Journal of Archaeological Science 32 (2005) 1346–1356
http://www.elsevier.com/locate/jas

Specialisation and wealth inequality in a model of a clustered economic network

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Received 28 January 2004

Abstract

In this paper we present an agent-based model of specialization, exchange and inequality within a clustered social network, with implications for the economic effect that contact with colonizing groups may have had on prehistoric indigenous populations.

Keywords: Agent-based modelling; Complex networks; Exchange; Kin networks; Mesolithic-Neolithic transition; Power laws; Prehistoric trade; Wealth inequality; Social networks

1. Introduction

An important economic phenomenon in prehistory is the emergence and maintenance of exchange networks between different specialists. The principle of *comparative advantage* in economics means that two economic actors are likely to do better by producing different products as specialists and trading with each other than by producing both products themselves in isolation. Specialization and exchange benefits so generally that the related behaviours may have been integral to early hominid evolution [26].

For this paper we used computer simulation to explore how an exchange network coevolves with the changing specializations of the agents within it. Through simulation, we can keep track of who is connected to whom through a mapping of the network and the specializations of each agent, and we can test the effects of simplified individual motivations for exchange, the make-up of the initial population of agents, and abstract representations of basic ideological dispositions such as the belief in private ownership.

Our computer simulation is vastly oversimplified compared to real human exchange networks, in which we are looking for patterns that emerge on their own under a significantly wide range of parameters and initial conditions. For example, modern networks of wealth [27,5] sexual partners [23] and others [1] often self-organize due to a simple tendency for the rich to get richer, such that each agent tends to acquire additional elements roughly in proportion to the number it currently has. A striking similarity among these networks is that the probability distribution of the number of connections each agent has follows a power law:

$$P(k) \sim 1/k^{\alpha}, \quad (1)$$

where α is positive and P is the probability that an agent has k connections with other agents. Qualitatively, the power law means that most of the agents in the network have only a few connections, while a few inevitably emerge with orders of magnitude more.

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0305-4403/$ - see front matter
doi:10.1016/j.jas.2005.03.008

Power-law distributions of wealth are ubiquitous for a wide range of economic scales [27,5]. Among pastoralist societies, for example, several ethnographic studies show differences in livestock ownership spanning two orders of magnitude [10,22,24,11,15,4]. For the Somali and Ariaal groups, Fig. 1 shows that the distribution of wealth per family, as measured in livestock, approaches a power-law form. Apparently, owners of large herds preferentially acquire additional livestock through the advantages of wealth itself [15,29,30].

1.1. Computer simulation of economic specialization

With the agent-based computer simulation described below, we aim to test whether specialization and wealth inequalities are natural, self-organizing qualities of a small-scale economy. Agent-based modelling allows us to test hypotheses for complex systems in the social sciences [8,12–14], including in archaeological studies of hunter-gatherer subsistence [19–21] and late prehistoric settlement [18]. Computer-simulated *agents* might represent individual people, households or villages that, importantly, have the ability to interact purposefully with their environment and with other agents [2,9]. In successive "time steps", the general sequence of an agent-based simulation is (a) each agent acts according to its rules and local environment; (b) the 'world' (the states of agents and their landscape) is changed according to the sum of all agent actions; (c) agents react to their new environment, and so on. The power of agent-based modelling lies in the iteration (repetition) of these agent interactions over many time steps, which may produce predictable patterns on the large scale, even as the details of the occurrences on the small-scale are unpredictable.

Being simple, our model gives us a chance to run multiple simulations to test how several parameters affect specialization, exchange and wealth inequality within a simplified social network.

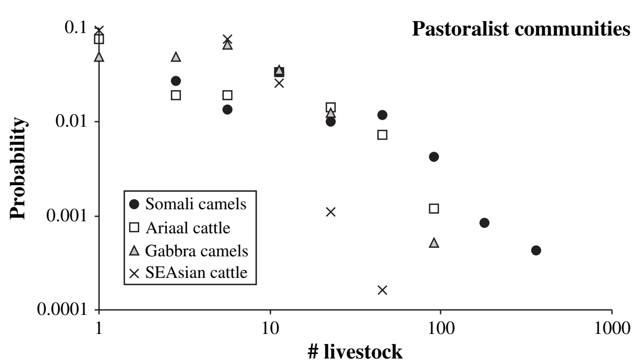

Fig. 1. Livestock ownership in pastoralist societies, as shown by distributions on a plot with logarithmic x- and y-axes. After [4], Fig. 2.6.

2. The model

Our model, programmed in Java and run on the agent-based platform RePast (v. 2.0; http://repast.sourceforge.net/), involves a network of agents who consume, produce and trade two different commodities. In an abstract version of a social network represented by dots and lines, the agents and their connections do not represent physical space, but rather "relational space" depicting which agents are accessible to each other for trade in a localized zone of interaction. Built upon an already-tested social network model [17], described below, our own model runs so that each agent, represented as a network node (Fig. 2), produces and consumes its own combination of two distinct products – product "A" and product "B" (we capitalize the names of model parameters – the trading of which between agents is represented by links in the network). Below, we first describe the social network model [17] and our modification of it for our own simulation, followed by our results and the effects of different parameters.

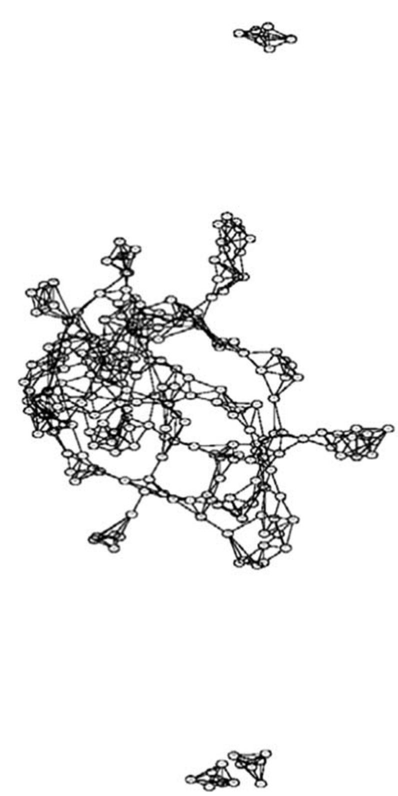

Fig. 2. Sample network generated by the Jin et al. [17] model, using the default values for the variable parameters and constant values of the fixed parameters listed in Table 1. From [17], Fig. 6.

2.1. The social network model of Jin et al. [17]

The network model we have adapted from Jin et al. [17] is simply a network of nodes (representing individual people) and links (their relationships with one another), which reproduces some patterns generally observed in real-world social networks, including a clustering quality (Fig. 2) that may be crucial to the dynamics of trade. To capture the essential elements of a social network, Jin et al. [17] have made three assumptions: (a) while meetings between random pairs of individuals occur, meetings are much more likely if the pair share a mutual acquaintance, (b) if, after becoming acquainted, a pair rarely meet, that acquaintanceship tends to be lost over time; and (c) the number of simultaneous acquaintanceships an individual can hold is limited.

The Jin et al. [17] model begins with a set of nodes (250 in the default model) with no connections. With the number of nodes remaining constant, connections are added and removed during the simulation according to three processes [17]:

(a) Random meetings. At each time step, a small, fixed fraction r_0 ($r_0 = 0.0005$ in default model), of the possible pairs of vertices are selected at random to meet. Each pair is given a new connection provided it does not have a pre-existing connection, and if neither of them has more than the maximum number of allowed connections per node (5 in default model).

(b) Meetings between those who share a mutual connection. At each time step, a certain fraction of connection-holding nodes are chosen, and for each, one pair of its neighbours is randomly chosen to meet. The number of pairs chosen is given by $r_1 n_m$, where r_1 is a model parameter ($r_1 = 2$ in default model), and n_m is the total number of mutual neighbours of pairs of vertices in the network, given by:

$$n_m = \frac{1}{2}\sum_i z_i(z_i - 1), \tag{2}$$

where z_i is the number of connections held by the ith node in the network [17]. As above, the meeting pair is given a new connection as long as they are not already connected, and if both have below the maximum number of connections (5 in default model).

(c) Loss of connections. At each time step, each connection has a small constant probability γ of being removed. In the default model, the removal probability per connection per time step is 0.005.

Through these simple rules, the model reproduces features of real social networks, in that individuals have more links to others within their community than to individuals from other groups, but clusters are connected by a few cross-network ties, often with a few clusters disconnected from the rest (Fig. 2). Due to mutual friendships, most broken connections are likely to be remade quickly, but as some are not remade, the network structure changes over time. Jin et al. [17] found that extremely high values of the connection-removal probability produced rapidly changing, dispersed network structures, while a low removal probability resulted in a static, highly-clustered network. The default parameters they chose for their RePast model (Table 1) represent a middle ground, by which the network that emerges is structured similarly to real-world social networks, and can still evolve.

3. Our model

In order to represent a simple trade network, we modified the Jin et al. [17] model by assigning independent, positive numeric variables to each agent (Table 1), which we call (product) A, (product) B and Strategy. Each agent's values for A and B, numerically between 0 and infinity, represent the amounts of A and B products that it possesses. The value of Strategy, bounded between 0 and 1.0 (0 = strictly A, 1.0 = strictly B), represents the relative amount of A vs. B that an agent produces in each time step. A Strategy value of 0.78, for example, means that the agent's production per time step consists of 78% A and 22% B commodities.

When the model is initialised, each agent is assigned a possession of A between 0 and ACap (default = 99 units), randomly chosen from a uniform distribution, and another randomly-chosen value for B, between 0 and BCap (default = 99). The initial Strategy value for each agent is randomly chosen between 0 and 1.0. Through interaction within the network, each agent's A and B possessions can change in two ways, (a) independently, through individual production and consumption, and (b) interactively, through commodity exchanges between agents. The Strategy value changes whenever agents are 'unhappy' with their economic situation, as described below. In our analyses we kept track for each agent of Wealth, the sum of the agent's A and B possessions at the particular time step.

3.1. Production and consumption

Independently, every agent produces and consumes at each time step, according to two global variables, called RDAProduce and RDAConsume, and the agent's Strategy variable. The global variable RDAProduce determines the total amount that each agent produces at the beginning of each time step, with the default set at

Table 1
Model parameters

Parameter	Description	Default value
Agent variables		
Strategy	Balance of A vs. B produced and consumed by each agent per time step (Eqs. (2)–(5))	
A	Amount of A products owned	
B	Amount of B products owned	
Wealth	A + B	
Price	'Agreed' value (in units of B) of one unit of A for a trade between two agents	
Degree	Number of connections to other agents	
Variable global parameters		
Margin	In 'Margin' mode, the difference in ownership that motivates a trade between two agents	25
RDAConsume	Units consumed by each agent per time step (see Eqs. (4) and (5))	2
RDAProduce	Units produced by each agent per time step (see Eqs.(3) and (4))	2
r_0	Probability two randomly-chosen agents are connected	0.0005
StrategyCap, ACap, BCap	Maximum Strategy, A, B value when initially assigned to agents via uniform distribution	99 (all 3)
Trade	Amount exchanged between two agents	2
Fixed global parameters		
HappyDegree	Number of connections below which an agent will adjust its Strategy	3
IncrementNeg	Maximum negative value (toward full Product B) for agent adjusting its Strategy	−1
IncrementPos	Maximum positive value (toward full Product A) for agent adjusting its Strategy	1.2
γ	For each link, the probability it is removed in the time step	0.005
r_1	Related to probability that two agents with a mutual connection are connected	2
NumNodes	Number of agents in model	250
MaxDegree	Maximum number of connections allowed for an agent	5

2.0 units. In each time step, each agent adds to its possession the amounts ΔA and ΔB, given by

$$\Delta A(t) = +\text{RDAProduce} \times \text{Strategy} \quad (3)$$

$$\Delta B(t) = +\text{RDAProduce}(1 - \text{Strategy}) \quad (4)$$

where t refers to the current time step. At the end of each time step, all agents consume according to a similar rule, involving the global variable RDAConsume, as given by

$$\Delta A(t+0.5) = -\text{RDAConsume} \times \text{Strategy} \quad (5)$$

$$\Delta B(t+0.5) = -\text{RDAConsume}(1 - \text{Strategy}) \quad (6)$$

where $t + 0.5$ refers to end of the current time step. The default value of RDAConsume is also set to 2.0, so by default the net flux of products (RDAProduce − RDA Consume) averaged over all agents is zero.

3.2. Trading

In each time step, after the production action, agents are allowed to exchange with each other, with one agent transferring a quantity of A in exchange for a quantity of B from the other agent. The global variable Trade (default = 2.0) determines either the number of units of A exchanged in each trade, or (as described below) the percentage of an agent's ownership offered in trade.

A Price that governs the number of units of B exchanged per unit of A is determined independently by each agent for every potential transaction, based on the agent's perception of how available each commodity is locally. We simulate this by having each agent 'look' at a random selection of its current neighbours (those to which it is directly connected), keeping a cumulative account of the B and A products owned. The Price is then the ratio of the neighbours' total B to total A. For example, if the three neighbours of an agent have 5 units of A and 3 units of B, 2 units of A and 3 units of B, and 6 units of A and 1 unit of B, respectively, the perceived Price is $(3 + 3 + 1)/(5 + 2 + 6) = 0.54$, meaning the agent currently believes that one unit of A is worth 0.54 unit of B. Because the Price is calculated from an agent's own unique point of view, any two agents most likely calculate different Prices. For this reason, each transaction occurs using the average Price ($0.5 \times$ [Price1 + Price2]) of two agents involved.

In our adaptation of the Jin et al. [17] model, a successful trade is an added prerequisite toward establishing a link between two agents. Trades are therefore possible between (a) agents meeting at random, (b) agents meeting through a mutual connection, or (c) agents already connected. A new link is only established if the two meeting agents successfully conduct an exchange.

The two versions of our model compare two alternative motivations for agents to trade with each other. The first is by 'Margin,' and the second by 'bestPrice'. Under the Margin rule, agents trade based on the need to fill deficiencies − if the difference in their respective possessions of a single commodity exceeds the global variable "Margin," then they engage in a trade from the agent with more to that with less. For example, if Agents 1 and 2 have 35 and 65 units of B, respectively, and the Margin is set at 10, then Agent 2 trades some of its B to Agent 1 in return for A, at their agreed-on Price. This Margin trade occurs regardless of the amount of A possessed by Agent 1, except in the case where Agent 1 did not possess enough A or Agent 2 not enough B to make the trade, in which case the trade is cancelled.

Under the 'bestPrice' rule, agents can trade by looking for the bestPrice available to them. Two agents considering a trade will calculate a mutual Price as described above, and then if each likes it, they trade. We allow two ways for an agent to accept a certain Price. The first is if the Price is greater than one in favour of what the agent is offering − if an agent can get 1.5 units of A in exchange for just 1 unit of B, it always likes this trade. The other motivation to trade is if the Price is better than offered by any of the agent's neighbours. To simulate this, the prospective trader looks at a selection of its neighbours and calculates a Price with each. If the trade that it is considering is at a more favourable Price, even if that Price is more than one, the agent agrees to it.

The global variable Trade is treated differently under the two rules. In the 'Margin' mode, Trade defines the number of units of A exchanged in each trade, with the number of units of B determined by the mutual Price determined by the two agents. 'Margin' trades we assume are more functional, representing materials needed for survival, and therefore a fixed amount is used. In the 'bestPrice' mode, Trade represents the percentage of ownership that the disadvantaged agent (the one receiving less for more) will offer, capturing the way that people consume in proportion to their wealth [6].

3.3. Adjusting Strategies

Each agent changes its strategy through small stochastic adjustments whenever it is not trading successfully. If two agents meet and fail to make a trade and if either agent has less than a certain fixed number of links − "HappyDegree", fixed at 3 (Table 1) − then that agent will update its Strategy value. Otherwise, if an agent already has a certain number of former trading partners (= current number of links), then it is still 'happy', and does not update its Strategy. If an update is called for, a small random value is added to the agent's Strategy value. This value is chosen from a uniform distribution between NegIncrement (default = −1.0) and PosIncrement (default = +1.2). The reason these two values are unequal is to avoid artificially forcing the model to split between the extremes. By biasing the drift in one direction, it becomes more significant to find agents actually adjusting their strategies in the opposite direction, as we will show below.

4. Results

Because the number of possible permutations of the several different parameters increases geometrically with the number of variables we are exploring, we cannot test results of all variables in all combinations. At this stage, we report the results of changing one parameter while the others are left at default values (Table 1), for runs in 'Margin' mode and in 'bestPrice' mode. We are primarily concerned with the effects on the Strategy and Wealth distributions. In each case discussed below, we present our results after averaging 10 model runs of 5000 time steps (results were not qualitatively affected by the number of time steps, unless stated otherwise).

4.1. Effects on Wealth

Under a range of parameters, the Margin rule produces a near-normal distribution of wealth (Fig. 3a). Also, if we create a net flux of wealth into the system by setting RDAProduce higher than RDAConsume, the wealth distribution remains similar shape with about the same width (note that the logarithmic x-axis makes the curves on right appear narrower), but the peak propagates outward as RDAProduce is increased, which increases the average wealth for all agents (Fig. 3a).

Under the 'bestPrice' rule, the wealth distribution is drastically changed. Running with the default parameters (Table 1) and a range of values of RDAProduce, the wealth distribution rapidly self-organises into a power law with slope near −1 (Fig. 3b). This power law is not totally surprising, since the trade that is occurring is similar to that modelled by [6]. However, unlike [6], we have not modelled any outside world which returns investments with interest. The power law wealth distribution in our 'bestPrice' model results entirely from trade. In fact, if the value of Trade is set to zero, the Wealth distribution does not change at all from its initial distribution of random assignments. There is a rapid transition, however, once the Trade value is made finite. One way to see this is by plotting the Wealth of the wealthiest agent as a function of Trade (Fig. 4). For small values of Trade, the wealthiest agent increases rapidly, then declines slowly above Trade = 0.5.

Fig. 5 shows how the shape and maximum extent of the Wealth distribution changes markedly with the value of Trade. The behaviour within the realms Trade = 0, 0 < Trade < 0.5 and Trade > 0.5 is so markedly different that the system appears to change via abrupt phase transitions. At Trade = 0, Wealth is uniformly distributed between 1 and 100, as assigned in the initiation of the model. At Trade = 0.1, Wealth

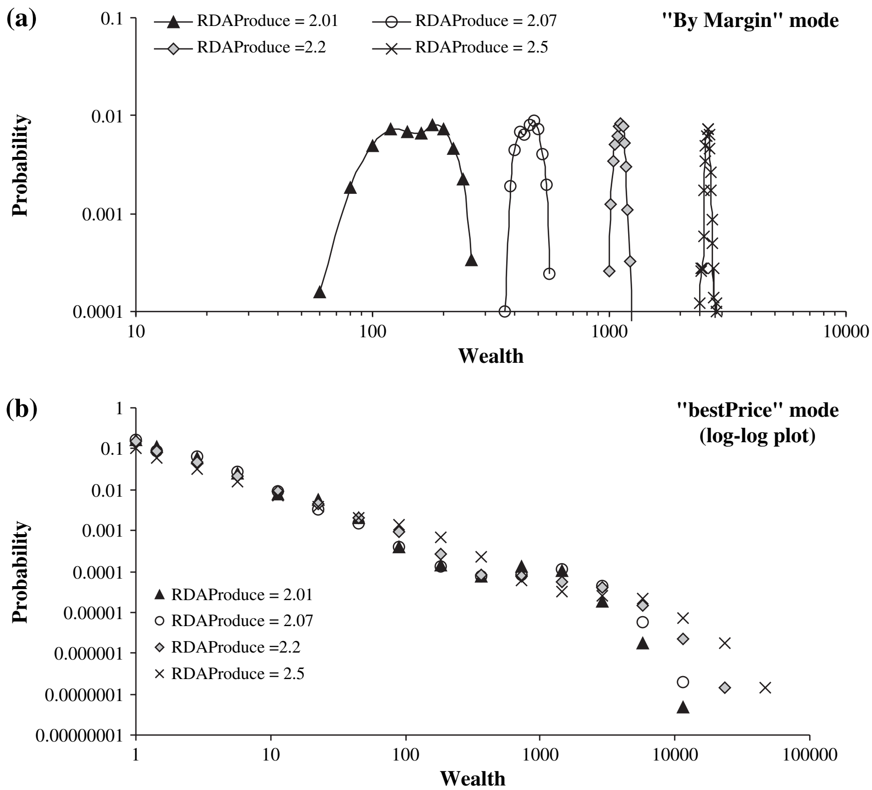

Fig. 3. Wealth distributions after the model was run for 5000 time steps (average of 10 runs) in (a) 'By Margin' mode and (b) 'bestPrice' mode, for different values of RDA produce (RDAConsume constant at 2.0). The histogram in (b) is binned by powers of 2, then normalized by the increasing bin sizes and total number of agents (250) to plot the probability. In the 'by Margin' model, increasing production just increases the average Wealth, while the variance stays roughly the same. Both axes are logarithmic in these plots, and note how the x-axis in (b) extends over five orders of magnitude.

disparity increased by two orders of magnitude, both richer and poorer. A power-law distribution forms by Trade = 0.4, extending over four orders of magnitude. As Trade is increased further, the power law fit becomes worse, and the tail recedes, until by Trade = 10 there is again an approximately uniform distribution over roughly two orders of magnitude (Fig. 5).

The effect of varying r_0 on the distribution of Wealth in bestPrice mode is subtle (Fig. 6), but the fit of a power law improves and the power law exponent, α (Eq. (1)), decreases as r_0 is increased from 0.00003 ($r^2 = 0.88$, slope = −1.26) to 0.0001 ($r^2 = 0.93$, slope = −1.19), to 0.001 ($r^2 = 0.95$, slope = −1.21) and to 0.01 ($r^2 = 0.98$, slope = −1.18).

4.2. Effects on Strategy

In this simulated economy, initial conditions greatly affect the eventual, essentially static distribution of Strategy values. The most important is the initial distribution of the possession of Product A and Product B among the agents at the start of a run. By setting the maximum initial possession of Product A variable at 1 (ACap = 1.0), we simulate the introduction of a new technology to a population, whereas by setting ACap to 99, we produce the analogue of a population of agents who have already had plenty of contact with production of A (though not necessarily producing A themselves). The effect of different ACap values is most dramatic in 'bestPrice' mode (Fig. 7). Perhaps surprisingly, the runs with ACap = 1 result in the most producers of A by the end of the run, even when we bias the drifting process

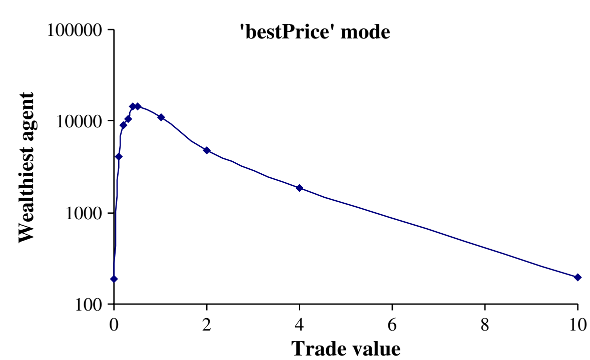

Fig. 4. The Wealth of the wealthiest agent after 5000 time steps in 'bestPrice' mode (average 10 runs), as a function of the Trade value. Note that the y-axis is logarithmic.

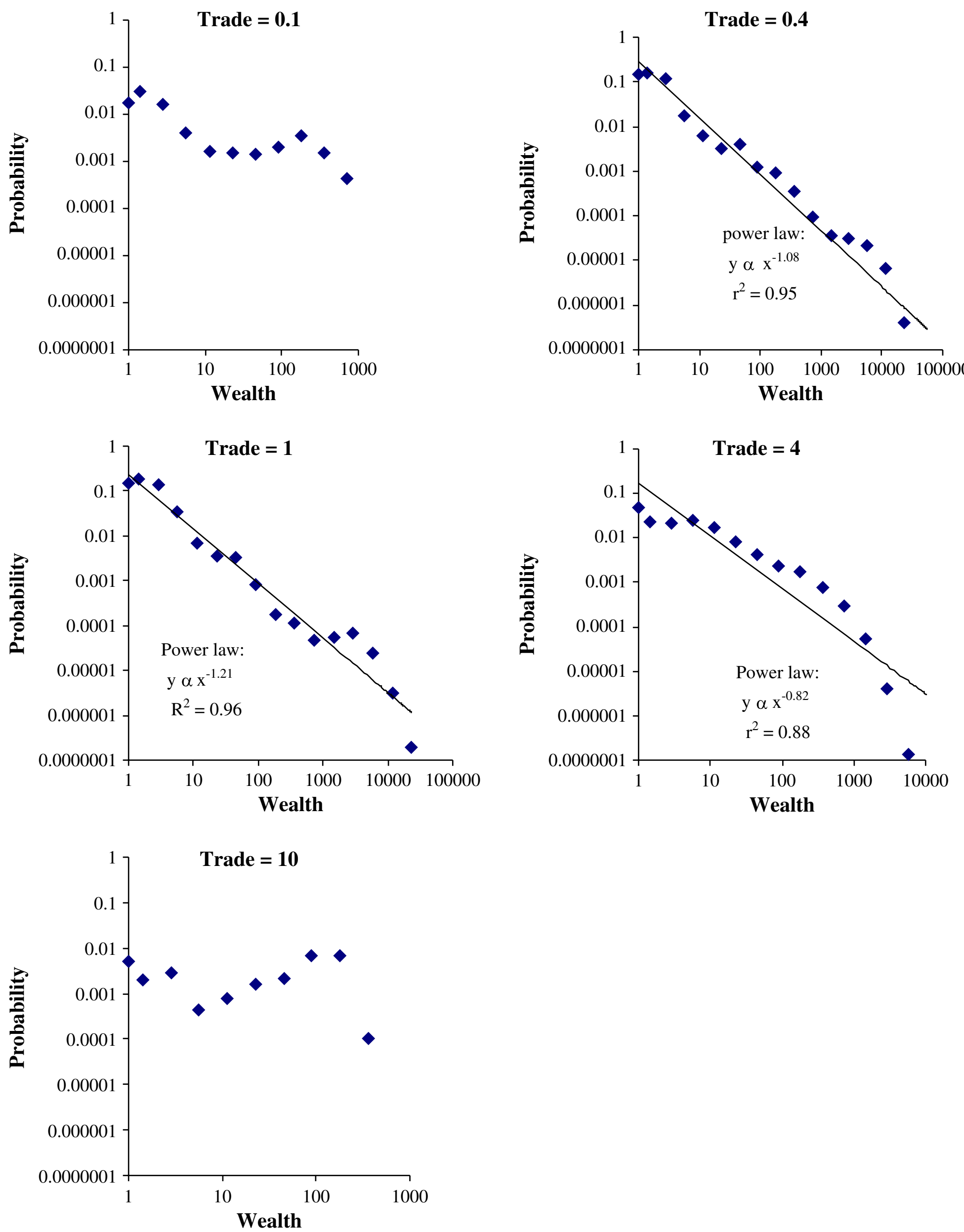

Fig. 5. Effect of the Trade variable on Wealth distribution in 'bestPrice' mode.

toward Product B by setting IncrementPos (toward Product A) to 1 and IncrementNeg (toward Product B) to 1.2.

The transformation actually takes place very quickly, as shown in Fig. 8. When we begin in bestPrice mode with no agent possessing more than 1 unit of A, we see that, over just a few time steps, many agents in the population quickly 'rush' toward high (high production of A) Strategy values (Fig. 8a). The reason for this is that, when all agents possess 1 unit or less of A, the relative Price of A is high compared with B. When agents make their decisions to adjust their Strategies after a failed transaction, their decision drifts in the direction of the most valuable commodity. For the first few time steps after starting with ACap = 1, product A is more valuable for virtually all agents. As more and more agents raise their Strategy value toward the total A production, the average Price of A declines, and the drift of strategies becomes more balanced. However, the legacy of the rush toward the open product A 'niche' is that there remains a relative abundance of producers of A to the end of the run at 5000 time steps.

As Fig. 8b shows, if the agents initially produce only B (StrategyCap = 1), and ACap is set at 1, then there is considerably less 'rush' to produce A. Finally, if

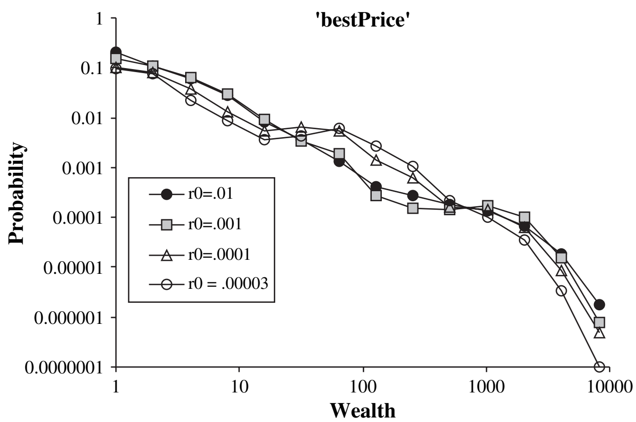

Fig. 6. Effect of r_0 (random connection probability) on Wealth distribution in 'bestPrice' mode (averaged over 10 model runs for each value of r_0), with all other variables at default values (Table 1).

StrategyCap is set to 1 but there is a wide range in initial possession of A (ACap = 99), then no majority of A producers emerges at all, even after 5000 time steps (Fig. 8c). Tests of the same initial conditions for the simulation run in 'Margin' mode (not shown) gave similar results because, as in 'bestPrice' mode, we also allowed Strategies in 'Margin' mode to drift with bias toward the commodity with the bestPrice.

The effect of the random connection probability r_0 on the Strategy distribution is shown by Fig. 9. For very small values of r_0, the population becomes more specialized, that is, there are modes at either end of the Strategy spectrum. Apparently, when r_0 is small, agents are more isolated, and therefore more 'unhappy' as they are unable to find trading partners.

5. Discussion

We find several general implications of our model, including the different wealth distributions in 'Margin' and 'bestPrice' modes, the importance of the initial conditions on the eventual distribution of Strategies, and the effect of the number of random connections in the network.

5.1. Margin mode vs. bestPrice mode and Mesolithic–Neolithic interaction

Perhaps our most important result is the difference in Wealth distribution resulting under 'Margin' mode vs. 'bestPrice' mode. In 'Margin' mode, where a trade occurs when two agents possess sufficiently different amounts of a certain commodity, Wealth is normally distributed. Under the 'Margin' rule, adding wealth to the economy helps all agents equivalently because commodities are continually transferred from those with more to those with less. In 'bestPrice' mode, where agents trade only if they both 'like' the Price of a commodity, the Wealth distribution is highly skewed, indeed a power-law distribution for a certain range of Trade, the parameter controlling the amount exchanged in each transaction. When Wealth is added to the bestPrice economy, the power-law distribution does not change, as the rich remain few and the poor numerous. This result resembles many other models in which those who make profitable interactions are more likely to make additional beneficial transactions (cf. [6,7]).

This difference between the Margin and bestPrice modes suggests a basic analogy to the profound ideological differences that likely existed between certain indigenous populations and incoming agricultural colonists, which is the direction we wish to take our modelling in the future. In society with delayed-return systems, such as agriculture, people are alienated from the yields of their labour and the rules of land ownership are for the exclusion of others [3]. In contrast, ownership for hunter–gatherers exists primarily in a custodial sense in which permission is always granted [16]. The seed for change may have come as the indigenous groups acquired a notion of private *material* property,

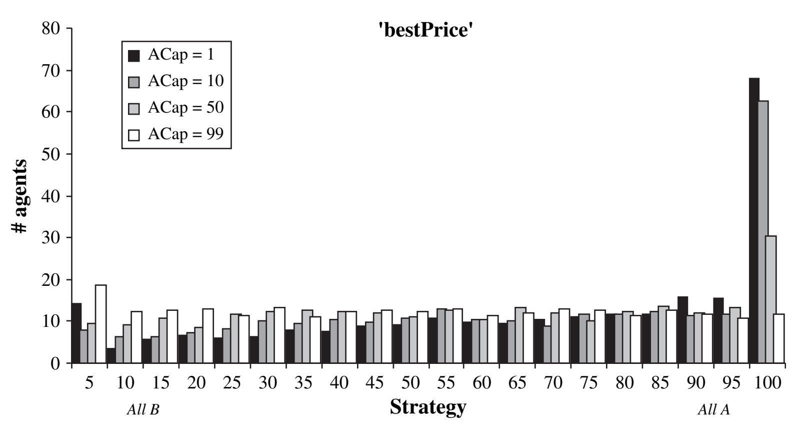

Fig. 7. The distribution of Strategy variables among the 250 agents after 5000 time steps (averaged over ten runs), in 'bestPrice' mode, for different limits of agents' initial possession of A ("ACap").

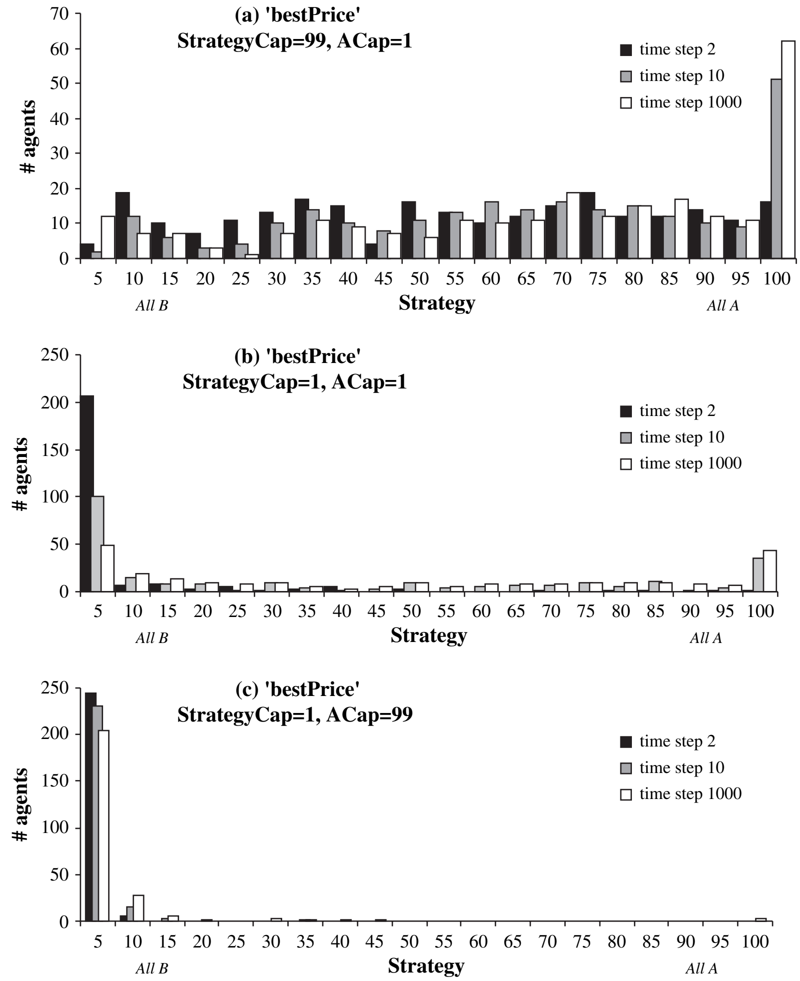

Fig. 8. The change in the Strategy values over time, for single runs in bestPrice mode from different initial conditions (all unmentioned variables at defaults). Note all simulations were biased away from Product B, with IncrementPos = 1.0 and IncrementNeg = 1.2.

leading to social competition over the trade of prestige items, analogous to a shift from 'Margin' mode to 'bestPrice' mode. Had the wealth disparity become like the highly unequal, nearly power-law distributions we see in the 'bestPrice' mode of our model, it would probably have favoured the agricultural groups with a pre-existing system of private ownership, which may have drawn foragers to immigrate into farmer communities (cf. [32,33]).

5.2. The effect of random connections

The Wealth distribution resembled a power law more and more as r_0 was increased. One might have expected

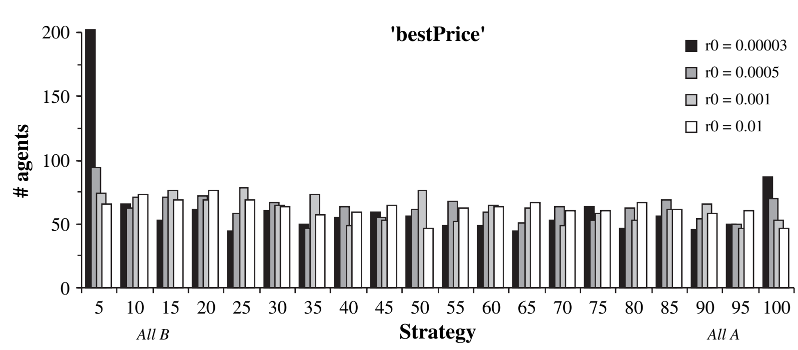

Fig. 9. The distribution of Strategy variables among the 250 agents after 5000 time steps (averaged over five runs), in 'bestPrice' mode, for different values of r_0 (the random connection probability). All other variables were at their default values, including a bias in the adjusting of Strategies toward Product B (IncrementPos = 1, IncrementNeg = 1.2).

that a high number of random connections might "short-circuit" the ability for wealthy agents to exploit poorer agents with only expensive options in their immediate neighbourhood – rather like charging $7 for a bagel at the airport. However, since we found more Wealth inequality in the interconnected (high r_0) network, it may be that random connections instead allow wealthy agents to exploit a greater portion of the network. Also, agents in the interconnected network become more specialized. An explanation may come from comparison with spatial models of multi-level selection, in which small, well-spaced patches of agents undergo more between-group selection than within-group selection, such that differences, including cooperative behaviour, can evolve between groups (e.g., [28,25]). Similarly in our model, the least interconnected network, analogous to a patchy landscape, is the most specialized and least exploitative.

5.3. The importance of initial conditions

In our model we also find an importance of initial conditions on the eventual distribution of Strategies. In 'bestPrice' mode, we observe a niche-filling effect: if the agent population is initiated with a mix of Strategies and product A is scarce, what follows is a 'rush' of agents changing their Strategies to become producers of A. The rush results from the opportunity to produce A when it is rare, and hence valuable, and there are agents who 'know' how to produce A immediately. We can make the analogy to an influx of a new population with knowledge of a new technology. If, however, product A is initially scarce but the agents are mainly producers of B, their Strategies do not move toward A nearly as overwhelmingly. This resembles the slower transition among people who must accept and learn a new technology, even one that is profitable to adopt. Finally, if we start with plenty of A then it is not valuable, its niche is filled, and there is no 'rush' to become producers of it.

An important feature of our model is that it does not explicitly specify the benefits and costs of using/producing A vs. B. An alternative model [31] considers the fixed benefits and costs of specializing in one of two tasks vs. remaining a generalist in both, from which it appears that the larger the group, the more likely specialists are to out-compete the generalists, and that, at the same time, divisions of labour that become increasingly unfair over time.

6. Conclusion

We have described an agent-based computer model that tests how specialization and economic inequality emerge as agents within a clustered social network exchange with each other. Our model suggests how substantial wealth inequality may be inevitable in small human communities, if the prevailing ideology is one of private ownership and trades are motivated by trading at the best 'price' rather than by basic need for the product. This difference suggests a basic analogy to the profound ideological differences that likely existed between certain indigenous populations and incoming agricultural colonists. More generally, our model should be substantially relevant to any archaeological case-study concerning the importance of wealth and its changing distribution through exchange.

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