

Animat Market-Trading Interactions as Collective Social Adaptive Behavior

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Abstract

We argue that human economic interactions, particularly bargaining and trading in market environments, can be considered as collective social adaptive behaviors. Such interactions are social in the sense that they depend on socially-agreed market regulations and communication protocols, and are collective in the sense that global market dynamics depend on the interactions of groups of traders. Moreover, the tools and techniques of adaptive behavior research could be profitably employed to build predictive models of existing or planned market systems. Despite these potential applications, we note that there is a near-total absence of papers in the adaptive behavior literature that deal with autonomous agents capable of exhibiting trading behaviors. We summarize work in experimental economics where human trading behavior is studied under laboratory conditions. We propose that such experiments could and should be used as ‘benchmarks’ for evaluating and comparing different architectures and strategies for trading animats. We present results from experiments where an elementary machine learning technique endows simple autonomous software agents with the capability to adapt while interacting via price-bargaining in market environments. The environments are based on artificial retail markets used in experimental economics research. We demonstrate that groups of simple agents can exhibit human-like collective market behaviors. These results invite a Braitenberg-style eliminative materialism perspective on the dynamics of experimental retail markets.

Keywords:

Microeconomics; Markets; Auctions; Trader-Animats; Widrow-Hoff Learning

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1 Introduction

The majority of research in adaptive behavior has concentrated on developing artificial autonomous agents (i.e., animats) that exhibit behaviors common to many species of animals. Typical examples are spatiotemporal behavior patterns such as obstacle-avoidance, wall-following, and navigation to goal locations. Few papers in the adaptive behavior literature have examined behaviors that are exhibited exclusively by humans, and very few indeed have considered human social interactions.

Human economic interactions, where buyers and sellers interact via some form of market mechanism or institution, are social in the sense that the agents in the market interact via socially agreed protocols and communication conventions. The overall dynamics of a market are the product of the collective behaviors of the agents in that market, and “antisocial” agents that ignore or contravene the protocols or conventions of the market may do so to their personal detriment, or possibly to the detriment of the entire market.

In this paper we argue that human economic interactions, particularly bargaining and trading in market environments, can be considered as adaptive behavior despite being uniquely human. One strength of adaptive behavior research is its equal emphasis on synthesis and analysis, both in explaining behaviors of animals and in designing animal-like artefacts. We argue that this approach can be applied to human economic activity, and in Section 3 we describe experiments where simple adaptive animats interact within environments based on experimental retail markets used to evaluate human trading behavior. We show that the collective behavior of the trading animats is similar to that of groups of humans.

Explanations of animat markets could have significant impact on the way in which comparable human activity is explained. If groups of simple artificial agents interact to exhibit market-level phenomena that are similar to those of human markets, explanations of how the phenomena arise in the artificial system may be viewed as candidate explanations for the same phenomena in human markets. Thus, adaptive behavior techniques can be used to build explanatory models of existing or planned market systems. It should also be possible to use such models for predictive purposes: at the policy level, the effects of possible changes in the organization of a market could be explored in simulation rather than by trial-and-(expensive)-error in the real world; at a more avaricious level, predictions of the future behavior of various markets offers manifest opportunities for generating income, so long as the predictions are accurate.

While we doubt that current agent technology and human performance data could be combined to create genuinely novel explanatory or predictive models, we do see this as a worthwhile and challenging aim for future work. One immediate problem is the need for a rigorous understanding of how the fundamental mechanistic interactions between trading agents in market environments gives rise to the overall desirable market dynamics, and what role (if any) adaptation techniques can play in tailoring the agents to their environments. Although traditional economics research is likely to offer many insights, we believe that the tools and techniques of adaptive behavior research may offer novel perspectives. Thus, in this paper we present results from experiments with abstract computational markets, directly based on abstract experimental markets used in economics research to explore human trading behavior.

Section 2 explains our arguments in more detail. We start, in Section 2.1, with a brief review of some fundamental issues in microeconomics, the branch of economics that deals with market behaviors. Section 2.2 then summarizes seminal work in *experimental economics*, where the trading behavior of small groups of humans in particular markets is studied under experimental conditions. The clarity of the experimental economics results, where theoretically predictable market dynamics emerge as a result of the collective behavior of the (human) trading agents, acts as one motivation for the development of adaptive behavior models of market activity. This issue is explored in more depth in Section 2.3, where we present our arguments for treating trading and bargaining behaviors as adaptive behavior. In Section 2.4 we discuss the near-total lack of relevant work in the published literature on adaptive behavior and the related field of artificial life; while Section 2.5 gives an overview of relevant work in the economics literature. Section 3 then presents details of our experiment methods and results. In this paper we concentrate on trading-animats in experimental retail markets; our experiences with these animats in non-retail-style markets are described elsewhere (Cliff, 1997; Cliff & Bruten, 1997a, 1997b, 1998).

2 Economics and Adaptive Behavior

2.1 Microeconomics

In the economics literature, a distinction is made between *microeconomics*, the study of the structure and dynamics of particular markets, and *macroeconomics*, the study of the structure and dynamics of entire

economies. Microeconomics is often characterized as being primarily concerned with the allocation of scarce resources via some market mechanism, which provides a set of arrangements for buyers and sellers to contact each other. In any particular market, the quantity of a commodity (good or service) that buyers are prepared to purchase at each possible price is referred to as *demand*, and the quantity of a commodity that sellers are prepared to sell at each possible price is referred to as *supply*. In general, the greater the price of a commodity, the fewer buyers will be inclined to make a purchase, and so the quantity demanded reduces: thus, if we plot price as a function of quantity, the *demand curve* slopes downward. In contrast, the greater the price of a commodity, the more sellers are inclined to sell, and so the quantity supplied increases: on a plot of price as a function of quantity, the *supply curve* slopes upwards. From these considerations, it is clear that at high prices the quantity supplied may exceed the quantity demanded (i.e., there is a surplus, or *excess supply*), and at low prices the reverse may be true (giving a shortage, or *excess demand*). But, at some intermediate price, the quantity demanded is equal to the quantity supplied: this is the *equilibrium price*, which ‘clears the market’: graphically, the equilibrium price (and quantity) can be determined by the intersection of the supply and demand curves. Throughout the rest of this paper, the equilibrium price will be denoted by P_0 and the equilibrium quantity by Q_0 . Some authors refer to Q_0 as the “clearing quantity”.

In theory at least, markets are *self-correcting*: if the supply and demand schedules remain fixed, the prices of transactions in the market (i.e., the *market price*) will tend toward P_0 . At prices below P_0 , there is excess demand: the suppliers can then choose only to sell to the highest-bidding buyers, and so the buyers have an incentive to bid higher prices, thereby raising the market price towards P_0 . At prices above P_0 , there is excess supply: buyers can then choose only to buy from the sellers with the cheapest offers, so sellers have an incentive to cut their offer prices, thus lowering the price towards P_0 . When the market price is at P_0 , neither buyers nor sellers have any incentive to change their prices, and so the system stabilizes. In this sense, the actions of a group of individuals in a market, each pursuing their own interests, can give rise to *price determination*, or *equilibration*, where the market price is P_0 and so the quantities demanded and supplied match at Q_0 . Because the equilibrium is a result of price-competition between the agents in the market, it is often referred to as a *competitive equilibrium*. Such competitive market mechanisms,

it is argued, can give efficient (or perhaps optimal) allocation of resources without centralized control or external intervention (e.g., by government regulation). A common ideal is *Pareto efficiency*: an allocation of resources is Pareto-efficient if no-one can be made better-off without someone else being made worse-off.

If there is no external intervention (e.g., price-caps imposed by some regulatory authority, such as a government), the system is said to be a *free market*. Free markets can give rise to ‘emergent’ collective behavior (convergence to competitive equilibrium) of the whole group which is in the best interests of that group (Pareto-efficient), despite the fact that each agent is operating only to satisfy self-interest. The group appears to be led by an ‘invisible hand’, in the metaphor introduced by Adam Smith in his 1776 book *The Wealth of Nations*. There are, however, conditions in which free markets fail to achieve an efficient allocation: see Begg, Fischer, and Dornbusch (1994, pp.264–265).

Conditions under which a market can attain equilibrium from a given set of initial conditions, and the nature of the approach to equilibrium, have been the subject of intense research in economics. Many models of equilibration assume *perfect competition*, where homogeneous indivisible units of a commodity are traded by large numbers of buyers and sellers, none of whom are sufficiently powerful to individually have any impact on market price, all of whom are aiming to maximize utility (i.e., sellers maximizing profits, buyers minimizing costs), and none of whom incur any costs in entering or leaving the market (Bannock, Baxter, & Davis, 1992, p.325). The nature or organization of some markets makes perfect competition unlikely or impossible, yet price determination can still occur. However, as the number of individuals in the market falls, the likelihood of collusion and the formation of rings or cartels increases: as the number of sellers is reduced, the market approaches an *oligopoly*, where the behavior of individual sellers in the market is highly dependent on the likely initiatives or responses of the other sellers. In such cases, the actions of individual buyers or sellers can have a significant impact on the market price, depending on the organization of the market.

2.1.1 Market Organization

Market organization concerns the regulations governing the information available to the agents in the market and the agents’ *opportunity sets* (i.e., the possible actions they can perform). Together, these affect the method by which a market price is determined. In most markets, prices are determined via some type

of *auction*.

One particular style of auction that has received significant attention in the literature is the *continuous double auction*, or CDA. In a CDA, a group of buyers and a group of sellers simultaneously and asynchronously announce bids and offers: at any time, a seller is free to accept the bid of a buyer, and a buyer is free to accept the offer of a seller. One practical reason for the interest in CDAs is that they have for many years been the basis of trading in major international financial markets (such as the London and New York stock exchanges): originally as open-outcry oral auctions taking place on the trading floor of the exchange, and latterly as electronic auctions taking place in the cyberspace of city-wide networks of computerized dealing rooms.

While there are many other styles of auction,¹ much work has been concentrated on CDAs, motivated by the fact that they are often very fast and efficient, despite (or possibly because of) the volumes of information exchanged:

“...markets organized under [CDA] trading rules appear to generate competitive outcomes more quickly and reliably than markets organized under any alternative set of trading rules. For this reason, [CDA] markets have been frequently investigated as a standard against which the performance of other institutions is evaluated.” Davis and Holt (1993, p.126).

This interest has resulted in a research literature discussing CDAs (see, e.g., Friedman and Rust (1992) and Davis and Holt (1993, pp.125–172) for reviews). The motivation for such work comes from a desire to better understand *how* the organization of the market, and the behavior of the traders in that market, affects the speed and efficiency of the market. This is summarized neatly by Rust, Miller, and Palmer (1992, p.156):

“Although the textbook ‘supply equals demand’ model may provide a good prediction of *closing* prices and quantities in [CDA] markets, it fails to explain the dynamics by which this happens. A more sophisticated theory is required to show how the trading process aggregates traders’ dispersed information, driving the market towards [competitive equilibrium]. The ... problem was clearly stated by [(Hayek, *Amer. Econ. Rev.* 35(4):p.530, 1945)]: “The problem is in no way solved if we can show that

¹Examples include the *English* (ascending-bid), *Dutch* (descending-offer), *Vickrey* (second-price sealed-bid), *posted-offer*, and *call* auctions: see Cliff (1997).

all facts, *if* they were known to a single mind, would uniquely determine the solution; instead we must show how a solution is produced by the interactions of people each of whom possesses only partial knowledge. To assume all the knowledge to be given to a single mind in the same manner in which we assume it to be given to us as the explaining economists is to assume the problem away and to disregard everything that is important and significant in the real world.”

Solving this problem, i.e. developing a theory of how the transaction prices of human traders converge on the theoretical equilibrium price, requires data gathered under controlled conditions. Such data has been generated by work in experimental economics, discussed next.

2.2 Experimental Economics

The use of ‘laboratory methods’ in economics, conducting controlled experiments to test theoretical hypotheses and predictions, has been of interest since at least the 1930’s: for historical reviews, see Davis and Holt (1993, pp.5–9) and Roth (1995, pp.4–21). In a typical simple experiment, a group of human subjects are each given the means to buy one unit of an arbitrary commodity; while another group are each given one unit of the commodity to sell. Each buyer will be given a *limit price*, the maximum that buyer should pay for a unit of the commodity; and each seller will be given a minimum limit price below which the seller’s unit should not be sold.² Typically, different buyers will be given different limit prices, as will different sellers. The distribution of limit prices determines the supply and demand, and hence the values of P_0 and Q_0 , for the experimental market. The subjects are then allowed to buy and sell within a particular market mechanism: in the early experiments, the markets were experimentally controlled open-outcry trading pits, but the vast majority of recent work has required the subjects to communicate via a computer network, which eases the control of free parameters and the recording of data.

Davis and Holt (1993) wrote the first comprehensive text covering the major areas of experimental economics, while Kagel and Roth (1995) edited a significant collection of critical surveys of the field: we refer the reader to those texts for further details. Meanwhile, in the rest of this section we summarize the first paper on experimental economics published by Vernon Smith, who helped establish the field and

²In the economics literature, a buyer’s limit price is more commonly referred to as the buyer’s *value*, and the seller’s limit price is more commonly referred to as the seller’s *cost*.

has since continued to be a prominent researcher: for a brief popular overview of his work, see Smith and Williams (1992), and for full details see his collection of papers spanning 30 years of research (Smith, 1992).

Smith (1962) reported on experiments performed over a six-year period starting in 1955. All of the experimental regimes are similar to that described above: a cohort of human subjects are divided into a group of sellers and a group of buyers, and the two groups then trade within some specified market mechanism. Each trader's individual limit price is private (i.e., is not known by any other trader). Each buyer is encouraged to trade in the market by being instructed to consider the difference between the given limit price and the actual transaction price for the commodity as pure profit. Furthermore, buyers are told it is better to make no profit and own the commodity than to go without (i.e., they are encouraged to 'trade at the margin'). Similarly, each seller is told to treat the difference between the transaction price and the given limit price as profit, and to trade at the margin.

Each experiment is run as a sequence of distinct trading periods or 'days'. At the start of each day, all traders are allowed to quote a price: sellers quote *offers* (e.g., "sell at \$2.50") and buyers quote *bids* (e.g., "buy at \$1.20"). The quotes continue, typically with both groups of traders altering their quote-prices (increasing bids and decreasing offers) in an attempt at securing a transaction. At any time, a buyer is free to accept a seller's offer or a seller is free to accept a buyer's bid. When this happens, the buyer and seller are considered to have entered into a binding transaction: for both traders, the number of units they are entitled to trade in is reduced by one, and when a trader's entitlement reaches zero that trader drops out of the market for the remainder of that trading day. This process continues until the quotes of the traders no longer lead to contracts being made, or when some predetermined time-limit (typically five or ten minutes) is reached, at which point the day ends. If there are more days to run, the entitlements of all traders are then restored to their start-of-day values and the market reopens for another day's trading.

In a typical experiment, trading in the first day is characterized by early transactions taking place at prices that differ significantly from the P_0 value: as the day progresses, transaction prices approach P_0 . On subsequent days, transaction prices are initially nearer P_0 , and approach it faster. In most of the experiments described by Smith (1962), only the prices of agreed transactions were recorded.

In the first eight experiments reported by Smith (1962), each trader is allowed to buy or sell only one

unit, although in later experiments this constraint was relaxed. Smith also experimented with changing the supply and demand during the experiment (i.e., after a few trading days, before the start of the next day's trading, a new set of limit prices were given to the subjects), and with having the buyers remain silent while only the sellers were allowed to quote offers: an experiment discussed in more detail in Section 3. Smith's results qualitatively indicated that the relationship of the supply and demand curves had an impact on the way in which transaction prices approached P_0 : whether P_0 was approached from above or below, and whether the P_0 value was actually reached or the transaction prices stabilized at a different value. Discussing these results in a subsequent publication, Smith states:

“What have I shown? I have shown that with remarkably little learning, strict privacy, and a modest number [of traders], inexperienced traders converge rapidly to a competitive equilibrium under the [CDA] mechanism. The market works under much weaker conditions than had traditionally been thought to be necessary. You didn't have to have large numbers. Economic agents do not have to have perfect knowledge of supply and demand. You do not need price-taking behavior – everyone in the [CDA] is as much a price maker as a price taker.” Smith (1992, p.157).

Smith's (1962) results were some of the first to demonstrate that markets consisting of small numbers of traders (e.g., 10–20) could still exhibit equilibration to values predictable from classical microeconomic theory. To appreciate why this is significant, it is necessary to consider the underlying supply and demand curves in more detail.

Consider, for example, five sellers (denoted by the letters A to E) and five buyers (F to J) each with an entitlement to trade one unit. For illustration, possible supply and demand curves are illustrated in Fig. 1. From the figure, it is clear that P_0 is \$2.50, and Q_0 is three.

As is evident in Fig. 1, the supply and demand curves for this experiment are stepped: this is because the commodity is dealt in indivisible discrete units, and there are only a small number of units available in the market. Thus, supply and demand in this simple market differs appreciably from the smoothly sloping curves of the idealized markets often illustrated in introductory economics textbooks. Such idealized markets are based on conditions where the step-changes involved can be treated as infinitesimally small.

Furthermore, most classical theories of price determination and equilibration assume or require a large number of traders: if an individual trader drops out of the market, the supply and demand curves remain

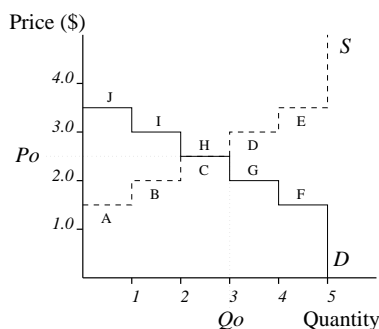


Figure 1: Supply and demand curves for ten traders. The supply curve is shown as a dashed line for extra clarity. There are five sellers (A to E), each with one unit to sell, and five buyers (F to J), each with the right to buy one unit. The step-changes in the quantities supplied and demanded are dependent on the limit prices of the individual traders, as indicated by the labels A to J . The intersection gives equilibrium values $P_0=\$2.50$ and $Q_0=3$.

essentially the same. But in markets with few participants, this is not the case. Consider the simple market illustrated in Fig. 1: if the first trade in the market is between seller C and buyer I (at a price, say, of $\$2.65$: giving profits of $\$0.15$ for C and $\$0.35$ for I) then these two traders drop out of the market, but the resultant supply and demand curves, and the values of P_0 and Q_0 , are significantly different; as illustrated in Fig. 2.

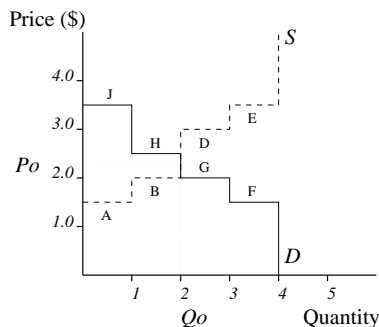


Figure 2: Supply and demand curves for eight traders. This is the market illustrated in Fig. 1, after traders C and I have agreed a transaction and left the market. The equilibrium price and quantity have altered. Now Q_0 is reduced to two, and P_0 is indicated at $\$2.25$, although technically it is no longer a scalar value: rather there is now a bounded range of possible equilibrium prices, from $\$2.00$ to $\$2.50$: what Davis and Holt (1993, p.131) refer to as a ‘price tunnel’; any price within this range could be an equilibrium value.

Matters are further complicated when the difference between the *underlying* and *apparent* supply and demand curves is considered.³ Each active trader in the market will be trying to make a profit, so buyers

³Smith (1992, pp.809–810) refers to the underlying supply and demand as the *market* supply and demand, and to the apparent supply and demand as the *seller’s offer array* and *buyer’s bid array*: referred to collectively as the bid-and-offer arrays (Davis & Holt, 1993, p.300).

will be quoting prices lower than their individual limit prices, and sellers will be quoting prices higher than their limit prices. Because the limit price of each trader is private (i.e., known only to that trader), the prices openly quoted by the traders give only a weak indication of the *underlying* supply and demand determined by the limit prices: the *apparent* supply and demand, based on the actual prices quoted, may be significantly different. Thus, Figs 1 and 2 show underlying supply and demand before and after the trade between *C* and *I*, but an observer of (or participant in) the market does not have access to this information: these underlying schedules can only be guessed at by the traders, and the only information they have available is the quote-prices observed (i.e., “heard”) in the market.

To illustrate the difference, assume that each trader aims for a particular ‘profit margin’, expressed as a percentage of the trader’s limit price. Say that we take the market of Fig. 1 and assign each trader a randomly chosen profit margin in the range 0% to 50%. Then the market might have the apparent supply and demand curves illustrated in Fig. 3. As can be seen, the apparent supply and demand differ significantly from the underlying curves illustrated in Fig. 1. The values of P_0 and Q_0 are different, and the ranking of the traders’ prices has altered.

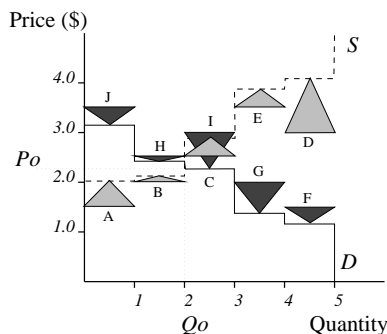


Figure 3: Bid-offer array for the ten-trader market illustrated in Fig. 1, given random profit margins between zero and fifty percent. Each buyer’s limit and quote prices are illustrated as dark inverted triangles, while each seller’s limit and quote prices are illustrated by light upright triangles: the base of each triangle indicates the trader’s limit price, while the apex indicates the trader’s quote-price. The array of bid-prices gives an apparent demand curve D , and the array of offer-prices gives an apparent supply curve S . The apparent supply and demand curves differ significantly from the underlying supply and demand shown in Fig. 1: see text for discussion.

Finally, it should be noted that the apparent supply and demand schedules are dynamic, and can alter rapidly. Because no trader has full knowledge of the underlying supply and demand, traders might base their profit levels on an initial guess that is then refined on the basis of the prices subsequently quoted by the competition (other members of the trader’s group) and opposition (traders in the other group, or

‘contraside’ (Bollerslev & Domowitz, 1992, p.226)), and on the basis of which quotes lead to transactions and which are ignored. In a CDA, such information arrives in a continuous asynchronous stream. Moreover, the underlying supply and demand dynamically shift as traders enter and leave the market.

Despite this, the humans in Smith’s experiments rapidly approach the competitive equilibrium predicted from theory. Figs 4 and 5 show some of Smith’s (1962) results. In both figures, the supply and demand curves are shown on the left, and the time series of transaction prices over a number of trading days is shown on the right. In Fig. 4, there are 11 buyers and 11 sellers, each with the right to buy or sell one unit: $P_0 = \$2.00$; $Q_0 = 6$. The shaded area in Fig. 4 indicates the available profit (or ‘surplus’ or ‘rent’) in the market: this is divided into two regions by the horizontal line at P_0 , and Smith (1962) hypothesized that the ratio of the areas of these two regions affected the nature of the approach of transaction prices to the theoretical equilibrium price. As is clear on the right of Fig. 4, transaction prices converge toward equilibrium over the five trading days, and the number of transactions per day varies from five to seven. In Fig. 5, there is excess demand (12 sellers but 17 buyers): transaction prices converge to equilibrium very slowly, and from below: when equilibrium is reached, there is evidence of some ‘overshoot’.

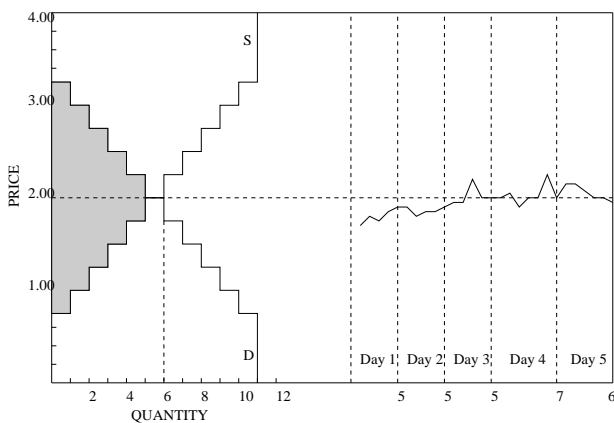


Figure 4: Redrawn from Smith’s (1962) Chart 1: see text for discussion.

Human beings are notoriously smart creatures: the question of just how much intelligence is required of an agent to achieve human-level market performance is an intriguing one. This question was addressed by Gode and Sunder (1993) who described a set of experiments similar in style to Smith’s, but which use “zero intelligence” (ZI) programs that submit random bids and offers to replace human traders in electronic CDA

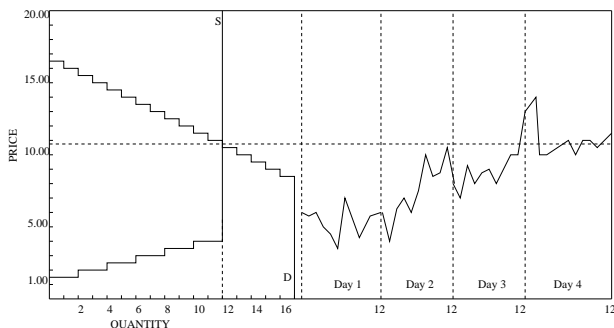


Figure 5: Adapted from Smith’s (1962) Chart 6. See text for discussion.

markets. They compare the results of these software-agent traders to results from human traders operating in (almost) identical experimental conditions.

As with Smith’s work, each ZI trader is given an entitlement to buy or sell a number of units, each with a particular limit price. The ZI traders generated quote prices at random. Gode and Sunder (1993) presented results from five experiments. In each experiment, a CDA market with specific supply and demand curves was run for a set number of trading days, once with humans, once with ZI traders that quoted randomly-generated prices without any constraint (referred to as unconstrained or “ZI-U” traders), and once with ZI traders that again quoted randomly-generated prices, but were constrained not to quote loss-making prices (so-called “ZI-C” traders). Significantly, and unexpectedly, the ZI-C traders appeared to give market performance that was much closer to the performance of human traders than it was to that of the ZI-U traders.

Thus, Gode & Sunder concluded that the CDA market’s attractive dynamics is not much affected by the intelligence, rationality, learning, or memory capabilities of the traders. Rather, it is due to the structure of the market (i.e., traders interacting via a CDA and prevented from loss-making transactions). Prima facie, Gode and Sunder’s result indicates that, so long as the market is structured correctly, traders with *no intelligence at all* can give human-like market dynamics. Gode & Sunder’s paper has had significant impact in the experimental economics literature;⁴ it is mentioned in the current edition of Simon’s classic

⁴For example, the following authors approvingly cite Gode & Sunder’s 1993 *JPE* paper on ZI traders: Bollerslev and Domowitz (1992, pp.230–231), Cason and Friedman (1992, pp.253, 258), Friedman (1992, p.19), Friedman and Rust (1992, p.xiii), Kagel and Vogt (1992, pp.292, 294), Rust et al. (1992, pp.160–161, 175), Davis and Holt (1993, p.132), Leijonhufvud (1993, p.2), Grether (1994, p.1082), Stahl and Wilson (1994, p.310), Anderson and Sunder (1995, p.186), Camerer (1995,

book *The Sciences of the Artificial* (Simon, 1996, p.32); and has even been discussed in Clark's latest book on the philosophy of cognitive science (Clark, 1997, pp.183–184).

However, we have recently presented analytic and empirical results which conclusively demonstrate that Gode & Sunder's results only occur in special circumstances, and that in general the ZI traders fail to give human-like market performance (Cliff, 1997; Cliff & Bruten, 1997b, 1997c). Thus, more than zero 'intelligence' is required of artificial trading agents to give human-like collective behavior and market dynamics. And because of this, methods developed in adaptive behavior research should be relevant.

2.3 Trading as Adaptive Behavior

Given that nonzero 'intelligence' is required of artificial traders to give human-like market dynamics, one possibility is to use traditional artificial intelligence (AI) techniques, based on deliberative reasoning with explicit representations of 'knowledge' or 'beliefs', as the foundation for building artificial trading agents. However, we believe that the assumptions underlying adaptive behavior research imply that it is a more attractive approach.

Although precise definitions are rarely articulated, much adaptive behavior research is consistent with the definition that a behavior is adaptive if, when an agent exhibits that behavior, it increases its chances of survival (or reduces its chances of ceasing to exist). This requires that the behavior is well-matched to the prevailing environmental conditions, and this carries an implicit assumption that the environment with which the agent interacts is nontrivial: i.e. that it is, to significant extents: complex, dynamic, unknown, unpredictable, and unforgiving of mistakes. Because of this, the agents studied in adaptive behavior are fundamentally *situated*, in the sense that their (inter)actions cannot be premeditated because it is impossible to predict with any accuracy all possible future conditions, events, or outcomes. Such situatedness requires that the agents are responsible for co-ordinating perception and action for extended periods of time without human intervention (i.e., that they are *autonomous*). Finally, adaptive behavior research typically places strong emphasis on the resource-limited nature of real-world interactions: agents

p.674) Hardle and Kirman (1995, p.228), Holt (1995, p.370), Kagel (1995, pp.570, 580), Luo (1995, p.226), Roth (1995, pp.52–55, 80–81), Sunder (1995, p.475), Cason and Friedman (1996, pp.1318, 1333), Conlisk (1996, p.678), Cox and Grether (1996, p.383), Jamal and Sunder (1996, p.276), McAfee and McMillan (1996, p.266), Steiglitz, Honig, and Cohen (1996, p.2), Van Boening and Wilcox (1996, p.461), Cason and Friedman (1997, p.320), Evans (1997, p.623), and Gode and Sunder (1997, pp.604–605).

in real environments do not have unlimited computational power or memory space or time in which to decide on appropriate actions. The stark contrast between these assumptions and those of the vast majority of work in AI is manifest.

Compare this explicit characterization of adaptive behavior with the situation faced by human traders in a real CDA market or in one of Smith's experiments: traders need to coordinate perception and action in the sense that they must accumulate and integrate data from diverse asynchronous sources, and act upon that data in good time (the value or integrity of much market data decays rapidly with time). In a competitive market, the environment is clearly dynamic and unforgiving. Relevant information (such as other traders' profit margins, or the information held by other traders) is rarely known or predictable, and it is unlikely that any trader will experience acts of kindness or selfless altruism. In real markets, traders that consistently fail to make profits will not last long. To summarise: if you're a trading agent, you can't be sure of anything except that the world is out to get you and that if you snooze you lose. For these reasons, trading agents need to be situated and autonomous. And, as adaptive behavior research is fundamentally concerned with the analysis or design of situated autonomous agents, there should be some use for adaptive behavior tools and techniques in studying or creating microeconomic systems. For instance, much work in adaptive behavior has explored the use of adaptation methods such as reinforcement learning (based on attempting to maximize "reward") and artificial evolution (based on attempting to maximize "fitness"). When trading agents interact within a market environment, measures of reward or fitness can be clearly and unambiguously equated with profit or utility.

Much work in microeconomics has been devoted to analytic studies (typically reliant on set-theory, differential calculus, optimization methods such as dynamic programming, and game-theory) that are based on a number of simplifying assumptions necessary to maintain tractability. Simulations of the sort common in adaptive behavior research could be built to explore models that are too complex for formal analytic treatment but sufficiently simple (relative to real systems) that they have useful predictive or explanatory power.

Given these arguments, it seems reasonable to expect that some prior work in the adaptive behavior literature will have explored issues in the collective behavior of agents that bargain and trade in market-

based environments. Yet, surprisingly, the adaptive behavior field seems to have almost totally ignored such issues.

2.4 (The Lack Of) Related Work in Adaptive Behavior

Given the arguments of the previous section, it would seem reasonable to expect that a fair proportion of papers in the adaptive behavior research literature (i.e. this journal and the SAB conference proceedings) should deal with economic behaviors. However, as far as we are aware, there is only *one* paper that deals explicitly with economic activity: this is Beltratti and Margarita's (1992) study of the evolution of trading strategies among heterogeneous artificial economic agents. Beltratti and Margarita worked with artificial 'stock markets' populated by trading agents with neural network controllers that determined their trading strategies. In markets seeded with three initial types of strategy ('smart', 'dumb', and 'naive'), the dumb strategies rapidly disappeared, leaving 'smart' and 'naive' to interact. The agents could profit by making accurate predictions of the price of stocks: naive agents made predictions based only on the most recent market price, while the predictions of the smart agents required more sophisticated information that was provided at varying levels of cost. Beltratti and Margarita found that the market dynamics were dependent on the cost of information supplied to the smart agents. While this work is novel and interesting, it is of very little relevance to price-determination or bargaining behaviors, because whenever two agents entered into a transaction, the price was (arbitrarily) set at the average of the predictions of the two agents (Beltratti & Margarita, 1992, p.495). Thus, it appears that no work published in the adaptive behavior conference proceedings or journals addresses the issues we are discussing here.⁵

Adaptive behavior research is often characterized as related to work in *artificial life* (a-life). Many papers in the a-life literature deal with systems that exhibit complex coherent global behavior arising from the interaction of groups of components which are individually simple in comparison to their global behavior. Given this focus, the price-equilibration of groups of traders operating in market-based environments would seem to be a natural candidate for a-life research.

However, the international a-life journal and conference proceedings show a distinct lack of such re-

⁵McFarland's work (e.g., McFarland (1990), McFarland and Boesser (1993)) uses microeconomics as a framework for comparing adaptive behavior in animals and robots, but does not explicitly address human economic behavior.

search. While there is a small core of work on the *iterated prisoner's dilemma*, a classic game-theory problem in which the emergence of cooperative behavior among non-altruistic agents can be explored, and which is of direct relevance to oligopolistic markets (see, e.g., Axelrod (1984), Stanley, Ashlock, and Tesfatsion (1993), and May, Bohoefter, and Nowak (1995)), we know of only two papers published in the a-life literature that explicitly study market trading strategies: Nottola, Leroy, and Davalo (1991) and de la Maza and Yuret (1994). Both of these papers report on the application of elementary evolutionary adaptation methods to optimize simple trading strategies for speculative markets, and both directly set all transaction-prices to be equal to P_0 via a centralized process that collects quote prices from all individuals, determines the supply and demand, and then calculates P_0 : Nottola et al. (1991, p.191), de la Maza and Yuret (1994, p.326). For this reason, neither of these two papers are relevant to the study of equilibration or bargaining behaviors.

The apparent lack of work in a-life on agents with bargaining behaviors for market-based environments is confirmed in a recent review paper by Tesfatsion (1997). The paper presents a summary overview of aspects of a-life especially relevant for the study of decentralized market economies. The two main areas of research activity discussed are: the combination of evolutionary game theory (e.g., iterated prisoner's dilemma) with preferential partner selection (i.e., the ability to choose or refuse particular opponents in the game); and an extension of this, where trade networks can form and evolve, using the prisoner's dilemma game to model risky trades between individuals. Thus, there is no emphasis on bargaining mechanisms in this work, and the indications from Tesfatsion (1997) are that little or no work in a-life is comparable to the work on trading agents discussed here.

2.5 Related Work in Economics

While component technologies common in adaptive behavior research (such as neural networks or genetic algorithms) have been used to good effect by economists, they have often been employed as pure engineering tools (e.g., for function approximation or parameter-optimization), and the modelling of groups of interacting autonomous agents in economic environments is still relatively rare in the economics literature.

There is, however, a small but growing group of economics researchers interested in studying computer

simulation models of adaptive agents in economic scenarios. Tesfatsion maintains a web-site⁶ devoted to “agent-based computational economics” (ACE). A notable example of ACE research is Epstein and Axtell’s (1996) ‘Sugarscape’ model, which has been used to study collective social behaviors (such as cultural transmission of information; combat; and trade) as emergent properties arising from individual interactions. Yet in the Sugarscape trade model there is no money (Epstein & Axtell, 1996, p.101) and hence no opportunity for studying the issues we address in this paper, i.e. bargaining and price formation. Similarly, Vriend (1995) explores the temporal evolution of trading strategies in populations of buyers and sellers, but the transaction prices are fixed externally. More recently, Kirman and Vriend (1997) have reported on an agent-based model of the Marseille wholesale fish market, where classifier systems (e.g. (Holland, 1975; Goldberg, 1989; Wilson, 1994)) are used as decision-making mechanisms in each agent. For buyers, these decisions concern which seller’s sales-point to queue at, and at what price fish may be purchased from that seller. For sellers, the decisions concern the quantity to supply, the price to ask, and how the queue of buyers at their sales-point will be handled.

Perhaps the most relevant work in the economics literature is research conducted at the Santa Fe Institute. Arthur (1993) discussed the idea of designing artificial agents that behave like human economic agents, and explored the use of a simple classifier system as an adaptation mechanism for developing artificial agents that could be calibrated against human learning data from experiments exploring the psychology of economic behaviors. The use of artificial agents in economic modeling offers two benefits. First, the costs associated with using humans are eliminated. Second, the use of computer simulations forces a degree of mechanistic rigour, and thus helps clarify what information and/or cognitive mechanisms are necessary and sufficient to produce the behaviors of interest. In this sense, the algorithms or programs that specify the behavior of the artificial agents can be viewed as ‘theories’ concerning the generation of comparable behaviors in real agents. However, Arthur’s 1993 paper did not deal with price-bargaining in auctions.

Subsequently, Arthur collaborated with others (Arthur, Holland, LeBaron, Palmer, & Tayler, 1997) to develop a system where autonomous software trading agents interact in an asset market, each using

⁶URL: <http://www.econ.iastate.edu/tesfatsi/ace.htm>.

a classifier system to adapt its trading strategy to changes in the market. The agents adapted their ‘expectations’ of future price movements, and Arthur et al demonstrated that the market dynamics were affected by the rate at which alternative expectations were explored: at low rates of exploration, the market settled to a predictable equilibrium, but higher rates led to complex dynamics, including temporary bubbles and crashes.

We know of two other papers in the economics literature that describe artificial trading agents similar to the ZIP traders developed here. These by Easley and Ledyard (1992) and Rust et al. (1992), discussed below.

Easley and Ledyard (1992) consider several theories for price formation and equilibration, attempting to explain how human traders converge to equilibrium. They introduce a mathematical notation which they use to describe specific hypotheses concerning trading strategies and equilibration in double-auctions; a number of analytic proofs then lead to three specific predictions, which they test by comparison to data from human experiments. Their trading strategies are simple mechanisms which rely on a memory of data from past trading days. Specifically, Easley and Ledyard’s trading strategies use the following information: the lowest-priced offer or transaction in the previous day’s trading; the highest-priced bid or transaction in the previous day’s trading; the most recent bid, offer and transaction prices in the current day’s trading; the time remaining to the end of the current trading day; and an indicator of whether the agent has traded in the current day. Easley and Ledyard’s traders are designed to trade only one unit per day, so this indicator is similar to the way in which the animat traders we introduce in Section 3 cease to be active once they have traded all their entitlement; however, our traders may enter into more than one transaction per day. As will also become clear in Section 3, Easley and Ledyard’s trading strategies require more memory than our animat traders, and also the Easley and Ledyard strategy is only fully effective after the first day of trading; yet it is often on the first day that the most significant shifts in behavior occur. Easley and Ledyard’s analysis relies on a simplifying assumption that is questionable in practice: they assume that, when more than one trader is interested in a transaction, the buyer bidding the highest price and/or the seller offering at the lowest price is/are guaranteed the transaction (Easley & Ledyard, 1992, p.70). Despite (or possibly because of) this, several of the experimental observations they present contradict their

theoretical predictions. Furthermore, as Easley and Ledyard (1992, p.87) note, their theory does not apply to experiments in which one side of the market is not allowed to bid or offer (e.g., retail markets), and it doesn't predict the effects of shifts in supply and demand curves. Cliff (1997) shows the responses of our animat traders when supply and demand alter, and the human-like equilibration of our traders in 'retail' markets is discussed in detail in Section 3. Because our traders give good performance in situations where Easley and Ledyard's work cannot be applied, it seems fair to claim that our traders are both simpler than, and an advance on, the work of Easley and Ledyard (1992).

Rust et al. (1992) report on a series of experimental economics tournaments they organized, where other researchers were invited to submit software agents that would compete against one another in a simplified double auction. The double auction was simplified by synchronizing it into a two-stage process that was iterated several times per trading day. In the first stage, all traders simultaneously quote a bid or offer, and these quotes are distributed to all traders. In the second stage, the trader with the highest current bid and the trader with the current lowest offer are given the option of entering into a transaction: they can either agree a transaction, or refuse. In addition to the array of bids and offers, each trader has access to public information which includes: the number of buyers; the number of sellers; the identities of the traders; the number of rounds (experiments), periods (days per experiment) and timesteps (iterations per day); the number of units each agent will have; and the distribution from which the unit limit prices are generated (Rust et al., 1992, p.164). The trading agents were allowed to be both buyers and sellers, although some researchers submitted seller-only or buyer-only strategies. A number of tournaments were held, and the different strategies were ranked in order of the profits they generated. Very few details are given of the specifications of the different strategies, so a detailed comparison with our animat traders is difficult.

However, a key difference between these tournaments and the experiments we report in Section 3 is that the tournaments involved *heterogeneous* groups of traders. Traders with radically different strategies could compete in the same market, and much of the focus in Rust et al. (1992) is on the way in which the different trading strategies interacted, both with a fixed number of different strategies and in 'evolutionary' tournaments where the relative numbers of the different trading strategies altered over time, so

more profitable strategies became more numerous than less profitable ones. In discussing the ‘population dynamics’ of the tournaments they state:

“We find that the top-ranked programs yield a fairly “realistic” working model of a [CDA] market in the sense that their collective behavior is consistent with the key “stylized facts” of human experiments. We also find that a very simple strategy is a highly effective and robust performer in these markets. This strategy was able to outperform more complex algorithms that use statistically based predictions of future transaction prices, explicit optimizing principles, or sophisticated “learning algorithms”. The basic idea behind the approach can be described quite simply: *wait in the background and let others do the negotiating, but when bid and [offer] get sufficiently close, jump in and “steal the deal”*. However, the results of our evolutionary tournaments show that when too many other traders try to imitate this strategy, market efficiency can fall precipitously. . . . Specifically, if too many traders “wait in the background”, little information is generated until just before the end of the trading period. This tends to produce “closing panics” as traders rush to unload their [units] in the final seconds of the trading period, resulting in failure to execute all potentially profitable transactions.” (Rust et al., 1992, p.157, original emphasis).

Thus, there is no focus in Rust et al. (1992) on exploring the behavior of homogeneous groups of traders in particular market environments such as the retail markets discussed here, or the several styles of bilateral CDA markets discussed in (Cliff, 1997). Furthermore, the reproductive success of the “wait in the background” trader strategy indicates that the ‘evolutionary’ tournaments can favor trading strategies that, when used to form homogeneous groups of traders, can give rise to market dynamics that are manifestly undesirable.

The significant issue here is that, to the best of our knowledge, while there is a small body of work in the economics literature describing agent-based simulations, little of that deals with price-negotiation in auction markets.

2.6 Conclusion

It is not clear to us why the published research in adaptive behavior, and also in artificial life, has largely ignored economic activity. We find it curious, given that there are strong reasons for considering economic activity as adaptive behavior. For surely, adaptive behavior research methods could (and should) be used to develop animats that engage in economic interactions. The clear correlation between profitability (or utility-maximization) and ‘fitness’ or ‘reward’ should allow for many of the tools and techniques of adaptive behavior research to be readily transferred to autonomous agents that interact with market environments. Like many environments in adaptive behavior research, markets can be dynamic, uncertain, and unforgiving.

Given that the simplified and constrained market environments introduced by Smith have formed the basis of much work in experimental economics over the last 30 years, it seems wise to commence by attempting to develop “intelligent” trading agents with the bargaining capabilities necessary for small groups of traders to show price-equilibration in market scenarios similar to those studied with human subjects in experimental economics. By concentrating on a defined class of environments, the sharing of techniques and comparison of data should be made more easy, just as the development of the *Khepera* robot has provided a *de facto* standard platform for robotics-based adaptive behavior research.

Because the full details of equilibration in markets of human traders are yet to be explained, the development of trader animats capable of price-determination as a collective behavior in market-based environments could advance our understanding of existing microeconomic systems and open up new application areas. Thus, we anticipate a melding of research in adaptive behavior and market microeconomics that we expect to be highly productive, and hopefully also highly profitable. In the remainder of this paper, we present results from our ongoing work directed at that aim.

3 Trading Animats

In the previous section we argued that human trading interactions in market environments can be considered as instances of adaptive behavior. To illustrate this, we gave an overview of Smith’s (1962) seminal work in experimental economics, where human traders interact within a given market mechanism under ‘laboratory’

conditions. Smith's work was one of the first demonstrations that the transaction prices of small numbers of traders, interacting via a continuous double auction (CDA) market, could rapidly and reliably approach the theoretical equilibrium price, with no need for a centralized 'auctioneer'.

We noted that traders in such markets are autonomous and situated, and that, because adaptive behavior research is fundamentally concerned with autonomous situated agents – either real (animals) or artificial (animats) – the problem of creating artificial trading agents should no longer be ignored by adaptive behavior research. We also noted that, although it may seem intuitively obvious that some form of 'intelligence' or adaptation is necessary in bargaining agents, Gode and Sunder's (1993) results appear to indicate that their ZI-C agents can exhibit human-like behavior in CDA markets; however, we have demonstrated elsewhere (Cliff, 1997; Cliff & Bruten, 1997b) that the ZI-C result only holds in very specific circumstances and thus, in general, some 'intelligence' in the form of adaptivity or sensitivity to previous and current events in the market *is* necessary. Hence, we give our trading agents adaptive capabilities by employing elementary machine-learning techniques. Because our agents are intended to have minimal intelligence, but not zero intelligence, they are referred to as "ZIP" traders: ZIP is an acronym for "zero-intelligence-plus".

In other publications (Cliff, 1997; Cliff & Bruten, 1997a, 1998) we have shown that our ZIP traders do not suffer from the failings that afflict Gode and Sunder's ZI traders. Furthermore, we have noted that the collective behavior of groups of ZIP traders is *human-like*, by which we mean that ZIP traders in experimental CDA markets give scores on the standard metrics of market performance that are very similar to those given by human traders in the same markets.

In this paper, we demonstrate that the market behavior of ZIP traders is human-like in another sense: ZIP traders fail to exhibit rapid equilibration in a particular style of non-CDA market, and their mode of failure is very similar to that of human traders in a similar non-CDA experiment reported by Smith (1962).

Smith (1962) reported results from an experimental model of common retail markets, where sellers announce prices and buyers either purchase at the offer price or ignore the offer, without giving any indication of what range of transaction prices they would be willing to bid. Smith's model was a modification of the CDA, rendered one-sided by preventing the buyers from quoting bid prices. Although this is a rather prim-

itive approximation to retail markets (since superseded by experimental studies of *posted-offer* markets: see, e.g., Davis and Holt (1993, pp.173–239)), the results from Smith’s experiment, and his explanation of those results, are intriguing. Smith’s expectation was that transaction prices would settle at levels higher than the theoretical equilibrium price, indicating that the structure of retail markets offers advantages to the sellers. But this did not happen: instead, transaction prices settled at levels significantly below equilibrium. Smith explained this as being due to buyers that never quite recovered from having been ‘badly fleeced’ in the early stages of the experiment, where transactions occurred at high prices before equilibration had driven them lower.

If groups of simple artificial agents interact to exhibit market-level phenomena that are similar to those of human markets, explanations of how the phenomena arise in the artificial system may be viewed as candidate explanations for the same phenomena in human markets. In this paper, we illustrate these arguments by means of an example. We present results from experiments where ZIP traders adapt and interact via price-bargaining in market environments based on the artificial ‘retail’ market Smith (1962) used in his experimental economics research, and we demonstrate that groups of simple agents can exhibit human-like collective market behaviors. We note that, while it is often tempting to offer explanations of human market behavior in terms of the mental states of the agents in the market, our agents are sufficiently simple that mental states can have no useful role in explaining their activity. Thus, explanations of the human-like collective market behavior of our agents cannot be phrased in terms of mental states; thereby inviting comparisons with Braitenberg’s (1984) influential “law of uphill analysis and downhill invention”, with eliminative materialism in the philosophy of cognitive science, and with dynamical-systems-based analyses of adaptive behavior.

Section 3.1 introduces the mechanisms of adaptation in ZIP traders. In Section 3.2, we present results showing that ZIP-trader ‘retail’ markets exhibit the same failure qualities as Smith’s human-trader ‘retail’ markets. From this, we argue that the simplicity of the ZIP trading mechanisms requires that explanations of their failures cannot be phrased in terms of mental states such as not recovering from being fleeced during a trading day earlier in the experiment. We further discuss the implications of this in Section 3.3.

3.1 ZIP Traders

The emphasis in our work is on creating *simple* autonomous software agents, or animats, for bargaining in market-based environments. This emphasis on simplicity comes not only from a desire for computational efficiency (important in engineering applications if hundreds or thousands of animats are active on a network), but also in a speculative scientific attempt at sketching the minimum mechanistic complexity necessary and sufficient for explaining human bargaining behaviors in specific market environments.

It is beyond the scope of this paper to present a full discussion of the rationale for the current design of ZIP trader agents, and from presenting exhaustive results. The intention here is to briefly summarize key aspects of the design before presenting illustrative results. Cliff (1997) gives a complete discussion of the design, shows results from many experiments in different types of market environment, and includes all the C source-code for the system. A recent thesis by van Montfort (1997) replicated our CDA results, and explored the use of our ZI traders in spatially distributed markets where there may be potentially hundreds or thousands of traders.

In common with much work in (human-based) experimental economics, most of our studies to date have considered markets where each trading agent remains either a buyer or a seller for the duration of the entire experiment. However, van Montfort (1997) demonstrated the use of our ZIP traders as arbitrage agents capable of buying units of commodity in one market for subsequent re-sale into another market, exploiting differences in price between the two markets.

Each ZIP trader operates by maintaining a *profit margin* that it uses for calculating the price it ‘quotes’ (offers or bids) in the market: the profit margin determines the difference between the *quote-price* the agent quotes and the *limit price* for the commodity the agent is trading. For agents designated as sellers, the limit price is the price below which they may not sell a unit of the commodity. For agents designated as buyers, the limit price is the price above which they may not buy a unit of the commodity. Hence, when two traders enter into a transaction, the seller’s profit is given by subtracting the seller’s limit price from the transaction price, while the buyer’s profit is given by subtracting the transaction price from the buyer’s limit price.

The ‘aim’ of each ZIP agent is to maximize profit generated by trading in the market. If an agent’s

profit margin is set too low, it will miss out on potential profit when it makes a transaction with another agent, so all agents are constantly trying to increase their profit margins. But if an agent sets its profit margin too high, it may miss the opportunity to make transactions with other agents, because the price it offers is less attractive than the prices offered by competing agents. Clearly, what it means for the profit margin to be “too high” or “too low” is dependent on the context of the market conditions, and varies dynamically. Thus, the problem of designing a trading agent can be considered as a combination of two issues: the *qualitative* issue of deciding *when* to increase or decrease the profit margin, and the *quantitative* issue of deciding *by how much* the margin should be altered.

For reasons discussed in detail by Cliff (1997), each ZIP trader makes the qualitative decision of when to alter its margin on the basis of four factors. The first factor is whether the agent is *active* in the market: agents are active until they have sold or bought their full entitlement of units of the commodity. The remaining three factors concern the last quote by any agent in the market: we refer to this as \mathcal{Q} . Each ZIP trader notes whether \mathcal{Q} was an offer or a bid, whether \mathcal{Q} was accepted (i.e., led to a transaction) or rejected (ignored by the traders in the market), and whether \mathcal{Q} 's price, $q(t)$, is greater than or less than the price the ZIP trader would currently quote. We refer to the price a ZIP trader i would quote at time t as that trader's *quote-price*, denoted by $p_i(t)$, which is calculated from i 's limit price $\lambda_{i,j}$ (for i 's j th unit of commodity) and i 's current profit coefficient $\mu_i(t)$ using $p_i(t) = \lambda_{i,j}(1 + \mu_i(t))$. Thus, a seller's profit margin is raised by increasing μ_i and lowered by decreasing μ_i , such that $\mu_i(t) \in [0, \infty); \forall t \forall i$. The situation is reversed for buyers: they raise their margin by decreasing μ_i and lower it by increasing μ_i , subject to $\mu_i(t) \in [-1, 0]; \forall t \forall i$.

The reality of continuous-time CDA markets is simulated on a sequential machine using a discrete event-based approach, where the atomic event is the issuing of a quote by a trader. The time interval between successive quotes is treated as irrelevant, and ignored. (Clearly, this is an assumption that would require revision in future, more complex simulations). On each iteration of the simulation, one trader is chosen at random from the list of currently active traders, using a uniform distribution. That trader (designated here by the index q) “quotes” its current quote-price $p_q(t)$. A “quotation” data-structure \mathcal{Q} is then instantiated with its “price” field $q(t)$ set equal to $p_q(t)$ and with its “type” field set equal to “bid” if the chosen trader

is a buyer, or “offer” if the trader is a seller. Copies of \mathcal{Q} are then issued to all contraside traders, which compare $q(t)$ to their current quote-prices. Each contraside trader c signals that it is “willing” to accept the quote if it would make at least as much profit from a transaction priced at $q(t)$ as from a transaction priced at its current quote-price $p_c(t)$. If there is more than one willing contraside trader, one is chosen at random using a uniform distribution. The chosen contraside trader then enters into a transaction with trader q : the relevant book-keeping adjustments are made for each traders’ accounts (possibly rendering one or both of the traders inactive); \mathcal{Q} is marked as “accepted” and is then distributed to all traders for use in deciding whether to alter their profit margins; the discrete transaction index t is incremented to a value $t + 1$; and the system starts a new iteration by again randomly choosing an active trader to issue a new quote. If no contraside trader is willing to accept trader q ’s quote, the quote \mathcal{Q} is marked as rejected and circulated to all traders for profit margin updating; a count of the number of rejected quotes since the last transaction is incremented; t is incremented; and the system loops back to randomly chose a new trader to quote. This iterative process continues for each trading day until the day’s end-conditions are met: the end-conditions are either that a pre-specified maximum number of transactions has occurred in that day, or that the counter of how many rejected quotes have occurred since the last transaction reaches a pre-specified maximum (e.g., 100).

A ZIP seller i raises its profit margin whenever \mathcal{Q} was accepted and $p_i(t) \leq q(t)$. It lowers its margin only if it is still active and \mathcal{Q} was a rejected offer with $p_i(t) \geq q(t)$, or if \mathcal{Q} was a bid that was accepted and $p_i(t) \geq q(t)$. Similarly, a ZIP buyer i raises its profit margin whenever \mathcal{Q} was accepted and $p_i(t) \geq q(t)$, and it lowers its margin when it is active and either \mathcal{Q} was a rejected bid with $p_i(t) \leq q(t)$ or \mathcal{Q} was an accepted offer with $p_i(t) \leq q(t)$.

Note that the value $q(t)$ is simply the current quote-price of one of the traders in the market: if that trader is designated by the index j then $q(t) = p_j(t)$. The criteria for deciding whether to raise or lower the profit margin are summarised in Table 1.

The quantitative issue of by how much the profit margin should be altered is addressed by using a simple machine-learning algorithm. Specifically, the learning rule we use is *Widrow-Hoff with momentum*, which also underlies back-propagation learning in neural networks Rumelhart, Hinton, and Williams (1986).

Agent Type	Active?	\mathcal{Q} Type	\mathcal{Q} Response	Inequality	Action
Seller	Either	Either	Accepted	$p_i(t) \leq q(t)$	Raise
Seller	Yes	Offer	Rejected	$p_i(t) \geq q(t)$	Lower
Seller	Yes	Bid	Accepted	$p_i(t) \geq q(t)$	Lower
Buyer	Either	Either	Accepted	$p_i(t) \geq q(t)$	Raise
Buyer	Yes	Bid	Rejected	$p_i(t) \leq q(t)$	Lower
Buyer	Yes	Offer	Accepted	$p_i(t) \leq q(t)$	Lower

Table 1: Summary of decision criteria for altering profit margin

Briefly, this adjusts the actual output of a system toward some *target* output value, at a speed determined by a learning rate β , and with a simple ‘memory’ or ‘momentum’ parameter γ . In each ZIP trader the target-price is a stochastic perturbation of $q(t)$, and each trader i uses this in combination with β_i and γ_i to adjust its profit-coefficient $\mu_i(t)$. The profit-margin update rule is:

$$\mu_i(t+1) = (p_i(t) + \Gamma_i(t)) / \lambda_{i,j} - 1$$

where $\Gamma_i(t)$ is a momentum term:

$$\Gamma_i(t) = \gamma_i \Gamma_i(t-1) + (1 - \gamma_i) \beta_i (\mathcal{R}_i(t) q(t) + \mathcal{A}_i(t) - p_i(t))$$

for $t > 0$, and $\Gamma_i(0) = 0 : \forall i$.

The target-price is generated by multiplying $q(t)$ by a *relative* coefficient $\mathcal{R}_i(t)$ and then adding a small *absolute* perturbation $\mathcal{A}_i(t)$. The values for $\mathcal{R}_i(t)$ and $\mathcal{A}_i(t)$ are stochastically generated from independent and identical distributions for each trader, every time $\Gamma_i(t)$ is calculated. When the trader’s profit coefficient is being increased, $\mathcal{R}_i = \mathcal{U}(1.0, 1.0 + c_{\mathcal{R}})$ and $\mathcal{A}_i = \mathcal{U}(0.0, c_{\mathcal{A}})$, where $\mathcal{U}(c_{lo}, c_{hi})$ denotes a uniformly distributed random real value over the range $[c_{lo}, c_{hi}]$. When the trader’s profit coefficient is being decreased, $\mathcal{R}_i = \mathcal{U}(1 - c_{\mathcal{R}}, 1.0)$ and $\mathcal{A}_i = \mathcal{U}(-c_{\mathcal{A}}, 0.0)$. For further details of how learning is implemented in ZIP traders, see Cliff (1997), Cliff and Bruten (1997a).

In the experiments reported in this paper the following parameter values were used. Each trader’s value for β_i was set randomly from $\mathcal{U}(\beta_{lo}, \beta_{hi})$ with $\beta_{lo}=0.1$ and $\beta_{hi}=0.5$. Each trader’s value for γ_i was set randomly from $\mathcal{U}(\gamma_{lo}, \gamma_{hi})$ with $\gamma_{lo}=0.0$ and $\gamma_{hi}=0.1$. When calculating $\Gamma_i(t)$, all traders use parameter-

values $c_{\mathcal{R}} = 0.05$ and $c_{\mathcal{A}} = 0.05$ in the distributions for \mathcal{R}_i and \mathcal{A}_i . The initial profit coefficients (i.e., $\mu_i(0)$) of the traders were set randomly from uniform distributions symmetric about zero, determined by two parameters: $\mu_{lo} = 0.05$ and $\mu_{hi} = 0.35$: each seller's value of $\mu_i(0)$ was set randomly from $\mathcal{U}(\mu_{lo}, \mu_{hi})$ and each buyer's value of $\mu_i(0)$ was set randomly from $\mathcal{U}(-\mu_{hi}, -\mu_{lo})$.

All our work to date has involved experiments where the values of the system parameters have been determined manually (i.e., by trial and error). Our experience is that the system is fairly robust in the sense that it is not particularly sensitive to variations in the system parameters. Nevertheless, the use of some kind of automatic tuning or optimization technique such as a genetic algorithm is an obvious possibility. Despite the documented difficulties of evolving situated autonomous agents for collective behaviors (Mataric & Cliff, 1996; Zaera, Cliff, & Bruten, 1996), evolutionary optimization of adaptive trading agents offers the possibility of specializing generic adaptive traders to the structure and dynamics of particular markets. Results from evolutionary optimization of ZIP parameters are presented in (Cliff, 1998).

3.2 One-Sided Auction ‘Retail’ Markets

In Smith's 1962 paper Smith (1962), all the experiments except one explored CDA markets. In the one non-CDA market, Smith examined the dynamics of a one-sided auction, where only sellers were allowed to quote offers: buyers were not allowed to quote bids, but passively observed the prices offered by the sellers. Each buyer therefore had the privilege of being able to ignore offer-prices that were too high and accept those that were within their range, without giving any indication of their limit prices. Smith proposed this as an approximation to an ordinary retail market, where sellers bear the responsibility of advertising their prices and buyers decide whether to buy or not without entering into any kind of bargaining or haggling process. Smith's results from this experiment are shown in Figure 6, which shows clear differences from the CDA market results shown in Figure 4.

Smith's comments on his expectations and actual results for this experiment are significant:

“Since sellers desire to sell at the highest prices they can get, one would expect the offer prices to be high, and, consequently, one might expect the exchange [i.e., transaction] prices to show a persistent tendency to remain above the predicted equilibrium. The result was in accordance with this crude

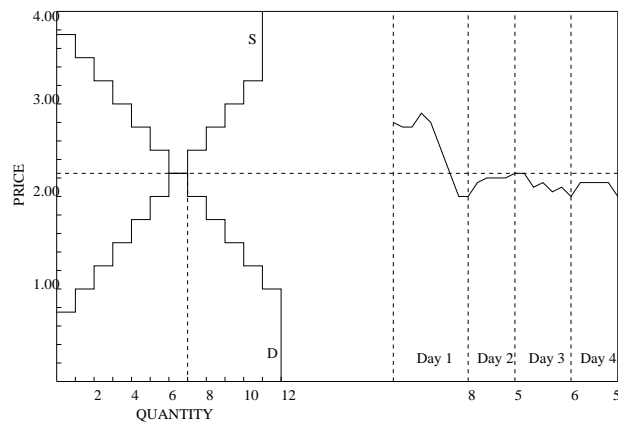


Figure 6: Left-hand side shows the market supply and demand, with theoretical equilibrium values $P_0=\$2.25$ and $Q_0=7$. Right-hand side shows time-series of transaction prices from four ‘days’ when traders interact via a one-sided (offer-only) ‘retail’ market. Numbers on the horizontal axis of the right-hand figure indicate market volume (quantity of transactions) for each day.

expectation in the first market period [i.e., day] only. . . . Since sellers only were making offers, the prices tended to be very much above equilibrium. Five of these offers were accepted at prices ranging from \$2.69 to \$2.80. . . . The competition of sellers pushed the offer prices lower and the remaining buyers made contracts at prices [of \$2.35, \$2.00, and \$2.00]. The early buyers in that first market period never quite recovered from having subsequently seen exchange prices fall much below the prices at which they had bought. Having been badly fleeced, through ignorance, in that first trading period, they refrained from accepting any high price offers in the remaining three periods of the test. This action, together with seller offer price competition, kept exchange prices at levels persistently below equilibrium for the remainder of [the experiment].” Smith (1962).

The ZIP traders can be used in a straightforward copy of Smith’s experimental retail market. The supply and demand curves for the ZIP market are shown in Figure 7. For reference, Figure 8 shows the transaction-price time-series resulting from one experiment where the supply and demand curves shown in Figure 7 were used in a true bilateral CDA market. As can be seen, the transaction prices of ZIP traders operating in a CDA market rapidly stabilize at values close to the theoretical equilibrium price of \$2.25. Figure 9 then shows the average results from 50 such experiments.

In Figure 10 we show the mean daily transaction prices from 50 experiments where the ZIP traders operate in Smith’s ‘retail market’. The same parameter values are used as in the experiments for Figures 8

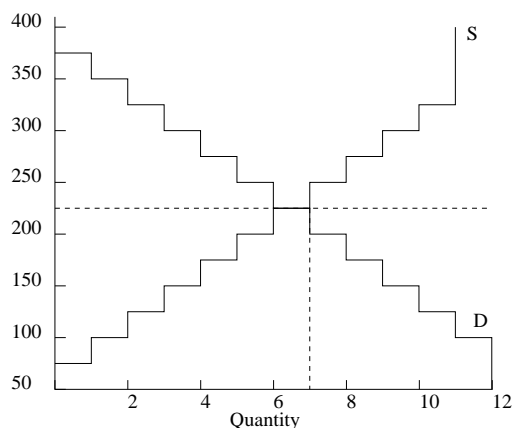


Figure 7: Supply and demand curves: 12 buyers and 11 sellers. Theoretical equilibrium price $P_0 = \$2.25$; quantity $Q_0=7$.

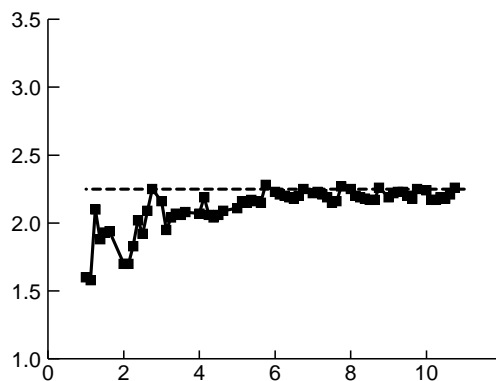


Figure 8: Transaction-price time-series from one experiment where the supply and demand of Figure 7 are used in a CDA market where both buyers and sellers can quote prices, for ten trading sessions or ‘days’. The horizontal axis shows the day number, the vertical axis indicates the transaction price.

and 9: the only difference is that the buyers are prevented from quoting bid-prices. As can be seen, the average transaction prices are typically less than \$2.00 (significantly below the P_0 value of of \$2.25). There also appears to be only very slow convergence towards P_0 , and little or no reduction in variance as the experiment progresses after Day 1. This apparent slow convergence and reduction in variance can be better understood by examining individual price trajectories: Figures 11 to 14 show time-series of the transaction prices in four individual experiments using ZIP traders in the ‘retail’ market with supply and demand as illustrated in Figure 7.

As can be seen, in all four experiments the market fails to converge to the P_0 value at all rapidly. Rather, in each experiment the transaction-price time-series shows some initial fluctuations and then converges to

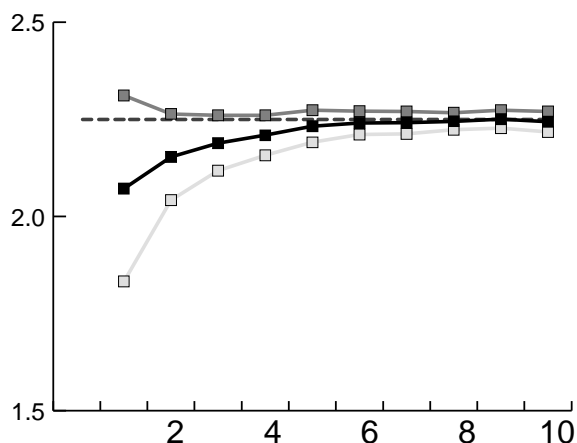


Figure 9: Mean transaction-price per trading session, averaged over 50 sets of results such as those shown in Figure 8. The horizontal dashed line shows the P_0 value. For each trading ‘day’, the graph shows the average value (black), and values plus (medium gray) and minus (light gray) one standard deviation, of the mean of the transaction prices in that day.

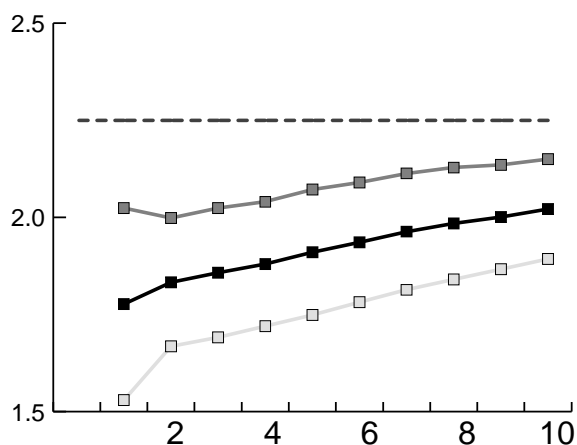


Figure 10: Mean ZIP transaction prices, averaged over 50 experiments, for ‘retail-market’ experiments with the supply and demand shown in Figure 7 ($P_0=\$2.25$). Format as for Figure 9

a fairly constant value by Day 4, but the value that is converged on varies: in Figures 11 to 13, all trades on Day 10 are within $\$0.15$ of P_0 , while in Figure 14 no trade is within $\$0.40$ of P_0 . As is clear in Figure 10, the price the market initially converges on is, on average, around $\$1.75$: approximately 80% of the P_0 value. Thereafter, very slow convergence toward the P_0 value can be seen. Thus, in the sense that our ZIP retail markets show a marked failure to exhibit the rapid equilibration seen in our ZIP CDA markets, there is a strong qualitative agreement between results from our ZIP traders and Smith’s (1962) observations of

human subjects in his experimental retail markets.

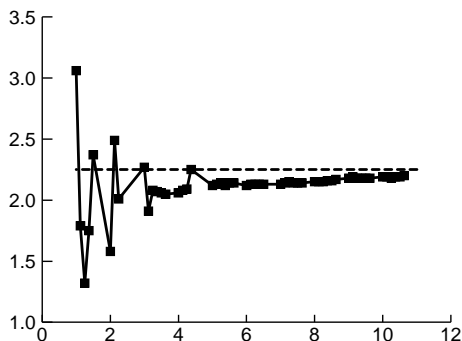


Figure 11: Transaction-price time series for one ‘retail market’ experiment, seed=3453.

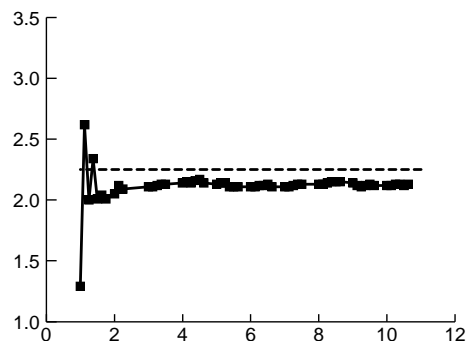


Figure 12: Transaction-price time series for one ‘retail market’ experiment, seed=3522.

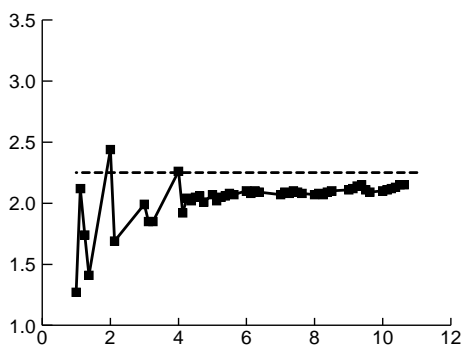


Figure 13: Transaction-price time series for one ‘retail market’ experiment, seed=3553.

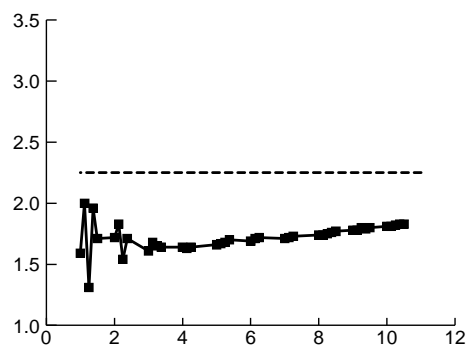


Figure 14: Transaction-price time series for one ‘retail market’ experiment, seed=3591.

Of the four single experiments illustrated, the price series in Figure 11 most closely resembles that of Smith’s subjects: only three transactions occur at transaction price more than a few cents above the equilibrium price; while many more occur at prices lower than equilibrium, which is approached from below, albeit *very* slowly. Smith’s explanation was that this is due to early transactions at high prices preceding a series of low-price transactions that induce a resistance to higher prices in ‘fleeced’ traders. Whether this explanation can apply to our ZIP traders requires a more detailed examination of the dynamics of individual experiments. Figure 15 shows text output from Day 1 of the market experiment shown in Figure 11: in the first four transactions, sellers announce a price and one or more buyers are willing to buy at that price (the buyer who gets the deal is chosen at random from those that are willing). In the fifth transaction, Seller 10 makes an offer of \$3.52 which is ignored by the buyers: Seller 9 then offers at \$3.51; this is also ignored

and Seller 9 offers again at \$3.50, which is again ignored; Seller 5 then offers at \$2.37, which is accepted by Buyer 0. For the sixth transaction, there is a sequence of 33 ignored offers, which ends when Seller 4 makes an offer of \$2.12 (having previously offered \$2.40, \$2.22, and \$2.16). For the seventh, there are 49 ignored offers before Seller 3 finally drops the offer price to \$2.07, and a deal is done. In the bargaining for the eighth transaction of the day, 100 quotes fail to find a taker, and the first day ends.

The effects this sequence of accepted and ignored offers has on the profit margins of the ZIP buyers and sellers is illustrated in Figure 16, which shows the apparent supply and demand curves and bid-and-offer arrays at the start of Day 1 and at the start of Day 2. As can be seen, the apparent supply and demand curves alter significantly over the first day. For intra-marginal units, the traders have increased their profit margins, flattening the supply and demand curves and bringing them closer together, thereby reducing the apparent surplus. For extra-marginal units, the traders have decreased their profit margins, again lessening the distance between the curves.

To better illustrate the alterations in the bid-and-offer arrays between the two states shown in Figure 16, Figure 17 shows the temporal progression of the arrays after each transaction in Day 1. As can be seen from the graphs labeled E to H, after four transactions the apparent supply and demand curves do not intersect, and so there is no theoretical equilibrium price or quantity. This gives rise to the sequences of ignored quotes illustrated in Figure 15 (5 before Figure 17E, 33 before Figure 17F, 49 before Figure 17G, and 100 before Figure 17H), which in turn lead to alteration of the traders' profit margins, thereby altering the apparent supply and demand so that eventually an intersection does occur, after which a transaction can take place. Typically, as soon as the apparent supply and demand curves intersect, two traders make a transaction and leave the market, and in doing so they alter the apparent supply and demand back to a state where no intersection occurs.

Figure 18 shows the bid-and-offer arrays at the start of each subsequent day in the experiment. As is clear, although the rank ordering of the traders varies as they alter their prices up or down by a few cents, there is very little change in the overall shape of the bid-and-offer arrays after Day 3. The fact that in this experiment the market initially converges on transactions around \$2.12 (i.e., less than the theoretical equilibrium price of \$2.25) is consistent with Smith's (1962) results from his experiment with

```

day 1 trade 1
Seller 7 offers at 3.060 1 traders willing to deal
Seller 7 sells to Buyer 1

day 1 trade 2
Seller 2 offers at 1.790 5 traders willing to deal
Seller 2 sells to Buyer 3

day 1 trade 3
Seller 0 offers at 1.320 8 traders willing to deal
Seller 0 sells to Buyer 8

day 1 trade 4
Seller 1 offers at 1.750 6 traders willing to deal
Seller 1 sells to Buyer 6

day 1 trade 5
Seller 10 offers at 3.520 No willing takers (fails=1)
Seller 9 offers at 3.510 No willing takers (fails=2)
Seller 9 offers at 3.500 No willing takers (fails=3)
Seller 5 offers at 2.370 1 traders willing to deal
Seller 5 sells to Buyer 0

day 1 trade 6
Seller 3 offers at 2.210 No willing takers (fails=1)
Seller 6 offers at 2.520 No willing takers (fails=2)
Seller 6 offers at 2.530 No willing takers (fails=3)
Seller 8 offers at 2.930 No willing takers (fails=4)
Seller 10 offers at 3.350 No willing takers (fails=5)
Seller 9 offers at 3.080 No willing takers (fails=6)
Seller 8 offers at 2.820 No willing takers (fails=7)
Seller 9 offers at 3.040 No willing takers (fails=8)
Seller 9 offers at 3.010 No willing takers (fails=9)
Seller 4 offers at 2.400 No willing takers (fails=10)
...
Seller 4 offers at 2.220 No willing takers (fails=15)
...
Seller 4 offers at 2.160 No willing takers (fails=24)
...
Seller 8 offers at 2.780 No willing takers (fails=32)
Seller 9 offers at 3.010 No willing takers (fails=33)
Seller 4 offers at 2.120 1 traders willing to deal
Seller 4 sells to Buyer 4

day 1 trade 7
Seller 10 offers at 3.350 No willing takers (fails=1)
...
Seller 8 offers at 2.780 No willing takers (fails=49)
Seller 3 offers at 2.070 1 traders willing to deal
Seller 3 sells to Buyer 2 1.180)

day 1 trade 8
...
Seller 8 offers at 2.760 No willing takers (fails=100)

```

Figure 15: Text output showing quotes and transactions (referred to in the output as “trades”) for Day 1 in the experiment of Figure 11. Much text has been deleted to increase clarity.

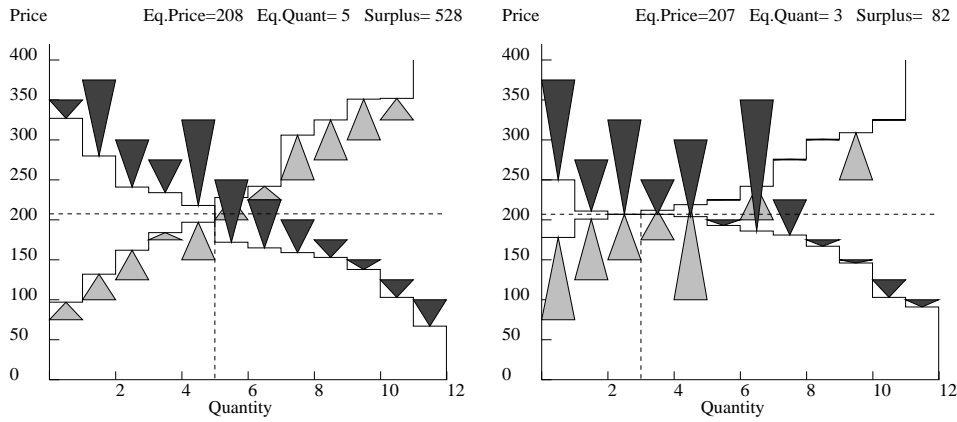


Figure 16: Bid-and-offer arrays in the experiment of Figure 11. Left: at the start of Day 1. Right: at the start of Day 2. Limit and quote prices are indicated using the format introduced in Figure 3: each buyer’s limit and quote prices are illustrated as dark inverted triangles, while each seller’s limit and quote prices are illustrated by light upright triangles: the base of each triangle indicates the trader’s limit price, while the apex indicates the trader’s quote-price. The array of bid-prices gives an apparent demand curve D , and the array of offer-prices gives an apparent supply curve S .

human subjects, where transaction prices also converged to a stable below-equilibrium level.

Thus, in addition to our demonstration in other publications (Cliff, 1997; Cliff & Bruten, 1997a, 1998) that ZIP traders can give human-like collective behavior in CDA markets, the results presented here show that the dynamics and the modes of failure of ZIP traders are also similar to those of humans in Smith’s (1962) one-sided auction experimental model of retail markets. The implications of this are discussed further in the next section.

To demonstrate that the difference in market organization (i.e., the difference between the CDA and one-sided ‘retail’ auction rules) accounts for the differences seen in the transaction-price data of the two markets, we close this section with the data in Figures 19 and 20. Both of these figures show price data from markets where the market organization is ‘retail’ for the first five days and then switches to CDA for the remaining ten days. As can be seen, once the market alters from retail to CDA, the transaction prices of the ZIP traders rapidly approaches the theoretical competitive equilibrium. Note that the *only* change is in the market organization: all other parameters remain the same, and none of the trader’s variables (e.g. $\mu_i(t)$ or $\Gamma_i(t)$) are altered when the organization is changed. Clearly then, the market organization is a primary cause of the equilibration failure.

Finally, it is sobering to note that with synthetic adaptive agents it is possible to record all manner of significant variables, both internal and external to the agent, and to visualize them in styles such as

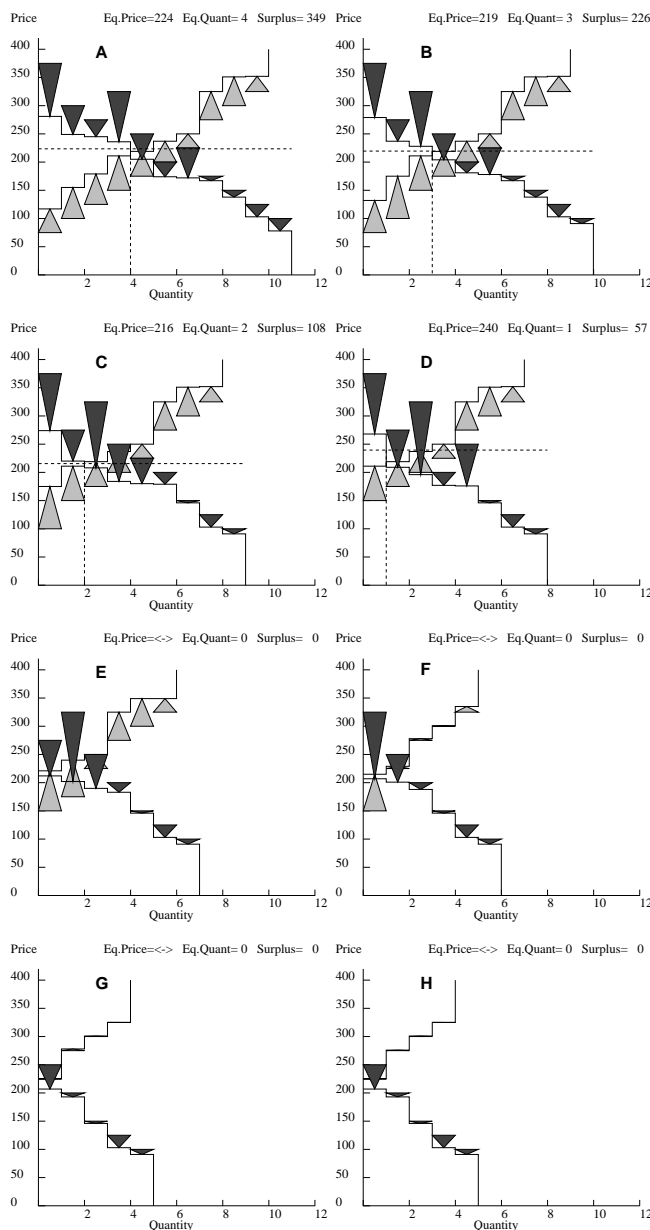


Figure 17: Temporal progression of bid-and-offer arrays for days 1 to 2 in the price series shown in Figure 11. Each graph shows the bid-and-offer arrays of the active traders after a transaction: A is after the first transaction; B is after the second transaction; And so on until H which is after the eighth (end of Day 1).

those shown in Figures 10 to 18. And this is from just one experiment, which took less than five seconds to run on a medium-power workstation (a Sun Sparc20). Clearly, hundreds or thousands of experiments can be run with artificial agents in the time it takes one experiment to be conducted with human subjects. Indeed, with one workstation, in one week it would be possible to run approximately 100,000 artificial-agent experiments: this is probably more experiments than have been run with human subjects in the

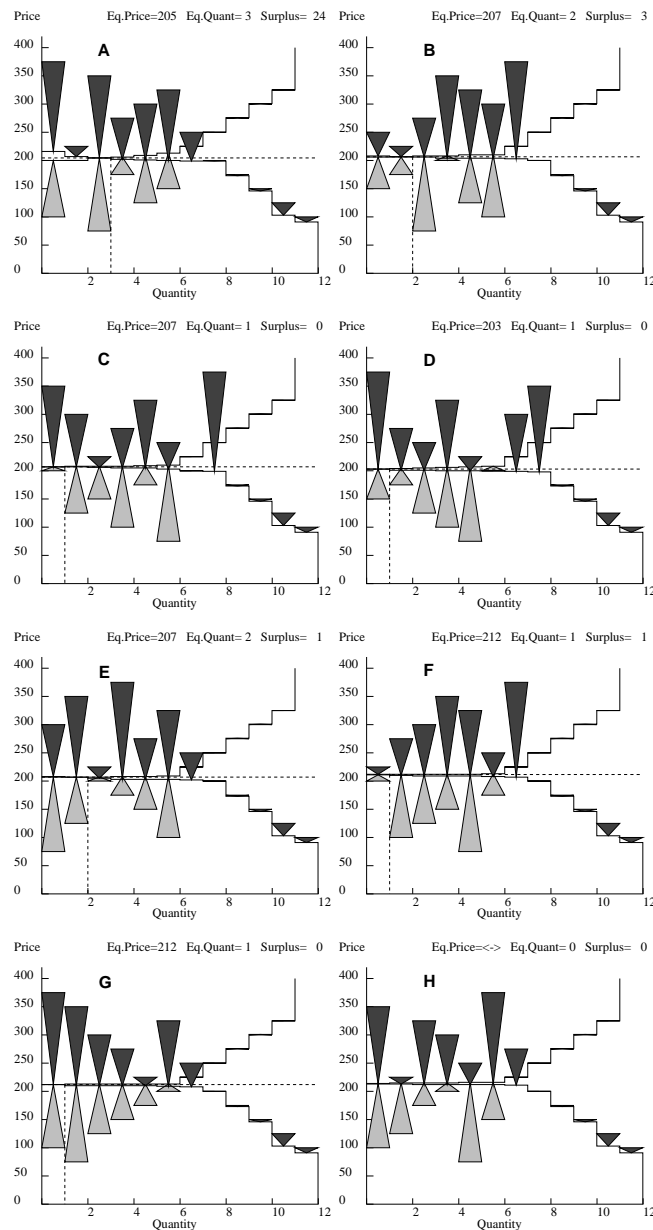


Figure 18: Temporal progression of bid-and-offer arrays for days 3 to 10 in the price series shown in Figure 11. Each graph shows the bid-and-offer array at the start of a day's trading: A is day 3; B is day 4; and so on until H which shows the start of day 10. See text for discussion.

entire history of experimental economics. But this is not necessarily an advantage: each experiment has the potential to generate masses of data; managing, visualizing, and analyzing the data to arrive at meaningful conclusions could present serious problems, and should be noted as a topic for further work.

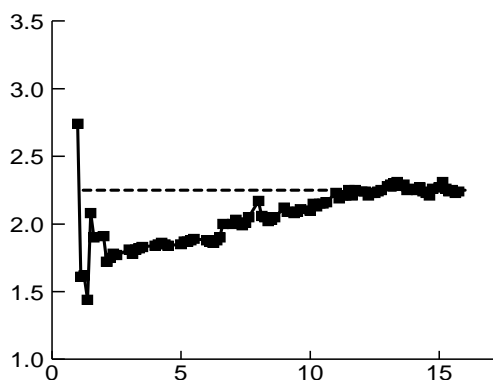


Figure 19: Transaction-price time-series from one experiment where the supply and demand of Figure 7 are used in a ‘retail’ market for the first 5 days, before switching to a CDA market for the last 10 days. The horizontal axis shows the day number, the vertical axis indicates the transaction price.

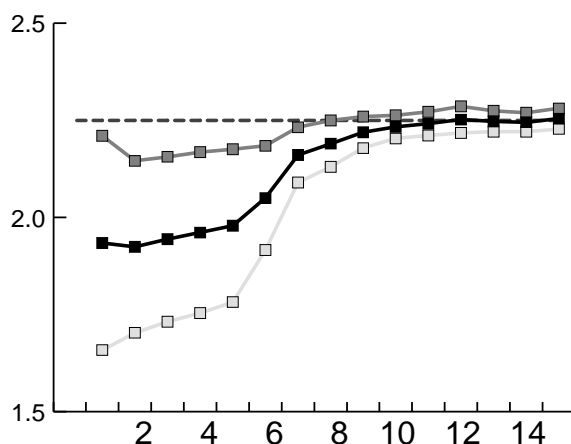


Figure 20: Mean transaction-price per trading session, averaged over 50 sets of results such as those shown in Figure 19.

3.3 Discussion

The similarity between our ZIP results and those from Smith’s human subjects suggests a line of reasoning similar to that underlying much adaptive behavior research. This reasoning relies on noting that there is one key difference between our results and Smith’s. Smith was working with human subjects, where there is a natural temptation to offer explanations in terms of mental states. In the passage quoted above, Smith talks of the human buyers “never quite recovering” from “having been badly fleeced”. It is not clear from the original text whether this account is inventive conjecture on Smith’s part, or the result of properly conducted post-experiment interviews. But even if these comments are the result of interviewing those

subjects who ended up as ‘fleeced’ buyers, the danger of introspective *a posteriori* accounts of behavior are well known.

The crucial difference then, between Smith’s work with humans and our work with ZIP traders, is that in the ZIP traders there are no place for such mentalistic descriptions of the behavior of the agents in the market. There is nothing, not even an evolved neural network, in which the ZIP agents could hide the mental states of ‘never quite recovering’ or noticing that they have been ‘badly fleeced’. Any explanation of what causes the ZIP-agent markets to approach equilibrium slowly and from below is *forced* to be framed in terms of the interactions of the simple ZIP adaptation mechanisms, because there is *nothing else* in the system that could cause the observable phenomena.⁷

Let us assume that a causal mechanistic explanation for how the collective behavior of ZIP traders gives rise to some market-level phenomena can be developed, and call it \mathcal{E} . Then \mathcal{E} can also be considered a candidate explanation for the behavior of groups of human traders. Naturally, if it can be demonstrated that the ZIP traders are using adaptation mechanisms that could not be employed or implemented by humans, then \mathcal{E} is a very weak explanation, or no explanation at all. But if such counter-arguments to \mathcal{E} cannot be readily advanced, \mathcal{E} should properly be considered as a putative explanation for the human behavior, which can be subjected to experimental evaluation or falsification. And, crucially, here \mathcal{E} cannot be phrased in terms of mental or emotional states, because the ZIP traders have nothing that corresponds to such states.

The failure of ZIP traders to rapidly converge on a competitive equilibrium (i.e., a steady sequence of transaction prices at the P_0 value) in ‘retail’ markets is due simply to the fact that although the buyer and seller profit-margins are altered symmetrically when in a CDA, the prevention of bids in the one-sided ‘retail’ market introduces an asymmetry: although the traders raise their margins under symmetric conditions, an active buyer b lowers its margin only when \mathcal{Q} was *accepted* at a price $q(t) \geq p_b(t)$, while an active seller s will lower its margin when $q(t) \leq p_s(t)$ regardless of whether \mathcal{Q} was accepted or not. In essence, this demonstrates that, despite the good equilibration properties of CDA markets where both buyers and sellers are trading according to the ZIP strategy described in Section 3.1, the asymmetry of opportunity sets

⁷Assuming, of course, that the code for the system has no bugs.

(i.e., the prevention of bids) in the ‘retail’ market severely hampers equilibration by ZIP traders because their trading strategies depend on the bilateral flow of information found in CDA markets. While it may be possible to alter the ZIP strategies to give good equilibration in retail markets, or even in both retail markets *and* CDA markets, the key issue here is that our explanation of ZIP traders’ failure to quickly reach a competitive equilibrium is not reliant on them having vague and difficult-to-define mental states such as ‘never quite recovering from being badly fleeced’.

By specifying and implementing simple synthetic trading agents, it is possible to demonstrate the same overall market behavior without relying on abstract or vague descriptions of the mental states of the participants in the market. In this sense, the work described here is similar to other work in adaptive behavior that is justified by the principle that it can be more fruitful and more parsimonious to attempt an understanding of how some behavior is generated by *synthesising* an artificial system that exhibits that behavior, rather than by *analyzing* a natural system that exhibits the same behavior: a principle that Braitenberg (1984) named the “law of uphill analysis and downhill invention”. Although it is often difficult to resist the temptation to describe the cognitive behaviors of animals (and humans in particular) in terms of mental states, there is growing support for a counter-approach, where the intention is to explain observed behaviors in terms of the dynamics of causal mechanistic interactions, rendering the mental-states-based accounts obsolete. These ideas first gained credence in the philosophy of mind, where they are most strongly associated with Churchland’s *eliminative materialism* (Churchland, 1979, 1989), and their relevance to work in artificial autonomous agents has been discussed by Smithers (Smithers, 1992), van Gelder (1992, 1998), Port and van Gelder (1995), Beer (1995), and Cliff and Noble (1997). Thus, our work here can be viewed as a step in the direction of adopting an eliminative materialism or dynamical systems perspective on the economic activity of human agents.

So, we have demonstrated here that ZIP traders can give results qualitatively similar to those of humans in ‘retail market’ experiments. In doing so, we have demonstrated a point of more general significance: that techniques common in adaptive behavior research can be used to cast new lines of inquiry on the human experimental economics data. Given that ZIP traders exhibit human-like behavior and have no mental states, of how much genuine use are mental states in the explanation of human market behavior?

4 Conclusion

The development of computational mechanisms that allow groups of software agents to exhibit bargaining behaviors in market-based environments satisfies a number of needs. Computational mechanisms such as ZIP traders can act as mechanistically rigorous statements of potential models of human bargaining behaviors, although it is likely that more complex mechanisms would be required to further account for the many subtleties and nuances of human behavior: empirical work in experimental economics and human psychology would also be necessary to validate any models. Once validated, such model agents could be used in the manner intended in the work of Arthur (1993) or Easley and Ledyard (1992), for conveniently testing theories concerning the behavior of humans in different market structures and conditions.

The arguments we presented in earlier papers (Cliff, 1997; Cliff & Bruten, 1997b, 1997c) indicate a need for bargaining mechanisms more complex than the constrained stochastic generation of bid and offer prices used by Gode and Sunder's (1993) "zero-intelligence" traders. The work on ZIP traders, reported here and in other papers (Cliff, 1997; Cliff & Bruten, 1997a, 1998) should be viewed as a preliminary sketch of what forms such bargaining mechanisms might take. The ZIP traders are more complex than Gode and Sunder's ZI traders, but only slightly, and in any case are manifestly much less complex than humans. Nevertheless, the results from the ZIP traders, both in terms of speedy equilibration in CDA markets and failure to equilibrate quickly in Smith's one-sided auction model of retail markets, are clearly closer to those from human experimental markets than are the results from ZI traders. It is reassuring to see that the ZIP mechanisms can give such human-like results, but there is much further work that could be done in exploring behavior of ZIP traders in more complex market environments, and in attempting to extend the behavioral sophistication of such traders without unduly adding to their complexity.

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