Simulated Social Networks and Partner Search: Linking Social Interactions and Demographic Outcomes

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Introduction: Simulated Social Networks and Demographic Outcomes

Demographic change is a product of a complex web of social interactions (Bongaarts and Watkins 1996). These interactions inform, motivate and facilitate demographic events such as family formation, childbearing and migration, and the social fabric on which these interactions take place has the form of a network defining links between individuals. However, the traditional concern of demographers with prediction and co-development of the discipline with probability theory has precluded a focus on these underlying causal mechanisms, instead focusing on describing a *'statistical individual'* (Courgeau 2012). This approach abstracts away individual behaviour in favour of determining the probability with which individuals experience certain events (such as death or childbirth).

In contrast, this paper attempts to show that by explicitly simulating individual behaviour and interaction, demographers have the opportunity to examine the potential **causes** of population-level patterns. More specifically, an agent-based simulation is used to examine the role of networks in partnership search and household formation. The research aims are detailed below:

1. Construct an agent-based simulation of interaction and partnership search over a dynamic social network.
2. To investigate the properties of the model in order to understand how it might be put to use in investigating the relationship between individual behaviour, network properties and patterns of partnership formation and demographic change.

Background

To understand why a recourse to Agent-Based Simulation is deemed appropriate for demographic analysis of partnership choice and household formation, we must first detail what current approaches in contemporary demography and related social sciences lack. To this end, a brief description of the methodological and epistemological allegiances of demography and particularly quantitative demography is helpful. It is argued that demography's focus on predictive forecasting and on statistical survey analysis has left the discipline under-theorised and ill-placed to analyse causal processes at the individual level and how these aggregate through interaction to give rise to population level effects (Greenhalgh, 1996; Ní Bhrolcháin & Dyson, 2007; Bachrach & McNicoll, 2003; Billari et al.,2006; Silverman et al., 2011) While the discussion is framed in general terms, given the focus of the report particular examples from and household demographics are provided.

A useful distinction can be drawn between demographic work at two levels of analysis; the Macro and the Micro. The former is concerned with broad aggregate population change, while the later generally is focused on the individual and the life course (Billari et al., 2006). Macro-Demography is associated with the use of demography in a forecasting context, and generally considers how population sizes, rates of events and proportions of states change over time. In the case of the household, the forecasting of rates of formation and dissolution largely conducted for planning purposes, to understand the future need for housing, for example (Keyfitz, 1987). The traditional way of forecasting future household stocks is the household headship rate method; this is purely extrapolative. The current proportion of household heads per adult is estimated for years in which

data is estimated, generally by age and sex. Given projections of future population the future number of households can be estimated either directly from current headship rates, or through some assumptions about how this 'rate' will change - generally through some simple extrapolation or regression modelling (Kono 1987, Pitkin 1987). While this is a reasonable way to obtain such estimates, at no point in this process is an attempt made to understand or model *why* past trends have taken place and incorporate this information into the model.
This focus on prediction rather than on theorising and isolating underlying causal processes is relatively common in macro-demography. This problem not unrecognised by demographers, and there are notable attempts to tackle the problem of how causal analysis might be furthered in the study of population (Ní Bhrolcháin & Dyson, 2007; Bachrach & McNicoll, 2003). However, it remains the case that our understanding of casual relationships in macro-demography is 'embarrassingly limited' (Keyfitz and Caswell, 2005 p.270), a fact underlined by the lack of success in producing 'structural' forecasting (that is, forecasts that predict population change based on social and economic covariates) (Booth 2006).

As well as modelling population change in the aggregate, micro-analysis at the individual level can shed light on the dynamic behaviour of populations. Much individual level work is focused on statistical analysis of survey data, allowing demographers to examine what characteristics of individuals are associated with particular behaviours and with propensities to move between life-course states. Such work is often informative; by understanding how these associations change over time one can understand what particular social or demographic groups are driving change at the macro-level, and hypotheses about what is actually causing these changes can be formulated. As an example, Lesthaeghe and Van Der Kaa's second demographic transition thesis (simplified somewhat) posits that the spread of 'post-materialist' values is responsible for delays in household formation and lower fertility; this theory is backed by survey and panel data that shows correlations between high scores on various measures such as attitudes towards gender, the family and personal fulfilment on one hand, and family-forming behaviour on the other (see Surkyn and Lesthaeghe (2004) and Lesthaeghe (2010)). However, the survey data alone does not explain *how* the spread of such values occurs, nor *why* they were adopted, nor how these values manifest themselves in individual decision making.

Greater levels of statistical sophistication can also be adopted in order to glean more information from surveys; in the case of the household, hierarchical multilevel models such as those advocated by Snijders (1999) allow us to further partial out variance explained by co-residence in households, as opposed to that explained by individual characteristics. Again, these techniques do not necessarily lead to greater information about the casual mechanisms underlying the processes in question: why is it exactly that households might explain some of the variance, and how do households come to decisions on what joint behaviour to adopt? The problems of making causal inference in social science, particularly through using statistical techniques to analysis survey data are well documented (eg. Freedman (1985), Goldthorpe, (2001), Freedman (1991), Holland (1986) , Ní Bhrolcháin & Dyson, 2007), and various tricks and techniques exist for trying to overcome these problems (see, for example, Angrist and Pischke (2009)) However, the contention here is that few of these approaches make any attempt to represent formally the way individuals make decisions, or the effect interactions between individuals have on the macro-level, or the feedbacks between the population and the individual levels (Epstein, 1996 ; Billari, 2006).

Some progress towards addressing these kinds of concerns is made by demographers working within the field of Micro-Simulation. On the face of things, micro-simulation takes a similar philosophy to the statistical techniques mentioned above: a population of individuals are instantiated in a computer program, and are moved from state to state on the basis of empirically determined transition probabilities (Wachter 1987). Simulating these transitions on an individual basis and aggregating the results to gain macro-level data allows much more detailed forecasts and reconstructions of population than would be possible with macro-forecasting, but additionally allow the possibility of including feedbacks between micro and macro-level variables, particular when considering things like marriage or labour markets (Van Imhoff and Post, 1998; Willekens, 2005, Zinn et al. 2009).

However, an additional benefit is the ability to maintain information about the links between individuals, and this advantage has been much used in the examination and forecasting of kinship networks (Reeves 1987, Smith 1987), but also represents a step towards the type of consideration of networks and interactions advocated in this report. Micro-simulators have also considered exploiting the flexibility of simulation techniques in order to explore the effect of different behavioural rules on macro-level variables (Murphy 2003). The early paper by Hammel (1979) combines these beneficial features by examining how different behavioural rules about the prohibition of incest affected the viability of small breeding populations, given the likely prominence of kin in the population and the proportions already married; feedbacks, links between individuals and behavioural rules are thus all considered to some extent.

Models of this type give precedents for the introduction of Agent-Based Computational Demography (Billari et al. 2006) in the next section. Before this, however, a brief discussion of the existing models of partnership and households from the economic tradition is offered, with particular emphasis on the models associated with Gary Becker (1981).

Economic approaches

In contrast to most demographic models, economics provides a formal framework defining the process by which individuals are assumed to come to decisions. In the classical micro-economic framework, individuals optimise their package of goods with reference to some ordering of possible packages, usually realised in a utility function (Varian, 2010). The utility function is considered a tool by which agents' preferences over all packages of goods can be represented mathematically. In order to make choice problems solvable analytically within this framework, a number of assumptions are required about the nature of economic agents are required. In particular, they are assumed to have preferences that complete, in that they are able to place all possible packages of goods in order. Preferences are also assumed to be transitive, in that if one good is preferred to another it is also preferred to all goods that are ranked below or equal to that second good. Additionally, assumptions are made about agent’s ability and desire to know and consume the optimal package of goods (ibid).

This discussion is relevant to our purposes because demographic choices can be formulated in economic terms. At base, micro-economics is concerned with how agents pursuing their own interests give rise to aggregate patterns (Mas-Colell, 1995). Gary Becker has been at the forefront of generalising the tools associated with this discipline for use in choice problems outside of the traditional realm of microeconomics, including crime and, more relevantly to our purposes, the demography of the family and the household (Becker, 1960, Becker, 1981). Becker's work on fertility, for example, examine considers that children are a consumer durable like any other, except that households are both the producers and consumers of such goods (Becker, 1960). Prospective parents, then, attempt to maximise the utility they would gain from 'consuming' children, set against the cost associated with 'producing' them. Preferences for children are heterogeneous, determined by 'tastes', that is, by non-economic individual factors exogenous to the model (culture, age, religion and so forth), and may prejudice 'quality' of children (i.e. the amount invested in their education) over quantity. Increases in income will result in more or 'better quality' children based on the relative income elasticity of each property (the assumption being that quality is considerably more elastic).

Such an analysis seems esoteric, as Becker is aware, (Becker, 1960) but it should be considered that it does it least provide an explanation and a formalisation of how and why people come to decisions about childbearing, something that is not always the case in demographic models. Becker provides a similar analysis of the wider workings of the household on his comprehensive "A treatise on the family" (Becker 1981). This describes a number of facets of household life from an economic perspective. For instance, the 'market' for marriage is considered, and the household is conceived of as a production unit in the same sense as the firm, in which inputs are transformed to outputs. Husband and wife are assumed to contract to divide their labour according to specialisation (with men assumed to more often contribute wage labour, and women household/informal labour). Innovations include the introduction of altruistic utility functions, in which utility of one household member depends positively on that of another.

However, Becker's models have come under criticism from a number of directions. In the first instance, the empirical adequacy of some of his models has been questioned. For example, Blake (1968) describes how Becker's fertility model struggles to show why poorer families tend to have more children; this would seem to necessitate a negative income elasticity for quantity of children, which brings in to question whether children can really be considered a consumer durable at all. Differing (culturally derived) tastes might conceivably account for differences between poor and rich families, but if this is the case then one might ask whether the economic model is of any use (ibid). Furthermore there are serious questions over whether modelling marriage as an effective contract and exchange between men and women based on specialisation was ever viable, let alone in a modern environment where women place within society is more equal than ever before.
More comprehensive critiques of Becker's project are made by Potts (2000) and Hodgson (1993) from within the framework of evolutionary economics, and are discussed in the next section as attention is turned to alternative ways of understanding social interaction from within a demographic context.

The Alternatives

Given the short-comings of traditional models of demographic phenomena examined in the preceding chapter, we must consider what alternatives are available. In particular, attention was drawn to the problems existing models have in representing the way agents make decisions and the way in which they interact. Considering demography from within the paradigm of complexity science is one way in which we can begin to recognise the importance of this second oversight. Central to complexity is the premise locally interacting units can give rise to unexpected macro-level effects, a phenomenon described as emergence (Epstein, 1996). Viewing such collections of units as a complete system, then, is essential to understanding how they behave, and given the analytical intractability of problems involving such systemic interactions and feedbacks among large populations, simulation methods are often required to this end.

Complexity science techniques are increasingly being applied in a number of contexts within social science, including demography. Agent based models of social processes have gained particular traction (Epstein 1996). Additionally, the field of evolutionary economics provides innovative ideas about how to model problems of choice and change within such complex social systems. A brief overview of these three fields is offered below.

Agent Based Modelling

The use of agent based simulation (ABS) in social science has gained credence in recent years as an alternative methodology that offers new ways of examining social processes (Epstein 1996, Billari 2006, Gilbert 2005). The potential advantages are numerous. Firstly, ABS allows the specification of interdependencies between the individual (or other 'agent') and the population level, meaning that feedback effects between the properties at the two levels of aggregation can be modelled dynamically (Gilbert, 2005). Secondly, local interactions between individual agents, often crucial in social process involving, for example, the spread of information, can be modelled where they are often ignored in other modelling paradigms (in traditional micro-economics, for example) (Epstein, 1996). Thirdly, population heterogeneity can be easily modelled, in agents attributes, in behaviour, and in the structure and nature of interactions (Epstein, 1996). Fourthly, ABS allows modellers to formalise hypotheses about causal mechanisms that link individual rules of behaviour to macro-level outcomes (Billari, 2006; Gilbert, 2005). Fifthly, and relatedly, the plausibility of these hypotheses can be tested systematically because of the freedom simulation methods give modellers to manipulate variables (ibid). If individual level behavioural rules give rise to simulated macro level patterns that match those observed in the 'real world', then it is at least possible that this causal mechanism is a suitable explanation for these patterns in the real world (Epstein, 1996, Peck, 2004). Finally, the use of behavioural rules allows the onerous data collection requirements needed for, by way of example, micro-simulation, to be sidestepped to some extent, saving expense and meaning that modelling can continue when data is just not available or cannot be realistically measured (Silverman, 2011).

Despite all these advantages, agent-based simulators should not get carried away about the efficacy of their tools. Despite the preceding point about testing the plausibility of causal mechanisms, we must accept that there are huge numbers of possible mechanisms that can give rise to a particular macro level pattern (Oreskes, 1994). Testing the generality and robustness of the relationships observed can increase our confidence in the mechanisms posited (Epstein, 2008), as can grounding them in theory and empirical evidence, whether quantitative or qualitative (Chattoe-Brown, 2011). Another difficulty with ABS is the concern over the extent to which the simulation can be said to correspond to the real world, and therefore the nature of the scientific knowledge that one gains from running and analysing the model (Dopfer, 2004; Rossiter, 2010). The ability of agent-based models to make predictions about the future value of some real variable is certainly questionable, but instead it is suggested that ABS give an understanding of how systems in response to particular stimulus, allowing the running of various scenarios that give an idea of the types of plausible system state (Epstein, 2008; Silverman, 2011; Rossiter, 2010).These misgivings aside, it is argued that these problems are surmountable by well-designed studies that take seriously the task of describing exactly what the nature is of the simulation's correspondence with the system under study, and what scientific knowledge can be gained from the work (Rossiter, 2010).

Surprisingly given the above discussion, and the overlap with already popular micro-simulation methods (eg. Hammel, 1979)), agent based models in demography are still relatively rare (Billari, 2006). There is a long tradition of work following in the footsteps of Thomas Schelling in using ABS to investigate urban segregation (Schelling, 1971; Bruch, 2006), and similarly there has been discussion within and without Demography advocating a greater use of agent-based modelling in examine urban neighbourhoods (Entwisle, 2007), but core demography has not benefited from much Agent-based treatment. One area were agent-based models have been utilised has been in the study of partnership. Billari (2007) modelled agent mate search as dependent on social pressure emanating from their peer groups, with the increased proportion of married agents amongst peers leading to an increase in the intensity of search. Similarly, Hills and Todd (2008) modelled partnership search as an annealing process, with agents looking to marry agents who shared similar characteristics to themselves (modelled as bit strings). The threshold of similarity above which an agent will accept another as a mate declines over time as agents 'lower their standards'. Both these models claim to be able to reproduce marriage hazard rates that are plausible in view of empirical patterns. This perhaps illustrates the problem with ABS mentioned above, that there are many different micro level rules that *could* give rise to macro level patterns; both hypotheses described above about how individuals make decisions about who to partner with produce empirically reasonable macro-level patterns (Oreskes, 1994).

Kniveton et al. (2011) provide another interesting use of demography in the sort of scenario generation role advocated in this report in the context of an examination of the effects of different climate change scenarios on the extent of migration from different regions of Burkina Faso. Agents decision making process depend on their resources and the information they have about the conditions abroad, as well as their mind-set and the local climactic conditions. The model describes how in fact greater effects of climate change do not necessary lead to more international migration, because migration behaviour requires the build-up of assets, which is difficult if the climate damages livelihoods.

These studies aside, agent based modelling appears to offer much to the discipline of demography but as yet has delivered little. Attention is now turned to the literature on evolutionary economics for examples of how agent-based modelling can address questions of change and irrationality in social systems.

Evolutionary Economics

Discussion of economic processes in evolutionary terms can be traced at least back to (Schumpeter1943), who described the way capitalist systems evolve by way of a process of 'creative destruction', a process akin to Darwinian natural selection. There remains controversy over the relevance of the term evolution in the context of economics, as some feel the use of biological terms is inappropriate for a social system, particularly given the past use of Darwinian metaphors to justify racist and reactionary ideologies (c.f Hodgson 1993, Hodgson 2002). Appeals to a biological basis for economics have also been used to justify the particular brand of 'economic imperialism' preached by Becker and others, in which economic tools are applied to the analysis of more general social systems (c.f. Hodgson, 1993; Becker, 1981). In both cases, scarce resources, self-interest and competition are assumed to be universal features of biology, sociology and economics, and 'natural' outcomes from the operation of these forces are generally assumed to give rise to optimal situations. The natural is assumed to be synonymous with the good. In fact, this relies on a somewhat mistaken conception of the nature of evolution and biological systems; in reality, evolutionary forces do not necessarily give rise to optimal solutions as organisms attempt to find satisfactory niches rather than maximal solutions, and self-interest is considered to be relevant in biology at the level of the gene rather than the individual (Hodgson, 1993; Dawkins, 1976).
Furthermore, Potts (2000) makes clear what he believes is another problem with this Neo-classical equilibrium theory. He claims it is built on the underpinning assumption that economic activity takes place on the completely interconnected, continuously integrable field space $\mathbb{R}^n$. This

assumption, Potts argues, is completely inappropriate for economic systems, and is the underlying cause of the majority of heterodox economic critiques of neo-classical microeconomics. The much criticised assumptions of perfect rationality and perfect information and recourse to analysis of static equilibria are all the result of this edict about the nature of economic space; complete interconnection between agents and markets demands that information be complete, and the constraints on preferences imposed by field space make irrationality difficult to treat while maintaining analytical tractability. Neo-classical treatment of time through continuous future markets are again the result of constraints of the field space; time can only be introduced as an extra dimension in the field and then optimised over (Potts, 2000).

In contrast, conceptualising economics as evolutionary allows an understanding of time that is non-reversible; it admits the possibility that individuals can err in their decision making; it gives the opportunity of studying non-equilibrium situations; and can cope with population variation, diversity and local interaction (Hodgson, 1993). These properties stand in marked contrast to the neo-classical framework (Loasby, 1989; Hodgson, 1993; Potts, 2000). Furthermore, evolutionary economic simulation models can take seriously the importance of defining the nature of economic space (Kirman, 2011). For Potts (2000), economic activity must be defined in terms of the connections between elements, and how these change, break and strengthen. These elements might be resources involved in the formation of technology, individuals in the organisation of a firm, or firms within a market or supply chain; but what matters is their configuration and the nature of the connections between them (or, crucially, the lack thereof).

The focus on dynamism and change, and perhaps, its Schumpeterian heritage, means that evolutionary economics has most often been employed in the study of innovation and creativity (Pyka2003, Potts2008). So why should agent-based demographers be interested in evolutionary economic models? While Becker's economic imperialism has been rejected above, there appears to be plenty of overlap between the problems of evolutionary economics and those of demography; both are often concerned with the ways in which people interact and the way in which they approach problems of choice (whether in the market-place or in a family context). Potts (2000) explicitly discusses the prospect of a 'second wave' of imperialism, in which evolutionary economic ideas can be applied to the demographics of the household, and the model described in the next chapter is an preliminary instantiation of a model of household formation, operation and dissolution sketched by Potts in this context.

Model and Methodology

The conceptual scheme that Potts' model is based upon assumes that connections between elements matter; this section follows closely the exposition in Potts (2000). At the lowest level, this means that the development of technology can be modelled as the combination of resources (through connections), with the product of combinations having the potential to be more valuable than the mere some of their parts. New technologies formed by connections of resources can then become new elements in higher-level technologies (that is, technologies formed from combinations of existing technologies). This system-element duality allows the bootstrapping, runaway qualities of technological development to be captured.

Economic agents, then, attempt to form beneficial technologies from the resources that are available to them. Even with a small number of resources, however, the number of possible technologies becomes very large. A 'perfectly rational' agent, in the neo-classical sense, would consider all possible combinations and pick the best. However, this is just not possible for real actors given constraints on time, knowledge and cognition. Instead, then, agents develop heuristic rules about the sort of technologies they want to consume/create. Agents are pragmatic searchers, not hyper-aware optimisers.

How is this modelled in simulation? Agents are endowed with a set of resources, represented by a bit string. Technologies are specific combination of the elements of these strings. In order to work out which elements to connect agents have a population of preferences, each representing a possible combination of resources which is hoped to be a good candidate technology. These preferences are both conjectural and incomplete; agents may find upon constructing the technology that they were wrong to prefer it, and some sites within the bit string are blank, representing parts of the technology that the agent is indifferent about. Referring to these incomplete, heuristic preferences saves agents from having to address the whole search space, and also properly represents the individual irrationality and uncertainty through the incompleteness and falsifiability of preferences.

Furthermore, through allowing preferences to evolve in response to external feedback, agents can adapt to novelty and learn from their environment. This requires submitting the agents' preference population to a genetic algorithm as a proxy for a learning process; in the version of the model created here, a very simple GA was used. Preferences were reproduced in the next generation in proportion to their success in use, while preferences were mutated with a tuneable probability. A number of mutation operators were used following Potts (2000):

- **Point Mutation**: Non-empty preference characters at a particular site can mutate to a different value.
- **Grow Preference**: Preferences of length *n* can grow so that a more complicated technology of length *n+1* is preferred.
- **Shrink Preference**: Preferences of length *n* can be considered too complicated, and the preference string becomes shorter.
- **Fill Preference:** An empty preference sites (where the agent is ambivalent about what element is placed there) is filled, and so the agent becomes more specific about the type of technology he or she prefers.
- **Empty Preference**: A filled preference site is emptied, making the agent less certain about possible good areas to search for technologies.
- **Shuffle Preference**: Elements in the preference bit string are shuffled at random.

One can think of the process of mutation as representing a human tendency to experiment, with possibly negative results. In order to provide feedback to the genetic algorithm, however, it is necessary to somehow score different technologies. This is done on the basis of a predetermined 'utility' function, that is not accessible or know about by the agents, similar to the set-up in (Sayama, 2011). The utility function is designed to reflect Potts' (2000) point about the importance of connection and the non-integrable nature of economic space by ensuring that the order and number of connections in a technology matter, and scores are not just the sum of parts. To this end, a random number is generated for each possible resource value, and a technology is scored by multiplying for each site that element's score by the position in the bit string it holds. Thus, longer resources strings are more disproportionately more valuable, and the same resources will get different scores if they are combined in different ways.

In this version of the simulation, agents are not favoured with any demographic characteristics - they are sexless, ageless, immortal network dwellers. However, demographic characteristics are latent in the underlying code, and there in future work on this topic it may be possible to utilise such characteristics. Additionally, resources in this case are psychological or otherwise internal to the agent, and may not be traded or used up.

Interaction

At present the focus has been only on individual agents, and not on their interaction. In this simulation, agents choose to interact with other agents based on a tag-matching process. One element from each agents preference population is 'displayed' during each interaction. If these preferences match, in the sense that each site in the other agent's preference string the element either matches the other agents or has an indifferent "#" (empty) character, the initiating agent may access the other agent's resource set in order to attempt to form a technology based on the preference displayed. Any resulting utility is attached to the relevant preference string in both agents, to inform the reproductive success of that preference. However, only the additional cost over and above what could have been obtained by that agent exercising the relevant preference alone is counted, to account for opportunity cost the interaction represents.

A single model time-step, then, involves a large number of attempted interactions between agents (scaled to allow enough interactions to ensure sufficient feedback for each agents GA), and then the reproduction of agents preferences according to the relative success of these interactions. In a more sophisticated model, an attempt would also be made to model partnership by allowing the creation of combinatorial 'multi-agents', where resources, technologies and decision-making, preferences and interaction could all be shared. This has been left for future work, however.

The Network

As has been intimated, the effect of interaction between agents depends not only on their nature but on how they are structured. Clearly, not all individuals in any moderately large population will interact regularly with every other agent. The obvious way to capture this is to embed agents within an network, where network vertices represent agents, and edges between agents representing that the two agents know each other and come into regular contact. Agents can then only interact with their network neighbours. The question is then what type of network the agents should be embedded in. The structure of networks has generated voluminous literature, with discussion of their small world nature and the nature of their degree distributions (Newman, 2003). Given the exploratory nature of this study, there has not been a great deal of focus placed on what type of networks the agents should be initialised on, and instead, the varying effects of parameters on the same type of initial network has been examined.

The framework developed by Watts and Strogatz (Watts, 1998; Watts, 1999) was used to generate the initial network; the parameters used for this purpose are given in the appendix (along with other parameters settings), and aim to initialise a network in the small world realm, that is, with an average shortest path length that is close to that for a random graph of the same size, but with a clustering coefficient that is much higher than the random equivalent (ibid). When considering dynamic network behaviour, some simple rules were postulated as to how network links could be created and destroyed along the lines of those proposed by Jin, (2001), but with edge weight data generated from the interactions between agents. Again, in a more specific application of the type of model explored here, a more rigorous and empirically grounded approach to setting these rules might be adopted, but for the present purpose simple rules were assumed to suffice.

In this instance, then, each agent rewires one of his network connections with a certain probability each time-step. Edges are weighted by the past utility attached to interactions between the two agents the edge connects, and this weight decays exponentially with time. An agent rewires by disconnecting his weakest neighbour, and adding an edge to one of his strongest neighbour's neighbours. For some simulation runs, in common with Jin (2001), the degree distribution of agents was managed probabilistically so that it remained close to its initial value.

A single model time-step, then, involves a large number of attempted interactions between agents, and then the reproduction of agents' preferences and the modification of network ties according to the relative success of these interactions. In the version of the simulation reported here, agents are not favoured with any demographic characteristics - they are sexless, ageless, immortal network dwellers.

Results

The previous sections attempted to motivate the use of agent based models with roots in network theory and evolutionary economics for use in better understanding processes underlying the demographics of the household, and described the features of the prototypical model used here to examine the feasibility of such a project. We now move on to describe how this model behaves so that its suitability for investigating demographic phenomena can be assessed. The highly abstract and exploratory nature of the model means there are a large number of variable parameters, and a larger number of possible 'structural' changes (involving making different assumptions about the processes that underlay the model behaviour) that would likely change model behaviour.

No attempt is made to try and systematically explore all elements of the parameter space in this section. Instead, some particular facets of the model are described that might be considered particularly relevant given the motivations for model building discussed above. Of particular interest are the effect on the evolution of preferences of the topological structure of interactions, the interaction between the processes of preference formation and network evolution, and the extent to which the types of resources and complexity of technologies that agents may form in their interactions with each other effects the overall model behaviour.

The model described in this section was coded in Python 2.7, and the Networkx Python package was used to handle network formation and evolution[1]. The R statistical programming language was used for analysis and graph plotting. Simulations were run with 200 agents only, for 400 time-steps in the case of dynamic networks, although longer run simulations were explored. Each parameter setting was run for 8-10 iterations in order to gain more robust results. Score values for resources elements were randomly assigned, but were set just once and kept the same between different parameter runs, as these were found to have a significant influence on the behaviour of the system.

Structure in Interaction

One of the primary contentions of the evolutionary economic approach is that the structure of interactions between matter (Potts, 2000; Kirman, 2011). Using the model constructed above we can observe how the agent's preferences and utility differ when they interact with other members of the population at random to when they interact only with their neighbours. Similarly, we can consider the differences between static and dynamic networks.

[1] The current version of the model code is available at https://bitbucket.org/jhilton/evoeconhousehold

Figure 1: Comparison of Average Agent Interaction Utility on Different Network Types

a) Agents endowed with 10 resources **b) Agents endowed with 5 resources**

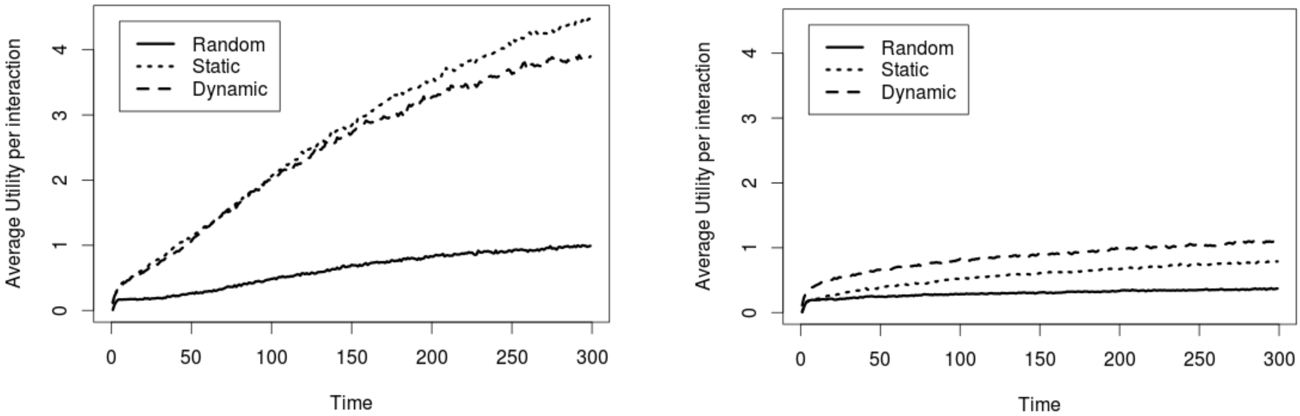


Figure 1 displays how average utility gained from interaction increases over time for random interactions, and for dynamics and static networks. As might be expected, when agents are forced interact with agents at random amongst the population, they are unable to gain enough information from these interactions to adapt their preferences in any useful way and therefore receive a low return in terms of utility. Because they have interaction with such a large number of other agents, they do not meet the same agent again frequently enough to evolve preferences to deal with that situation; the amount of noise in the system is too large.

When we consider the behaviour of a static network in figure 1a we see a rather different picture emerging. Because agents always interact with the same agents time and again, they quickly evolve mutually beneficial preferences, and are able to gain rewards in terms of utility, and hence agents on static networks have higher utility rewards than their equivalents on dynamic networks or in randomly interaction populations.

A dynamic network, where agents tend to meet the same agents repeatedly, but in which they rewire their connections according to the success of their interactions, shows slightly lower average utility than in the case of static network for our default parameters. Here, the need to cope with novelty would appear to require more time adapting, which results in lower utility overall. However, if we alter the number of resources each agent holds, dynamic network agents actually perform better than those on a static network because, it is suggested, of their ability to 'search out' agents with useful resources, who are now less likely to already be in the agents neighbourhood. This effect can be seen in Figure 1b; note that overall level of utility is much lower, however.

These results are not unexpected, but it is worth drawing attention to here because of the link to neo-classical economic models: the idea of local interactions is meaningless in these sorts of models, as is the idea that agents are unable to find an optimal solution to their trading. Thus, the introduction of evolved preferences and network interaction to our model helps shows how microeconomic assumptions might be misleading, although this result is fairly trivial and perhaps does not require simulation to infer.

Network Evolution

We have seen how, when embedded in a dynamic network, agents evolve preferences that enable them to interact with each other and increase their utility. But how does the topology of the network in which they are embedded behave? The results presented so far have been produces of models where agents are constrained to remain close other initial average degree distribution, by introducing a probability of break or making a tie that is proportional to the extent to which that agent is over- or under- connected; this can be interpreted in terms of the cognitive or social constraints on the number of friends it is possible to maintain (Jin, 2001).

Figure 2: Network Clustering and Average Shortest Path Length over the course of the simulation

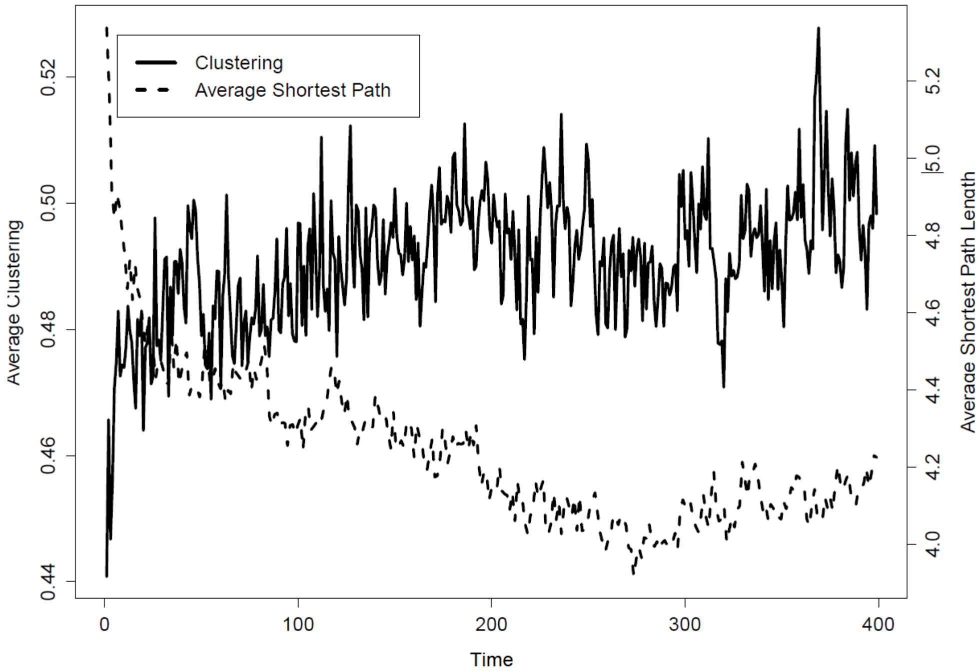
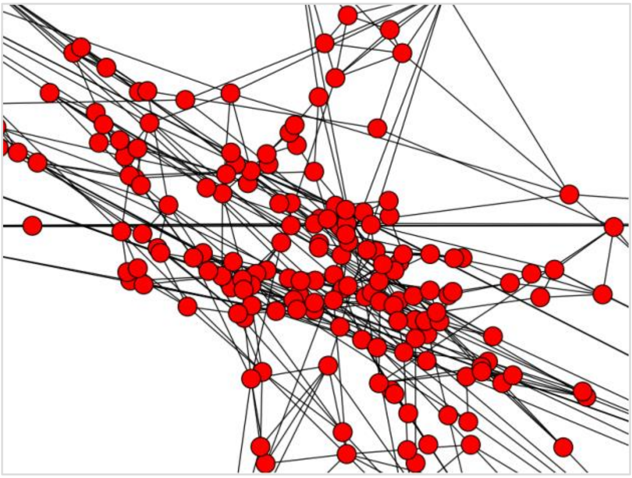


Figure 2 shows how the clustering and shortest path length statistics for such a model. These seem to indicate a 'small world' type model, with an average path length close to the random equivalent (around 4 in this case), and a level of clustering that remains high. Figure 3a displays the topology of a similar network (albeit one based on slightly different parameters). Distinct clusters are visible, as well as the more disconnected individuals who are off screen on this image.

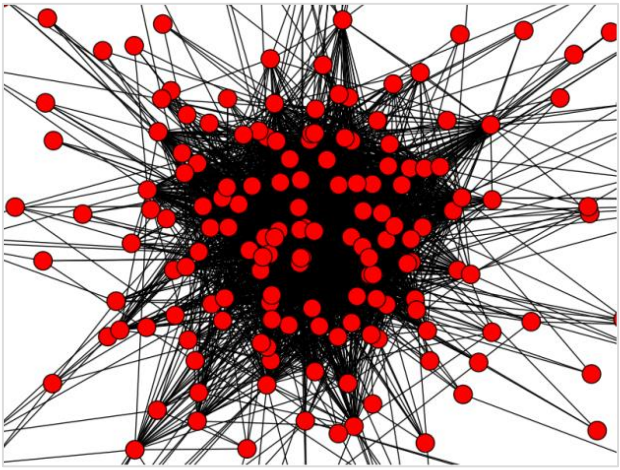
It is also possible to allow agents to gain as many links as they want, and not attempt to lose edges if they become over connected. In this case, the graph tends to approximate a random graph relatively quickly, and a super-connected cluster of nodes with high degree distribution dominates the group, as in figure 3b Degree distributions in such a case follow a familiar scale-free type pattern, with large numbers of low degree nodes and ever fewer numbers at higher degrees, although the fit of this curve was not explicitly examined. Instead, the decision was made to focus on the case were numbers of 'friends' remains roughly equal across agents (Jin, 2001).

Figure 3: Visualisations of simulated networks

a) Constrained number of network neighbours



b) Unconstrained number of neighbours.



Preference Evolution

So far we have not discussed in detail the process of preference evolution and the nature of populations produced, the so called 'meso-level' of evolutionary economics (Dopfer, 2004). Figure 4 shows details of the distribution of certain properties of agents' individual preference populations, across all agents and all simulation runs on the default settings. We see that agents tend to evolve preferences that have some outward facing sites, that is, some of their preference sites refer to resources held by other agents, indicating that agents are indeed evolving preferences to facilitate interaction with others.

Similarly, the maintenance of some heterogeneity in the preference populations (Figure 4c) by almost all agents suggests that agents maintain flexible preferences that allow them to interact with more than one neighbour[2].

Intriguingly, ad hoc comparison of the preference strings of neighbouring agents suggests that 'interlocking' preferences are developed, where blank sites on one agent match with filled sites on a neighbour, suggesting that tag matching drives the preference selection process. This may explain the varying distribution of 'filled' (ie non-blank) sites in figure 4b. A more systematic approach to investigating this process is required for future work however, however. Less interesting is the convergence to longer preference strings (figure 4d) as these provide more utility by design, it is unsurprising that preference have converged towards this value. It does provide some indication that the GA is having the desired effect, however.

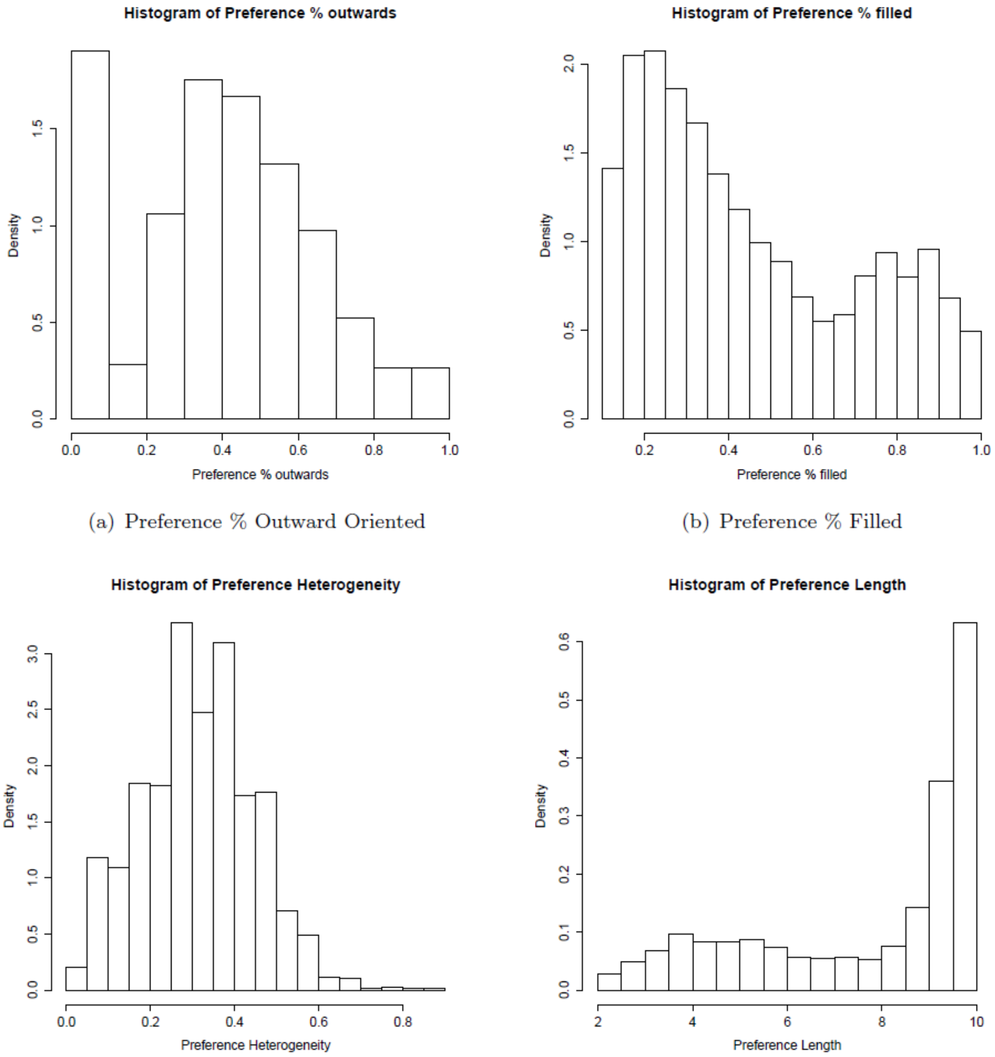
Neglected areas

As previous intimated, the nature of the model means that the potential variations that could be examined are very large. The above results do however give a flavour of how the model behaves. However, other investigations could potentially form interesting areas for examination. For instance, the tag-matching process by which the agents transmit information to one another was not examined here. Similarly, the effect of the relative time-scales on which the network and the preference evolution occurred was examined only briefly through manipulation of the rewiring probability, and the full effect on edge persistence was not examined. The effect of the way in which combinations and interactions were scored was also overlooked - this looks to be a

[2] Heterogeneity is measured here as the number of unique preferences in the population over the preference population size for each agent (50), giving a range from 1/50 (very homogenous) to 1 (very heterogenous)

potentially significant parameter if few resource types are involved, given that a large difference between runs was found if the randomly generated scores attached to resources values were allowed to vary between runs.

Figure 4: Preference Population Metrics



(a) Preference % Outward Oriented

(b) Preference % Filled

(c) Heterogeneity Index

(d) Preference Length

Discussion

The model described above provides a point of departure from statistical and microeconomic models of social interaction in that it allows a hypotheses about the process underlying interaction to be modelled, and recognises the importance of locality and imperfect information. The model also maintains in the medium term a structure that fits some authors' characterisation of social networks (Watts 1998, Jin 2001), and takes seriously the importance of history and chance; an agent's evolved preferences will depend upon what other agents it has happened to be connected to through the network structure.

The addition of full demographic characteristics including birth, death and household formation onto the generalised model of interaction discussed in this above, and the introduction of a threshold network link strength above which a household can be created, allowing the modelling of partnership by the creation of combinatorial 'multi-agents', where resources, technologies and decision-making, preferences and interaction can all be shared. This will also allow the creation of hazard rates for 'marriage' and 'divorce', as the passing of these thresholds can be treated as demographic events.

Statistical emulation techniques developed for use in analysing complex computer simulations (Oakley and O'Hagan 2002, 2004) can then facilitate the calibration of the model to empirical data on partnership formation. The hypotheses of Potts (2000) and Hills and Todd (2008) regarding a link between increased 'cultural complexity' and the tendency towards later partnership formation can then be tested. This will be achieved systematically varying the parameters relating to individual resources as a proxy for such complexity, and examining the temporal pattern in the resulting simulated partnership hazard rates. Additionally, the effect of different networks structure and search strategies on such hazard rates can then be tested and observed. Having a test bed for examining the relationship between demographic outcomes and social network evolution is potential of value to the discipline; particularly given greater concern in recent years with how social networks affect demographic outcomes (Montgomery et al. 1998, Entwisle 2007).

Conclusion

The work detailed in this paper makes two small contributions to our understanding of how social networks affect demographic outcomes. **Firstly**, it describes a plausible model of social interaction over a dynamic social network, in which agents have incomplete, evolving and falsifiable preferences as to who they would like to interact with. Given the importance of social interaction to demographic outcomes, this may prove a useful point of departure for future work. **Secondly**, a version of this model augmented with demographic attributes could be used to examine how the nature of the networks on which social interactions take place affect partnership choice and household formation – it is hoped that future work will address this challenge.

A wider research agenda, inspired by the suggestions of Chattoe-Brown (2009), might consider the opportunities for integrating qualitative data with agent-based social interaction models such as the one described here. Rich micro-level ethnographic or interview based detail about the structure of social networks and/or the nature of human decision making should be formalised in agent-based simulations, and the causal implications for macro-level population change examined through experimentation.

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