Chapter 4

Results

What we now have is an artificial society in which we can ‘grow’ social structures (Epstein and Axtell 1996). This particular virtual laboratory or CompuTerrarium captures situations where problems of economic organization can be solved, by choosing among different structural forms for organizing transactions.

It was developed to investigate (the outcomes of) the process in which multiple, boundedly rational agents adaptively learn to make this choice. The focus is on this process, because that is believed to be necessary to be able to explain and predict which organizational forms are used for different transactions. It is not considered relevant to do a rational analysis of which forms should optimally be used, for the reasons explained in Chapter 2. If one wants to allow for the information generated during the course of bilateral exchanges to play the role it deserves and, consequently, for trust and differential preferences to develop (which one has to do for the reasons given in Chapter 1), then one has to model those bilateral exchanges and the individual agents involved in them. Here, it has been chosen to do so by building the agent-based model described in Chapter 3 and simulating the model on a computer.

Several issues are addressed in this chapter. First of all, the model was primed (Section 4.1). Before a model can be used, the extent has to be established to which changes in the parameters and the structure of the model cause changes in the results. If the results are highly sensitive,
then they are not very robust and conclusions can not be drawn from them with much confidence; if, alternatively, the results are not sensitive to changes in the parameters, then those parameters do not 'work'. The same holds for changes in the architecture of the model. The difference with experimental variables is that if results are not sensitive to—do not depend on—changes in those, then this is a result. A model can be used to answer the question of what the influence on the results is of a change in one or more experimental variables; the answer 'none' is as interesting an answer as other answers are.

Results from the first series of experiments with the model are reported in Section 4.2. This experiment allowed an initial test of the plausibility of the model, which was assessed by examining whether a particular (undisputed) result from TCE would emerge. This is the relation between increasing asset specificity and more insourcing relative to outsourcing.

With confidence in the sensitivity and plausibility of the model, the two main points of criticism of TCE can be examined, one with respect to TCE's assumption rather than investigation of optimal outcomes (Section 4.3), and the other with respect to the role of trust and loyalty next to opportunism (Section 4.4). Finally, we leave the comparison and confrontation with TCE behind and move to experiments that our model does and TCE does not allow and for which there is, therefore, no way to make a comparison with TCE. An initial exploration of some more of these dynamics of the model was started in Section 4.5; in fact, towards the end of this thesis, the real work of systematically exploring the model developed here is just about to begin. This illustrates how the emphasis in this thesis has been on developing the approach and a suitable model, rather than on applying it.

4.1 Priming the Model

The simulation model described in Chapter 3 did not come about instantly; it was developed over the course of a period of time. During the development of the model, results were constantly generated, and con-
4.1. PRIMING THE MODEL

Inclusions from those results were fed back into the model-development. From the perspective of the current version of the model, this has resulted in a number of decisions concerning the construction of the model and the setting of parameters. Apart from giving interesting insights into the model and what it represents in its own right, this 'sensitivity analysis' has led to the parametersetting for an initial set of experiments as listed in Table 4.1. The complete list of parameters and variables is given in Table C.1 in Appendix C, along with the value range allowed for each. Some of the changes made to the model over the course of its development are discussed below. The parameter-setting in Table 4.1 was used in the experiments reported in Section 4.2.

Each simulation run involves 12 buyers and 12 suppliers and lasts for 500 timesteps. At several locations in the model, numbers are drawn from pseudo-random number generators. For example, such draws are necessary to settle the ranking of alternatives to which equal scores are assigned, as explained in Section 3.3.3. They are only required for practical purposes, however; they have no meaning in themselves. In establishing the preference-ranking, it does not matter which of two or more agents to whom the same score was assigned is placed higher on the ranking; what matters is that the ranking is established. Simply using the numbers that identify agents to solve this problem would lead to agents identified by lower numbers to gain a systematic (dis-)advantage over agents identified by high numbers, so the assignment is randomized. Another example is that, in selecting values for $\alpha$ and $\tau$, each agent needs to draw two pseudo-random numbers. It is irrelevant which particular number it is; what matters is that values for $\alpha$ and $\tau$ are chosen and which values

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Footnote: The roots of the model can be traced back to one I worked on with John Miller and Kathleen Carley while I visited Carnegie Mellon University in early 1996. Results from previous versions of the model were presented at the 1997 workshop on Computational and Mathematical Organization Theory in San Diego, at the Society for Computational Economics’ 1998 and 1999 annual conferences on Computing in Economics and Finance in Cambridge (UK) and Boston, respectively and at the European Association for Evolutionary and Political Economy’s 1998 annual conference in Lisbon, and were published as SOM Research Reports 97B53 and 99B41, (Klos and Nooteboom 1998), and (Klos and Nooteboom 2001). The results presented here have not yet been presented or published elsewhere.
are chosen more often than others. It would also have been possible to simply pick the value with the largest strength, but that would leave the agents too little room for exploration, because the first value chosen may then be chosen forever thereafter. The point is that pseudo-random numbers can be used to solve problems, but they do have an effect on the results. In order to diminish this influence, each run is repeated a number of times (25), and results are (sometimes) presented as averages across those 25 runs (and across all agents). In other cases, the focus is on the individual run or on the characteristics of the individual agents involved.

<table>
<thead>
<tr>
<th>parameter/variable</th>
<th>value used</th>
</tr>
</thead>
<tbody>
<tr>
<td>general</td>
<td>(cf. Table C.1)</td>
</tr>
<tr>
<td>number of buyers, $I$</td>
<td>12</td>
</tr>
<tr>
<td>number of suppliers, $J$</td>
<td>12</td>
</tr>
<tr>
<td>number of runs, $R$</td>
<td>25</td>
</tr>
<tr>
<td>number of timesteps, $T$</td>
<td>500</td>
</tr>
<tr>
<td>number of values for $\alpha \in [0, 1]$</td>
<td>5</td>
</tr>
<tr>
<td>number of values for $\tau \in [0, 0.5]$</td>
<td>5</td>
</tr>
<tr>
<td>renormalization constant $C_\alpha$</td>
<td>$3d_i$</td>
</tr>
<tr>
<td>renormalization constant $C_\tau$</td>
<td>$3d_i$</td>
</tr>
<tr>
<td>baseTrust, $b$</td>
<td>0.3</td>
</tr>
<tr>
<td>initTrust(subject)</td>
<td>0.75</td>
</tr>
<tr>
<td>trustFactor</td>
<td>0.5</td>
</tr>
<tr>
<td>per buyer $i$</td>
<td>differentiation, $d_i$</td>
</tr>
<tr>
<td>per supplier $j$</td>
<td>offer quota, $a_i$</td>
</tr>
<tr>
<td>acceptance quota, $a_j$</td>
<td>3</td>
</tr>
<tr>
<td>scaleFactor</td>
<td>0.5</td>
</tr>
<tr>
<td>learnFactor</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 4.1: Parameters and variables used in the simulation.
4.1. PRIMING THE MODEL

Learning

The speed of learning of the reinforcement learning algorithm that the agents use depends on the size of the renormalization constant, relative to the increases, and on the number of available alternatives to choose from (cf. Arthur 1993). Strengths are increased with realized profit, which depends on product differentiation, among others. For this reason, the renormalization constants have also been made dependent on the value used for \( d \). In particular, three times the value of \( d \) was used to initialize the strengths of the different values for \( \alpha \) and \( \tau \); when \( d = 0.35 \), for example, \( C_\alpha = C_\tau = 1.05 \). Each possible value was assigned a strength equal to the appropriate value of \( C \) divided by the number of strengths, i.e. the number of values for \( \alpha \) and \( \tau \)—5 in the experiments. Initially, fixed values were used for \( C \), but this resulted in a learning process whose sensitivity to changes in the experimental variable, \( d \), varied with \( d \). Because increases in strengths consist of realized profit, lower increases occurred in experiments with lower values for \( d \); the agents did not get the opportunity to explore, but locked in to the region in the problem space they were plugged into at the start of the simulation.

Furthermore, only values between 0 and 0.5 were allowed for \( \tau \), because higher values had too high an influence on the results. If there are 5 possible values between 0 and 1, then choosing either one of the three highest values results in a score-advantage of the current partner of at least 0.5. This is an advantage that alternative partners can almost never surpass, which means that agents very often stick to their first partner, into which situation the simulation then locks in. Using only values for \( \tau \) between 0 and 0.5 gives the agents room to experiment with different values without getting locked into their initial situation.

Initial Trust

Furthermore, each agent's initial trust in another agent was set at 0.75. It needs to be this high, because otherwise suppliers can never be more attractive than a buyer considers himself. Initially, suppliers enjoy no economies of scale or experience, so buyers have to be attracted to them
by trusting them highly and by weighting profitability relatively low. If initial trust is not set high enough, buyers never prefer suppliers and nothing ever happens in the simulation.

It could be argued that the buyers should foresee suppliers’ scale economies and have a higher preference for them on that basis. The observation above has wider implications, however. The issue is that the advantages of the market in terms of scale-economies that TCE assumes do not come about instantly and only under certain circumstances. Time has to be allowed for these advantages to build up and this observation also forces one to allow for the fact that sometimes they do not even build up at all. More generally, studying economic systems at the level of individual agents and the relations among them focuses attention on the way these kinds of micro-motives influence macro-behavior (Schelling 1978).

**Quota**

Finally, each buyer’s offer quota was fixed at 1, and each supplier’s acceptance quota was set to 3, which means that each buyer has a supplier or he does not, in which case he supplies to himself, and that each supplier can supply to a maximum of 3 buyers. In previous experiments with each supplier \( j \)'s acceptance quota \( a_j \) set to the total number of buyers \( I \), the system quickly settled in a state where all buyers buy from the same supplier. For this reason, suppliers were only allowed a maximum of three buyers. This limits the extent of the scale economies that suppliers can reach—the consequences of this decision are elaborated on below.

### 4.2 Adaptive Economic Organization

In a first series of experiments, the aim was to test whether the model was able to reproduce the relation between increasing asset specificity and more insourcing relative to outsourcing. This would lend credibility to the model, because it is a known relation that is also used in TCE. Because asset specificity is related to product differentiation, the value of
$d$ was varied in 6 experiments: $d = 0.25, 0.35, \ldots, 0.75$. Before going to the results, however, it is worthwhile to consider what may be expected from the simulations.

The experimental variable ‘differentiation’ of the buyers’ products is tied to the specificity of the assets that suppliers invest in to support their production for those buyers. Initially, therefore, the buyers are confronted with the score-differentials given in Table 4.2, and represented graphically in Figure 4.1. The values in Table 4.2 are calculated as follows. The score that a buyer $i$ assigns to a supplier $j$, is (see Section 3.2):

$$\text{score}_{ij} = 0.5(d_i + d_i \delta_{i,j} + (1 - d_i)e_{i,j})^{\alpha_i} \cdot t_i^{(1-\alpha_i)}.$$  

Note that the buyer’s profit in a relation with a supplier is only half the total profit that is made in the relation. The score that buyer $i$ assigns to himself is equal to $d_i$, because that is his profit when he makes and he uses $\alpha = 1$ to calculate his own score (see Section 3.3.3 for the reason for this). The values in the table give the difference between these two, in the first timestep of the simulation, when all these values are the same for all buyers.

As differentiation increases, the number of distinct values for $\alpha$ that yield a net score-advantage for suppliers—which they need for buyers to consider them acceptable—decreases, so we may expect less outsourcing

<table>
<thead>
<tr>
<th>$d$</th>
<th>0.00</th>
<th>0.25</th>
<th>0.50</th>
<th>0.75</th>
<th>1.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>0.50</td>
<td>0.23</td>
<td>0.06</td>
<td>-0.05</td>
<td>-0.13</td>
</tr>
<tr>
<td>0.35</td>
<td>0.40</td>
<td>0.17</td>
<td>0.01</td>
<td>-0.10</td>
<td>-0.18</td>
</tr>
<tr>
<td>0.45</td>
<td>0.30</td>
<td>0.11</td>
<td>-0.04</td>
<td>-0.15</td>
<td>-0.28</td>
</tr>
<tr>
<td>0.55</td>
<td>0.20</td>
<td>0.03</td>
<td>-0.10</td>
<td>-0.20</td>
<td>-0.28</td>
</tr>
<tr>
<td>0.65</td>
<td>0.10</td>
<td>-0.04</td>
<td>-0.16</td>
<td>-0.25</td>
<td>-0.33</td>
</tr>
<tr>
<td>0.75</td>
<td>0.00</td>
<td>-0.12</td>
<td>-0.22</td>
<td>-0.30</td>
<td>-0.38</td>
</tr>
</tbody>
</table>

Table 4.2: Difference between suppliers’ initial scores and a buyer’s own score ($= d$) for different values of differentiation and of the buyer’s $\alpha$.  

4.2. ADAPTIVE ECONOMIC ORGANIZATION
CHAPTER 4. RESULTS

Figure 4.1: Score differentials in Table 4.2. This graph shows the advantage to suppliers in the first timestep of the simulation for different combinations of $d$ and $\alpha$.

when differentiation increases. If $d = 0.75$, there is no value for $\alpha$ that gives suppliers a net advantage so we may expect no outsourcing at all in that case.\footnote{In initial runs of the experiment, this was confirmed, which is why the experiment $d = 0.75$ is not reported.} Notice that for \textit{any} $d < 0.75$, no matter how much smaller, the suppliers do have a net advantage which, as soon as matches occur, may increase when suppliers’ economies of scale and experience increase as they supply to more than 1 buyer and in longer-lasting relations. The situation in Table 4.2, therefore, is likely to shift in favor of suppliers as time progresses. In general, then, we would expect more making (and less buying) when differentiation is increased in the different experiments. This corresponds to TCE’s predictions about this relation. We would also expect the proportion outsourced to increase over time in each individual run. Note that while the second prediction can not be compared to TCE, because time is involved, the first prediction corresponds to TCE, as derived from the characteristics of the relations between several variables uses in TCE, that were also incorporated in our agent-based simulation.
model. This does not mean that we would predict optimal outcomes to emerge or that we can even assess what those are, but just that some of the characteristics of the outcomes we predict will correspond to the outcomes TCE would predict. Also note that the type of model we use allows us to make hypotheses about the sequencing of events. Knowledge generated this way leads to the understanding about how processes lead to outcomes that is necessary to design interventions in processes with the purpose of influencing outcomes (cf. Nooteboom 2000, see Section 2.2).

The proportion of economic activity under hierarchichal (as opposed to bilateral) governance in the different experiments is shown in Figure 4.2. Each line represents one experiment, corresponding to a value for $d$. The graph shows the proportion of all production that is carried out by the buyers rather than by suppliers, averaged across 25 runs. As expected, the proportion made is higher when differentiation is high than when it is low. Also, the proportion made decreases initially, which was also expected, because the advantage to outsourcing only increases over time from the initial values given in Table 4.2, as explained above. In addition, for lower values of differentiation, there are more immediate returns to outsourcing, because suppliers can generate scale economies.
right away. For higher values of differentiation, outsourcing is only preferred as relations last longer and suppliers are able to generate economies of learning in the production for individual buyers. This is apparent as the slower decrease in the proportion made for higher values of differentiation than for lower values, where the gains from trade due to economies of scale can be reaped right away; it takes time for long-lasting relations (which are the prime source of outsourcing-advantage when differentiation is high) to prove their worth. It also takes time for buyers to find a partner to build up the long-lasting trust relation with that they need for generating economies of learning.

This is a second occasion on which we can point to the importance of market-making: a market has to be made before it can be used, and the process in which it is made by the participants involved has important characteristics of its own. When \( d \) is low, economies of scale are important and it matters whether or not a situation arises in which a small number of suppliers each supply to a large number of buyers. The buyers a supplier supplies to may differ from each timestep to the next—what matters is the number of buyers involved. When \( d \) is high, economies of learning are important and the identity rather than the number of buyers involved matters. This is the situation when the more efficient structures can only be built on time.

### 4.3 Optimal Outcomes?

With confidence in the model on the basis of the plausibility test in the previous section, we are now able to confront our model with TCE. Recall that there were two main points of criticism. The first is that TCE uses a rational analysis to predict what boundedly rational agents will do, and the second is that TCE ignores the role of trust next to opportunism. The first of these issues is addressed in this section; the second in the next section (4.4).

A model was constructed that involves individual agents. They are confronted with problems of organizing and given a decision-making apparatus and the ability to adapt their decision-making behavior to what
they perceive to be successful. This allows us to investigate whether the optimal outcomes that TCE hypothesizes will in fact arise. We have chosen to do this by studying the buyers’ profits. These profits in each of the experiments, again averaged across the 12 buyers and across 25 runs of each experiment, are shown in Figure 4.3. This figure shows that

![Figure 4.3: Buyers' profits.](image_url)

buyers do better when differentiation is high, but they also obtain higher absolute returns in that case—profits are a function of differentiation. The picture can be made clearer and experiments can be compared when this phenomenon is compensated for. This can be done by normalizing profit, i.e. by dividing the buyers’ profits by the maximum profit they can potentially make in each experiment, which also depends on the current value of differentiation. The maximum attainable profit is the profit a buyer makes when he outsources to a supplier with whom he has an infinite relation (in order to generate maximum economies of learning) and who supplies to an infinite number of buyers (in order to generate maximum economies of scale). The latter factor, however, is limited by the fact that the suppliers’ acceptance quota is set to 3, as mentioned above. When this is taken into account and each buyer’s profit is divided by his profit in an infinite relation with a supplier with 3 buyers, Fig-
Figure 4.4 emerges—notice that the $y$-axis was re-scaled to 0.5–1 to make these results clearer.

If differentiation is higher, the buyers are organizing closer to their optimum. In all cases, the gains from trade defined in the model dictate that the optimum is to outsource. Even though the proportion outsourced is highest when differentiation is low (Figure 4.2), the buyers are furthest away from their optimum in that case! The reason is that it is not just outsourcing that is required, it also matters which supplier is outsourced to—this has to be a supplier that supplies to 2 other buyers at the same time, so as to be able to attain the maximum scale efficiency in the denominator of the ratio that normalized profit is. This is especially important when differentiation is low, because asset specificity is then low as well, so there are relatively many general purpose assets on which scale economies operate. The optimum can therefore be defined as a situation in which the 12 buyers together outsource to 4 suppliers, each of whom supplies to 3 buyers. This is not a common network configuration, as witnessed by Figure 4.5, which shows the buyers’ normalized profits in each of the 25 individual runs of the first experiment ($d = 0.25$). In some of the runs, the required network configuration emerges, but in

![Figure 4.4: Buyers' normalized profits.](image-url)
most runs it does not. Average normalized profits stabilize at several levels; lower levels corresponding to more suppliers being involved and less scale economies being generated on the whole. At the highest level, reached in only 2 out of 25 runs, the 12 buyers outsource to 4 suppliers (with their maximum of 3 buyers each) and no buyer makes anything. The average across these 25 experiments (approximately 0.87) is the line ‘$d = 0.25$’ in Figure 4.4.

When $d$ is higher, buyers organize closer to the optimum. While the optimum—in terms of efficiency—always dictates outsourcing, these buyers outsource less and still organize closer to the optimum. The reason is that the advantage to outsourcing is lower when $d$ is high than when $d$ is low, because although there are more profits to be made, they also have to be shared with the supplier. In addition, it takes time for the market’s advantage to materialize, and the buyers are also more dependent upon their supplier. A break in a relation has serious consequences in this case, because the economies of learning that the supplier has built up are lost, and can only be rebuilt in time. When $d$ is low, on the other hand, any supplier is as good as the next, in this respect, just as long
as he also supplies to several other buyers. When $d$ is high, the buyers are more in control of their own performance when they make than when they outsource.

## 4.4 Adaptive Agents

The second point of criticism of TCE, next to its assumption rather than investigation of optimal outcomes that was addressed in the previous section, is how it ignores the fact that trust and loyalty may build up between individual agents. It does this because it would be too complex to include the influence of information generated during the course of bilateral exchange. Fortunately, we now have a model of individual agents and concrete bilateral exchanges, that allows us to do precisely that. These results are discussed in the current section.

The buyers adapt the value they use for $\alpha$ and $\tau$. As explained in Section 3.4.2, the weighted averages of $\alpha$ and $\tau$ for each agent indicate the emphasis they put on other agents' profitability vs. their trust in those other agents and on their own loyalty. The agents' learning can be represented as an adaptive walk across the fitness-landscape on the multi-dimensional problem space that is defined by $\alpha$ and $\tau$. Such adaptive walks are illustrated in Figure 4.6. This figure shows the combinations of weighted averages for $\alpha$ and $\tau$ (see equation 3.9) on the $x$- and the $y$-axis, respectively, that each of the 12 buyers in experiment $d = 0.25$ maintains through time. Each agent starts at coordinates (w.a. $\alpha$, w.a. $\tau$) = (0.5, 0.25) in the center of the graph; this is the average when $C_{\alpha}$ and $C_{\tau}$ are distributed evenly across the 5 possible values allowed—in [0, 1] for $\alpha$ and in [0, 0.5] for $\tau$. Although they all start at the same position, the agents follow different trajectories through the problem space. At the start of those, the agents take relatively large steps through the problem space, in search for better performance. These large steps are possible initially, because the strengths associated with the different values for $\alpha$ and $\tau$ and therefore the probabilities of each of these possible values being chosen, are still more or less equal. The large steps occur because each agent's environment still changes radically from each timestep to
4.4. ADAPTIVE AGENTS

Figure 4.6: The 12 buyers’ adaptive learning in the space of $\alpha$ and $\tau$ in the first run of experiment $d = 0.25$.

The next. As the agents form progressively better internal models of their environment, their behavior becomes less erratic and the steps they take from each timestep to the next become smaller.

The three different types of trajectories in Figure 4.6 suggest that there may be locations in the space that attract the agents. Before firm conclusions can be drawn about those, however, the system should be studied more carefully and using the appropriate apparatus. What can already be noted is that it is apparently possible for different agents to develop different behaviors, while all of them still progress to higher levels of performance. This is indicated, for example, in Figure 4.7, which shows the plot of the 12 buyers’ profits and their weighted average $\tau$, in the same run as depicted in Figure 4.6. The performance that an agent obtains depends not only on his own behavior, but also on the behavior of the
other agents in the system. The system could be thought of as annealing over time, leading to a state in which the agents are all attuned to one another. The extent to which such a state is stable to ‘invasion’ by other types of agents is the subject of current work.

In Figure 4.8, the graphs for the individual buyers in Figure 4.6 (taken from the first run of experiment $d = 0.25$), are averaged and compared to the averages across the other 24 runs of the experiment. Note that a great deal of information is lost in this aggregation. It can easily be seen how averaging sweeps all the variation at the level of the individual agents (as illustrated in Figure 4.6, for example) under the rug. Because the trajectories that the individual agents follow through time lead away from the starting point in the center of Figure 4.6 in different directions, averaging inevitably leads to values around the center. In order to vi-
Figure 4.8: Buyers’ adaptive learning in the space of \( \alpha \) and \( \tau \) in each of 25 runs of experiment \( d = 0.25 \).

visualize roughly the same amount of variation as in Figure 4.6, it was necessary in Figure 4.8 to rescale both the axes. The center of the search space was kept in the center of the graph, the \( x \)-axis was rescaled from 0–1 to 0.3–0.7 and the \( y \)-axis from 0–0.5 to 0.15–0.35. It would be interesting to find out in more detail precisely which global regularities emerge from the individual agents’ motivations and how, but to systematically analyze the enormous amounts of data generated at the level of the individual agents would constitute a new line of inquiry by itself. The current research has aimed at the development of the agent-based computational approach to transaction cost economics issues; systematic exploitation is beyond the scope of this thesis.
4.5 Alternative Initialization

In previous sections, the plausibility of the model has been tested and results from the model have been analyzed in the areas of the two points of criticism of TCE. We are now ready to leave TCE behind altogether and to start exploring the dynamics of the model in their own right. A final series of experiments has therefore explored the dynamics in the simulation when different ‘worlds’ are created, as a setup to more elaborate testing of hypotheses concerning systems of innovation (Nootboon 1999a). These different worlds are defined in terms of the initialization of the strengths of the different values for $\alpha$ and $\tau$. Figure 4.9 shows how the

![Figure 4.9: Different ways of initializing strengths.](image)

strengths for the 5 possible values for $\alpha$ were initialized in the experiment $d = 0.25$ reported above (on the left) and in the some of the experiments with $d = 0.25$ reported below (on the right). When $d = 0.25$, $C_\alpha = C_\tau = 3d = 0.75$. In the previous experiments, this total was distributed evenly over the 5 possible values for $\alpha$, yielding absolute (relative) initial strengths of $0.15$ ($0.20$)—for $\tau$, the same holds, except that 5 values between 0 and 0.5 were used, as explained above (Section 4.1). In the following experiments, the emphasis was either put on small or on large values for $\alpha$ and $\tau$. Half of $C_\alpha$ and $C_\tau$ was assigned to one extreme value, and the other half was distributed evenly across the remaining 4 values, as illustrated in the right-hand picture in Figure 4.9. Because relative rather than absolute strengths are used, the initial weighted average for low $\alpha$ is $0 \cdot 0.5 + (0.25 + 0.5 + 0.75 + 1) \cdot 0.125 = 0.3125$. 


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high \( \alpha \) and 0.15625 (0.34375) for low (high) \( \tau \). Rather than at (0.5, 0.25) as above, the co-adaptive dynamics in the agents’ problem spaces start at the four combinations of low and high weighted averages for \( \alpha \) and \( \tau \).

Figure 4.10 shows the buyers’ adaptive walks in their search space of

![Figure 4.10: Buyers’ adaptive learning in the space of \( \alpha \) and \( \tau \) in different experiments, starting from different initial positions.](image)

weighted average \( \alpha \) and \( \tau \), averaged across all buyers in the population and across the 25 runs of each experiment. When analyzing the fact that the trajectories that the agents follow lead to higher values of \( \alpha \), the following observation has to be taken into account. In all cases, outsourcing is more profitable than insourcing, no matter what the degree of product differentiation—it just takes time for this advantage to materialize when \( d \) is high compared to when it is low, because when \( d \) is high, higher profits are obtained as a result of economies of learning, which only increase over time. In order for buyers to outsource more and to become more
profitable, therefore, suppliers have to become more attractive than buyers consider themselves, which means that buyers have to assign higher scores to suppliers than they do to themselves. The point is that if trust is higher than profitability, then low values for $\alpha$ yield the highest scores, while if trust is lower than profitability, the highest scores are obtained with high values for $\alpha$. The fact that the agents seem to be learning to use higher values for $\alpha$ indicates that trust increases more slowly than profitability. This also explains why, over time, the agents learn to use higher values for $\alpha$ when $d$ is higher, since increases in profitability are more dependent on the passage of time in that case. In addition, it explains why the agents learn to use higher values for $\alpha$ when $\tau$ is low than when it is high, since if $\tau$ is low, there is more switching and less trust builds up, so buyers need to focus on suppliers’ profitability rather than on their trust in them in order to consider them attractive.

Figure 4.10 shows the high-level trend in the trajectories of the individual agents. However, even more information than in Figure 4.8 is lost as compared to the plot for the individual agents (Figure 4.6). Individual agents wander about their own search space that is coupled to other agents’ search spaces in a non-linear fashion. This ‘process of becoming’ at the level of the individual agents needs to be studied in order to gain insight into why agents behave the way they do.