1 Resource Inequality in Multi-Agent Systems

1.1 Introduction

This section explores another variation of the previous models, but with agent heterogeneity. The general topic of this section is to explore how inequality can develop and change in multi-agent systems which share a resource. There is a lot of empirical research which looks at changing levels of inequality both internationally between nations and within nations Roser and Ortiz-Ospina (2019). The right level of inequality for each nation and/or group of people is subjective and views are often polarized within different countries/continents and income levels about what the right amount is The World Bank (2016), Figure 1. This is also an important area for research given the increase in advanced technology which could automate many tasks in society which could in turn lead to increased inequality Dellot et al. (2019).

Smith and Choi (2006) formalises these differing opinions on inequality into two categories - the benefits which hierarchy brings to all which is termed *mutualism* and the costs being exploitation or coercion by one segment of society against the interests of the remaining members (elites exploiting commoners or slaves). Smith and Choi (2006) goes on to suggest that these scenarios are useful when best viewed as a continuum rather than a dichotomy, which is what is generally seen in the data in Figure 1.

The United Kingdom has one of the most comprehensive datasets on inequality through time Roser and Ortiz-Ospina (2019). This shows a general trend of a Gini Index between 50-60 from the 1680s to 1911 and from post World War 2 to the present day between 30-40, Figure 2. There has also been a lot of research looking at the share of income amongst different parts of the population. Typically these datasets look at the share of income the top 1% earn compared to the rest of the population, Figure 3. The two figures show a disparity between english speaking developed countries and non-english speaking developed countries. Over the twentieth century english-speaking countries have shown a U-shaped fall from 1920 to 1980m followed by a rise to the current day, however non-english speaking countries have shown a gradual decline over the course of the twentieth century. Obviously these are just datasets and do not provide any information on the underlying reasons for these trends. The underlying reasons for these changes may be due to cultural reasons, networking between countries, and

Figure 1: Differing opinions on the preferred level of inequality in a nation. Taken from Figure 1.7 in The World Bank (2016) .

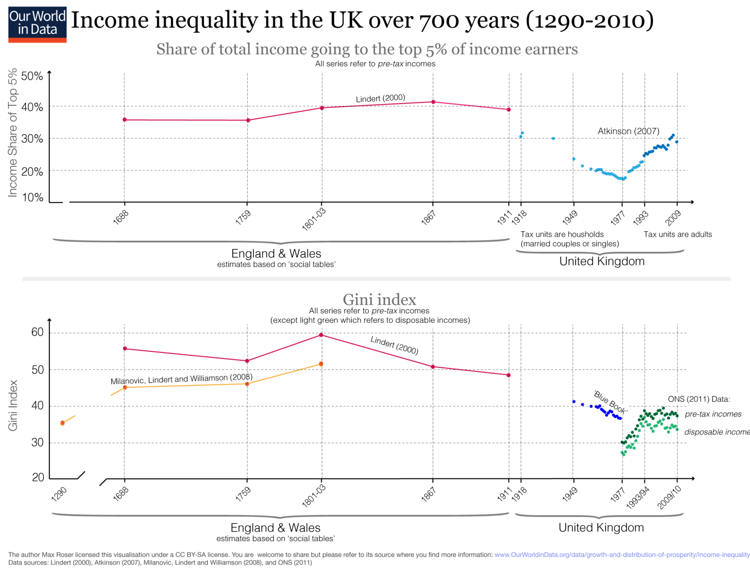

Figure 2: Income Inequality in the United Kingdom over 700 years. Taken from `https://ourworldindata.org/income-inequality` .

global conflict for instance the second world war.

Gini Coefficient (Normalised values of the Gini Index between) data from The World Bank has been collated for the years 1980-2015 for 161 countries and territories, 4. The full dataset can be found at `https://data.worldbank.org/indicator/SI.POV.GINI`. This is the largest amount of data available from this particular source. Whilst the dataset shows a lot of noise, it importantly shows general boundaries all *stable* societies appear to have to exist in. The mean gini coefficient for all the data is 0.39. The maximum gini coefficient is 0.66 and the minimum is 0.16. In general one standard deviation above and below the mean are between 0.3 and 0.55.

The data introduced so far provides macro-scale aggregate information on income inequality of large-scale societies through time. It does not provide information on the underlying interactions, behaviours or societal structures that lead to inequality changing through time. It is also of interest to understand whether commonalities can be drawn between modern large-scale

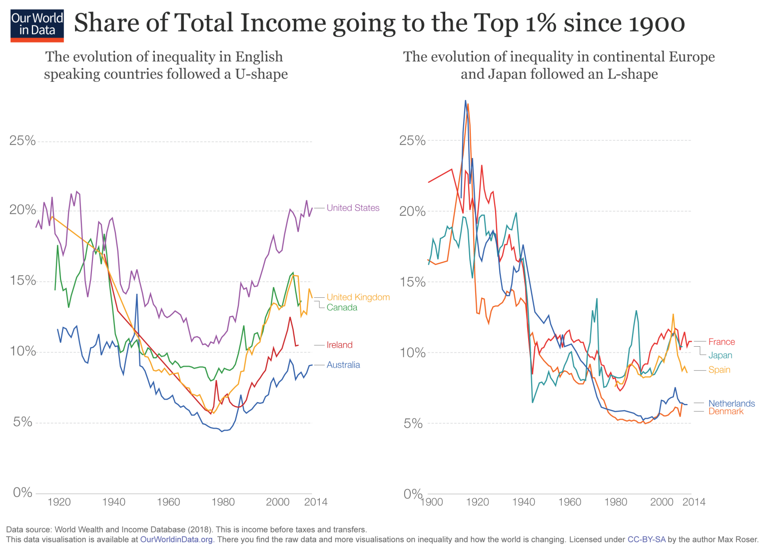

Figure 3: Share of Total Income going to the Top 1% since 1900. Taken from `https://ourworldindata.org/income-inequality` .

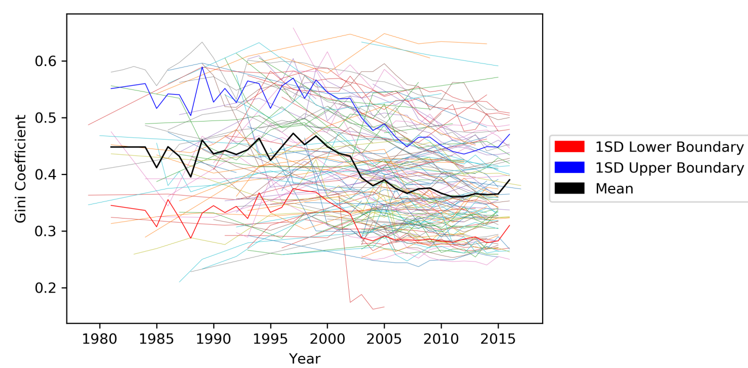

Figure 4: Collated data on Gini Coefficient for 161 countries and territories between 1980-2015. The mean and one standard deviation are shown in bold. .

societies and small-scale traditional societies in terms of inequality. Section **??** gives examples of a number of traditional societal resource distribution systems and attempts to discuss the commonalities and differences between traditional and modern distribution systems and more abstract distribution systems in general.

Borgerhoff Mulder et al. (2009) offers a comparison of intergenerational inequality between different traditional small-scale societies and modern large-scale societies in terms of three types of wealth - material, relational and embodiment. They conclude that traditional horticultural and hunter-gather societies have lower material intergenerational inequality than pastoral and agricultural societies, which is principally due to material wealth being more easily transferred in pastoral and agricultural societies. Borgerhoff Mulder et al. (2009) also offer a comparison between traditional small-scale societies and modern large-scale societies finding that horticultural and hunter-gatherer societies have similar intergenerational inequality to Nordic social democratic countries such as Denmark, Sweden and Norway whereas pastoral and agricultural societies have similar intergenerational inequality to more unequal nations such as the United States and Italy.

As mentioned at the start of the section, this model uses a variation of the models in the previous sections with additional agent heterogeneity with the aim of exploring how inequality can develop in such a system. Smith and Choi (2006) introduces a number of scenarios for exploring the emergence of inequality in small-scale societies based on game theory and evolutionary ecology. These models look at the interaction between different agents which have different roles and how their interaction leads to stable equilibria. It is looking at the very origin of hierarchy and inequality in small-scale societies which can be readily applicable to understanding how people interact in groups in the modern world such as in the workplace. **?** provides a model to look at the emergence of cooperation within what can be described as a spatial hierarchy, an indigenous irrigation system in Bali. This puts agents into a fixed physical geography which creates a hierarchy, but the social institutions in the model lead to an equitable society evolving. The model includes interactions between adjacent agents in the form of imitation. For example a farmer will copy an adjacent agents irrigation practise if it is more successful than theirs. The model presented in this section follows such a model.

This model is developed and influenced by a lot of literature from social and network science. Section **??** gives a brief overview of research looking at social influence in both networks and grids. The simple model introduced shows how patterns can form on a random grid based on how each cell will change their state based on their neighbourhood of cells. Variations of this pattern are shown to occur in many biological systems, most visibly on the skin animals such as lizards Edelstein-keshet (2017). More relevant to this research is how the neighbourhood of a particular cell can affect it's behaviour. Over the course of the 20th century their has been a lot of research on social networks which is thought to aid in linking micro-social behaviour with macro-social trends Granovetter (1973). The strength of the tie between two actors is thought to have importance Granovetter (1973); Marlow et al. (2012). The strength of ties presents a dichotomy, with a large amount of research showing stronger ties (peers and friendships) lead to greater influence on behaviour, such as the uptake of smoking in social groups Mercken et al. (2010), however because of the strong ties, the behaviour of the individuals is likely to be similar. Weak ties have a lower influence on behaviour but the behaviour between the individuals is likely to be more contrasting, possibly leading to tipping points or regime shifts within groups when a change occurs.

1.2 Research Questions

Section 1.1 introduces the topic on income inequality in societies, both from empirical data and simple simulation models. The aim of this section is to build a model small-scale society which can then be tested to understand how minor changes in the model lead to changes in the income inequality at a global scale within the model. The following sections build the model in steps with a description of changes added to the model and the affect these have on results.

1.3 The Model

The previous models were built to optimise space and the maximum number of receiver cells to distribution cells (Section **??**), apply a resource distribution system to such models (Section **??**) and finally allow the system to create resource (Section **??**). As stated in the Research questions, this model aims to look at how inequality can develop in a system. This is done in this model by allowing heterogeneity, that is each distribution cell has a different resource need.

Firstly the model uses the same space optimising algorithm as in Section

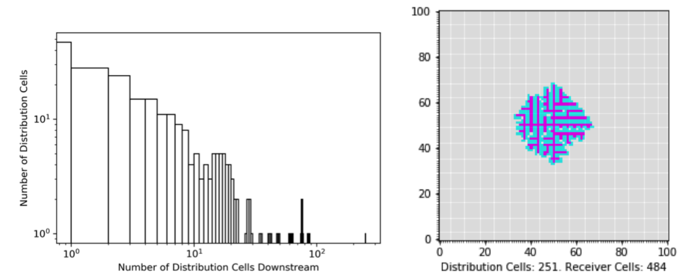

Figure 5: *Left* - Histogram showing the power law number of distribution cells downstream. *Right* - The system analysed.

??. The number of distribution cells each has downstream is found to be a power law, Figure 5.

1.3.1 Agent Individual Preference

In order to model agent heterogeneity, a statistical distribution is used. Figure 6 shows a histogram of randomly selected points from a normal distribution. The mean is 1.0 and the standard deviation is 0.1. One value is randomly selected from this dataset, the *agent individual preference* which is assigned to each agent added to the simulation. The value is used to calculate each agents wealth need by multiplying the agent preference by their own or their neighbours wealth dependent on the simulation. This particular simulation is purely random, with no *path dependence* Mahoney (2000). Figure 7 shows the result of a system with 40 agents with random sampling from the same distribution each time step. As can be expected, it produces a noisy dataset which echoes the distribution parameters input into the model.

Path dependence can be added quite simply by using the value of the agent in the previous time step as the mean for the normal distribution calculation of the agent to be added. Figure 8 shows the changing agent preference with path dependence. A histogram of the spread of the data at the final path data point is shown in Figure 9. As can be shown, the distribution has a greater spread due to each agent being influenced by a normal distribution and its path through time. The result has commonalities with the well-known concept in computer science - *a random walk*.

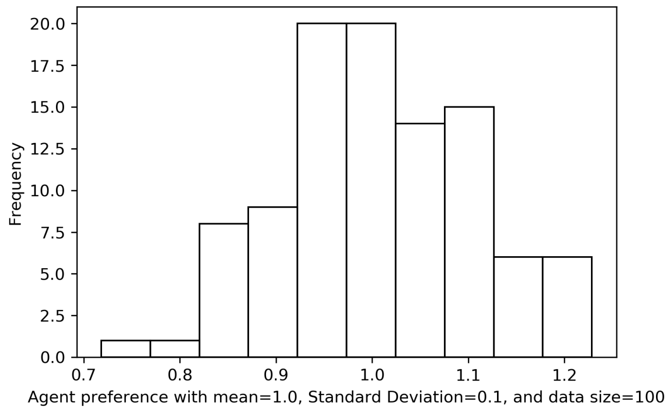

Figure 6: Normal distribution taken from random data points with each value being mutually exclusive.

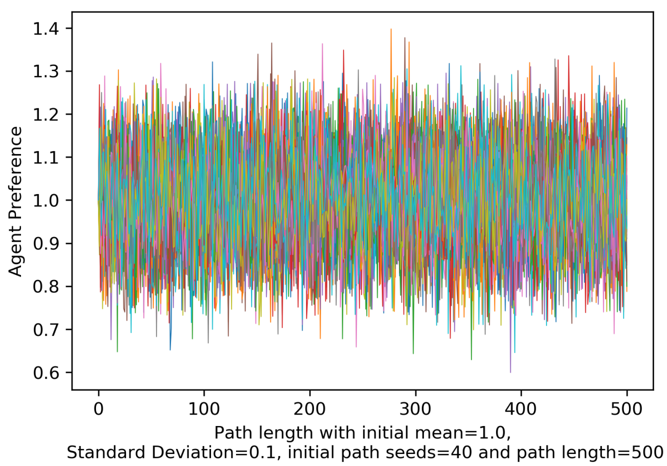

Figure 7: Normal distribution taken from random data points with each value being mutually exclusive.

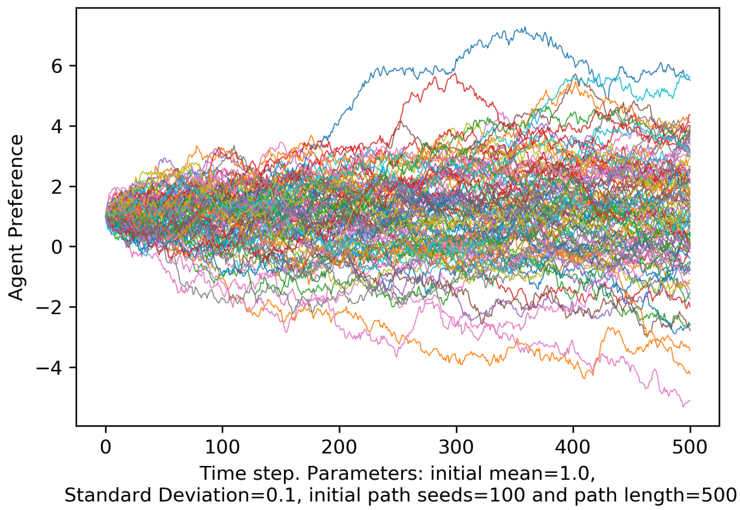

Figure 8: 100 simulations for agents with path dependence on their individual past state.

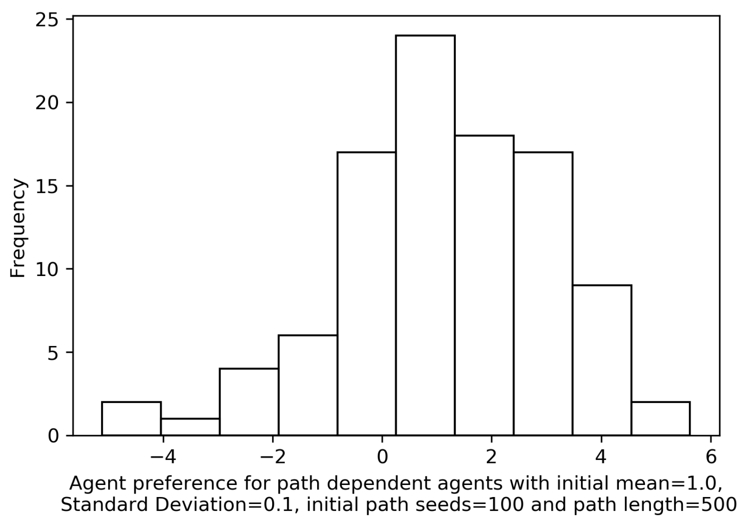

Figure 9: Final path data point for all agents in Figure 8.

1.3.2 Agent Network Influence

Agent preference can also be derived from the influence of other agents within a particular agent's network. Obviously there are many ways in which agents may interact with each other, this is a topic which has it's own field of study *Network Science*. In this case an example is shown of agents being influenced by a maximum of two other agents and themselves. Each agent uses the same initial parameters for a normal distribution as previously (mean=1.0 and standard deviation=0.1). And each time step the agent preference is calculated by finding the mean of its own previous preference in addition to the nearest preference higher and lower. Obviously there must be one agent with the highest preference and one with the lowest and these will only depend on their previous preference and the nearest higher or lower. Figure 10 shows the result of this simulation for 100 agents over 500 time steps. The distribution of all the agent's preferences for the final time step is shown in Figure 11. The figure shows a stark difference in behaviour when compared to an agent only dependent on it's own preference - Figure 8. The system seems to behave more as one with any large shifts moving the whole system and not isolated to one particular agent. This is not surprising given that by networking each agent to its nearest in terms of preference, it essentially networks them all together. The behaviour of the system can be thought of as being similar to *Flocking*, which has been modelled in simulations of 'boids' Reynolds (1987).

1.3.3 The Formation of Groups

Sections 1.3.1 and 1.3.2 explore two extremes or fixed points of a phase space of interaction, one being agents which do not interact with one another and the other being agents with strong interconnectivity. Figure 7 explores the other extreme of no dependence whatsoever. In between these extremes are likely to be systems of small group formation. An attempt at looking at this has been made by adding an influence threshold to each agent. In this scenario, agents will only depend on their previous preference for their future preference, unless other agents are within their preference threshold. The result of this simulation shows a system which under the same parameters can produce a lot of diversity, such as normally distributed data, bimodal distributed data which can change through time. Figures 12 and 13 shows an example of network influence where there appears to be two dominant groups. The emergence of groups is more obvious in simulations of a smaller number of agents, typically with an influence threshold slightly higher than

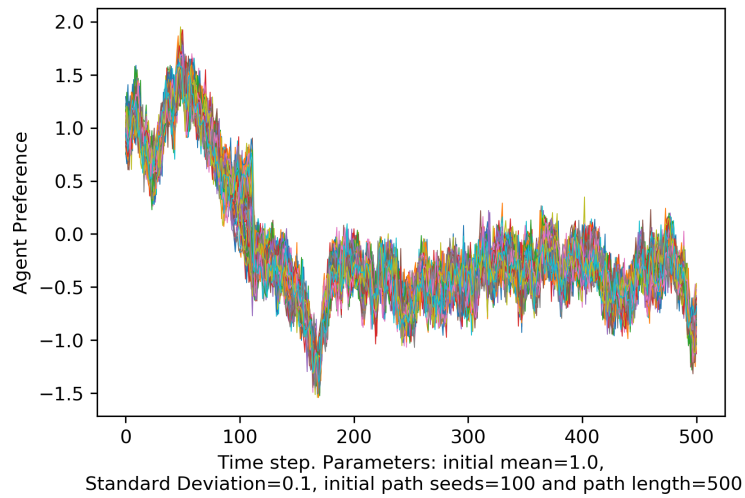

Figure 10: 100 agents with nearest preference networking.

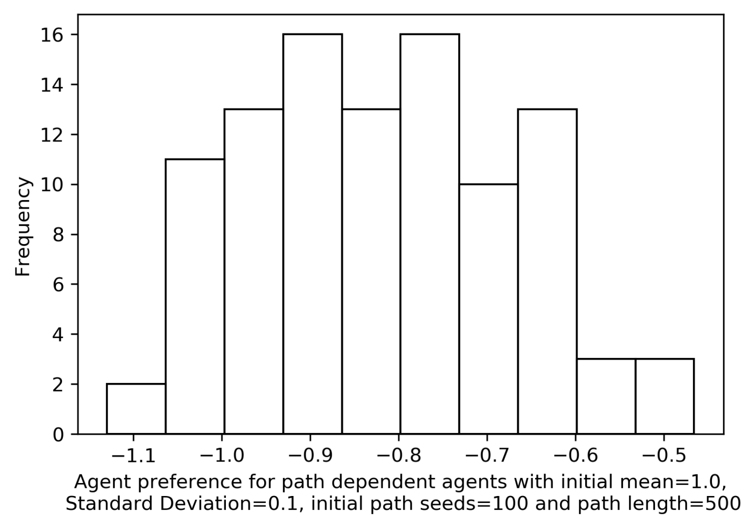

Figure 11: Final path data point for all agents in Figure 10.

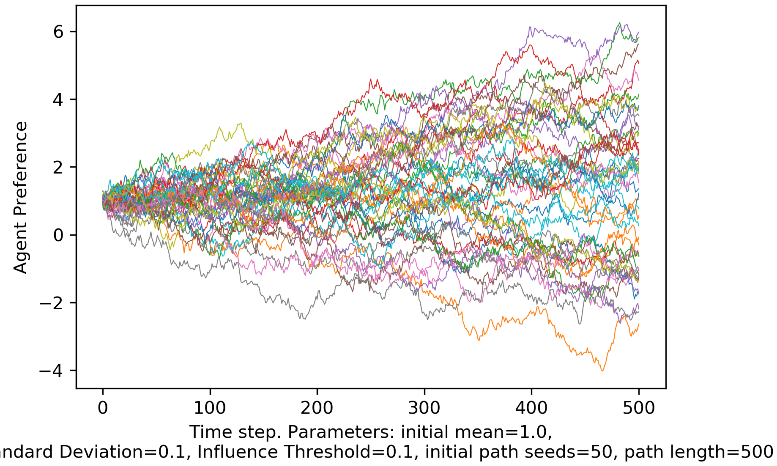

Figure 12: 100 agents with an influence threshold.

the standard deviation (eg, SD=0.1 and influence threshold = 0.15), Figures 14 and 15.

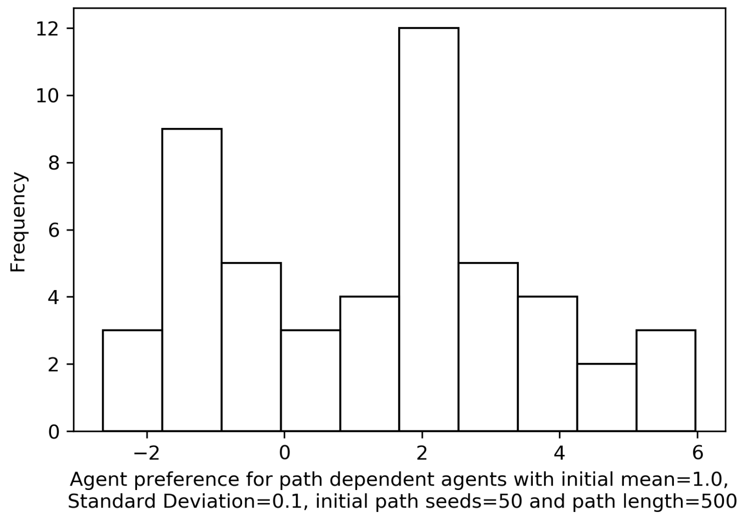

Figure 13: Final path data point for all agents in Figure 12.

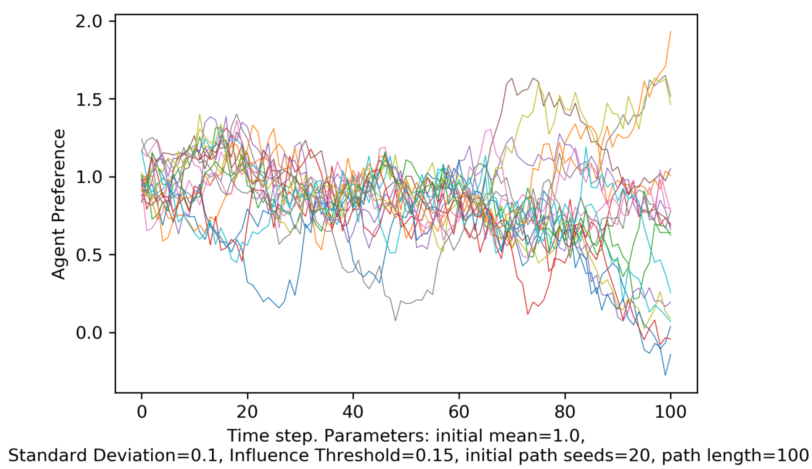

Figure 14: 20 agents with an influence threshold.

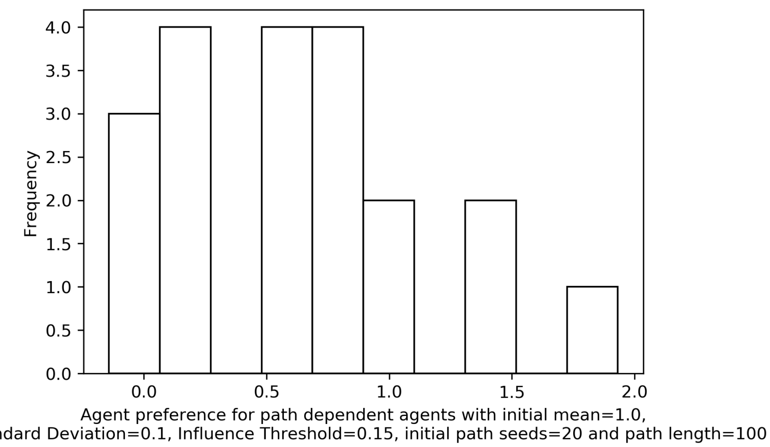

Figure 15: Final path data point for all agents in Figure 14.

There is an infinite number of possibilities to explore the different ways in which agents interact to form their preferences even with this abstract method. The following sections explore these different ways of agents interacting within the resource distribution model. The agent preference affects each agent's *need* and is multiplied by the agent's wealth or the agents neighbourhood wealth (dependent on the model) and added to the need already required by the agent for resource, adding RCs and DCs.

1.4 Results

The following sections explore the effect of different models of interaction between agents on the overall resource distribution system through time.

All the simulations use the same basic parameters as shown in Table 1.

1.4.1 Agent Individual Preference

The Agent Individual Preference model is based on the model of agent interaction as set out in Section 1.3.1. In this model each agent isn't influenced by any agent in it's network. Instead, each agent's initial preference is taken from a normal distribution of the previous agent with the mean being the previous agent's preference and the standard deviation taken as 0.1. Figure 8 shows the effect of individual path preference overtime without any distribution of resource.

Model Parameters	Value
Array Size	(50, 50)
Initial Coordinates	(25, 25)
Time steps	300
Resource added per time step	300
Initial Resource per DC	0
Initial Resource per RC	0
Resource used per RC per Time step	1
Cost to add DC	5
Cost to add RC	5
Optimum RC Resource	3
Growth Type	Deterministic
Maximum Growth?	No
Mortal Cells?	Yes, DCs are removed if their RCs have no resource for 10 time steps
Agent preference?	Yes, but dependent on the model.

Table 1: General Parameters in the model for Section 1.4

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Forty simulations for the agent individual preference model were run. As can be seen the majority of the models follow the pattern of an initial increase in both DCs and RCs at the start of the simulation followed by a quick contraction and reduction in the number of cells, Figure 16. A plot of the Gini Coefficient for all the models shows on average the Gini Coefficient is very high (after the initial growth), with a mean of *0.82*, Figure 17.

The reason for the type of growth observed is likely to be due to initially each agent not having much resource, which reduces the agent need to normal levels (need for expansion and maintenance),and after a number of time steps the agents begin to gain wealth depending on their individual preferences. In turn this reduces the amount of resource passed down through the system which leads to its contraction and reduction in number of cells. So there is a positive feedback of resource increase per agent or at least for agents with a preference for increased resource. The agents which persist until the end of the simulation, are the agents closest to the source, and it appears that there preference does not matter, all that matters is their

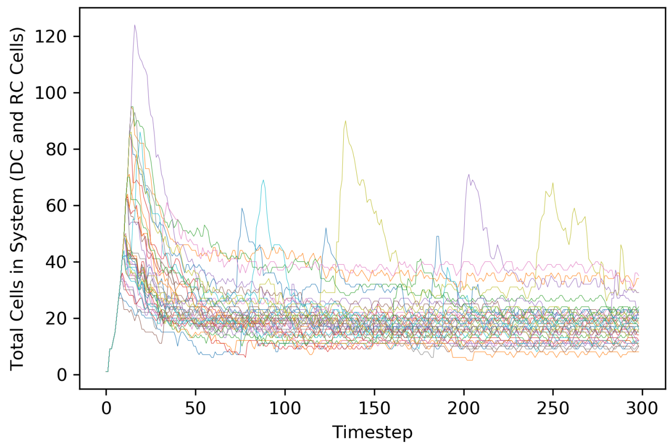

Figure 16: Forty simulation runs showing the total resource in the data number of cells in the system.

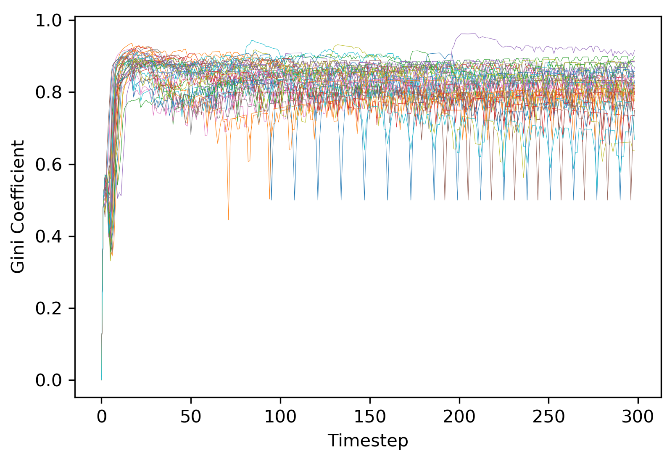

Figure 17: Forty simulation runs showing the Gini Coefficient through time.

position in the system.

There are a few anomalies in this model where the simulations show large fluctuations in the number of agents. An example is shown in Figure 18. Analysis of the mean individual agent preference and total preference shows correlation between the drop in number of cells and drop in agent preference, Figure 19. A plot showing all the agent preferences over the course of the simulation is shown in Figure 20. The plot shows a number of agents which persist over the course of the simulation, these are likely to be the agents closer to the source. Over the course of the simulation a number of offshoots occur from these main agents, but not many of these persist. As can be seen the preference of the persistent agents varies widely over time indicating that the preference isn't important for their survival. The path of these agents is also similar to those seen in Figure 8 which is to be expected given the same interaction model is used. An animation of the model can be found at `https://youtu.be/yXUOtqeIWTA`. The animation shows the the sudden growth at time step 130 is synchronised, it occurs across the whole systems, whereas the growth at time step 250 is asynchronous, it occurs in one part of the system. Looking at the agent preference data in Figure 20, it shows a general trend before time step 130 in reducing the agent preference across the system. This does not occur before the sudden growth at time step 250. It is therefore likely, that although there is no influence between the agents, by chance all the agents reduced their preference at the same time leading to more resource being passed down through the system at this moment.

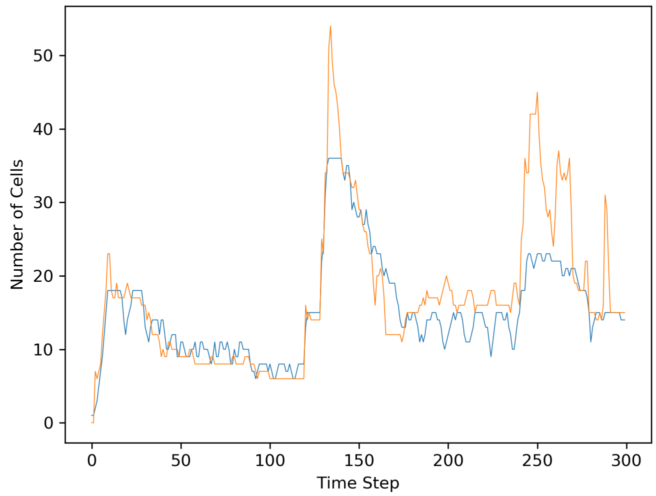

Figure 18: Number of Distribution Cells (blue) and Receiver Cells (orange) for the agent individual preference model showing fluctuating behaviour.

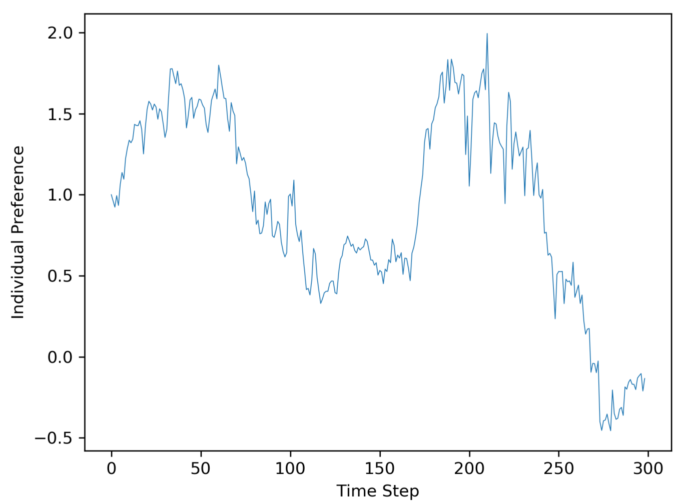

Figure 19: Mean individual preference of the system through time for the simulation in Figure 18.

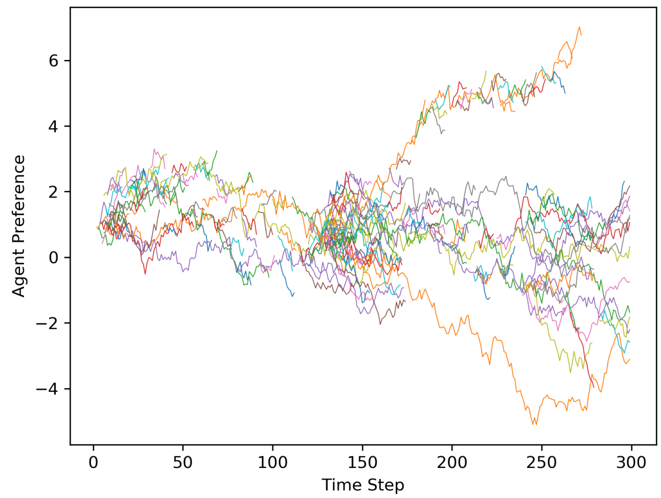

Figure 20: Individual Preference data for the system through time for the simulation in Figure 18.

1.4.2 Agent Network Influence

The Agent Network Influence model introduced in Section 1.3.2 shows how a system of agents which influence each other can behave. With each agent connected to those with the nearest higher and lower preference, the system becomes closely connected with little noise. When exploring such interactions on a spatial model such as the resource distribution model there are many different possibilities of agent interaction which can be explored, for example the distance with which agents can connect with one another. In order to explore how such behaviour can affect the whole system many simulation runs using different parameters were undertaken. The general parameters are the same as shown in Table 1. Details on the specific simulations explored are shown in Table 2. The *Number of Neighbours* is the maximum number of neighbours each agent can be influenced by. The influence of neighbours affects both the individual agent preference and the individual agent need. To find the agent preference, the mean of the neighbour's preference is calculated and then calculated from a normal distribution. The individual agent need is calculated as the mean wealth of the neighbours multiplied by the individual agent preference. This way of calculating has been done to take into account the spatial aspect of the model. The number of neighbours is also affected by the *Neighbourhood Size* which is the distance in each direction which agent is can influence a specific agent; the *agent's neighbourhood size.*

Model Parameters	Value
Number of Neighbours	1 - 9
Neighbourhood Size	5 and 10
Number of Repeat Simulations	20

Table 2: Parameters changed for each simulation for Section 1.4.2

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Using the parameters in Table 2 generated 360 unique simulation models. This created over 1GB of data including graphs, animations and text files. This was subsequently analysed which is reported in the rest of this section.

Figure 21 shows the total number of distribution cells per time step for all 360 simulations. A histogram of the total number of distribution cells at time step 300 is shown in Figure 22. Across all the simulations a trend of smaller systems is observed - the majority of simulations have around 50 distribution cells. This is likely due to agents increasing their individual wealth, decreasing the size which the system can expand to. There is also a small amount of simulations with over 150 distribution cells. The Gini Coefficient has also been plotted for all 360 simulations, Figure 23. The mean Gini Coefficient for all simulations over all time steps is 0.64. A histogram of the Gini Coefficent at time step 300 is shown in Figure 24. A general trend of decreasing Gini Coefficient with increased number of neighbours per agent is found, Figure 27 and increased system size with increased number of neighbours, Figure 28.

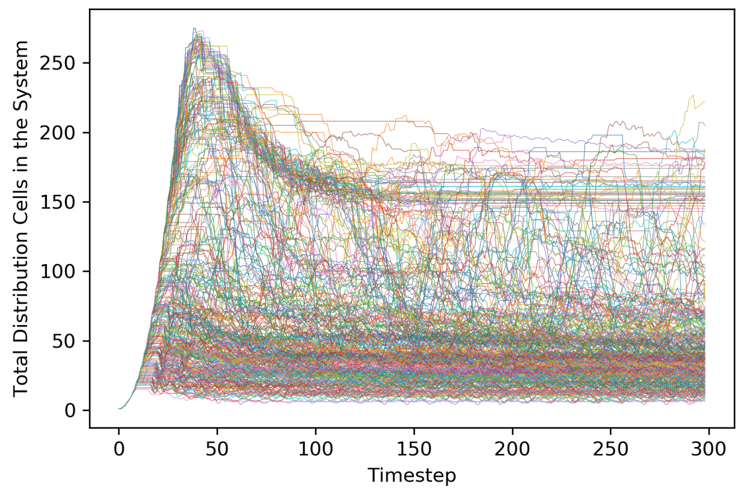

Figure 21: Number of Distribution Cells per time step for all 360 simulation in Table 2.

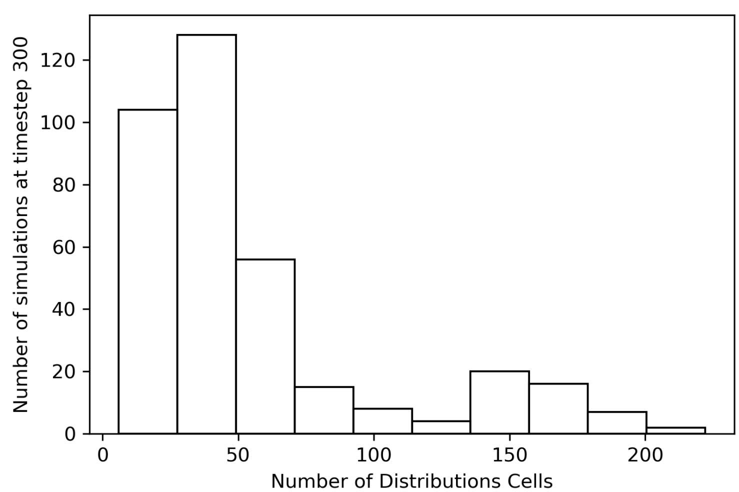

Figure 22: Number of Distribution Cells at time step 300 for all 360 simulation in Table 2.

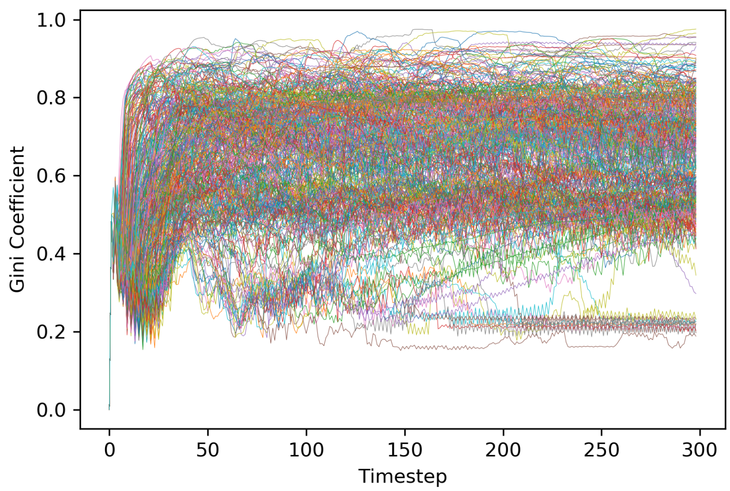

Figure 23: Gini Coefficient per time step for all 360 simulation in Table 2.

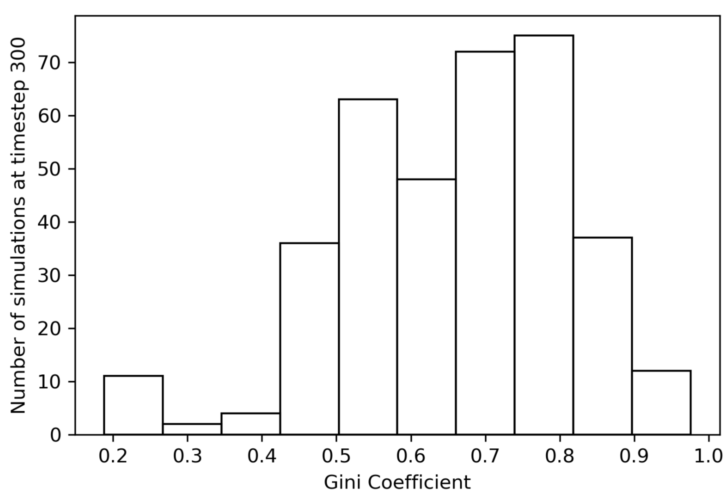

Figure 24: Gini Coefficient per time step for all 360 simulation in Table 2.

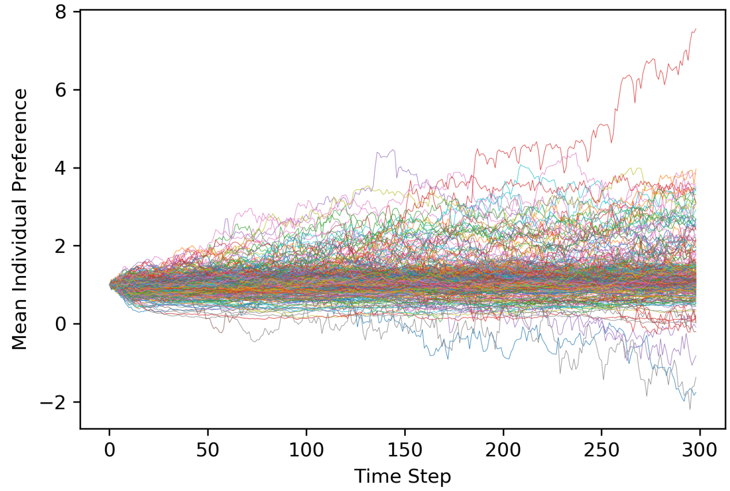

Figure 25: Mean agent preference per time step for all 360 simulation in Table 2.

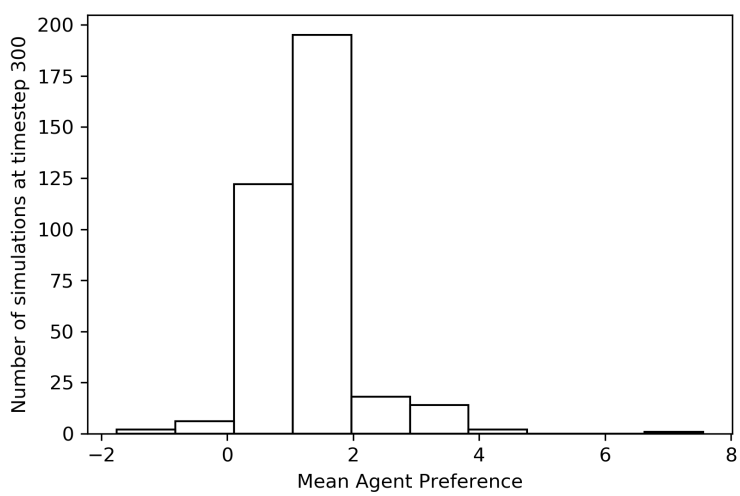

Figure 26: Histogram of mean agent preference for final time step for all 360 simulation in Table 2.

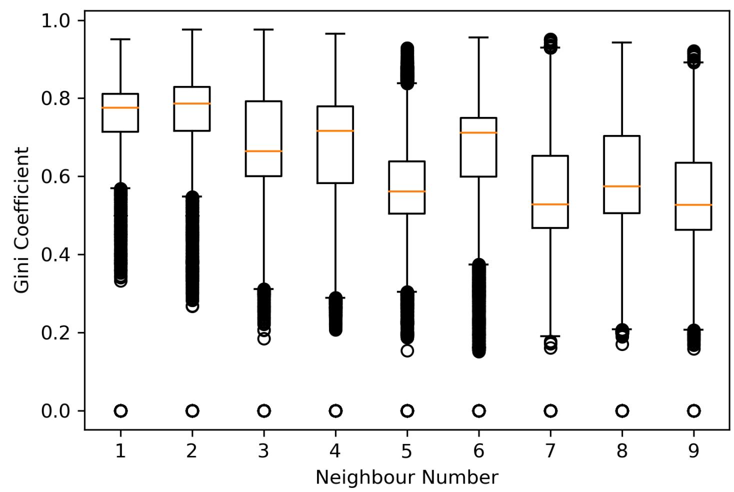

Figure 27: Box Plots for all 360 simulation showing the changing Gini Coefficient for Agent Neighbourhood Number in Table 2.

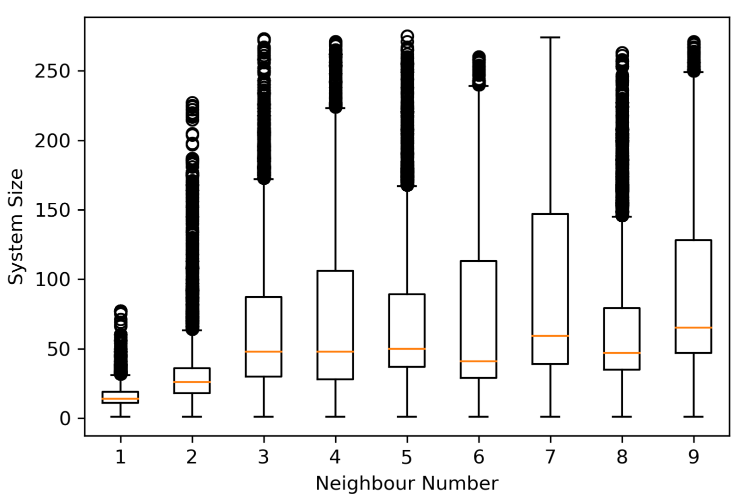

Figure 28: Box Plots for all 360 simulation showing the changing system size for Agent Neighbourhood Number in Table 2.

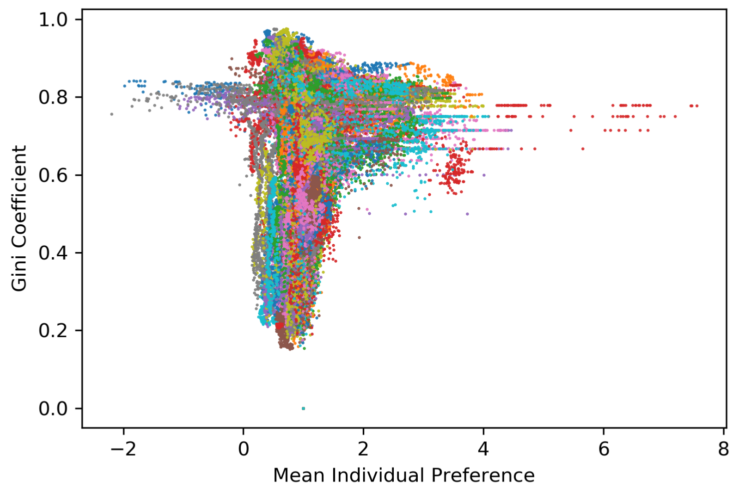

Figure 29: Gini Coefficient verses mean individual preference for all 360 simulation in Table 2.

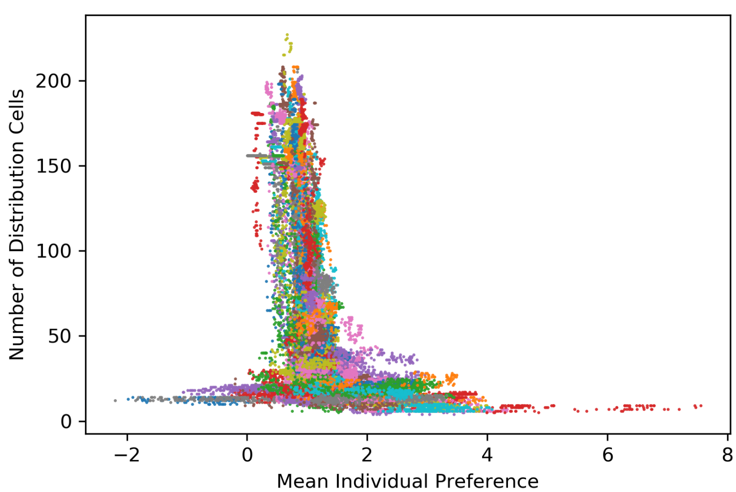

Figure 30: Number of Distribution Cells verses mean individual preference for all 360 simulation in Table 2.

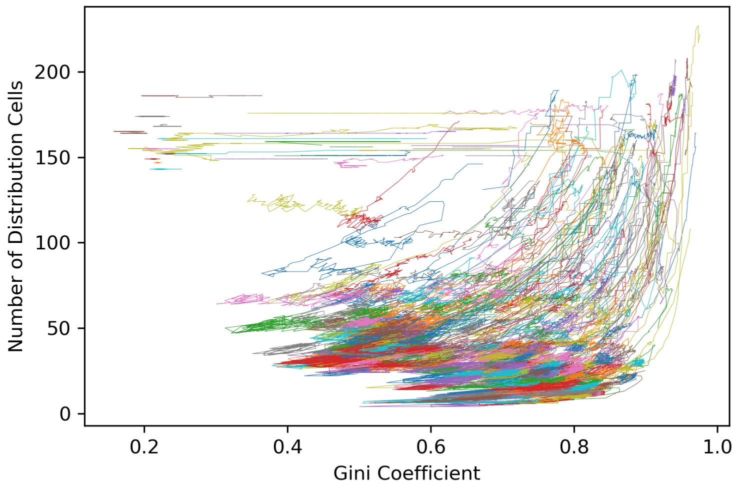

Figure 31: Gini Coefficient plotted against the Number of Distribution Cells between time steps 200 and 300 for all 360 simulation in Table 2.

Further simulations were undertaken with larger neighbour number and neighbourhood size. The parameters are shown in Table 3, leading to a further 300 simulations. The results are shown in Figures 32, 33, 34, 35, 40, 41 and 42.

Model Parameters	Value
Number of Neighbours	10-19
Neighbourhood Size	10, 11 and 15
Number of Repeat Simulations	10

Table 3: Parameters changed for each simulation for Section 1.4.2
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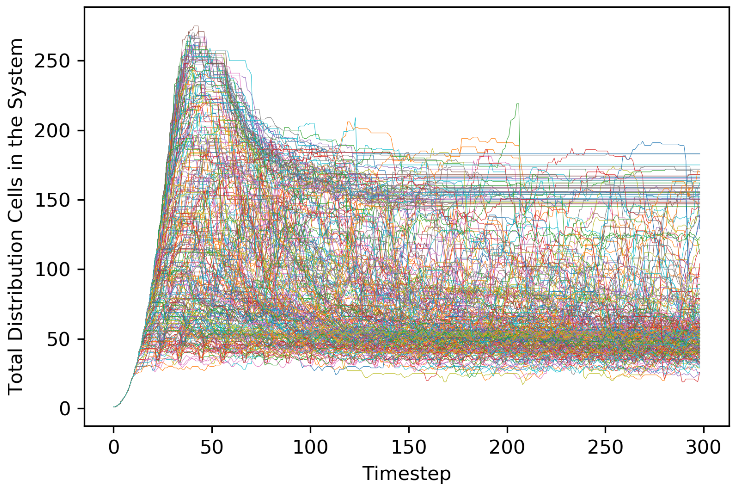

Figure 32: Number of Distribution Cells per time step for all 300 simulation in Table 3.

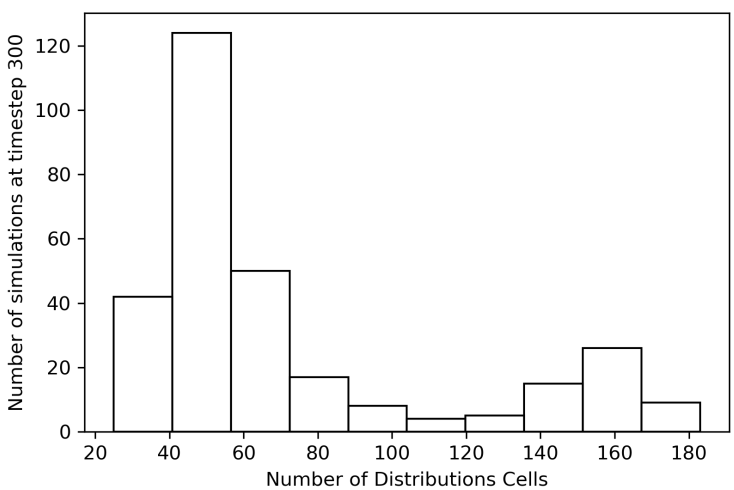

Figure 33: Number of Distribution Cells at time step 300 for all 300 simulation in Table 3.

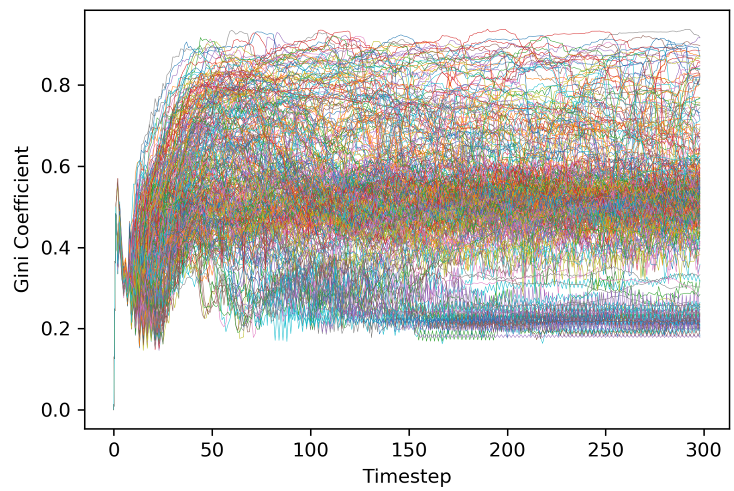

Figure 34: Gini Coefficient per time step for all 300 simulation in Table 3.

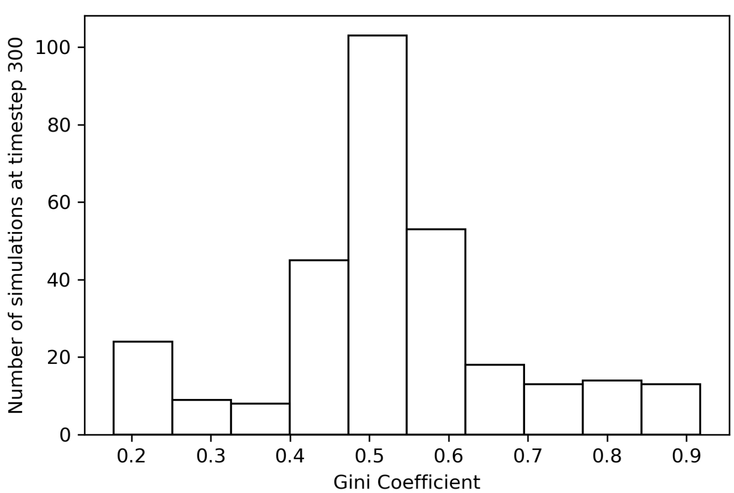

Figure 35: Gini Coefficient per time step for all 300 simulation in Table 3.

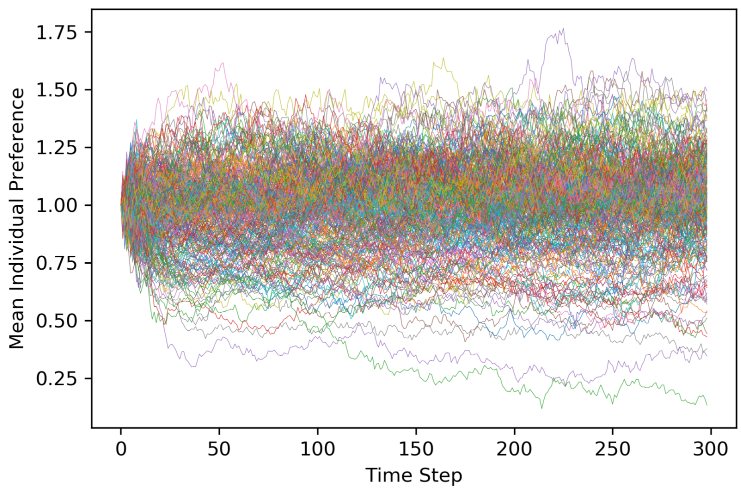

Figure 36: Mean agent preference per time step for all 300 simulation in Table 3.

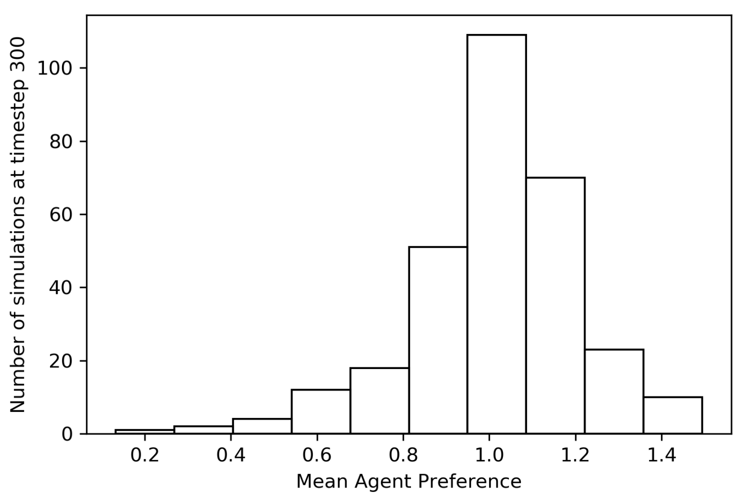

Figure 37: Histogram of mean agent preference for final time step for all 300 simulation in Table 3.

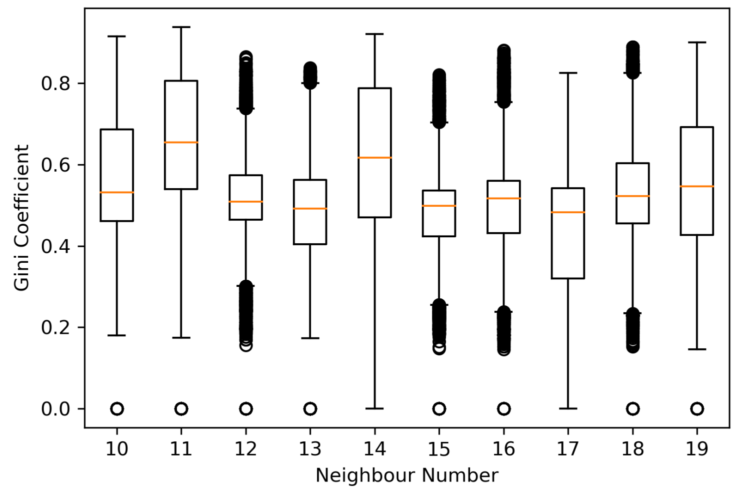

Figure 38: Box Plots for all 300 simulation showing the changing Gini Coefficient for Agent Neighbourhood Number in Table 3.

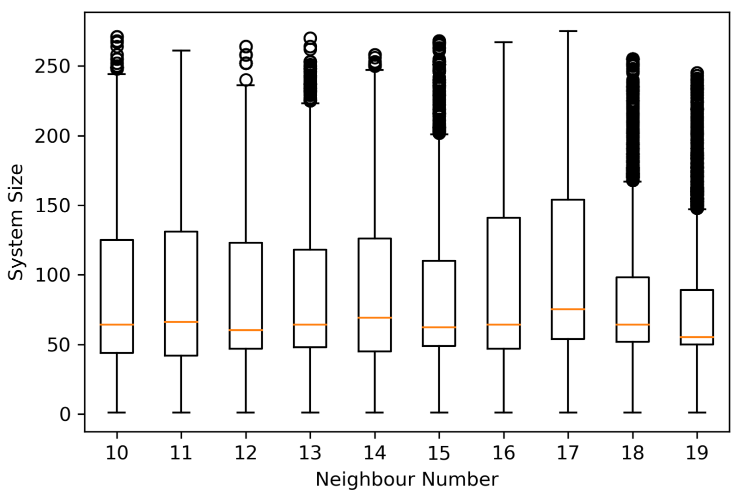

Figure 39: Box Plots for all 300 simulation showing the changing system size for Agent Neighbourhood Number in Table 3.

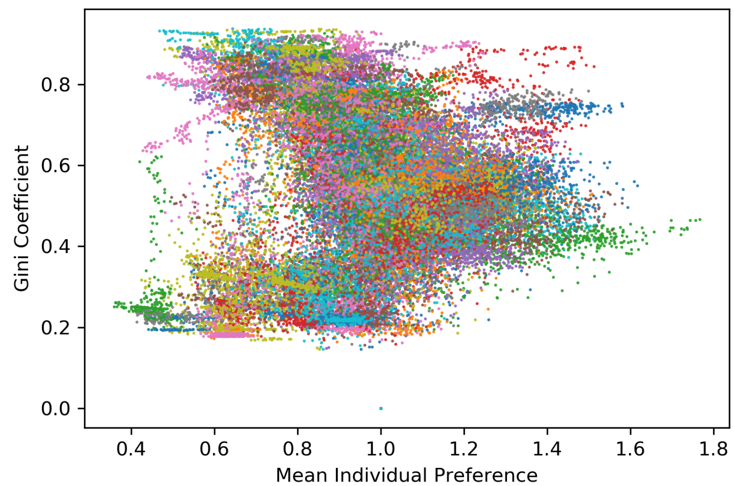

Figure 40: Gini Coefficient verses mean individual preference for all 300 simulation in Table 3.

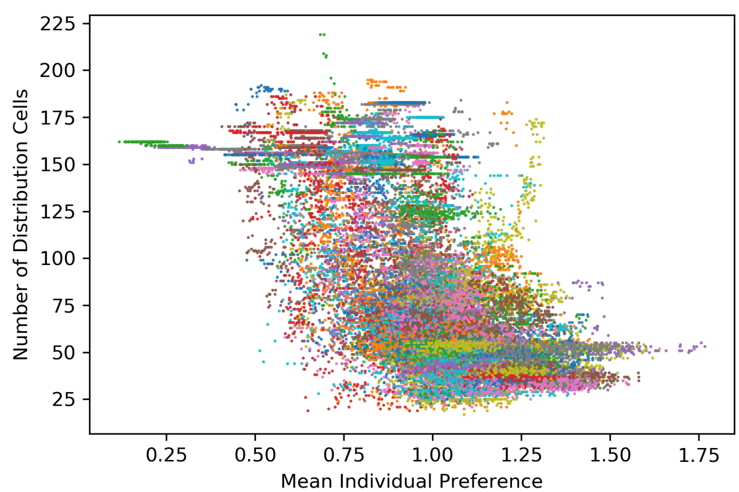

Figure 41: Number of Distribution Cells verses mean individual preference for all 300 simulation in Table 3.

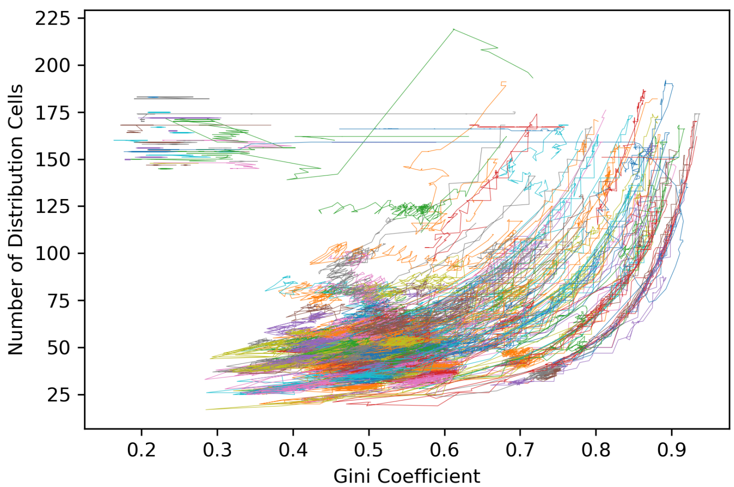

Figure 42: Gini Coefficient plotted against the Number of Distribution Cells between time steps 200 and 300 for all simulations in Table 3.

Discussion The Gini Coefficients found from these simulations seem to generally be greater than those observed in empirical data for modern societies (See Section 1.1). Although the data appears to be more similar to those observed in traditional societies, as can be seen in the data on th UK over the past 700 years, Figure 2. However as the neighbourhood size and neighbour number is increased for each agent the Gini Coefficient is reduced as shown in the box plots for increased neighbour number, Figures 27 and 38. This increased connectivity also leads to a more stable larger population, Figures 28 and 39. The mean agent preference also seems to show a slight increase in agent preference over time, Figure 26 and 37.

The reason for the Gini coefficient being comparable to traditional societies might be due to the rigid societal structure of these systems as this model has strong spatial characteristics which is similar to perhaps an indigenous irrigation system. The greater connectivity leading to larger more stable populations might be due to the decrease in extreme agent preferences as shown by the differences between Figures 25 and 36. The slight increase in agent preference over time might be due to a selection pressure operating on the system. With increased agent preference, agents will need more resource leading to proportionally more resource being passed to them. As shown in the histograms in Figures 26 and 37 the agent preference is slightly asymmetrical with more agents having a preference greater than 1. This is very subtle, indicating that this or at least the mean agent preference is not a dominant mechanism in changing the system size or Gini Coefficient. Plots of the Gini Coefficient against the mean individual preference are shown in Figure 29 and 40. For lower connectivity there appears to not be a significant relationship between mean individual preference and Gini Coefficient, Figure 29. However the plot does show the possibility of more extreme agent preference being linked to great Gini Coefficient values. For systems with greater connectivity (Figure 40), the relationship between Gini Coefficient and mean individual preference seems to show moderate levels of inequality (0.4-0.6 Gini Coefficient) being linked to greater a mean individual preference above 1, and very low levels and very high levels of inequality being linked with generally lower than 1 individual mean preference. To further understand the reasons behind this trend more detailed is required. However it is thought that the reason for this trend might be that for high levels of inequality only a few agents are required to have high individual preferences which would not be reflected in the mean individual preference.

Analysis of Grouping in Results The plots showing the Gini Coefficient and Number of Distribution Cells for the final 100 time steps of each simulation provide information on possible groupings or basins of attraction which the system may grow towards (Figures 31 and 42).

Three main groups are identified as follows and referred to in Figure 43:

1. Small system (generally between 25 and 75) with a Gini Coefficient between 0.35 and 0.7.

2. Large systems (150 to 175) with a low Gini Coefficient between 0.2 and 0.3.

3. Fluctuating systems with changing size between 50 and 175 and Gini Coefficient between 0.7 and 0.9. Systems appears to follow an ordered path in Group 3 and may pass to and from Group 1.

To understand further the processes leading to the formation of these different groups, example systems from each group are analysed further.

Group 1 The parameters for this example are those shown in Table 1 with the simulation specific parameters shown in Table 4. Figure 44 shows it is

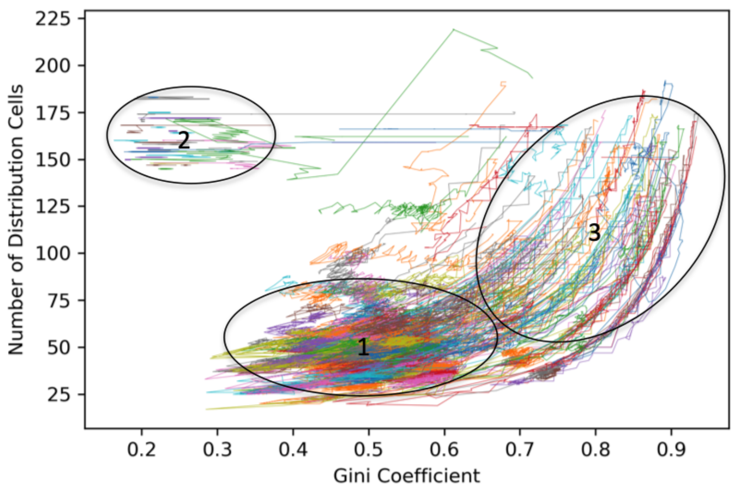

Figure 43: Labelled Groupings for Distribution Cells and Gini Coefficient. For simulations from Table 3.

located within Group 1 and Figure 45 shows the number of cells per time step. The number of Cells shows a rapid growth then fall which is common in all the simulations. The reason for this has already been explained previously as it takes time for agents to accumulate resource and increase their need based on their preference and their neighbours. For the majority of the simulation, the number of cells is reasonably constant with minor fluctuations. All the individual agent preferences for each time step are shown in Figure 46. Whilst there is a lot of noise in this figure, group formation can be seen. This can be thought of as similar to the concept of niche construction as mentioned in the literature review in sections **??** and **??** with each of the clusterings of agents being a separate niche. This clustering of preferences is also reflected in the resource per agent per time step, Figure 47. Two distinct groups are formed which have similar resource which is likely the reasons for the low Gini Coefficient. The networking within the model between the groups has not been analysed. This is likely to play a dominant role in the formation and maintenance of groups.

Model Parameters	Value
Number of Neighbours	19
Neighbourhood Size	10

Table 4: Parameters selected for Group 1 simulation

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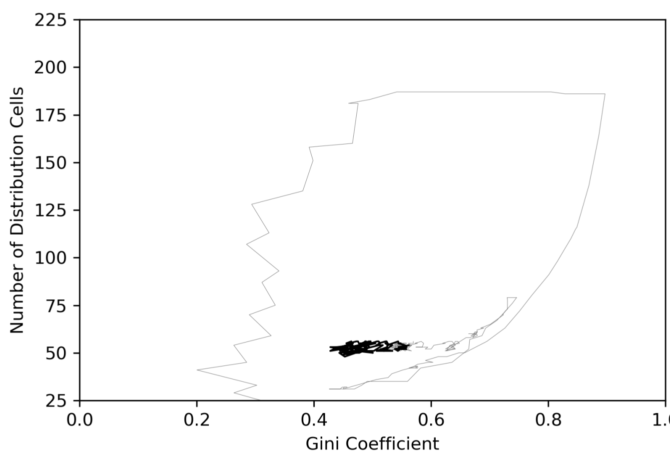

Figure 44: Number of Distribution Cells verses the Gini Coefficient for Group 1 example. Parameters from Table 4.

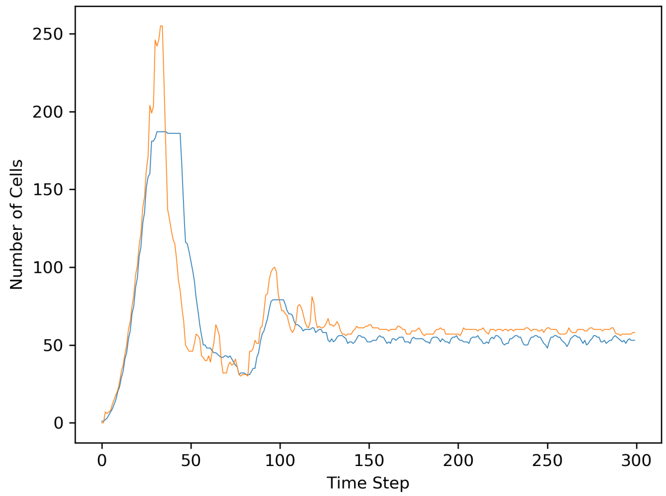

Figure 45: Number of Distribution and Receiver Cells per time step for Group 1 example. Parameters from Table 4.

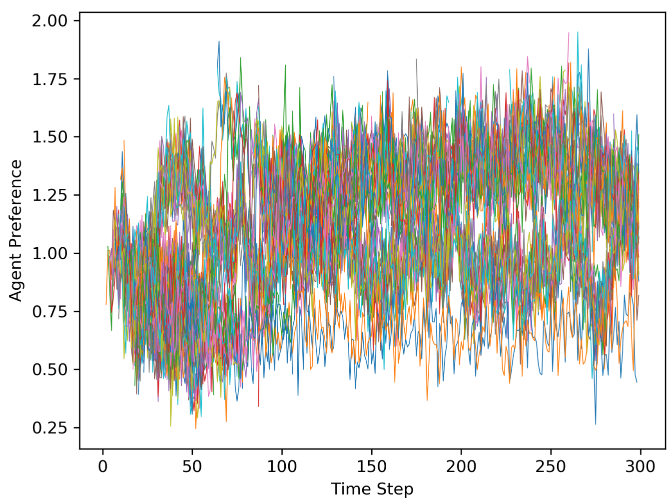

Figure 46: Individual agent preferences over the course of the simulation for the group 1 example. Parameters from Table 4.

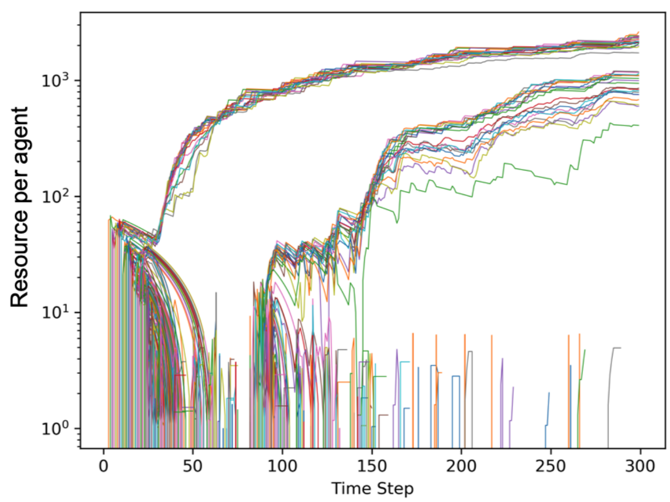

Figure 47: Resource per Agent for Group 1 example. Parameters from Table
4.

Group 2 The parameters for this example are those shown in Table 1 with the simulation specific parameters shown in Table 5. The changing number of distribution cells and Gini Coefficient per time step is shown in Figure 48. The black area is the location of the simulation in the final 100 time steps which is within Group 2. Figure 49 shows the number of Distribution Cells and Receiver Cells per time step. After the initial growth, the simulation seems to reorganise in order to maximise the number of receiver cells to distribution cells. The reason it is doing this is uncertain. The individual agent preferences each time step are shown in Figure 50. Whilst the group 1 preferences showed the formation of niches, the group 2 agent preferences show one group formed with little variance. This indicates a highly connected agent population. The resource per agent per time step is shown in Figure 51. This shows a gradual reduction in resource per agent for each time step.

Model Parameters	Value
Number of Neighbours	10
Neighbourhood Size	10

Table 5: Parameters selected for Group 2 simulation

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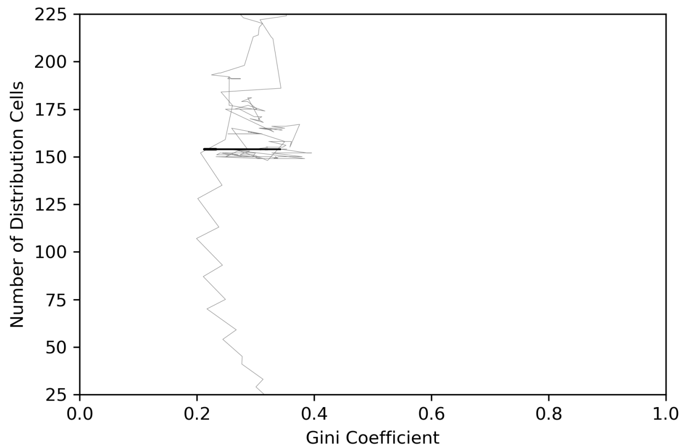

Figure 48: Path of Distribution Cells verses the Gini Coefficient for Group 2 example. Parameters from Table 5.

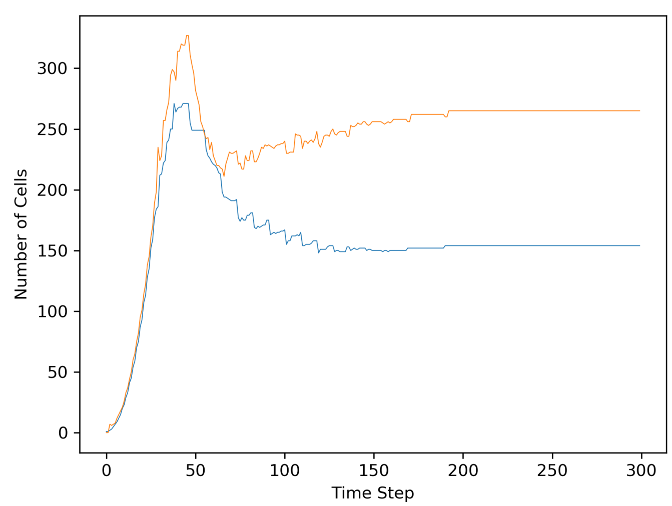

Figure 49: Number of Distribution and Receiver Cells per time step for Group 2 example. Parameters from Table 5.

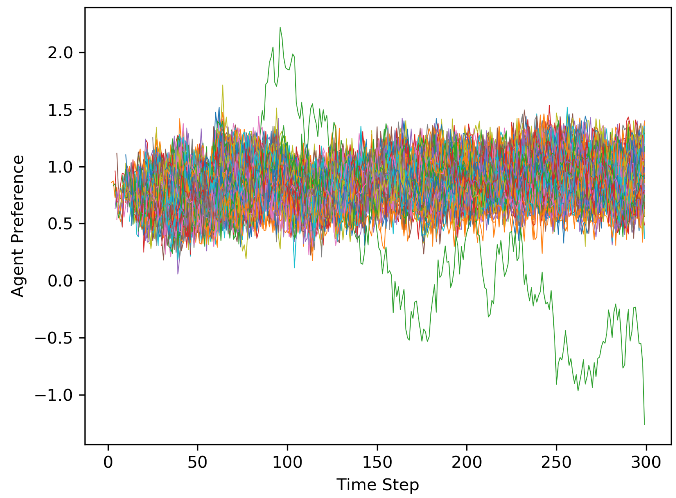

Figure 50: Individual agent preferences over the course of the simulation for the group 2 example. Parameters from Table 5.

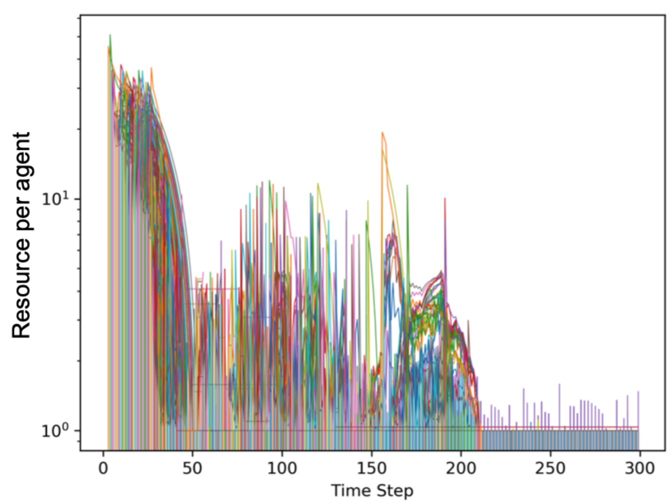

Figure 51: Resource per Agent for Group 2 example. Parameters from Table 5.

Group 3 The parameters for this example are those shown in Table 1 with the simulation specific parameters shown in Table 6. The changing number of distribution cells and Gini Coefficient per time step is shown in Figure 52. The black area is the location of the simulation in the final 100 time steps which is within Group 3. Figure 53 shows the number of Distribution Cells and Receiver Cells per time step. This shows the oscillating fluctuating behaviour which was previous described for group 3. The individual agent preference per time step shows a lack of niches formed, but more fluctuating behaviour than for Group 2, Figure 54. This fluctuating also seems to correlate with that seen in the number of distribution cells. The resource per agent data (Figure 54) shows the possible formation of *classes* with some agents persisting and obtaining increased amounts of resource whilst others being removed from the system and new agents added when the system grows again. This is likely to relate to the agents closer to the source. The ones closer to the source are able to persist for longer periods.

Model Parameters	Value
Number of Neighbours	16
Neighbourhood Size	15

Table 6: Parameters selected for Group 3 simulation

.

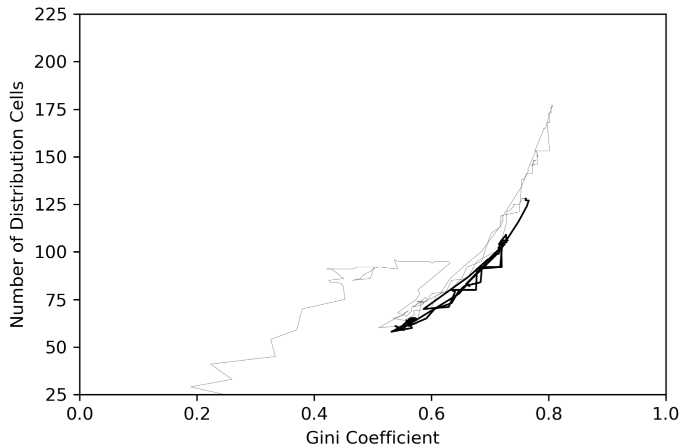

Figure 52: Path of Distribution Cells verses the Gini Coefficient for Group 3 example. Parameters from Table 6.

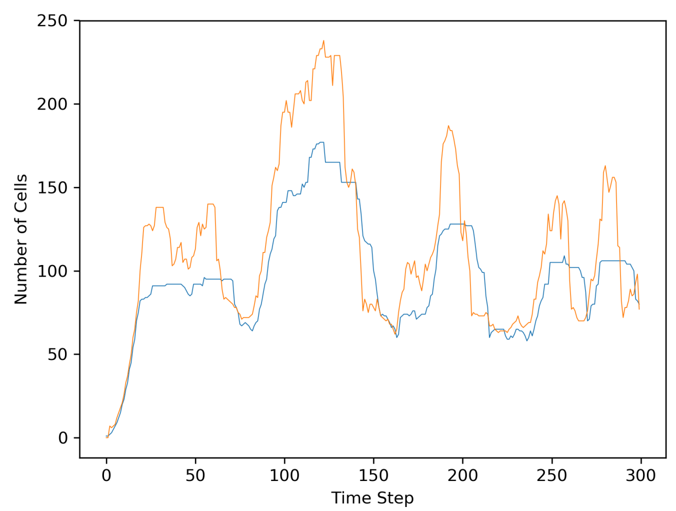

Figure 53: Number of Distribution and Receiver Cells per time step for Group 2 example. Parameters from Table 6.

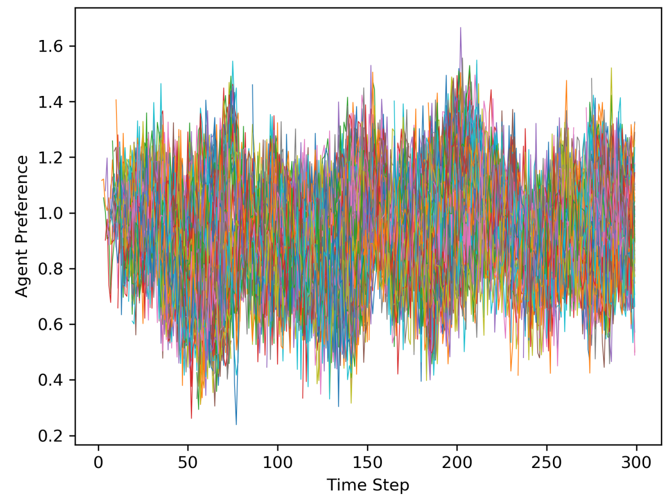

Figure 54: Individual agent preferences over the course of the simulation for the group 3 example. Parameters from Table 6.

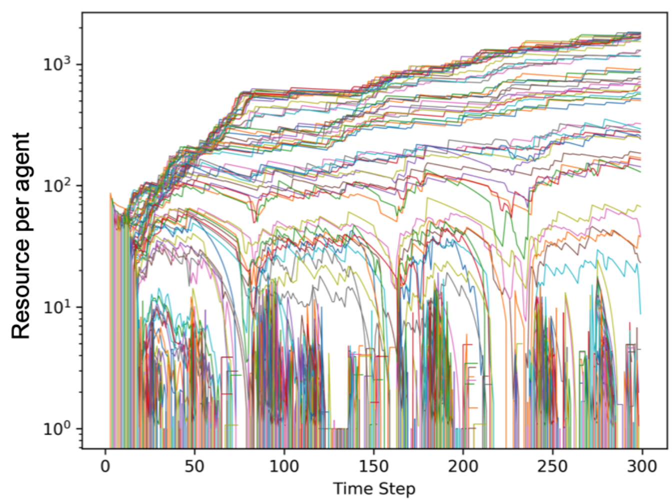

Figure 55: Resource per Agent for Group 3 example. Parameters from Table 6.

Discussion of Groups By looking more in depth at the behaviour of examples from each of the groups (1,2 and 3) a deeper understanding of the differences and possible mechanisms leading to their behaviour has been found. The number of neighbours and neighbourhood size do not seem to be dominant parameters in leading to a certain group type. Instead the networking of the system and stochastic choices of agents may play a role.

The data showing the individual agent preferences through time and the individual agent resource through time shed light on the degree of connectivity in the system which seems to be affecting the inequality and size of the system.

Before drawing conclusions on whether the behaviours observed in the examples above are dominant in different groups, additional examples need to be analysed. To further understand how connectivity, agent preference and agent location in the system lead to different system level behaviour, further analysis and visualisation of many simulations is required. This may also require more systematic and automated forms of analysis such as Principle Component analysis or network analysis.

It is hypothesised that horizontal (favourable networks with other agents at similar distance from the source) and vertical networking (favourable networking with other agents further or closer to the source) may play an important role. The dynamics of this may be quite complicated and counter-intuitive. For instance initially increased vertical networking may be viewed as leading to a lower Gini Coefficient but it may increase instability. Further modelling of this networking is required to test these theories.

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