2. The importance of structural rationality: understanding market institutions[1]

Shyam Sunder

Market structure and properties are critical features of finance. Computer simulations with simple artificial agents reveal that certain important market outcomes are robust while others are sensitive to trader intelligence. Such simulations yield insights into the crucial question of why some markets, when populated by cognitively bounded human traders, closely approximate predictions based on utility maximization, while others exhibit systematic deviations from such predictions (see Gode and Sunder 1993a; Huber et al. 2010).

Since economic equilibria have often been derived under the assumption of optimum trading behavior under an idealized market form (Walrasian tatonnement 1874 [1973]), it has often been taken for granted that equilibrium outcomes are largely a consequence of trading strategies. In fact, far-from-optimum trading strategies can also yield near-equilibrium outcomes, making individual behavior and market outcomes substantially independent of each other. In contrast, knowledge of equilibrium is not of much help in devising profitable trading strategies. Indeed, vast masses as well as most professionals who engage in daily economic transactions have hardly any knowledge of "equilibrium."

The elegance and generality of the general equilibrium theory of economics is derived, in significant degree, from its abstraction from the structural details of economic institutions. In identifying the fixed points of competitive economy under utility maximizing behavior of agents, the theory leaves open the question of how, and under what conditions the economy might reach such equilibria. Out-of-equilibrium behavior, dynamics and plausibility of the process remain open questions.

Beginning with Economics 101, the fiction of Walrasian tatonnement—an artificial auction form which is rarely observed in practice—is used as a make-believe stand-in for the process of arriving at equilibrium. In day-to-day encounters, most economic institutions hardly correspond to this idealization. Scarf (1960) proved that the strategic behavior of agents can prevent even simple economies from arriving at competitive equilibrium through tatonnement, and Hurwicz (1972) showed that agents have economic incentives not to reveal the truth that the Walrasian auction assumes them to reveal through their excess-demand functions in order to arrive at competitive equilibrium. A variety of modifications proposed for the Walrasian tatonnement fail Hayek's (1945) decentralization test. In an economy where a great deal of information (preferences, endowments, and opportunity sets) is inherently private and therefore decentralized, assuming the existence of an omniscient central planner to help achieve the equilibrium in the economy does not inspire faith in Adam Smith's (1776) invisible hand.

In addition to its problems with dynamics and truth-telling pointed out by economists, competitive equilibrium under Walrasian tatonnement is criticized for being predicated on optimizing behavior by agents. Can untutored people, acting largely by intuition and without any significant computational assistance, arrive at optimum individual decisions in even simple, much less complicated, contexts? Some seven decades of cognitive psychology have marshaled evidence that the answer to this question is negative. The late twentieth century rise of behavioral economics, with its focus on "irrational" behavior and the consequences of such behavior for economic systems, is a result of gradual accumulation of skepticism about the competitive equilibrium theory from several directions.

While the theory is under attack, many of those who might be expected to defend the ramparts have either given up or turned hostile. I believe that the competitive equilibrium theory is not only worth defending but is also as robust as its strongest proponents believe it to be. In the following text, I present my argument.

Moving from one level to another, it is possible to create paradoxes and puzzles; however, they tend to disappear when we recognize that their source often lies in reductionism. Birds' beautifully colored feathers are not all made from dyes or pigments; many of their bright colors are the result of how nanofibers in the feathers are arranged to scatter light of varying wavelengths. To verify, crush a brightly colored feather between your fingertips and see its varied colors turn to dull brown or gray (Saranathan et al. 2012). The Chinese Room debate in artificial intelligence literature explores whether computers have, or can have, cognitive states and the power to think (Searle 1980; Hauser 1997). The macro-level ideas of cognitive state and thinking are probably implemented in the brain through micro-electrochemical events in neuronal networks. In what sense can we say that both birds and airplanes fly? Beyond parallels between the aerodynamics of feathers and wings, and the thermodynamics of bird metabolism and jet engines, the comparison of flying breaks down, leaving little in common between these two types of flying.

2.1 WHAT HAPPENS INSIDE MARKETS?

Economic science is the study of the interplay between want and scarcity; wants can be unbounded, but not resources. This interplay occurs in its most intensive form in competitive markets. Although much theoretical and empirical analysis has been devoted to the study of how markets function, our understanding of why they behave as they do remains far from complete. I shall discuss a new, simple characterization of what happens inside markets—statistical interaction between the elemental forces of want and scarcity. This characterization yields a simple though powerful technique to probe deeply into the dynamics of markets. I share what we have learned so far using this technique, and an outline of a continuing research program. I will dwell briefly on the advantages and limitations of this method of research and its implications.

Modern introductions to the elements of economics derive market equilibria from individuals maximizing their utility under constraints. From Adam Smith to the modern mathematical derivation of the first fundamental theorem of welfare economics, this maximization is etched into the consciousness of every student. In laboratory economics experiments, rewarding subjects based on their performance to encourage them to maximize their payoffs is a standard practice. A claim that the conditions approaching the classical predictions of the first fundamental theorem are achievable in small classroom environments without such actual or attempted maximization would have met with deep skepticism as recently as a few decades ago.

Now, because of a largely serendipitous discovery, we can claim that quite weak forms of individual rationality, certainly far short of maximization, when combined with appropriate market institutions, can be sufficient for the market outcomes to approach the conditions of the first fundamental theorem. These individual rationality conditions of no-loss are so weak as to be almost indistinguishable from the budget or settlement constraints imposed on individuals by the market institutions themselves. These findings have important implications for finance in the rapidly growing world of artificial intelligence. A review of what we have learned is a part of building minimally rational foundations for economics.

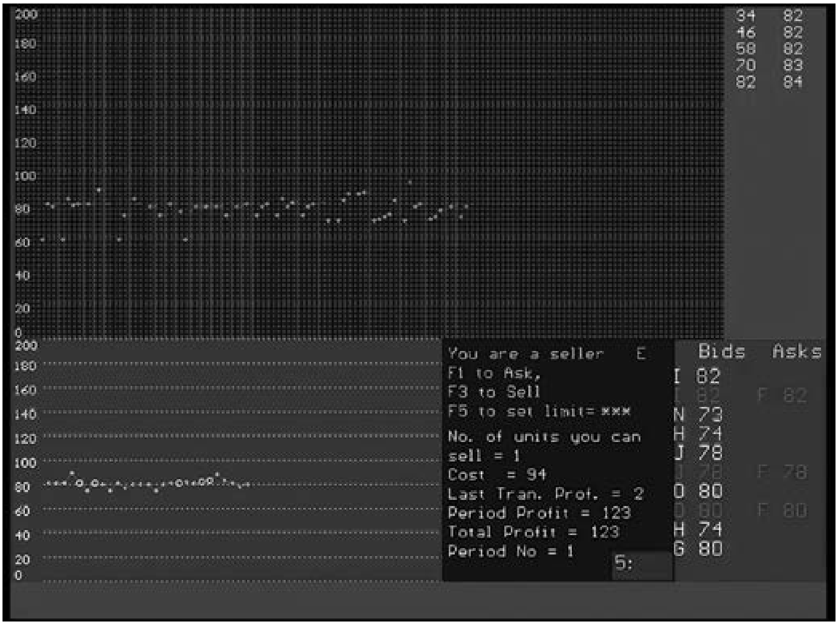
When I first saw Charles Plott present his human experimental results on competitive equilibrium at a workshop at the University of Chicago in Winter 1980, it surprised me that this rapid convergence to competitive equilibrium can occur in double auctions that have, at most, only a faint resemblance to the Walrasian tatonnement story used to explain the equilibrating process in markets. As a result, I started doing my own economics experiments with human subjects, focusing first on information processing and formation of expectations in market settings before moving to simpler commodity markets.

I developed Market 2001 as a software platform for conducting research and teaching in 1984 at the University of Minnesota with the help of an IBM equipment grant—three personal computers and software to link them together in a network. In 1987, the stock market crashed. The popular press, and most investigative reports blamed the crash on program trading. I was skeptical about why computer program trading per se would cause such a precipitous decline in market prices. If Artificial Intelligence (AI) algorithms mimicked human intelligence, they should yield comparable results, only faster. I decided to design and teach a new course on program trading at Carnegie Mellon hoping to learn about the internal workings of the double auction process and the structure of algorithmic trading strategies that make money in double auctions. Dan Gode and I expanded the Market 2001 software to include human as well as robotic (algorithmic) traders and developed a higher-level language in which students could write their trading strategies.

The data generated in lab markets were saved on a computer, and a program, called REVIEW, could be used to read the data from the files and replay it on the computer screen in the same format and order in which the traders in the laboratory saw it. The market described below consists of 12 traders (six buyers and sellers each) and we see the screen of one of the traders (Trader E who had been assigned the role of a seller). The traders in this 1989 market were mostly MBA students in my Program Trading course at Carnegie Mellon University. Figure 2.1 shows what the traders saw on their computer screen.

As shown in the top right window, this trader has the right to sell up to six units of an unspecified good. If they sell their first unit, it will cost $34, the cost of the second unit is $46, and so on. These are not sunk costs; they are incurred only if the trader sells the unit. They can only sell them in the specified order, one at a time. Their personal supply function is private, and they do not know the market supply or demand functions. The prices of the units which have already been sold at this point in trading are shown on the right next to the costs. The "ticker tape" in the right bottom window shows bid prices and bidders are shown on the left in chronological order; ask prices and asker identities are shown on the right-hand side. When a bid and ask are matched a transaction takes place. An asterisk indicates a market event that involves the trader whose screen we see.

The large window on the top left shows bids and offers in white dots, and completion of a transaction following a sequence of bids and asks in vertical lines. The window in the bottom left charts the sequence of transaction prices. The bottom middle window shows that by pressing key F1, Seller E can state the price at which they are willing to sell a unit, and by pressing key F3 they can sell to the current highest bidder in the market. The lower part of this



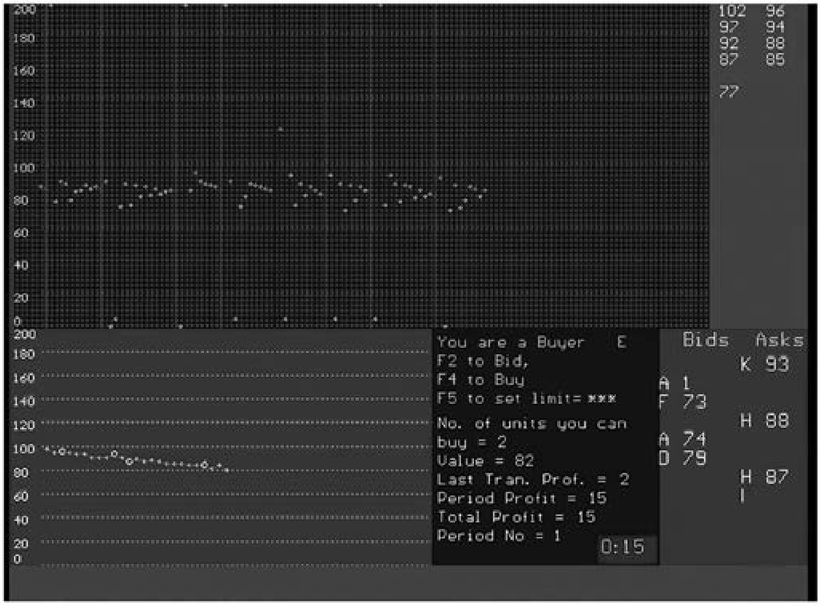
Source: Author's research website: https://spinup-000d1a-wp-offload-media.s3.amazonaws.com/faculty/wp-content/uploads/sites/53/2019/06/DA_Human.mp4.

Figure 2.1 Trading screen of market 2001 (human traders)

window shows the accounting data on the number and cost of units and the profits made. The time remaining in the trading period is shown in a small window in minutes and seconds.

As you can see, the transaction prices in this market quickly settle down in the low eighties. Economic theory predicts prices in the \$82–86 range where the demand and supply functions intersect. Though the student traders did not know the market demand and supply functions or the equilibrium price, these markets quickly converge to the theoretical prediction of the competitive equilibrium model. After thousands of laboratory experiments of this type, beginning with the work of Edward Chamberlin, Vernon Smith, Charles Plott and many others, it is now a well-established result; therefore, behavior of this double auction market carries no surprise.

After students in the class were comfortable trading in a double auction using keyboard and screen, I asked each of them to write their trading strategies in a computer program. Twelve such computer programs traded in the market with six each assigned the role of a buyer and a seller. Figure 2.2 shows the results of a trading session among robot subjects (algorithms) with the demand and supply functions unchanged from the human market.

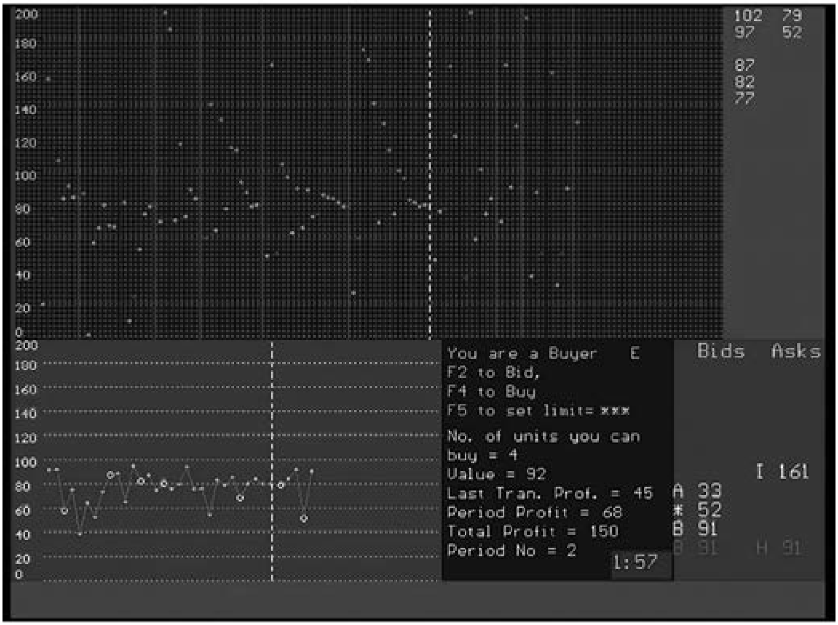


Source: Author's research website: https://spinup-000d1a-wp-offload-media.s3.amazonaws.com/faculty/wp-content/uploads/sites/53/2019/06/DA_AI.mp4.

Figure 2.2 Trading screen of market 2001 (student algorithm traders)

The coded trading strategies (algorithms) submitted by the students bore little resemblance to one another, and to their authors' own keyboard trading behaviors. In this market, the transaction prices started near \$100, the mid-point of the \$0–200 price range, but soon settled down in the equilibrium price range of \$82–86. A significant amount of excess volatility persisted throughout this market, even after several periods. One might conclude these programs "learned" more slowly than the human traders did; even after several periods, there are many more bids and offers per transaction in this market than in the market with human traders.

Students (mostly MBAs but a few from computer science) found it difficult, conceptually and technically, to write trading strategies. They wanted their algorithms to compete against mine and asked me to write one. Dan and I wrote a trading strategy, and Figure 2.3 shows the results of a market populated with 12 clones of this program, six each as buyers and sellers. The demand and supply functions remain unchanged.

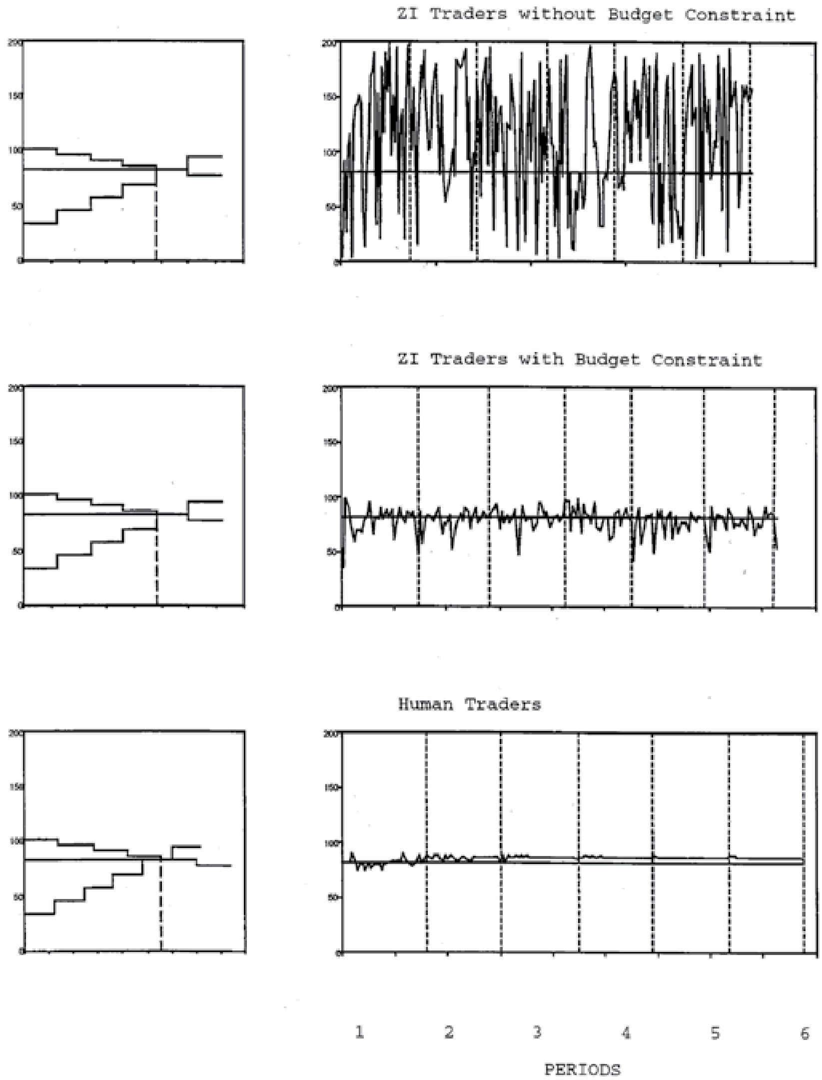


Source: Author's research website: https://spinup-000d1a-wp-offload-media.s3.amazonaws.com/faculty/wp-content/uploads/sites/53/2019/06/DA_ZI-C.mp4.

Figure 2.3 Trading screen of market 2001 (zero-intelligence traders)

This third market exhibited greater variability in prices than the previous two did. But its convergence to close vicinity of equilibrium price was a surprise to us. The strategy consisted of one line of computer code: sellers picked a uniformly distributed random number between their cost and $200 and submited it as their ask whenever they had the opportunity; similarly, buyers submitted a uniformly distributed random number between 0 and their value as their bid. The only constraint this strategy imposed on traders was that they were not to propose a price which, if accepted, would incur a loss. That's all, no maximization, no memory, no learning, no natural selection, and no arbitrage. And yet, prices in this market also converged to near the equilibrium prediction of economic theory.

In Figure 2.4, the bottom panel shows the price chart from six periods of double auction market populated by student traders. The top panel shows the price chart from a market populated by zero-intelligence agents unconstrained by no-loss criterion (ZI-U). The middle panel shows the six periods of ZI-C market (same as Figure 2.3) traders with constraints. The market demand and supply functions in all three panels are identical. Note that a great deal of the large difference between top and bottom panel price charts is made up by imposition of no-loss constraint on zero-intelligence traders.

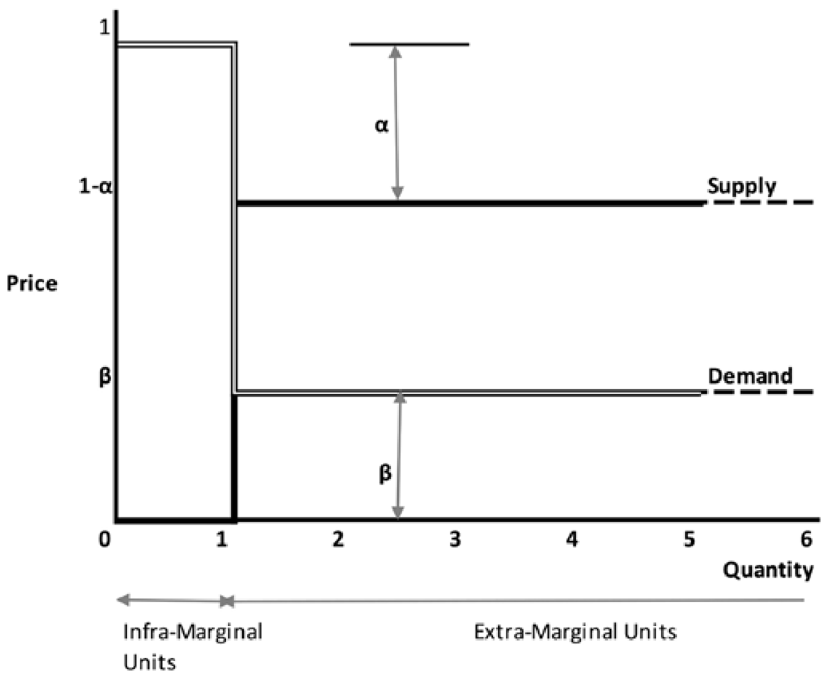


Source: Fig. 1 from Gode and Sunder (1993a).

Figure 2.4 Demand and supply and transaction prices in markets with ZI-U, ZI-C, and human traders

Since my introduction to economics, I had thought of competitive equilibrium as an outcome of individual striving to maximize personal gain. From Adam Smith to the modern mathematical derivation of the first fundamental theorem of economics, this maximization had been engraved into our economics consciousness. Performance-based rewards to human subjects in laboratory experiments, to encourage them to maximize their rewards was, and still is, an important part of the experimental method. Yet, we find that in this market, prices converge without any attempt on the part of the traders to maximize. When we reviewed data on allocative efficiency, we were in for an even greater surprise: the allocative efficiency of the third market was virtually the same as the efficiency of the first market—around 99 percent. Since the trading was among algorithms, there was no mystery about their behavior. We know for sure that they did not maximize because we created these traders. We were convinced this must be the result of bugs in the software.

Dan Gode and I spent months looking for errors in our computer programs, parameters, data, analysis. We found many bugs, but none that changed

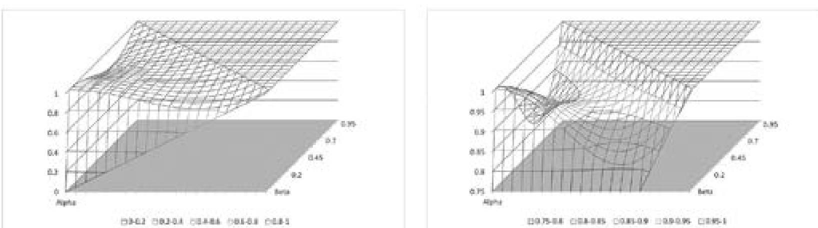


Source: Reproduced from Fig. 1 in Gode and Sunder (1993b).

Figure 2.5 *Model demand and supply functions* these results. After endless replications of these simulations, we resorted to simple mathematical modeling to check if we could derive what the computer simulations were telling us. We derived closed form solutions from simple models and compared the model predictions against results of more realistic market simulations. Our aim was not to model human behavior accurately; we assumed simple trading behavior to gain insights into markets with human versus AI traders.

Figure 2.5 shows the demand and supply functions for a simple market with only a single intra-marginal unit for sale (cost = 0) and a single unit for purchase (value = 1). In addition, an unlimited number of additional units with cost = ($1 - \alpha$) are available for sale and an unlimited number of additional units with *value* = β are demanded. In a synchronized double auction all traders have the opportunity to submit their respective bids and asks before the highest bid and the lowest ask are matched to determine if they cross and to complete a transaction.[2]

Figure 2.6 shows the expected efficiency of the double auction on the vertical axis when the value of parameters α *and* β is varied between 0 and 1 on the two horizontal axes. Expected efficiency is 100 percent when α and β are both 0, and when the sum of the two parameters exceeds 1. Otherwise, the expected efficiency drops below 100 percent, achieving a minimum of about 80 percent with an infinite number of extra-marginal traders. This shortfall of minimum efficiency (from 100 percent) gets smaller as the number of extra-marginal traders declines. This simple model shows that the results shown in Figure 2.3 (and the middle panel of Figure 2.4) for markets populated with zero-intelligence traders are a logical consequence of the statistical interaction among bids and offers under the rules of double auction.



Source: Reproduced from Fig. 2 in Gode and Sunder (1993b).

Figure 2.6 Expected efficiency with changes in the cost and value of extra-marginal units

Fortified by the knowledge that the results of our simulations were not totally ridiculous, we called our programs "zero-intelligence" traders and presented our results at an experimental economics conference at the University of Arizona. It was pointed out to us that these results might be an artifact of the demand and supply functions we used. That took us back to the lab for more simulations and more modeling.

The simple ZI traders used to obtain these results have a precedent. Becker (1962) showed that if consumers choose randomly within their budget sets, their demand curves slope downwards. However, Becker assumed Walrasian tatonnement, and did not analyze the role of institutional rules. Gode and Sunder (1993a) synthesized Becker's random choice within opportunity sets with Vernon Smith's (1962) double auction market institution. We studied the efficiency of Smith's double auction markets populated with "zero intelligence" traders, that, like Becker's consumers, choose randomly subject to market rules. The following summarizes what we learned.

Allocative efficiency measures a market's contribution to aggregate social welfare (but not its distribution across participants). When demand and supply intersect, possibility of extra-marginal traders displacing intra-marginal traders arises in double auctions and other commonly used market mechanisms. Traders to the right of the intersection are the extra-marginal traders, and those to the left are the intra-marginal traders. Extra-marginal buyers do not value the goods as much as the intra-marginal buyers do and the cost of goods to extra-marginal sellers is higher than it is to intra-marginal sellers. Maximum surplus is extracted, that is, efficiency is 100 percent if intra-marginal buyers buy from intra-marginal sellers (thus no extra-marginal traders trade).

Gode and Sunder (1997, 2004) identify three causes of inefficiency: (1) traders participate in unprofitable trades, (2) traders fail to negotiate profitable trades, and (3) extra-marginal traders displace intra-marginal traders, that is, the aggregate profits are not as high as they could be.

If resources are allocated by fiat or other non-market mechanisms, then efficiency can be arbitrarily low, even negative, depending on the shape of extra-marginal demand and supply. The freedom to refuse others' bids or asks will not increase efficiency if buyers do not know that they should not pay more than a good's value to them, and sellers do not know that they should not accept less than the good's opportunity cost to them. Accordingly, we assume that traders are free to refuse offers, and have the judgment to avoid losses. Efficiency is still zero if a buyer, who values the good more than the seller, cannot find a seller, or the two cannot agree upon a price. We show how call auctions and continuous auctions affect the probability of a buyer finding the right seller. Assuming simple trader behavior, we also show how increasing the number of rounds of bids and asks increases the probability that the buyer and the seller will find a mutually profitable price. This is a simple observation, but one that may explain the high efficiency of double auctions that allow multiple rounds relative to sealed bid auctions that allow only a single round.

The third source of inefficiency still remains extra-marginal traders displace intra-marginal traders. If an extra-marginal buyer with value *Ve* buys instead of an intra-marginal buyer with a value *Vi*, the efficiency loss is (*Vi* – *Ve*). This displacement is undone if instead of consuming the good himself, the extra-marginal buyer resells it to an intra-marginal buyer. However, in the real world such reselling may be limited because of transaction costs—the need to consume the good and informational asymmetry at the time of resale. Accordingly, experimental markets and game-theory models disallow such resale. We also do the same. Similarly, if an extra-marginal seller with cost *Ce* sells, instead of an intra-marginal seller with cost *Ci*, then the loss in efficiency is (*Ce* – *Ci*), This displacement is undone if, instead of producing the good itself, the extra-marginal seller buys it from an intra-marginal seller. We disallow such subcontracting as well. Note that re-trading is different from multiple rounds of bidding and asking for a given trade, which we allow.

Given limits on re-trading, the interesting question is: What determines inefficiency due to displacement? Multiple rounds of bids and asks, that is, multiple opportunities to negotiate, which reduce inefficiency due to the second source. If the auction ends after the first round, expected efficiency with ZI traders is only 50 percent; further rounds raise this lower bound to 81 percent.

The expected loss of efficiency when intra-marginal traders are displaced is a product of the magnitude of inefficiency from displacement and its probability. The magnitude of inefficiency depends only on the shape of extra-marginal demand and supply, which are often ignored, but the probability of displacement depends, in addition, on the market rules.

Without a price system, there is random allocation so that the probability of displacement converges to 1 as the number of extra-marginal buyers increases. Efficiency approaches zero as the redemption values of extra-marginal buyers approaches zero. (It could be negative if extra-marginal sellers are also present.) The imposition of the Binding Contract Rule and the Price Priority Rule creates a price system in its most basic form. This system discriminates against extra-marginal bidders because their redemption values are low, and their lower bids are given lower priority. Increasing the extra-marginal buyers' redemption values increases the probability of displacement but lowers the loss of efficiency when displacement does occur. This market-level trade-off raises the lower bound on expected efficiency from zero to 75 percent. *This market-level trade-off exists even if individuals do not trade off profit from a bid against the probability of it being accepted.*

The Double Auction Rule (allowing sellers to ask, as well as buyers to bid) increases efficiency to 81 percent in a synchronized double auction, because now an inefficient trade requires both the intra-marginal ask and the intra-marginal bid to be lower than the extra-marginal bid; in a sealed-bid auction, inefficient trade requires only the latter. The Accumulation Rule (accumulating bids and asks before matching) makes price priority more effective because extra-marginal buyers cannot get the unit merely by bidding before the intra-marginal buyer. For example, in a sealed-bid auction without accumulation, that is, if the unit is sold to the first bidder, the probability of displacement is $n/(n+1)$, which is the same as that without a market. The probability of displacement decreases as more bids are accumulated before ranking. A continuous auction's efficiency is lower than that of a synchronized auction because of the same effect. Making bids and asks public also increases efficiency because of the extra-marginal traders.

High efficiency of double auctions is largely due to the rules that define them. It is possible to identify and rank a few basic rules that account for most of the efficiency. Successive imposition of these rules reduces the probability of inefficient exchanges among traders. The results may help market designers understand the effect of market rules on efficiency. We summarize the results in the following paragraphs:

(1) Markets defined by their rules have characteristics of their own, largely robust to significant variations in the behavior of participating agents. Allocative efficiency—fraction of the maximum possible surplus extracted—is one such characteristic.

(2) Markets, double auctions especially, are powerful social institutions. They may have evolved in human societies because of their survival value to their users.

(3) Adam Smith's conclusion that social-level economic efficiency arises from the individual pursuit of self-interest is more general than is commonly understood. Aggregate economic (social) efficiency is achievable in double auctions even if agents act randomly within their budget or no-loss constraints. Random choice within one's opportunity set, as Gary Becker (1962) posited, is, at best, an extremely weak form of "pursuit of self-interest."

(4) Economists' use of maximization assumption to derive market equilibria, and cognitive psychologists' finding that when acting by intuition alone, individuals often do not maximize, are not necessarily in conflict with each other. Market institutions are society's artifacts to overcome human cognitive limitations. In classical environments, markets can approach the aggregate maximum surplus extraction even if the individuals do not know how to do so.

(5) The efficiency of markets is predominantly a function of their rules. The following features play important roles:

(a) The shapes of extra-marginal segments of supply and demand functions influence the efficiency of surplus extraction.
(b) Two rules jointly raise the efficiency substantially by lowering the probability of displacement of intra-marginal by extra-marginal traders (Gode and Sunder 1997):

   (i) buyers and sellers abide by their bids and asks,[3] and
   (ii) priority by disadvantage: higher bids have priority over lower bids and lower asks have priority over higher asks.

(c) As demand and supply functions are varied, the expected loss of efficiency approaches an upper bound. If extra-marginal buyers value the goods much less than intra-marginal buyers, the magnitude of efficiency loss is high, but its probability is low because the two basic rules prevent extra-marginal buyers from being the high bidder (and extra-marginal sellers from being the low asker). If extra-marginal buyers value the goods nearly as much as intra-marginal buyers, then they can bid almost as high, increasing the probability of displacement, which is offset by the decrease in the magnitude of loss from displacement. Note that even though at the micro level, individual zero-intelligence traders do not trade off profit from a proposal and its probability of being accepted, at the market level there is a trade-off between the magnitude of efficiency loss and its probability (Gode and Sunder 2004).
(d) Double auctions may be more efficient than one-sided auctions such as sealed-bid auctions, because in double auctions more conditions must be fulfilled for an inefficient trade to occur.
(e) Auctions that batch or accumulate bids and asks before picking the highest bid and lowest ask, such as call auctions, may be more efficient than continuous auctions, where a transaction occurs as soon as a bid exceeds or equals an ask. However, continuous auctions may still be favored in some contexts because they have a faster price discovery. In other words, there is a trade-off between allocative efficiency and price adjustment speed.
(f) Allowing traders to observe market data increases efficiency because it allows intra-marginal traders to outbid/undercut extra-marginal traders more quickly.
(g) Repeat bidding. The successive application of these rules reduces the probability of inefficient trades.

(6) Single market findings about double auctions generalize to a set of multiple interlinked markets. If inventories are maintained between the

markets, the effect of market discipline weakens, and allocative efficiency declines (Bosch-Domenech and Sunder 2000).

(7) The Walrasian tatonnement is a valuable model that captures the asymptotic behavior of markets but does not organize the data from the process of arriving at equilibrium well. The zero-intelligence model is a simple model that captures the dynamics of markets and well organizes the data from the early part of trading. The two models, in combination, may do a better job than either can do alone of helping us to understand the behavior of markets.

(8) Double auction asset markets with state uncertainty and imperfect information converge to the same equilibrium derived by assuming that the traders are profit-maximizing Bayesians, irrespective of whether the traders are (1) Bayesians, (2) empirical Bayesians, or (3) biased heuristic traders, who use heuristics well known to be biased from studies in cognitive psychology (Jamal and Sunder 1996, 2001).

(9) ZI models function well in general equilibrium environments. ZI markets are virtually guaranteed to arrive at the contract curve or the Pareto efficient allocation (Gode et al. 2004; Crockett et al. 2008).

Our approach differs from game theory, empirical studies of archival data, laboratory experiments with human traders and mimicking human traders by computers. Game theory moves away from perfect competition and Walrasian tatonnement to provide valuable insights into markets. However, it is often difficult even to prove the existence of equilibrium, let alone solve it, for most double auctions.[4] We assume simple agent behavior for tractability, not to challenge or criticize maximization assumptions. We use a mathematical model instead of field data to control demand, supply, and market rules to explore expected efficiency loss due to displacement, the product of the magnitude of efficiency loss and its probability.

2.2 CONCLUDING REMARKS

The use of artificial intelligence in finance and other fields is dominated by attempts to meet or beat human intelligence by a chosen index of performance appropriate to each context (also see Simon 1978, 1996). These efforts are centered on finding ways of increasing the intelligence of artificial agents through analysis, machine learning or other methods to achieve this goal. This chapter reports on an effort in which the goal of gaining a better understanding of properties of social institutions—markets in particular—is sought by populating them with minimally intelligent agents (called zero-intelligence agents), and examining institutional performance. Computer simulations with ZI agents reveal robustness of certain market outcomes, and sensitivity of others, to trader intelligence. Analyses of data from simulations help address some important questions about why certain markets, even when they are populated by cognitively bounded human traders, yield outcomes predicted by models predicated on utility maximization, while others exhibit systematic deviations from such predictions. Certain kinds of intelligence—extraction of social surplus—appears to be embedded in the rules and structure of markets and social institutions.

Forces of want and scarcity, operating within simple exchange institutions such as double auction, can be sufficient for classical economies to approach competitive equilibrium. An understanding of how the externally observable rules of social institutions of markets (North 1990) can cause the price systems to efficiently aggregate unobservable individual preferences (Hayek 1945), and why simple individual behavior can generate highly efficient allocations in markets, is a step toward unraveling the mystery of the invisible hand as well as building foundations of minimal rationality economics. As physicist Murray Gell-Mann (1994) wrote in *The Quark and the Jaguar*: "In an astonishing variety of contexts, apparently complex structures or behaviors emerge from systems characterized by very simple rules."

Markets "give occasion to general opulence" through participants' "regard to their own interest" (Adam Smith 1776). Our analysis and simulations of markets populated by zero-intelligence agents suggests that the relentless pursuit of self-interest is not always necessary for markets to be efficient; weak pursuit of self-interest may be sufficient for efficient allocations in aggregate.

NOTES

1. I am grateful for participant comments on an earlier version of this chapter prepared as one of three Annual Distinguished Lectures at the Centre for Computational Finance and Economic Agents (CCEFA), University of Essex, UK. I thank my research collaborators Dan K. Gode, Karim Jamal, Antoni Bosch, and Shabnam Mousavi for helpful comments and suggestions and Elizabeth Viloudaki for editing.
2. Synchronized double auction is an assumption made for analytical convenience; the results shown in Figures 2.1, 2.2, and 2.3 were obtained in a double auction that matched each crossing bid and ask in a transaction as they arrived.
3. In certain markets not considered here (e.g., second-price auctions) the actual payment differs from the bid or the ask.
4. See Wilson (1985), Friedman (1984), and Easley and Ledyard (1992).

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