
Employing Agents to Develop Integrated Urban Models: Numerical Results from Residential Mobility Experiments

2

Oswald Devisch, Theo Arentze, Aloys Borgers,
and Harry Timmermans

Abstract

Multi-Agent systems are a powerful technique to analyse spatially distributed systems of heterogeneous autonomous actors with bounded information and computing capacity who interact locally. A review of recent urban models relying on multi-agent technology learns however that these models at best only start to explore this potential. In this paper, we present a model, simulating the process of residential mobility, fully exploiting the agent-potential, integrating behavioural concepts such as joint-decisions making, bounded rationality, pro-active reasoning, cognitive mapping, etc. We will discuss the conceptual framework, analyse some numerical results and make suggestions as to how to validate such an ‘artificial-society’ model.

Introduction

Judging from the recent number of publications, conference-proceedings, and research projects, multi-agent systems seem to be a highly popular technique to develop urban simulation models (Batty 2005). One way to explain this popularity is to refer to the anthropomorphic character of agents. According to Epstein (1999) “agent-based modelling is especially powerful in representing spatially distributed systems of heterogeneous autonomous actors with bounded information and computing capacity who interact locally.” (pp.42). Such a tool in effect allows modelling (spatial) behaviour at the level of individual decision-makers with each decision-maker pursuing own goals, exhibiting a unique lifestyle and life-course, based on a personal cognitive representation of his/her environment, perceiving and learning

O. Devisch • T. Arentze • A. Borgers • H. Timmermans (✉)
Urban Planning Group, Department of Architecture, Building and Planning, Eindhoven University
of Technology, P.O. Box 513, Eindhoven 5600MB, The Netherlands
e-mail: H.J.P.Timmermans@bwk.tue.nl

this environment on the basis of own experiences, being part of a self-selected social network, interacting with other agents according to own standards, etc.

To give an indication of the popularity of multi-agent systems, the following list is a selection of agent-based models only addressing the process of residential relocation: *sprawlSim* (Torrens 2001), *Obeus* (Benenson and Harbash 2004), *Abloom* (Otter 2000), Diappi's gentrification model (Diappi and Bolchi 2006), *Mabel* (Lei et al. 2005), *Sypria* (Manson 2005), etc. In spite of this list and in spite of the fact that agent-based models already circulate within urban planning for almost a decade (e.g. the *Free Agents in a Cellular Space* models developed by Portugali (2000) date from 1999), hardly any appears to exploit the potential of multi-agent systems as advocated by Epstein. Agents in *sprawlSim* (Torrens 2001), for instance, might indeed pursue goals in that they are constantly searching for housing best matching their preferences (regarding the typology and tenure type of the house, and regarding the socio-economic and ethnic composition of the neighbourhood), and might indeed exhibit unique life-courses (consisting of three life-course-stages: young, middle and senior), but they have no cognitive representation of their environment, do not learn, are not part of a social network, etc. A similar assessment can be made of all other listed models, suggesting that these models typically address not more than one behavioural concept (e.g. information search in case of the *Abloom* model), with the intention of only reproducing one particular (spatial) phenomenon (e.g. gentrification in case of Diappi's model). One of the reasons for this sub-optimal usage of the multi-agent potential is the complexity inherent in these systems. Though such models, because of their anthropomorphic nature feel intuitively correct, the incorporation of abstract behavioural concepts (e.g. learning and anticipation) and the high number of attributes (e.g. agent and environment characteristics) render validation of multi-agent systems against empirical data a sheer impossible task. Moreover, a coherent theoretical framework integrating the above behavioural concepts does not exist (Waddell 2001). The listed models try to circumvent these difficulties by limiting the number of behavioural concepts and considered attributes, as such excluding themselves of ever fully exploiting the potential typical of multi-agent models.

The model presented in this paper is developed to explicitly employ this potential. Rather than limiting the number of concepts or attributes, we chose to limit the research-scope of the model: only addressing one clearly framed spatial process, namely residential mobility. Residential mobility refers to the process of households making short-distance moves, moves typically not related to a change in job, as opposed to migration referring to households making long-distance moves, typically caused by a change in job (Dieleman 2001). To even further frame the research-scope only the behaviour of a particular population segment is modelled, namely that of students at the University of Eindhoven, being the second largest university in the Netherlands. The model framework is general enough though to be applicable to households in general. Within the context of student residential mobility, the model then integrates the behavioural concepts, listed earlier, in one framework, and proposes a method to validate the model.

The paper is structured as follows: section “[Empirical Findings and Conceptual Framework](#)” lists a number of empirical findings related to residential mobility in general, and describes how these findings are integrated in a conceptual framework only considering students. Section “[Validation and Model Implementation](#)” illustrates how this framework is implemented paying special attention to the issue of validation. Section “[Model Experiments and Numerical Results](#)” summarizes and discusses a selection of numerical simulation results. Section [Conclusions and Discussion](#), finally, rounds off with some conclusions. As the title suggests, the focus of this paper is on numerical results. The conceptual framework (section [Empirical Findings and Conceptual Framework](#)) and the framework implementation (section [Validation and Model Implementation](#)) are, for this reason, only briefly introduced. For a more complete description, see Devisch (2007).

Empirical Findings and Conceptual Framework

McCarthy (1982) classifies moving as a complex behaviour entailing a series of choices rather than one single decision. Those choices, which may not all be present in every case, include the decisions to consider moving, to undertake an active search, and whether and where to move. This classification has since been adopted by a number of scholars (e.g. Clark and Flowerdew 1982; Fransson and Mäkilä 1994; Goetgeluk 1997; Oskamp 1997; Dieleman 2001), and forms the starting-point of this research. The three-stage process is based on the assumptions that households always have an ideal house and housing environment in mind, a situation perfectly answering the needs of the household, and that moving is motivated by the household’s desire to reach this ideal situation (McCarthy 1982). Mostly, this ideal house (or ‘desired housing circumstances’ as referred to by McCarthy) is simply the house the household is currently living in, or is at least very similar to this house. Over time though, needs and desires might change, as well as the house and housing environment. Because of these changes, the ideal and the current situation no longer match. The factors causing this discrepancy are referred to as triggers, ‘triggering’ the household to re-consider its current housing-situation. As long as this discrepancy remains acceptable, considerations will remain considerations. Beyond a certain threshold however, this discrepancy might reach such proportions that the household decides to take action. In the context of housing, actions to improve one’s situation could be moving house, renovating the current house, changing job, renting out a room, and so on. Note that moving is thus not an end in itself, but rather a means to restore a situation that grew wrong (McCarthy 1982). The choice of action depends on how close this action will bring the household to its desired housing circumstances. Each action requires effort, constraining the choice. The decision to consider moving can for this reason be interpreted as a double decision: firstly deciding whether to become dissatisfied or not, and secondly deciding which action to pursue. The first decision is based on triggers, the second on constraints. Triggers could be said to be either related to the household itself, such as, for instance, changes in the life-course of the household

(e.g. marriage, birth of children, etc.) (Oskamp and Hooimeijer 1999), changes in the employment situation (Dieleman 2001), etc.; or to the housing situation of the household (van der Vlist et al 2001), such as, for instance, the need to modernize the house, changes in the direct neighbourhood (e.g. lack of parking-space, a feeling of unsafety, etc.), changes in the relative environment (e.g. closing of a school, a shop, etc.), changes in the social environment, etc. Constraints evidently include financial resources, but also factors such as, discrimination (Clark and Flowerdew 1982), attitudes and norms (Lu 1998), knowledge regarding the housing-market, etc.

In case the household indeed considers moving, it will have to search for candidate houses to move to. Searching involves a number of decisions: what to search for, where to search, how to search, how long to search, which selection criteria to take into consideration (Huff 1982). The high number of decisions plus individual time constraints and (lack of) search experience lead households to adopt highly personal search strategies, ranging from superficial to exhaustive searching. Search strategies can evolve over time: the more urgent the objective, the less exhaustive the search will be. Independent of the objective, household can either search through interaction with their environment (e.g. driving around), or through interaction with media (e.g. newspapers, Internet, social networks, real-estate firms, etc.). In case the search is successful and the household did collect a number of promising candidate houses, it will have to choose one to move to.

Choosing implies evaluating and selecting. A household chooses on the basis of a number of evaluation criteria. The type, number and relative importance of these criteria might vary among the members of the household, requiring negotiating to overcome possible variations in preferences (Molin 1999). Households are assumed to choose among alternatives on the basis of expected consequences of these alternatives. In most cases, though, these consequences are not known with certainty. Rather, decision-makers have some (subjective) beliefs regarding the likelihood of various possible outcomes (March 1994). Choosing thus involves risk, having to make decisions without being totally certain. A decision-maker can portray more or less risky behaviour, referred to as risk-seeking versus risk-averse behaviour. A choice either leads to an improvement or to a worsening of the current situation. A risk-averse individual assigns a bigger weight to the possibility that it will worsen than that it will improve; a risk-seeking does the opposite. In the situation where all household members agree upon the choice of a dwelling and the household agrees with the real-estate firm selling the house upon a transaction-price, the household moves.

In most cases, this three-stage process of considering moving, searching and choosing is not a linear process. Factors such as time-stress, a limited housing supply, insufficient resources, discrimination, and so on, might make that the household is forced to revise its original expectations, modify its moving goals, and as such may have to keep on searching, move into alternative, less-preferred dwellings or even abandon the consideration of moving all together (McCarthy 1982; Goetgeluk 1997; Dieleman 2001).

Households make decisions in a housing-market, so that the choice-behaviour of one household has repercussions on the choice-behaviour of other households: an

increase in turnover rate in the housing stock might, for instance, increase housing prices, limiting the opportunities of other households to move. In other words, there is a reciprocal relation between the decision of the single household and its residential environment (Dieleman 2001). It is this reciprocal relation that Epstein (1999) tries to capture in his artificial agent societies: the idea is, that by modelling behaviour at the level of individual agents, and by letting these agents interact, these interactions will scale up to regularities observable at the macroscopic level. Empirical research indeed confirms the existence of these regularities. Related to residential mobility, a distinction can be made between regularities related to the household population and regularities related to the housing-market.

A first population-regularity is, for instance, the so-called ‘housing-ladder’; households do not seem to move randomly but instead move according to a ‘hierarchy of tenures’, dictated by the stages of their life-course: in the Netherlands newly formed households typically move into the private rental sector before they access the owner housing market, to then, in due course, move up to larger and more expensive owner-occupation (Goetgeluk 1997; van der Vlist et al. 2001; Clark and Huang 2003). In reality though, because of ample economic resources and lack of supply, households often remain stuck somewhere along this ‘ladder of success’ or even move back down the ladder, as is for instance often the situation in case of divorce. A second population-regularity is known as ‘geographical sorting’; “The uneven spatial distribution of the housing stock, defined in terms of quality, tenure, and price, leads to a geographical sorting of households by type, income, and race over the urban mosaic” (Dieleman and Mulder 2002, pp.48). Or, as Waddell puts it “Birds of a feather flock together” (2001, pp.8), implying that neighbours are often similar in socio-economic characteristics, lifestyles and consumption behaviour.

Housing-market regularities, on the other hand, are, for instance, the existence of sub-markets, typical of markets trading in heterogeneous goods (Clark and Van Lierop 1986), each with highly differentiated prices and housing-regulations. As traded goods become more heterogeneous, markets become increasingly thin, and the true market value of the good becomes less well known. Under these conditions, prices are influenced both by the characteristics of the products or services in question, and by the bargaining skills and power of the buyers and sellers (Harding et al. 2003). Because of the existence of these sub-markets and because households only purchase houses infrequently, with a small proportion of households active at any time, “small changes in aggregate behaviour of a few households can, locally at least, have a significant effect on prices” (Alhashimi and Dwyer 2004, pp.4). A second housing-market-phenomenon is related to the fact that the construction of new housing is a complex and time-consuming process. As a result, the housing-market can only slowly react to changes in demand (van der Vlist et al. 2001). This slowness is even further increased by government regulations, subsidies and taxation, credit rationing, patterns of ownership, and so on. As a result, in a market with no vacancy and a high demand, a tiny increase in supply will dramatically increase the prices. Both regularities suggest that a housing-market is never in equilibrium.

Recall our ambition of developing an urban model fully exploiting the agent potential. This ambition will only then be attained when the model is able to

generate the above macroscopic regularities (i.e. both on the level of the population and the housing-market) by modelling the described three-stage process of considering moving, searching and choosing.

As mentioned in the introduction, residential mobility is, in our model, limited to a particular population-segment, namely students studying at the Eindhoven University of Technology. This leaves us with two types of agents: students and landlords: students search for residences to rent and landlords offer residences for rent. Each single student, or agent, is defined by a set of six characteristics, namely: gender, age, study-year, budget, whether or not he/she is living with his/her parents, and whether or not he/she is living together with another student. Similarly, each residence is defined by a set of six characteristics, namely: residence-typology, residence-size, dwelling-typology, dwelling-size, relative location and population-type. All students entertain a particular lifestyle made explicit through their preferences, regarding housing, activities (e.g. studying, sporting, going-out, etc.), and luxury goods (e.g. clothing, hobby, etc.). We assume that students always try to improve, or at least maintain, their current lifestyle. Over time though, this lifestyle may change; either because of changes in their life-course –a student might, for instance, meet a partner with whom he/she wants to live together– or because of changes in their living environment –for instance, cheaper and better housing might become available. Consequently, we assume students to have a constantly changing latent demand for alternative housing, which becomes more dramatic when the discrepancy between needs and preferences and the current housing situation becomes more dramatic. In contrast with the empirical findings, we assume in this research that only life-course changes will trigger a student to consider moving. Concretely, on the basis of the student-characteristics and -preferences, seven student-profiles and ten preference-profiles are defined. Student-profile 1, for instance, refers to students who are not yet in their third year and still live with their parents. Preference-profile 7, for instance, refers to students having a preference for living in a one-room apartment, located in the centre of Eindhoven. With each change in student-profile, the student potentially changes preference-profile. The student will thus only consider moving, the moment he/she changes preference-profile. The probabilities that any of both changes occur are captured in transition-probability tables composed on the basis of statistical data provided by the University, three surveys, and assumptions.

We assume furthermore that students will not only react to these changes as they occur, but will also try to anticipate these changes, as such behaving pro-actively. Practically, each student continuously evaluates whether it would be more beneficial to move to an alternative residence, to move back to the parental home, or to stay in his/her current place of residence. This evaluation is based on the utility the students expect to derive from pursuing any of these actions. We assume in this respect that students are boundedly rational (Simon 1955), i.e. that they do not (fully) know the future consequence of present activities, and that they only have access to limited amounts of information. Consequently, students make decisions on the basis of their cognitive knowledge regarding their housing-market, such as knowledge about the availability of particular residence-types, the price-category of

these types, the relative location, etc. Given that most students only move a limited number of times during their student-career, this knowledge will evidently be incomplete. Students will thus have to search to increase this knowledge by consulting lists of residences for rent, denoted as information-sources, and representing, for instance, newspapers, Internet sites, but also social networks, etc. Information-sources typically only provide partial information on the listed residences, for instance telling nothing about the presence of communal spaces, the amount of natural light, sound-insulation, etc. The assumption is therefore that once a student found candidate alternatives, he/she will always visit these alternatives for inspection, gaining full knowledge. On the basis of this knowledge, the student then selects the alternative best meeting his/her preferences, and will finally negotiate, in agreement with a possible partner, with the landlord over a price at which to rent the residence.

As pointed out in the empirical findings, this process of searching, visiting, and negotiating is rarely a linear process, but can rather be described as a co-evolutionary, partly recursive process in which students explore only fragments of the housing-market and collect information to various degrees of detail, thereby simultaneously updating their knowledge, in this way reducing uncertainty.

Validation and Model Implementation

As mentioned in the introduction, one of the reasons that the potential attributed to multi-agent systems, to date, has not been fully exploited, is the difficulty of validating such systems. In their article 'Modelling and prediction in a complex world', Batty and Torrens (2005) point out two rules that are, in their words, central to the process of developing good models: the rule of parsimony and the rule of independence in validation. True multi-agent systems are in principle not able to meet both rules. The rule of parsimony (also known as Occam's Razor) states that one model is better than another one if it can explain the same phenomena with a lesser number of intellectual constructs. The large number of attributes and behavioural concepts, inherent of multi-agent systems results in a virtually infinite number of possible system states, turning the comparison of two alternative agent-models (and thus the question as to whether one model is more simple than another one) into a sheer impossible task. The rule of independence in validation states that a theory, which is induced using one set of data needs to be validated against another independent set. The difficulty here is that agent-based models typically require more data than is available, and as Parker et al. (2003) argue, rely on abstract concepts, such as learning and trust, which are often ill-defined or not easily measured. In both cases, this goes at the expense of validation.

On the basis of these arguments, one can only conclude that it is impossible to develop good agent-based models (i.e. models meeting the rule of parsimony and the rule of independence in validation). Looking at why these two rules are defined in the first place, Batty and Torrens come up with 'prediction': "a traditional model gets the present right in order to predict the future" (Batty and Torrens 2005, pp.758).

True multi-agent systems, in contrast, can, because of their virtually infinite number of possible outcomes, never claim any definite prediction. The purpose of developing such systems thus has to be sought elsewhere. Epstein (1999), in this respect, comes up with the proposal to employ agent-based models to conduct, what he refers to as “laboratory science”. Rather than making predictions regarding the direction in which particular phenomena might evolve, the purpose is to try and understand the principles governing these phenomena: “One can do perfectly legitimate ‘laboratory’ science with computers, sweeping the parameter space of one’s model, and conducting extensive sensitivity analysis, and claiming substantial understanding of relationships between model inputs and model outputs, just as in any other empirical science for which general laws are not yet in hand” (pp.51). Within the four walls of the lab, agent-based models could help tracing the ramifications and boundary conditions of theories and hypotheses, running plausibility checks on the empirical expectations that flow from theories, and systematically testing alternative explanations. Parker et al. (2003) summarize the benefits of what they refer to as ‘explanatory models’ as follows: “they allow modellers to: (1) demonstrate that a set of rules can lead to the outcome of interest – test theory; (2) explore other possible causes that could lead to the same outcome – formally exploring the robustness of the proposed causal explanations; and (3) discover outcomes not originally anticipated” (pp.326). Benefits that, according to Oskamp (1999), can even be more enlightening than uncertain forecasts.

Adopting ‘understanding’ as the purpose of agent-based models would imply that the criterion for such models to be labelled ‘good’ would in the first place be ‘transparency’: in order to (substantially) understand the relationship between input and output, one needs to be able to continuously trace back cause and effect, and link both to actual data and observations, or to intuition or present knowledge. This last requirement is particularly important to guarantee that the generated patterns and behaviours are not just the result of system artefacts, but indeed correspond to real life phenomena. In search of this transparency, Epstein (1999) talks of reality as “a massively parallel spatially distributed computational device with agents as processing nodes”, all paying tribute to the laboratory-science-motto “If you didn’t grow it, you didn’t explain its emergence” (pp.43). With this in mind, we can add a second criterion characterizing a good multi-agent system, namely: the more macro-regularities a set of micro-specifications can generate, the better the model.

Before we describe the actual numerical results from our residential-mobility experiments, let us first illustrate how we tried to meet the two ‘agent-validation-rules’ – transparency and number of macro-regularities- potentially allowing us to integrate all the behavioural concepts summarized in the conceptual framework. Regarding the second rule, maximize the number of generated macroscopic regularities, we are, as we will illustrate in the next section, indeed able to generate most of the regularities described in the previous section by only modelling the three-stage process, such as, the existence of a housing-ladder, sub-markets, a housing-market in disequilibrium, etc. Regarding the transparency rule, transparency is pursued, firstly, by translating all behavioural concepts to one behavioural

PROBLEM AREA	
C	condition set
condition space	
A	action set
action space	

Fig. 2.1 General structure of a decision table (Figure from Verhelst (1980))

principle, namely the concept of utility maximization, and, secondly by implementing the conceptual framework incrementally, introducing behavioural concepts one by one, as such allowing for a gradual validation, in that initially, the number of constraints is set to a maximum reducing the number of potential interferences to a minimum. Gradually, the number of constraints is released, adding more complexity (and thus uncertainty). With each step, not only the input of the model but also the phenomena emerging out of the model, come closer to reality. In total six, so-called, scenarios are developed, starting with the relatively simple case of unboundedly rational students, making non-joint decisions in a stationary housing-market, and ending with pro-active boundedly rational students, making joint decisions and negotiating with landlords in a non-stationary housing-market. Four of these scenarios will be addressed in this paper. For the remaining two, we refer to Devisch (2007). To even further increase this transparency, we adopted three formalisms to structure the conceptual framework: Decision Tables, Activity Diagrams and Decision Trees, returning in each scenario, making the assumptions relevant to that scenario explicit. As the number of behavioural concepts increases, the formalisms grow more complex. Let us now shortly situate all three formalisms.

A Decision Table is “a table that represents the exhaustive set of mutually exclusive conditional statements within a pre-specified problem area. It displays the possible actions that a decision-maker can follow according to the outcome of a number of relevant conditions” (Verhelst 1980, pp.9). As Fig. 2.1 illustrates, a Decision Table is composed of a condition set, a condition space, an action set and an action space. The condition set holds the premises (or conditions) an action has to meet to answer the problem specified in the problem area. The condition space holds all the values these conditions can take. The action set collects all potential actions the decision-maker can pursue under the listed conditions. The action space collects the potential action-states of each action. Any vertical linking of an element out of the condition space with an element of the action space generates an if-then decision-rule: if condition X has value Y then pursue action Z. In our model, Decision Tables are employed to represent the cognitive image of an agent regarding his/her environment. We will return to this in the next section.

Activity Diagrams are a class of diagrams developed within the Unified Modelling Language (UML) -a standard language for specifying, visualizing, constructing, and documenting engineering artefacts in object-oriented software (Bauer et al. 2001). The main reason to particularly use Activity Diagrams is to model the workflow behind such artefacts. An Activity Diagram (such as the one in Fig. 2.2) is composed of forks, branches, and activities: a fork is used in situations where multiple activities occur at the same time, for example, when performing an

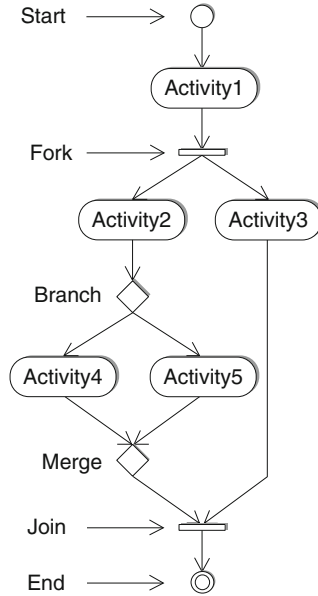
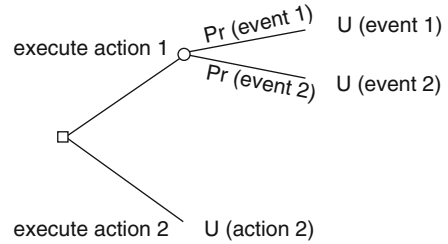


Fig. 2.2 Example of an activity diagram (Figure from Gooch (2000))

activity, an agent – at the same time- collects information on his surroundings. A branch is used in situations where the choice of activities depends on a set of conditions, for example, an agent having to decide whether to move to a new house or stay in the current house. A branch is always followed by a merge indicating the end of the conditional behaviour started by that branch. Similarly, a fork must be followed by a join before transitioning into the final activity state (Gooch 2000). In our model, Activity Diagrams are employed to schematise the sequence of actions that agents undertake to improve their lifestyle.

A Decision Tree is a method to formalize problems in decision-analysis (Neapolitan 1990). In general, a Decision Tree consists of nodes, leafs, and arcs; nodes represent decisions, leafs represent choice-alternatives, and arcs connect decisions with choice-alternatives. There are two types of nodes: decision-nodes and nature-nodes, representing two types of decisions. In a decision-node, the decision-maker is in control, implying that he/she can select his/her favourite choice-alternative, whereas in a nature-node, the decision-maker is not in control over which alternative is selected, for instance, whether it will rain or not. It is referred to as a nature-node because we can conceive Nature making a selection according to a chance mechanism (Neapolitan 1990). Let us consider the decision-problem depicted in Fig. 2.3, involving two interdependent decisions, one of which the decision-maker is in control, and one where he/she is not. This interdependency is incorporated constructing a tree with multiple levels. Each path of arcs, going from the root node to one of the terminal nodes, represents a possible sequence of decisions, either made by nature or by the decision-maker. What the decision-maker does is

Fig. 2.3 Example of a decision tree; the square node represents a decision node and the circular node represents a nature node; U represents utility



evaluating all these scenarios (or paths in the tree), assigning a utility (U) to all nodes in the tree, to then execute the scenario promising the highest utility. In our model, Decision Trees are employed to model the decision-making process of agents, evaluating which action to pursue.

Model Experiments and Numerical Results

The four scenarios we will discuss are, beginning with the most simple one, (1) unboundedly rational students making non-joint decisions in a stationary housing-market, (2) unboundedly rational students making joint decisions in a stationary housing-market, (3) unboundedly rational students making joint decisions in a non-stationary housing-market, and (4) boundedly rational students making joint decisions in a non-stationary housing-market. For each of these scenarios we will plot, when relevant, the three decision-formalisms. Furthermore, two categories of numerical results will be presented: one showing results on the level of the whole student population, and one showing results on the level of the individual student. The population-results include (a) the number of moves a student makes on average per change in preference-profile, (b) the time-period between changing preference-profile and the first move, and (c) the increase in utility generated by the first move. Population results are plotted in tables, and are included to illustrate the emergence of the sought-after macroscopic regularities. The individual-results, on the other hand, include the life-and move-courses of single students. These results are plotted as graphs, and are included to illustrate the variety in emerging behaviour.

Technically, each simulation starts with an initial population of 1,000 student-households, consisting of either one or two students. At the start of the simulation, all of these students either live with their parents or rent a residence. On top of these rented-out residences, there initially also is a supply of empty residences available for rent. Each simulated year, graduated students leave the simulation. To guarantee that the population remains approximately constant, 200 new student-households enter the simulation each year. One simulated year consists of 52 time-periods. Each of these time-periods, each student evaluates his/her current housing-situation, potentially considering moving to a new residence. Each student grows older once a year, on his/her birthday, possibly changing student-profile (and thus preference-profile). We furthermore assume that students are not resistant to change their

current situation (so that even slight improvements might make students move), and that the rents of all residences are equal to zero (so that the rent has no impact on the location-choice). These two assumptions are introduced to simplify the assessment of the model outcome. Simulations where students are indeed resistant to change and where rents are not set to zero are addressed in Devisch (2007).

We will now discuss the four selected scenarios, firstly specifying the parameter settings (both regarding the housing-market and the student-population), to then analyse the numerical results and assess the model specifications.

Unboundedly Rational Students Making Non-joint Decisions in a Stationary Housing-Market

The housing-market is stationary, implying that the supply of residences available for rent remains constant. Recall that each residence is defined by six housing-attributes, all but one having three attribute-values, making up $3^5 \cdot 2 = 486$, so-called, residence-classes. The supply of empty residences available for rent is defined in such a way that it is exhaustive, i.e. that all 486 residence-classes are present. Students are unboundedly rational, implying that they are, at all times, aware of all residences on the housing-market that are available for rent, and know all details of these residences. As such, they are able to perfectly assess the utility they will derive from living in each of these residences. Non-joint decision-making implies that, in case a student lives together with a partner, one of both makes the decisions, irrespective of the preferences of the other one.

Before we discuss the numerical results, let us first illustrate this scenario with the three decision-formalisms introduced in the previous section, beginning with the Decision Table. A Decision Table structures the knowledge of a student regarding his/her housing-environment. The condition-set, for instance, lists all attributes a student considers relevant to assess a candidate residence. The condition-set lists all the relevant values of these attributes, with each column representing the residence-class introduced earlier (i.e. unique combinations of all residence-attributes). In the action-set, the student will then classify all these classes according to whether he/she would like to live there yes or no, as such cognitively structuring his/her environment. In order to decide whether he/she could indeed live in a particular residence-class, the student simply evaluates whether he/she would derive more utility from this class than from his/her current housing-situation. The Decision Table in Fig. 2.4, for instance, belongs to a student with a preference-profile 2, currently living in a one-room apartment in the centre of the city.

The Activity Diagram structures the sequence of actions that the student undertakes to improve (or at least maintain) his/her current lifestyle. In the current scenario, the student can only choose between three actions, namely to stay in the current residence, to move to an alternative residence, or to move back to the parental home. This leads to the simple Activity Diagram of Fig. 2.5.

The Decision Tree is employed to model the decision-making process of the student, evaluating which action to pursue. Since the student can choose between

KNOWLEDGE STUDENT i									
C1	dwelling-typology	student-housing		hospita		apartment		parents	
C2	residence-typology	1	2	-		1	2	-	
C3	relative location	center	univ.	-	-	center	univ.	-	-
C4	populatiom-type	-	-	-	-	-	-	-	-
C5	dwelling-size	-	-	-	-	-	-	-	-
C6	residence-size	-	-	-	-	-	-	-	-
A1	acceptable res-class v	Y	N	Y	N	N	N	Y	N

Fig. 2.4 Decision table of a student with preference-profile 2

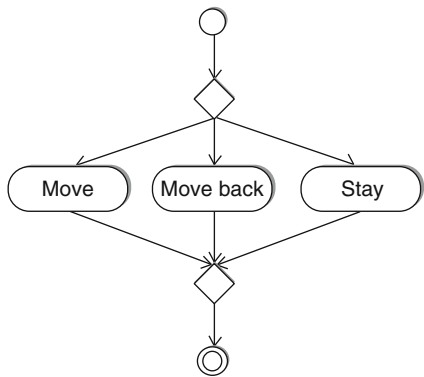


Fig. 2.5 Activity diagram of unboundedly rational students in a stationary housing-market

three actions, the Decision Tree has three branches (see Fig. 2.6). The decision to consider moving involves evaluating all residences available for rent to then select the one best matching the preferences of the student. Since the student is unboundedly rational, and is as such able to perfectly assess the market supply, he/she is in control of all decisions so that all nodes in the tree are Decision Nodes.

Results

Judging from Table 2.1, the average number of moves per change in preference-profile is 1.00, implying that each student wanting to change residence, actually finds an alternative and moves. This is evident as each student has perfect knowledge regarding the housing-market, and as all residence-classes are continuously available for rent. This also explains why the number of time-periods between the change in preference-profile and the first move is 0.00. The average increase in utility due to changing residence is 21.23 %, implying that the student improves his/her housing-situation significantly. Again, this is evident, as the perfect housing-market guarantees students to always find a residence perfectly matching their preferences. Important to mention is that, in case of students living together with a partner, only the moving behaviour of one of both is recorded, namely of the student making the decisions.

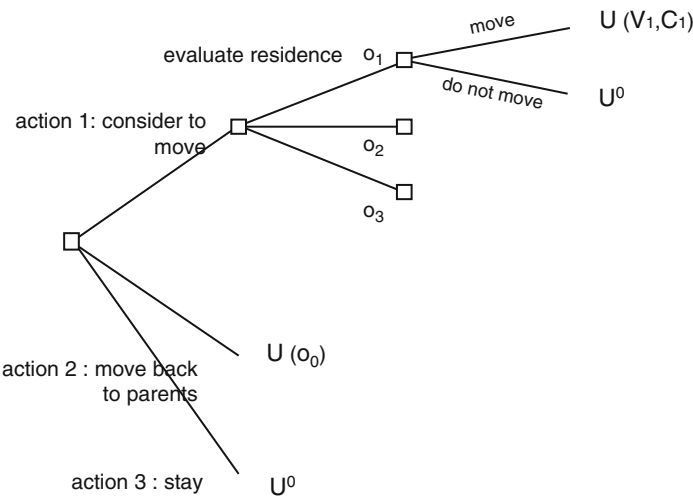


Fig. 2.6 Decision tree of an unboundedly rational student in a stationary housing-market; o represents a residence; $U(v, c)$, $U(o_0)$ and U^0 represent the utilities the student expects to derive from living in, respectively, a residence belonging to a residence-class v and price-category c ; the parental home o_0 ; and the current residence

Table 2.1 Average results on the level of the whole population (in the experiment without joint decision-making, only the moving behaviour of the student making decisions is recorded)

	No joint decision- making	Joint decision-making	Non- stationary housing- market	Boundedly rational/no initial knowledge	Boundedly rational/ learning
Number of moves per change in preference- profile	1.00	0.95	3.39	0.56	0.56
Increase in utility related to the first move after changing preference- profile	21.23 %	21.42 %	18.96 %	23.88 %	24.90 %
Number of time-periods between changing preference-profile and the first move	0.00	0.20	1.47	14.73	9.41

The graph depicted in Fig. 2.11 plots the life- and move-course of a random student, living together with another student. At time-period 521, the student changes preference-profile (i.e. from 10 to 9), starting living together with a student with a differing preference-profile (i.e. 3). Since students do not make joint decisions, one of both will end up in a residence not matching his/her preference-profile. In this case it is the student with preference-profile 3, i.e. the partner.

Concluding, the scenario is realistic, firstly in that changes in the life-course of a student indeed make him/her consider moving. It is not realistic in that each consideration instantaneously results in a move to a residence perfectly matching the preferences of this student (neglecting a possible partner). As such, the housing-market is continuously in equilibrium.

Unboundedly Rational Students Making Joint Decisions in a Stationary Housing-Market

The housing-market remains identical to the previous scenario. Regarding the population settings, the difference is that students now make joint decisions over which actions to pursue, potentially having to overcome diverging preferences. In our model, joint decision-making is implemented by defining a simple additive utility function, where the individual utilities are scaled depending on the impact each student has on the final decision. For more realistic group utility functions, see a/o Zhang et al. (2005). The changing from non-joint to joint decision-making has no impact on the decision formalisms as such. In case of joint decision-making, the Decision Table of both partners is in effect, whereas in case of non-joint decision-making, only one Decision Table is used.

Results

Judging from Table 2.1, the number of moves per change in preference-profile is slightly lower than one (0.95), implying that there are students that do not relocate in spite of changing preference-profile. It is indeed possible that in those cases of two students living together, one of both changes preference-profile, but where both nevertheless decide to stay in the current residence. The average increase in utility is slightly higher compared to the scenario without joint decision-making, 21.42 % vs. 21.23 %. In the joint-case, students living in a residence not perfectly matching their preferences when they are a couple, will experience a relatively high increase when they divorce and are suddenly able to find their ideal residence. As mentioned, in the non-joint case, there is only one of both partners making decisions (as such always ending up where he/she wants), explaining the above difference in utility.

If we again look at the life- and move-course of the student discussed in the previous scenario (depicted in Fig. 2.11), but now allow this student to make joint-decisions, we see that it is now our student (and not his/her partner) that ends up in a residence not matching his/her preference-profile, suggesting that joint decision-making indeed has effect.

Concluding, the scenario is more realistic than the previous scenario, in that students, living together with a partner with a differing preference-profile, will have a lower utility-gain (i.e. when moving together) compared to students of which both partners have the same preference-profile. The scenario is still not realistic in that the majority of students still move exactly once per change in preference-profile, implying a market in equilibrium.

Unboundedly Rational Students Making Joint Decisions in a Non-stationary Housing-Market

The market turns non-stationary, implying that when a residence is let out, it is no longer available to other students until those who rent the residence move out again. Because residences temporarily disappear from the market, the supply changes continuously. In the stationary scenario, this is not the case since the supply is artificially kept constant. As in the previous scenario, the initial supply is exhaustive, implying that all 486 residence-classes are available for rent. The population settings are identical to the previous scenario, implying that students remain unboundedly rational and make joint decisions. As such, nothing changes to the mental representation (i.e. the Decision Table) and the decision-process (i.e. the Decision Tree) of the students. The Activity Diagram, on the other hand, changes slightly. In a stationary market, the housing-supply remains constant so that a student only evaluates the situation on the housing-market when he/she experiences a change in his/her life-course. In a non-stationary housing-market, on the other hand, the supply fluctuates, so that the opportunity to improve ones lifestyle is constantly present. Consequently, the student has to, at each moment in time, evaluate the situation on the housing-market. This is graphically represented by adding an extra branch to the Activity Diagram (see Fig. 2.7), closing the action sequence.

Results

Judging from Table 2.1, students move significantly more when the market is non-stationary, than when it is stationary (3.39 vs. 0.95 times). They also seem to gain less utility during their first move, and sometimes even have to postpone moving (i.e. the number of time-periods is bigger than zero) because they are not able to find an acceptable alternative. These are all direct consequences of switching to a non-stationary housing-market, a market where residences that are let out, are no longer available to other students until these students move out again. Moreover, the supply changes continuously, so that a student might continuously come across better alternatives, and as such might move multiple times per change in preference-profile. The opposite is also true, a student being unable to find any acceptable residence because all are rented out. He/she will then have to stay in his/her current residence, postponing moving till better residences turn available again.

To illustrate the high number of moves, take for instance student 3,734 (depicted in Fig. 2.11), changing preference-profile twice, but moving seven times. The first change in preference-profile is at period 653, when the student decides to move away from his parents. He does find a residence, but this residence is not really satisfactory as he moves three times without changing profile. The second change in preference-profile is at period 757, but does not result in a move. This happens only five periods later, at 762, and a second and third time at 820 and 871. So less than half of the moves are triggered by a change in profile, all the others by a fluctuating supply.

Concluding, the unboundedly rational – non-stationary scenario is realistic, firstly, in that students do substitute preferences (i.e. do not end up in a residence matching

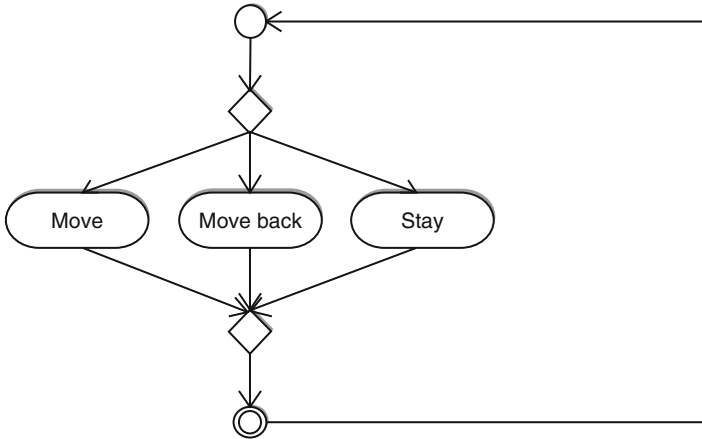


Fig. 2.7 Activity diagram of unboundedly rational students in a non-stationary housing-market

their preferences as student 3,734 illustrates). The difference with the stationary scenario is that this substitution is much more severe. Secondly, in that students have to compete over the same residences, so that some do not directly find an alternative residence upon changing preference-profile, having to postpone moving. The housing-market is thus no longer in equilibrium. The scenario is not realistic in that the number of moves per change in profile is too high. This is a direct result of our scenario settings: all residence-classes are available for rent, students have no resistance against change, and rents have no impact. The consequence is that students move, even if the new residence only slightly improves their housing-situation.

Boundedly Rational Students Making Joint Decisions in a Non-stationary Housing-Market

The initial housing-market settings are identical to that of the previous scenario. The population-settings differ in that students are now boundedly rational, i.e. they are rational in the sense that they are utility maximizers, but differ from unboundedly rational students in that they are unable to assess all choice-alternatives available on the housing-market, either because they are cognitively constrained or because they do not have access to all information. Consequently, boundedly rational students base their decisions on beliefs regarding what is available on the housing-market, and continuously collect information to update these beliefs. Recall from the conceptual framework, that in addition to having to decide, at each moment in time, whether to move or stay (as in the scenario of unboundedly rational students) students now also have to decide whether to consult information-sources (search) or to visit a residence for inspection. Once a student selected and executed one of these actions, he/she updates his/her beliefs. This results in the extended Activity Diagram

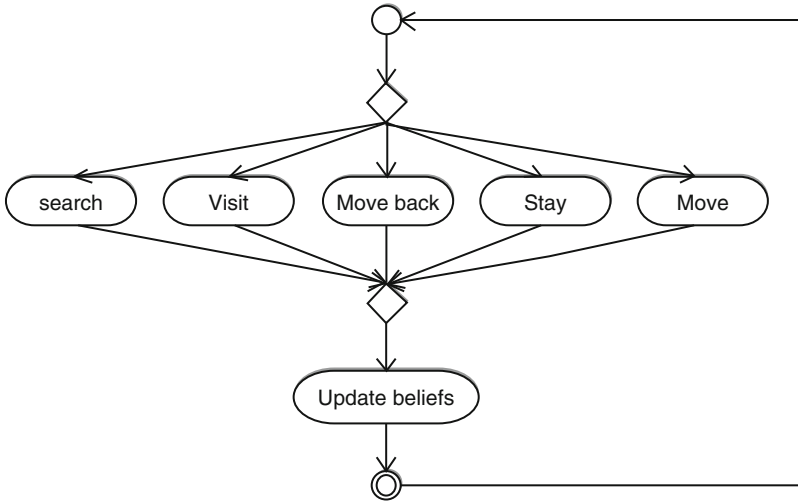


Fig. 2.8 Activity diagram of boundedly rational students in a non-stationary housing-market

depicted in Fig. 2.8. As the diagram illustrates, the three-stage process of searching, visiting, and moving is indeed not a linear but rather a co-evolutionary, partly recursive process, in line with what the empirical findings pointed at.

A student relies on his/her Decision Table to categorize which residence-classes he/she considers acceptable to move to, and which ones not. When a student comes across a residence for rent, he/she will then consult his/her Decision Table, find the residence-class matching the residence for-rent, and check whether it is worth considering moving to. In the scenario where the student has full information regarding this residence for rent, this screening-process is simple, in that the student is certain about the values of all residence-attributes. In the scenario where the student lacks information though (i.e. the scenario we are implementing now), this screening-process will have to be based on beliefs. In our model, a student has beliefs regarding the content of all information-sources and regarding all residence attribute-values. Since students finally have to decide whether or not to accept a residence (be it on the basis of beliefs or not), we propose to store these beliefs as extra rows in the action-set of the Decision Table (see Fig. 2.9). Action A2 would then, for instance, imply that students have to define the probability that the population-type of a residence, specified by the conditions in each column, is mono. On the basis of these probabilities, students will then calculate the utility they expect to derive from living in a particular residence on the basis of which they will classify it as either acceptable or not. Each time a student collects new information on his/her environment, either when he/she consults an information-source or when he/she inspects a residence, he/she learns about the housing-market, and can update his/her beliefs. The Decision Table thus represents the current knowledge of the student regarding his/her environment.

KNOWLEDGE STUDENT i								
C1	dwelling-typology	student-housing		hospita		apartment		parents
C2	residence-typology	1	2	1	2	1	2	–
A1	acceptable res-class v	Y	Y	N	N	N	Y	N
A2	pr (pop-type = mono)							–
A3	pr (pop-type = slightly mxd)							–
A4	pr (pop-type = mixed)							–
	...							–
A15	pr (category in source 1)							–
A16	pr (category in source 2)							–
	...							–

Fig. 2.9 Decision table of a student with preference-profile 2

Compared to the scenario of unboundedly rational students, the decision-tree (depicted in Fig. 2.10) is significantly more complex: firstly, the tree grew an extra branch (i.e. a visit branch), secondly, some branches grew an extra level, and thirdly, not all nodes are decision nodes, implying that the student is no longer in control of all decisions, caused by the fact that he/she no longer possesses full information on all choice-alternatives.

Results

In order to assess the impact of turning from unboundedly into boundedly rational decision-makers, we will run two experiments: one where students have no initial knowledge regarding their housing-market (i.e. their beliefs are uniform) and do not update their beliefs, and one where students do have initial beliefs and do update their beliefs (i.e. do learn). In short, having initial beliefs is, in swarmCity, defined as students having full knowledge regarding the housing-market the moment they enter the simulation, and learning is, in swarmCity, defined as students using a variety of update heuristics to tune their beliefs to recently collected information. For the full specifications of how the initial knowledge is defined, and of how the update heuristics work, we refer to Devisch (2007).

As Table 2.1 illustrates, boundedly rational students move significantly less per change in preference-profile than unboundedly rational students (0.56 vs. 3.39 times). This is a direct consequence of the introduction of information-sources: since boundedly rational students can only consult one source per time-period, their search-area is only a fragment of the search-area of unboundedly rational students. Scanning the whole housing-market would take these students a number of time-periods (as opposed to 1 time-period in the case of unboundedly rational students). What the table also illustrates is that boundedly rational students seem to gain more utility during their first move than unboundedly rational students (24.90 % vs. 18.96 %). This is a consequence of the fact that boundedly rational students always consider the possibility that there are better alternatives available, as such searching significantly longer (9.41 vs. 1.47 time-periods), potentially resulting in better moves. The high number of time-periods can also be traced

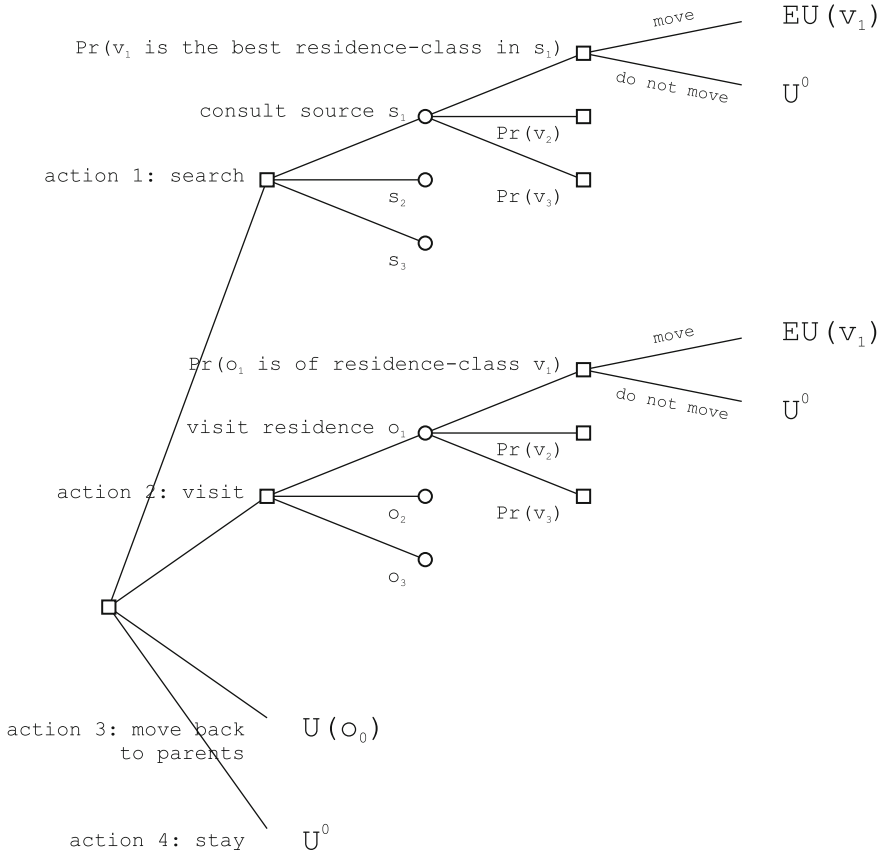


Fig. 2.10 Decision tree of boundedly rational students in a non-stationary housing-market

back to the introduction of information-sources. The difference between students that do and don't have initial knowledge, and do and don't update their beliefs is only significant what concerns the number of time-periods, implying that students with knowledge know where to search and are thus able to faster find an acceptable alternative.

The life- and move-course of a randomly selected student (depicted in Fig. 2.11) illustrate the recursive character of the three-stage process: between time-periods 575 and 615, he systematically alternates searching with visiting. The graph also illustrates the variation in search strategies: for his first move (i.e. between time-periods 567 and 575), our student first consults all available sources, to only then inspect his first residence; whereas for his second move (i.e. between time-periods 575 and 615), he alternates searching with visiting.

Concluding, boundedly rational students behave more realistic than unboundedly rational students, first and foremost, because their behaviour is less uniform given the personal beliefs of each student. A second illustration of this more

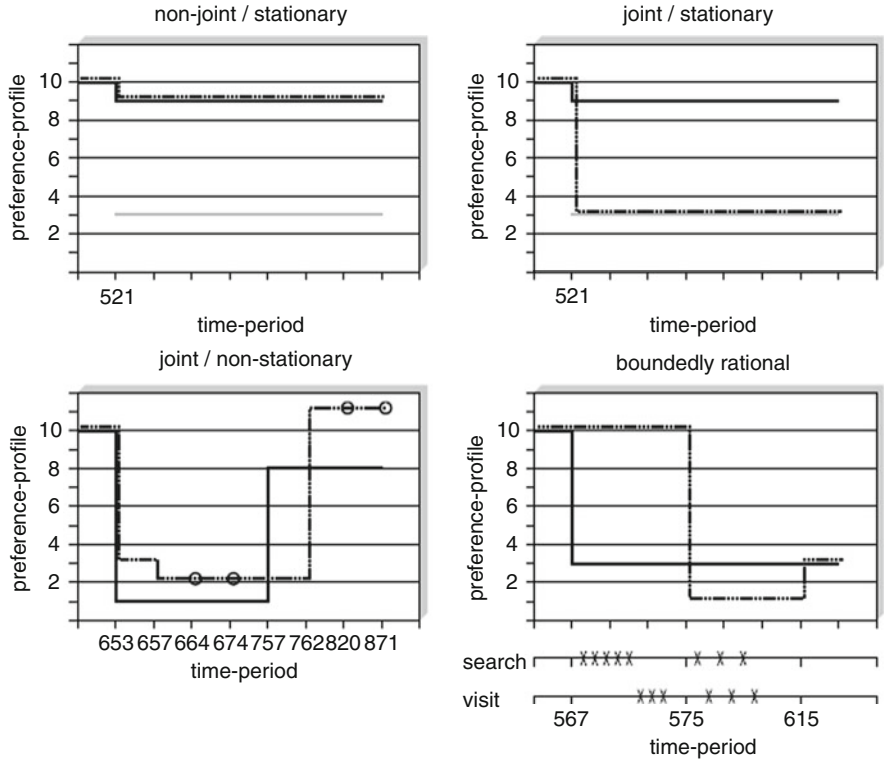


Fig. 2.11 Results on the level of single students; the life-course is indicated as a *full line*, the move-course as a *dotted line*. The life-course of an eventual partner is indicated in *grey*. The o-signs indicate moves within the same profile

realistic behaviour is that boundedly rational students – on average- move less than once per change in preference-profile, whereas unboundedly rational students – on average- move up to three times. A third illustration is that the majority of students do not end up in a residence matching his/her preferences (as can be concluded from the high number of moves) in order to find a residence, suggesting that the housing-market is highly competitive. A fourth illustration is the relatively long period that it – on average- takes for students to find an alternative residence. Where some immediately stumble across an acceptable alternative, others only find this alternative after a thorough market study. Apart from that, boundedly rational students do not behave realistic; firstly because they do not forget anything they've learned so that, for instance, once a student believes that, at a certain time-period, a particular information-source is not worth consulting, he/she will never consult this source again even though the content might change totally. A second point where their behaviour is not realistic is that some students move residence just before they change preference-profile, so that their

new residences is sub-optimal, almost from the moment they moved in. In reality, students anticipate changes.

Conclusions and Discussion

According to Epstein (1999) multi-agent systems are especially powerful in representing spatially distributed systems of heterogeneous autonomous actors with bounded information and computing capacity who interact locally. A review of recent urban models relying on multi-agent technology learns however that these models at best only start to explore this potential. One of the reasons is that the increase in behavioural complexity is difficult to validate numerically. The purpose of this research was to develop an urban model fully exploiting the potential attributed to multi-agent systems. In order to attain this ambition, we firstly limited the scope of our research to one urban process, namely residential mobility, and secondly defined two rules to validate our model, namely maximizing transparency and maximizing the number of generated macroscopic regularities. To meet the rule of transparency, we integrated a considerable number of behavioural concepts into one framework and developed this framework around the principle of utility maximization. Moreover, we structured this framework relying on three formalisms: a Decision Table, an Activity Diagram and a Decision Tree. To even further increase the transparency, we implemented this framework in an incremental fashion: introducing and assessing new behavioural concepts step by step. Concerning the second rule, the numerical results indeed confirm that the model is able to generate a number of the macroscopic regularities pointed at in empirical research such as the emergence of a housing ladder, sub-market competition, substitution of housing preferences, market disequilibrium, etc.

References

- Alhashimi H, Dwyer W (2004) Is there such an entity as a housing market? In proceedings of the 10th annual pacific rim real estate conference, Bangkok
- Batty M (2005) Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals. MIT Press, Cambridge, MA
- Batty M, Torrens P (2005) Modelling and prediction in a complex world. *Futures* 37:745–766
- Bauer B, Müller JP, Odell J (2001) Agent UML: a formalism for specifying multiagent interaction. In: Ciancarini P, Wooldridge M (eds) *Agent-oriented software engineering*. Springer, Berlin, pp 91–103
- Benenson I, Harbush V (2004) Object-based environment for urban simulation, OBEUS user's guide. Environmental Simulation Laboratory, Tel Aviv University, Israel
- Clark WAV, Flowerdew R (1982) A review of search models and their application to search in the housing market. In: Clark WAV (ed) *Modelling housing market search*. Croom Helm, London, pp 4–29
- Clark WAV, Huang Y (2003) The life course and residential mobility in British housing markets. *Environ Plann A* 35(2):323–339

- Clark WAV, Van Lierop WFJ (1986) Residential mobility and household location modelling. In: Nijkamp P (ed) *Handbook of regional and urban economics*, vol I. Elsevier Science, Amsterdam
- Devisch O (2007) In search of a complex-system model, the case of residential mobility. Ph.D. thesis, Eindhoven University of Technology, Eindhoven
- Diappi L, Bolchi P (2006) Gentrification waves in the inner-city of Milan. In: Van Leeuwen JP, Timmermans HJP (eds) *Innovations in design & decision support systems in architecture and urban planning*. Springer, Dordrecht, pp 187–201
- Dieleman FM (2001) Modelling residential mobility; a review of recent trends in research. *J Hous Built Environ* 16:249–265
- Dieleman FM, Mulder CH (2002) The geography of residential choice. In: Aragonés JI, Garling T (eds) *Residential environments: choice, satisfaction, and behavior*. Bergin & Garvey, Westport, pp 35–54
- Epstein JM (1999) Agent-based computational models and generative social science. *Complexity* 4(5):41–60
- Fransson U, Mäkilä K (1994) Residential choice in a time-space perspective: a micro-simulation approach. *Neth J Hous Built Environ* 9(3):265–283
- Goetgeluk R (1997) *Bomen over wonen: woningmarktonderzoek met beslissingsbomen*. Ph.D. thesis, Universiteit van Utrecht, Utrecht
- Gooch T (2000) Object oriented analysis and design team, Kennesaw State University. <http://pigseye.kennesaw.edu/~dbraun/csis4650/A&D/index.htm>
- Harding JP, Rosenthal SS, Sirmans F (2003) Estimating bargaining power in the market for existing homes. *Rev Econ Stat* 85(1):178–188
- Huff JO (1982) Spatial aspects of residential search. In: Clark WAV (ed) *Modelling housing market search*. Croom Helm, London, pp 106–129
- Lei Z, Pijanowski BC, Alexandridis KT, Olson J (2005) Distributed modeling architecture of a multi-agent-based behavioral economic landscape (MABEL) model. *Simulation* 81(7):503–515
- Lu M (1998) Analyzing migration decisionmaking: relationships between residential satisfaction, mobility intentions and moving behavior. *Environ Plann A* 30(8):1473–1495
- Manson SM (2005) Agent-based modeling and genetic programming for modeling land change in the southern Yucatan peninsular region of Mexico. *Agric Ecosyst Environ* 111(1):47–62
- March JG (1994) *A primer on decision making: how decisions happen*. The Free Press, New York
- McCarthy K (1982) An analytical model of housing search and mobility. In: Clark WAV (ed) *Modelling housing market search*. Biddles, London, pp 30–53
- Molin E (1999) Conjoint modeling approaches for residential group preferences. Ph.D. thesis, Eindhoven University of Technology, Eindhoven
- Neapolitan RE (1990) *Probabilistic reasoning in expert systems: theory and applications*. Wiley-Interscience, New York
- Oskamp A (1997) Local housing market simulation, a micro approach. Ph.D. thesis, University of Amsterdam, Amsterdam
- Oskamp A, Hooimeijer P (1999) Advances in the microsimulation of demographic behavior. In: van Wissen LJG, Dykstra PA (eds) *Population issues: an interdisciplinary focus*. Plenum Press, New York, pp 229–263
- Otter HS (2000) *Complex adaptive land use systems: an interdisciplinary approach with agent-based models*. Academic/Eburon, Delft
- Parker DC, Manson SM, Janssen MA, Hoffmann MJ, Deadman P (2003) Multi-agent systems for the simulation of land-use and land-cover change: a review. *Ann Assoc Am Geogr* 93(2):314–337
- Portugali J (2000) *Self-organization and the city*. Springer, Berlin
- Simon H (1955) A behavioral model of rational choice. *Q J Econ* 69(1):99–118

- Torrens PM (2001) Can geocomputation save urban simulation? Throw some agents into the mixture, simmer and wait . . ., CASA working paper series, paper 32, Centre for Advanced Spatial Analysis, University College London, London
- van der Vlist AJ, Gorter C, Nijkamp P, Rietveld P (2001) Residential mobility and local housing market differences. Tinbergen institute discussion paper, Tinbergen Institute, Amsterdam
- Verhelst M (1980) De praktijk van Beslissingstabellen. Kluwer, Deventer/Antwerp
- Waddell P (2001) Towards a behavioral integration of land use and transportation modeling. In: Proceedings of the 9th international association for travel behavior research conference, Queensland
- Zhang J, Timmermans HJP, Borgers AWJ (2005) A model of household task allocation and time use. *Transp Res B* 39(1):81–95



<http://www.springer.com/978-3-7908-2863-4>

Emergent Phenomena in Housing Markets
Gentrification, Housing Search, Polarization

Diappi, L. (Ed.)

2013, XIV, 186 p., Hardcover

ISBN: 978-3-7908-2863-4

A product of Physica-Verlag Heidelberg