperfect rationality nor the problem of disparate and diverse information can be addressed; the latter is not even the case if you allow for only two disparate levels of information, let us say informed and non-informed individuals.

What happens in the real world is an outcome of the interaction of numerous individuals, each of whom may have different preferences, different information levels and different attitudes. A system with a set of autonomous decision-makers (agents) who individually assess their situation and exhibit repetitive interactions based upon their idiosyncratic rules is called a multi-agent-model; it can give us valuable insights into the nature of the real system it attempts to emulate. If, as often has been formulated, a market is an open complex adaptive system with endogenous evolution, the only chance to get a deeper understanding of how it works will be to look at its dynamics, driven by individual decision making. If we do so, we possibly will capture emergent behavioral patterns which are the result of interaction and which are decoupled from the behavior of the individuals: the whole is more than its parts.

The 2008 meeting of researchers in Artificial Economics takes place in Innsbruck (Austria). The most distinguished scholar of our school was Eugen Ritter von Böhm-Bawerk, one of the protagonists of the so-called Austrian School of Economics. Agent-based modeling and complexity economics draw a lot of inspiration from and give a lot of inspiration to Austrian Economics. Central to this school of thought is the uncompromising use of methodological individualism and

subjectivism: whatever happens in society has to be explained by going back to the actions of individuals; these individuals need not be perfectly rational, but they are assumed to exhibit at least meaningful and selfish decisions (as opposed to irrational agents, noise traders etc.). Austrian Economics always deals with ‘human action’ (Mises): It must be possible to explain why people do what they do. A theory, e.g. efficient markets theory, where in the end nobody has an incentive to do anything, is a sterile intellectual gimmick. In a perfect equilibrium as a result of competition, nobody competes; such theories are rather theories of human non-action than of human action. We are happy that some of the papers presented in the workshop will fit very well in the Böhm-Bawerk-tradition of Austrian Economics.

At the Innsbruck University School of Management agent-based modeling has quite a long tradition. The first paper of an artificial stock market with heterogeneously informed agents was published in 1997: it tried to resolve the famous information-paradox (Grossman/Stiglitz) without referring to market imperfections or to irrational decision making (as noise-traders) and showed that in a stock market you may be better off if you have less information than others (a typical result emerging from an agent-based approach). A lot of further work has been done in this field, partly using computer simulations and partly adopting an experimental approach. With respect to the objective of learning more about the dynamics of complex systems such as a market, both approaches have their merits, but also their shortcomings. Both stem from the dominant role of heterogeneous agents making individual decisions. If we want to gain reliable knowledge of how real human beings view their decision problems, which factors they take into account, how they deal with information overloads and other items, experimental economics with real people will be the more appropriate approach. If, however, we try to understand the underlying properties of a complex system, computer simulations will do better: with artificial agents we get economically ‘pure’ results which are not blurred by the bounded rationality of real agents. In both cases, however, macro phenomena grow on the sound ground of methodological individualism with autonomous agents; that is what counts.

All papers in this book have been selected in a double-blind reviewing process. They cover various topics within the area indicated in the title “Complexity and Artificial Markets”.

The papers in Part I use agent-based simulations to deal with market mechanisms. The main concern of the *LiCalzi/Pellizzari*-paper is the market microstructure: how does resampling affect allocational efficiency in different market protocols? *Giulioni/Bucciarelli* observe the Pescara wholesale fish market with respect to its price dynamics. *Milone* studies the consequences of pre-trade quote disclosure on the market performance in different scenarios.

Part II is devoted to evolution and is decision making. *Anufriev and Hommes* show in an experimental study how different forecasting strategies perform in an evolutionary switching mechanism. *Raberto, Teglio, and Cincotti* focus on households’ beliefs formation and financial preferences, based on concepts from prospect theory. *Fernández-de-Córdoba and Navas* present an evolutionary model and show under which conditions a Walrasian equilibrium is likely to emerge in an economy.

Garabedian presents an agent-based consumption model that is applied to the purchase decision for ethical goods.

Part III deals with information economics in a broad understanding. *Hule and Lawrenz* investigate the impact of information quality and the intensity of interaction on some stylized facts in financial markets. *Hofstede, Jonker, and Verwaart* create an agent-based model emphasizing the micro-dynamics of trust in a long-term trade relationship. Combining experimental economics and agent-based computational models *López-Paredes, Posada, Hernández, and Pajares* explain individual behavior of agents in a signaling game.

In Part IV, methodological issues prevail. *Livet, Phan, and Sanders* start from an ontological view and study the relationship between a given problem, experimental design, and modeling individual choice in different types of agent-based computational economics. *Van-der-Hoog, Deissenberg, and Dawid* present some new developments in the well-known agent-based model of the European economy called EURACE. *Grevers and Veen* compare the two main methodological approaches in social sciences, the systems approach and the individual-based approach, with special emphasis on agent-based computational economics.

It is almost a tradition of the Artificial Economics meetings to bring together people from computer science, natural sciences, philosophy, cognitive sciences, economics and finance, and other areas. The two invited speakers give evidence of this basically interdisciplinary approach. *Peter Henning*, coming from theoretical quantum physics, visited the world of financial markets at the Deutsche Börse AG, switched to computer science and, for the time being, teaches informatics, economics, e-learning and related fields. He, too, has a strong relationship to Tyrol as he supported for years the ‘Bozner Treffen’, an annual meeting of scientists coming from various disciplines. *Peter’s* paper deals with different types of evolutionary processes: under which conditions can evolution serve as a bridge between biology and economics? *Alan Kirman* comes from neoclassical economics, but studying the link between micro and macro behavior he was a pioneer in agent-based computational economics; at an early stage he understood that economic activity is better viewed as the product of a complex self-organizing system than of corresponding to the behavior of an individual maximizer; with Innsbruck he is familiar as one of the speakers in the famous ‘Böhm-Bawerk-lecture’ given annually by some of the most distinguished economists from all over the world. *Alan* teaches at the Université de la Méditerranée near Marseille. His paper deals with rationality and organization in artificial markets.

Innsbruck,
May 2008

Klaus Schredelseker
Florian Hauser

Acknowledgements

We would like to thank all the members of the Scientific Committee who refereed the papers, gave most valuable comments to both editors and authors, and made it possible to publish this volume in time:

- **Frédéric Amblard**, Université Toulouse, France
- **Bruno Beaufls**, Université des Sciences et Technologies de Lille, France
- **Olivier Brandouy**, Université des Sciences et Technologies de Lille, France
- **Charlotte Bruun**, Aalborg University, Denmark
- **Andrea Consiglio**, Università degli Studi di Palermo, Italy
- **Wander Jager**, University of Groningen, The Netherlands
- **Marco Janssen**, Arizona State University, United States of America
- **Philippe Lamarre**, Université de Nantes, France
- **Michele Marchesi**, Università Cagliari, Italy
- **Luigi Marengo**, Sant'Anna School of Advanced Studies, Italy
- **Philippe Mathieu**, Université de Lille 1, France
- **Nicolas Maudet**, Université Paris-Dauphine, France
- **Akira Namatame**, National Defense Academy, Japan
- **Paolo Pellizzari**, Università “Ca’ Foscari” di Venezia, Italy
- **Denis Phan**, GEMAS CNRS & Université Paris IV Sorbonne, France
- **Juliette Rouchier**, GREQAM, France
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- **Elpida Tzafestas**, National Technical University of Athens, Greece
- **Murat Yildizoglu**, Université Montesquieu Bordeaux IV, France
- **Stefano Zambelli**, Trento University, Italy

We acknowledge financial support for the conference by the **Austrian Bundesministerium für Wissenschaft und Forschung** and by the **Vizerektor für Forschung at the University of Innsbruck**. Without these grants the realization of this conference would not have been possible. We also thank **Philip Herdina** for helping us with proofreading the papers.

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Part I
Market Mechanisms

Chapter 1

Zero-Intelligence Trading Without Resampling

Marco LiCalzi and Paolo Pellizzari

Abstract This paper studies the consequences of removing the resampling assumption from the zero-intelligence trading model in Gode and Sunder (1993). We obtain three results. First, individual rationality is no longer sufficient to attain allocative efficiency in a continuous double auction; hence, the *rules of the market* matter. Second, the allocative efficiency of the continuous double auction is higher than for other sequential protocols both with or without resampling. Third, compared to zero intelligence, the effect of learning on allocative efficiency is sharply positive without resampling and mildly negative with resampling.

1.1 Introduction

In a recent paper, Mirowski (2007) argues that we are witnessing a “shift to a market-centered theory of computational economics” (p. 214). He attributes an important strand in this shift to the ramifications of Gode and Sunder (1993). This seminal paper is widely credited¹ with showing that the continuous double auction can attain allocative efficiency and convergence to the equilibrium price in the absence of trader intelligence. Such zero-intelligence (henceforth, ZI) is modeled by replacing human subjects with computerized agents that generate random quotes.

As Mirowski himself acknowledges, “there is still substantial dispute over the interpretation of their results” (p. 216); e.g., see Brewer et al. (2002). The boldest claim is that an appropriate market institution can override the cognitive limitations of individuals to achieve allocative efficiency and discover the equilibrium price. On the other side of the fence, the sharpest criticism is offered by Gjerstad and Shachat

¹ See Footnote 5 in Gjerstad and Shachat (2007).

(2007). This paper provides a fresh and careful reading of Gode and Sunder (1993) that makes two points: first, convergence to the equilibrium price does not actually occur in Gode and Sunder (1993); second, the key condition for allocative efficiency is the *individual rationality* of the agents rather than the *market discipline* imposed by the continuous double auction.

Based on this, Gjerstad and Shachat (2007) conclude that “individual rationality is both necessary and sufficient to reach” allocative efficiency (p. 7). This argument is backed up by the claim that Gode and Sunder (1993) deal with a special case of the B-process for which Hurwicz et al. (1975) prove that in an economy without externalities a random but otherwise individually rational behavior converges to a Pareto optimal allocation.

In fact, this claim rests on a subtle but far from innocuous assumption made in Gode and Sunder (1993) that has gone largely unnoticed in the literature. We quote from Gode and Sunder (1993, p. 122): “There are several variations of the double auction. We made three choices to simplify our implementation of the double auction. Each bid, ask, and transaction was valid for a single unit. *A transaction canceled any unaccepted bids and offers.* Finally, when a bid and a ask crossed, the transaction price was equal to the earlier of the two.” (Emphasis added.) We call the emphasized assumption *resampling* because under zero intelligence it forces all agents who have already uttered a quote to issue a new (random) one after each transaction.

This paper studies the consequences of removing the resampling assumption. We obtain three results. First, under zero intelligence, individual rationality without resampling is not sufficient to attain allocative efficiency in a continuous double auction; hence, the *rules of the market* matter. On the other hand, with or without resampling, the allocative efficiency of the continuous double auction is higher than for the other sequential protocols we consider; hence, this market protocol is still the most effective among those. Third, when zero intelligence is replaced by a simple variant of the algorithm mimicking learning-based human behavior proposed in Gjerstad and Dickhaut (1998), we find that the effect on allocative efficiency is sharply positive without resampling but tends to be mildly negative with resampling.

1.2 The Model

We use a setup inspired to Gode and Sunder (1993). There is an economy with a large number ($n = 5000$) of traders, who can exchange single units of a generic good. Each agent is initialized to be a seller or a buyer with equal probability. Each seller i is endowed with one unit of the good for which he has a private cost c_i that is independently drawn from the uniform distribution on $[0, 1]$. Each buyer j holds no units and has a private valuation v_j for one unit of the good that is independently drawn from the uniform distribution on $[0, 1]$. By individual rationality, each seller i is willing to sell his unit at a price $p \geq c_i$ and each buyer j is willing to buy at most one unit at a price $p \leq v_j$.

Gode and Sunder (1993) make the three simplifying assumptions cited above. We maintain the first one and restrict all agents to trade at most one unit. The third assumption selects the continuous double auction as the market protocol that regulates the interactions between traders. We expand on this and compare the allocative efficiency of four different sequential protocols, including of course the continuous double auction. These four protocols are: the continuous double auction, a nondiscretionary dealership, a hybrid of these two, and the trading pit. The first three are described in detail in LiCalzi and Pellizzari (2006, 2007a).

Briefly, in the continuous double auction (henceforth C) traders sequentially place quotes on the selling and buying books. Orders are immediately executed at the outstanding price if they are marketable; otherwise, they are recorded on the books with the usual price-time priority and remain valid until the end of the trading session. In the trading pit (henceforth T), traders are randomly matched in pairs: each agent in a pair utters a quote and, if compatible, they transact at a price equal to the average of their quotes; this transaction price is made known to the market, but its participants have no access to the offers exchanged within a pair.

In the dealership (henceforth, D) there is a specialist who posts bid and ask quotes valid only for a unit transaction. Agents arrive sequentially and can trade only at the dealer's quotes. Right after a transaction is completed, both dealer's quotes increase (or decrease) by a fixed amount k when the agent completes a purchase (or a sale); hence, the bid-ask spread Δ remains constant. Clearly, completing a trade between a buyer and a seller by going through the dealer is costly: for instance, if trader i sells one unit to the dealer that is immediately after resold to buyer j , the dealer pockets a value of $\Delta - k$. In this respect, the presence of the dealer negatively affects allocative efficiency. On the other hand, because the dealer guarantees a fixed bid-ask spread, it has a stabilizing effect on price dispersion that is usually beneficial.

For a large range of values, the force of these two effects vary in a predictable manner. Hence, the instantiation of k and Δ is influential but not crucial: we assume $k = 0.005$ and $\Delta = 0.05$ throughout the paper. The choice of the initial dealer's quotes, instead, is more delicate: when these happen to be far away from the equilibrium price, the effect on allocative efficiency may be relevant because the first few trades tend to occur on the same side of the market (until the dealer's quotes get closer to the equilibrium price). Except for a final comment in Sect. 1.3.3, we mute this issue and assume that the initial quotes exactly straddle the (theoretical) equilibrium price. Finally, the hybrid market (henceforth, H) combines the continuous double auction with the dealership: agents have access to the dealer's quotes as well as to the offers from the public recorded in the book. The initialization for H is the same used for D; that is, $k = 0.005$, $\Delta = 0.05$ and the initial dealer's quotes straddle the equilibrium price.

Each of these four protocols is organized over a single trading session, where all agents participate. Their order of arrival is randomly selected. Whenever a transaction takes place between two agents, their own orders are removed from the market and the agents become inactive. The difference between assuming resampling or not is the following. Under no resampling, each agent gets only one chance to act: he can trade up to one unit (if he finds a suitable quote) or, limitedly to C and H, utter his

own quote (that remains valid until the end). The market closes after all agents have had their chance to act. Under resampling as postulated in Gode and Sunder (1993), until an agent completes a trade and becomes inactive, the refresh following a trade may give him a new chance to act. Therefore, the number of chances for actions is much greater under resampling, and this tends to increase allocative efficiency. To minimize this bias, we assume that under resampling the market closes when, following a refresh, all the active agents have issued a quote and no transaction has occurred.

Two more differences separate the book-based (we call them “literate”) protocols C and H from the “illiterate”² protocols D and T. First, the book in C and H offers to the current agent an option to store his quote, extending his opportunity to trade in the future; on the contrary, D and T limit his options to immediate trade or no trade at all. Second, the book makes quotes from past traders available to the current agent, presenting him with a larger set of potential counterparts for his trade; on the other hand, for illiterate protocols the only available counterpart is the dealer in D and a single partner in T. In other words, a literate protocol expands the opportunities for trades as well as the pool of potential counterparts. These differences are not a crucial issue under resampling, because a trader returning to the market faces a new opportunity to trade, usually at different conditions. However, as we discuss below, they have a substantial effect when resampling is not allowed.

We use two different behavioral assumptions in our tests. Under zero intelligence, when an agent i must issue a quote, he picks a random number from the uniform distribution on $[0, v_i]$ if he is a buyer and from the uniform distribution on $[c_i, 1]$ if he is a seller. This behavior corresponds to zero intelligence under individual rationality and is called ZI-C in Gode and Sunder (1993). The second behavioral assumption is a simplified version³ of the learning model introduced in Gjerstad and Dickhaut (1998), where each trader transforms the empirical acceptance frequencies to generate beliefs and then issues the quote that maximizes his expected surplus with respect to these beliefs. This approach is in general quite sensitive to fine details in its initialization and implementation. However, it can be calibrated to effectively mimic the basic features of human behavior in experimental trading markets. See Gjerstad (2007) for more details and an improved version of the original (1998) model.

Our implementation is the following. We discretize the unit interval $[0, 1]$ for prices by assuming a “tick” equal to $1/200 = 0.005$. Let $H_t(x) = \#(p \leq x)$ denote the empirical cumulative frequency of past transaction prices at time t . Each buyer i starts up with a uniform “prior” described by the cumulative distribution $F_i(x) = \min\{(x - nbv_i)^+, 1\}$ on the ticked prices contained in the interval $[bv_i, v_i]$, where $b = 0.8$. (For a seller i , we assume by symmetry a uniform distribution over the interval $[c_i, (1 - b) + bc_i]$.) This initial distribution is associated to a coefficient a_i that defines the stubbornness of i ’s initial beliefs; we assume that a_i is an integer drawn (once for each agent) from the uniform distribution on $\{1, 2, \dots, 100\}$. When

² This terminology is non-standard, but less convoluted than a plain “non-book-based.”

³ The most notable difference is that we do not assume bounded recall of past transactions.

a buyer i is called up for trading at time t , he combines his “prior” with the empirical distribution $H_t(p)$ and derives a “posterior” cumulative distribution $P(p \leq x)$ that is proportional to $a_i F_i(x) + H_t(x)$. Then buyer i issues a bid b that maximizes his expected utility $(v - b) \cdot P(p \leq b)$. (Sellers’ behavior is analogous.)

1.3 Results

We are interested in the allocative efficiency of different market protocols under zero intelligence. As usual, allocative efficiency is defined as the ratio between the realized gains from the trade and the maximum feasible gains from trade. This measure is adimensional, facilitating comparisons. We compare the allocative efficiency of the four protocols described above under both zero intelligence and our version of the learning model proposed in Gjerstad and Dickhaut (1998). Since we view the role of the dealer as a mere feature of the protocol, his final gains/losses are not included in the computation of the allocative efficiency.

1.3.1 Test 1: Does Resampling Matter?

Assume zero-intelligence trading. The left-hand side of Fig. 1.1 shows as datapoints the allocative efficiency of the continuous double auction *with resampling* for 100 different runs. The right-hand side shows the same information for the continuous double auction *without resampling*. The y-axes use the same scale, so that it is possible to directly compare the results under the two assumptions by visual inspection: the higher the level, the higher the allocative efficiency.

The average allocative efficiency is 0.96 with resampling and 0.52 without resampling. Visual inspection strongly suggests that the distribution of the allocative efficiency with resampling stochastically dominates the distribution without

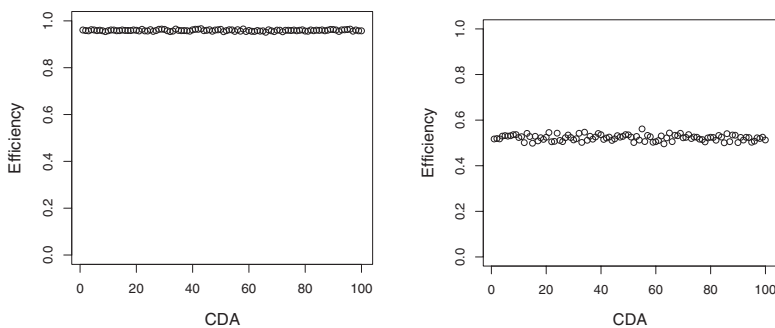


Fig. 1.1 Allocative efficiency for C with (left) and without resampling (right)

resampling. More modestly, we claim that under resampling the expected value of allocative efficiency is higher. This is supported for any practical level of confidence by the directional version of the Wilcoxon signed-rank test. (Here and in the following, by a *practical* level of confidence we mean a p -value lower than 10^{-5} .) Limited to our experiment, therefore, we conclude that *ceteris paribus* resampling yields a higher allocative efficiency than no resampling. In short, resampling truly matters a lot.

1.3.2 Test 2: Which Protocol Performs Better Under Zero Intelligence?

Our second test extends the first one by looking at the effects of resampling under zero intelligence for other sequential protocols. Each protocol is identified by its initials on the x -axis and by a different color: the continuous double auction (C) is in black; the nondiscretionary dealership (D) is in red; the hybridization (H) of the continuous double auction with a dealership is in green; and the trading pit (T) is in blue. The left-hand side of Fig. 1.2 reports for each protocol the allocative efficiency *with resampling* for 100 different runs, as well as the sample average at the bottom of each column. The right-hand side shows the same information for the continuous double auction without resampling. Again, the y -axes use the same scale so direct comparison is possible.

We make two claims. The first one is that, for each protocol, allocative efficiency with resampling is significantly much higher than without resampling. This confirms and reinforces our earlier claim that the assumption of resampling matters a lot. The data in black concerning the continuous double auction (C) are reproduced from Fig. 1.1 and need no further commentary. The data in red regarding the dealership (D) report a sample average of 0.91 with resampling against 0.33 with no resampling. Analogously, the data in green regarding the hybrid protocol (H) give a sample average of 0.94 with resampling against 0.42 with no resampling. Finally,

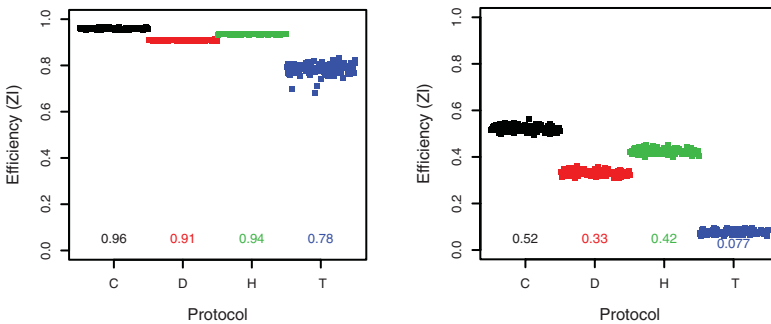


Fig. 1.2 Allocative efficiency with (*left*) and without resampling (*right*)

the sample averages for the trading pit (T) is 0.78 with resampling and 0.077 with no resampling. For each protocol, the directional version of the Wilcoxon signed-rank test supports the significance of the difference with and without resampling for any practical level of confidence.

We conclude that the introduction of the resampling assumption has a dramatic positive effect on allocative efficiency under zero intelligence. Hence, this assumption introduces an important bias that undermines Gode and Sunder's (1993) claim that "the primary cause of the high allocative efficiency of double auctions is the market discipline imposed on traders" (p. 134), unless such market discipline is not taken to include resampling as well.

Two minor observations are worth making. First, regardless of the resampling assumptions, allocative efficiency is higher for literate protocols. The reason is that they give each trader access to a larger pool of counterparts. Second, the differences in the allocative efficiency of the trading pit are exaggerated by the minor modeling assumption that traders are matched in pairs. This implies that several pairs end up being formed by traders on the same side of the market who are bound not to trade. Therefore, we have also tested the alternative assumption that buyers and sellers are matched in pairs, making sure that each pair is formed by agents on the opposite side of the market. In this second case, the sample average of the allocative efficiency without resampling is 0.15. No qualitative conclusion is affected, although it is obvious that the trading pit works much better if traders can be screened in buyers versus sellers before being matched. (For each of the other protocols, the adirectional version of the Wilcoxon signed-rank test supports at any practical level of confidence the claim that it makes no difference for allocative efficiency to have buyers and sellers arrive in random order or alternately.)

Our second claim is that the allocative efficiency of the continuous double auction with or without resampling is higher than for other sequential protocols; hence, this market protocol remains more effective under zero intelligence. This is easily detectable by visual inspection of the two tables in Fig. 1.2. The directional version of the Wilcoxon signed-rank test supports the claim that C yields a higher expected allocative efficiency than H (the highest competitor) for any practical level of confidence, both in the case of resampling (left) and no resampling (right). This confirms Gode and Sunder's (1993) intuition that the continuous double auction provides an important and natural benchmark for allocative efficiency under zero intelligence. The next test inquires whether this remains true under more realistic assumptions about agents' behavior.

1.3.3 Test 3: Does Learning Make a Difference?

Our third test extends the previous one by looking at the allocative efficiency of protocols under the alternative assumption that traders learn and optimize according to a slightly simplified version of the model in Gjerstad and Dickhaut (1998). We consider first the case without resampling, and then the case with resampling.