Socio-dynamic discrete choice: Theory and application

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7 SOCIO-DYNAMIC TRINARY NESTED LOGIT: APPLICATION

In this chapter, we continue our study of the simulated evolution of choice behavior over time with positive feedback due to network effects, using computational techniques from the field of multi-agent based simulation. To achieve this, the discrete choice estimation results controlling overall mechanisms related to individual heterogeneous preferences are embedded in a computational version of the model created using the Repast multi-agent based modeling platform. An important extension is that we now consider a case where there are shared unobserved attributes of the choice alternatives. We revisit a classic approach to statistical prediction in such a situation given an observed sample of decision making agents in a population, namely the nested logit model. Additionally a key feature is that we explicitly consider non-global interactions, in an example with a social and spatial network structure that we can visualize and analyze using geographic information systems tools and techniques.

Table 7.1 highlights the contribution of this dissertation relative to the context of existing literature along the dimensions of the discrete choice model kernel, the specification of the systematic utility, the approach to studying behaviour over time and the interaction framework.

In Chapter 6 results are presented for a binary logit model with non-global interactions and other explanatory variables included in the utility for a parameter sweep of network density across a series of networks in the abstract class of random networks. In this chapter we present results for the behavior over time of a nested logit model with non-global interactions, using an empirical treatment of which decision makers influence each other defined on the basis of socioeconomic group and spatial proximity of residential location. We deliberately choose the nested logit model as a starting point for this chapter in incrementally extending existing literature. In Chapter 8 we will consider more complex discrete choice models.

In section 7.1 we present a strategy for introducing social and spatial network interdependencies in choice models as a generic feedback effect. In section 7.2 we will review the data available to us, make a hypothesis regarding a network of commonality between different agents in different places based on common attributes in terms of social grouping between places, and estimate coefficients for the models presented. In section 7.3 we will estimate a benchmark nested logit model with a global (fully connected) network and the only explana-

Table 7.1: Contribution of the dissertation in the context of existing literature by other authors. By the designation "Empirically defined" is understood a fully specified systematic utility containing the feedback effect as well as attributes of choice alternatives and/or characteristics of decision making agents.

CHOICE KERNEL	SYSTEMATIC UTILITY	BEHAVIOR OVER TIME	GLOBAL NETWORK	LOCAL NETWORK
Binary logit	Feedback only	Theoretical equilibrium	Brock, Durlauf; Appendix A	Ioannides
		Transition dynamics	Blume, Durlauf; Aoki; Chapter 3	Chapter 6 ∮ 6.2
	Empirically defined	Transition dynamics	a)	Chapter 6 ∮ 6.3, ∮ 6.4
Multi-nomial logit	Feedback only	Theoretical equilibrium	Brock, Durlauf; Chapter 4	Diverse physicists
		Transition dynamics	Supplement	Supplement
	Empirically defined	Transition dynamics	a)	Chapter 7 ∮ 7.4
Nested logit	Feedback only	Theoretical equilibrium	Chapter 5	b)
		Transition dynamics	Chapter 7 ∮ 7.3	Chapter 7 ∮ 7.5, ∮ 7.6
	Empirically defined	Transition dynamics	a)	Chapter 7 ∮ 7.4, ∮ 7.7

a) Non-identifiable if an alternative specific constant is included

b) Analytical solution only possible for abstract network classes tory variable in the systematic utility being the field variable. In section 7.4 we will make a hypothesis regarding a network of commonality between different agents in different residential districts based on common attributes in terms of social grouping between districts, and we will estimate coefficients for the model with field variables for residential district and socioeconomic group. In section 7.5 we will return to the benchmark model to study in more detail the impact of initial conditions and network size on emergent outcomes. In section 7.6 we will study in more detail the impact of sociographic networks on the emergent outcomes, in scenarios for clusters and overlapping groups. In section 7.7 we will come back to the fully specified empirical model again to study in more detail the impact of the utility parameters and the network connectivity on the emergent outcomes.

In this chapter we will find that the simulated evolution of choice behavior over time with positive feedback due to network effects is critically sensitive to the discrete choice estimation results defining the individual heterogeneous preferences. Heterogeneity matters! The emergent outcomes are remarkably, dramatically different not only with the inclusion of heterogeneity in the systematic utility in the extension of the model from one including the feedback effect only versus an empirically defined systematic utility, but also with the inclusion of shared unobserved heterogeneity in the extension of the model from multinomial logit to nested logit. This finding in turn opens a wide spectrum of research along various dimensions for more detailed understanding of the impact of agent heterogeneity on emergent outcomes for any policy related considerations.

7.1 CONCEPTUALIZING SOCIAL-SPATIAL NETWORKS

In conceptualizing the interaction framework, a distinction is hypothesized between social versus spatial interactions and between identifiable versus aggregate interactions. We speak of interaction between "identifiable" decision makers when the links in the network are well known and explicitly defined on an individual decision maker by decision maker basis. We speak of interaction between "aggregate" decision makers when interdependence is assumed to take place only at an aggregate level with links being defined, for example, more generally based on decision maker characteristics. We speak of "spatial" network interactions when the interdependence represents a confluence of decision makers in geographic terms. For example, decision makers may be linked based on spatial proximity of residential location, work location or some other geographical point of reference such as school, childcare, shopping, healthcare, leisure/recreation or other relevant activity location. We speak of "social" network interactions when decision makers are linked based on social circles. The decision makers need not be proximally situated in geographical terms and the interaction is not necessarily centered at a particular geographic point of reference; interaction may take place at a distance, so to speak.

The framework for the mechanisms of interactions is proposed as follows:

- Interactions among individuals within households – for example, joint residential location choice in a dual income earner household (Timmermans et al, 1992); coordinating activity schedules and travel patterns within a household.

- Interactions between identifiable households proximally situated in a spatial network – for example, both nuisance from neighbors as well as conversely satisfaction with neighbors are very strong factors in the inclination to move house, both for under 55 and over 55 age groups in the Netherlands (Hooimeijer and van Ham, 2000); coordinating carpooling with neighbors or co-workers.

- Interactions between identifiable households associated in a social network, not necessarily proximally or tangentially situated in a spatial network – for example, attraction to a particular municipality in choice of residential location because friends or family live there; awareness about availability of certain alternatives in the choice set generation process through information transmission in the social network via friends, family, neighbors and/or co-workers, be that the suitability of a particular neighborhood in residential location choice, or the suitability of using a park-and-ride transferium for a commute, or the existence of a carpool facility.

- Interactions between a household and the aggregate actions of other households proximally situated in a spatial network – for example, high volatility or conversely stagnancy of turnover in housing stock in a particular neighborhood affecting the general desirability of a neighborhood or the possibility to move there; social pressure to own a car because other neighbors or other co-workers on average do, regardless of whether there is any direct social contact with these persons; improved feasibility for higher level of public transit service associated with higher volume of public transit ridership in a particular region.

- Interactions between a household and the aggregate actions of other households associated in a social network, not necessarily proximally or tangentially situated in a spatial network – for example, preference for a particular type of housing situation (as opposed to preference for a specific municipality); social acceptance of cycling or public transit because friends, family, neighbors and/or co-workers also cycle or use public transit.

Table 7.2: Interaction mechanism framework: some illustrative examples. Global interactions between a decision maker and the aggregate actions of other decision makers in the entire sample population (general societal bandwagon effects) may be addressed as the special limiting case of a fully connected network.

INTERACTIONS	IDENTIFIABLE	AGGREGATE
Spatial network	Coordinating carpooling with neighbors	Feasibility of high level of public transit service
Social network	Personal awareness about mode choice alternatives	Social acceptance of cycling / public transit

- Interactions between a household and the aggregate actions of other households in a (sub)population, not necessarily associated in a social network nor proximally or tangentially situated in a spatial network – because of a general trend or societal bandwagon effect.

Furthermore, an important distinction can be understood in this particular problem domain among (social and/or spatial) network interactions impacting choices, such as transport mode choice, which do not necessarily endogenously affect the household's reference position in a network (eg. whether a household chooses carpool versus transit in a multi-modal trip, or chooses a uni-modal trip, will not spatially affect the fact of who the household's neighbors or co-workers are), as opposed to network interactions impacting "sorting" type choices, such as residential location choice, which obviously endogenously impact the household's reference position in a spatial network and potentially also within a social network (eg. in moving to a new neighborhood a household per definition acquires new neighbors).

In summary, illustrative examples of such interactions along the above described dimensions for the exogenous network case in the given problem domain, that is, transportation mode choice, are provided in Table 7.2.

Typically survey data for interaction between identifiable decision makers would include explicit information on the relevant networks for each decision maker for the decision of interest. The members of the networks might then in turn be surveyed. In travel demand data collection a typical practice is to sample households from the population and then survey all members of that household above a certain age. As of the time of embarking on the current research, we were unaware of any travel demand datasets that would take, for example, a "snowball sampling" approach collecting explicit information on inter-household networks of decision makers. As suggested in Table 7.2, some examples of research questions we might like to answer relating to inter-household networks include spatial coordination/feasibility and social awareness/acceptance in the take-up of various transportation mode choices. In absence of survey data on interaction between identifiable decision makers at inter-household level, we turn instead to consider aggregate interactions between decision makers and use a priori beliefs about the social and/or spatial dimension of interactions to formulate the connectivity of the network.

In the case study to be discussed, we have rich socioeconomic data for each respondent as well as the geographic location of each respondent's residence. This allows us to define aggregate interactions by grouping agents into geographic neighborhoods or into socioeconomic groups where the influence is assumed to be more likely. In the simplest case, these groups are assumed to be mutually exclusive and collectively exhaustive and each agent n belongs to one and only one group g. The agent is influenced by the average choice behavior of his or her group, and the influence by other groups is assumed to be negligible. At a global level, the picture is a fragmented or disconnected network of clustered groups. If we are interested in equilibrium behavior, the consequences of such an assumption are important: there is no transmission of influence across groups, and the global picture is a weighted average behavior of the separate clusters. Thus we consider the case with overlapping groups, with agents for example connected by social group as well as by residential district. This leads to a giant cluster for the empirical example under consideration, with the important implication that influence can spread throughout the entire population.

In section 7.2 we will review the socioeconomic and geographic data available to us. Starting in section 7.3 we will finally consider the evolution of choice behavior over time. Although it is important to begin with a well-specified model before adding subsequent elaborations, note that the techniques presented here could be applied to any choice model.

7.2 DATA PREPARATION

7.2.1 *Overview of the Data*

The data to be used in this case study originates from activity based travel questionnaires administered by the Municipality of Amsterdam Agency for Infrastructure, Traffic and Transport (dIVV) during the period 1992-1997 in Amsterdam and a neighboring suburb to the south of the city, Amstelveen.

The data set received from the dIVV is a subset of their modal split database containing only the direct home-work trips and direct work-home trips from this database, where the purpose of the trip at the non-home location is classified as either 'work' or 'business.' Geographical location is given in terms of the centroid of a traffic analysis zone (TAZ). There are 381 TAZ centroids in Amsterdam (nrs. 1-381) and 48 TAZ centroids in Amstelveen (nrs. 414-461), with a total of 933 TAZs in the whole of the Netherlands. Records with origin, destination or residence TAZ listed as 0 have been removed by the dIVV from the database. Mode choice is collected in 10 categories. The database furthermore includes only records of trips where respondents have indicated one of the first six choices of the ten options:

- External system public transit (364 trips)
- Internal system public transit (862 trips)
- Car driver (2446 trips)
- Car passenger (252 trips)
- Moped/motorcycle (65 trips)
- Bicycle (1379 trips)
- Taxi (*excluded*)
- Not applicable (*excluded*)
- Walking (*excluded*)
- Other (*excluded*)

The data is organized by trip (5368 direct home-work or work-home trips), grouped by respondent (2925 respondents who have made these trips), household (2328 households with a respondent who made such a trip) and address (2321 addresses where there is a household with a respondent who made such a trip). Although the subset includes only the direct home-work (`hw`) and work-home (`wh`) trips, some information about tours can be inferred from the sequential number of the trip in a given respondent's entire daily sequence as in Table 7.3.

Some issues:

- Commute trips with stops underway are not included, only direct trips.
- It isn't possible to distinguish, for example, between on the one hand, 1 home based tour having 4+ trips between the outward journey-to-work and the return journey-to-home, versus on the other hand, 2 home based tours having stops underway on the return journey-to-home trip of the first tour, as well as stops underway on the outward journey-to-work trip of the second tour.
- Some respondents indicate returning "home" or starting from "home" that is not their primary residential address.

Table 7.3: Inferred daily tour sequence. Gaps in a respondent's entire daily sequence (as inferred from the sequential numbering of the trips) due to trips with other trip purposes that were not made available in the subset of data released by the municipality, are given by empty brackets ( ). The "hw-wh" sequence can actually be further distinguished: with no stops between (1577); with stops between but work location is same (235); with stops between and different work locations (170).

INFERRED SEQUENCE	MINIMUM TOURS	RESPONDENTS
hw-( )	1	606
hw-( )--hw-( )	2	4
hw-( )--hw-wh	2	15
hw-( )--hw-wh--hw-wh	3	1
hw-wh	1	1982
hw-wh--( )-wh	2	3
hw-wh--( )-wh--hw-wh	3	1
hw-wh--hw-( )	2	20
hw-wh--hw-( )--hw-wh	3	1
hw-wh--hw-wh	2	103
hw-wh--hw-wh--hw-wh	3	6
( )-wh	1	166
( )-wh--hw-( )	2	5
( )-wh--hw-wh	2	8
( )-wh--( )-wh	2	3
( )-wh--( )-wh--hw-( )	3	1
Total respondents		2925

- Some respondents indicate going to 2 or more work locations.
- It isn't clear whether the data from the given day is typical or an anomaly for that respondent.

The database is built from cross-sections carried out in five rounds over a period of six years, with different respondents (a so-called rolling "pseudo-panel"). In fact, however, because each of the five rounds are cross-sectional samples over respondents living in different – practically non-overlapping – regions, it might be difficult to separate a temporal year effect from a geographical residential location effect. To visualize the data, we create a thematic map. See Figure 7.1.

The five samples are roughly as follows:

- 1992 – Suburb (Amstelveen)
- 1994 – East and west middle ring (Amsterdam)
- 1995 – South middle ring and southeast annex (Amsterdam)
- 1996 – North and west garden cities (Amsterdam)
- 1997 – Center and south (Amsterdam)

The pale grey circles in the map indicate the centroids of the traffic analysis zones in Amsterdam and Amstelveen adhered to by the dIVV. Residential locations of sampled respondents are known to the precision of a TAZ centroid. Red dots represent the residential locations of (clusters of) direct-commuting respondents choosing public transit, green diamonds show the (clusters of) bicycle users, blue circles show the (clusters of) car drivers, pink squares show the (clusters of) car passengers.

To visualize the geometry of roadways and train stations, we also create a second thematic map. See Figure 7.2. Major roadways – including the important A10 ring road around Amsterdam – are shown in red, and secondary roadways are shown in orange. Other roads are shown in green and blue. Train stations of the national railway system are shown with red stars. The national 4-digit postcode regions and the dIVV travel analysis zone centroids are shown in gray, and the 4-digit postcode regions sampled by the dIVV during the period 1992-1997 are shown in the background with the same coloring scheme as in Figure 7.1 to guide the eye in comparison.

Some initial first impressions: Zones with minimal public transit service show no public transit users in the database, for example in Amstelveen (southern suburb) and North Amsterdam (across the bay); car users are distributed across the entire region in practically all zones; bicycle users are absent in the most peripheral zones in far Amstelveen, far East Amsterdam, Southeast and North Amsterdam and far West Amsterdam; there are some regions in the city center with high public transit service and no transit users.

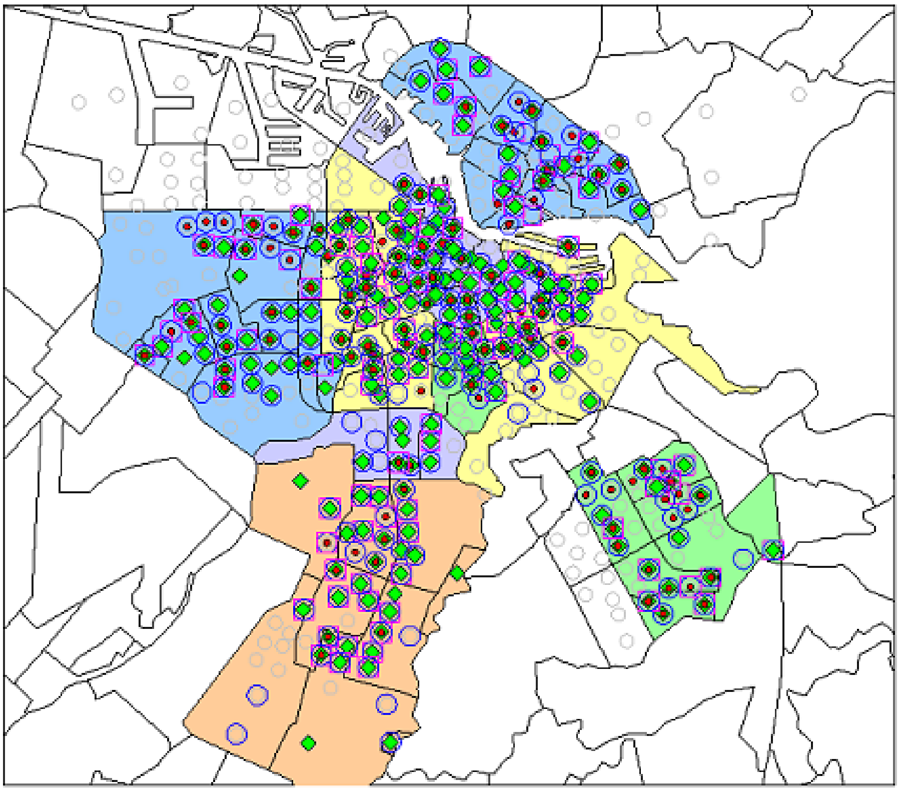
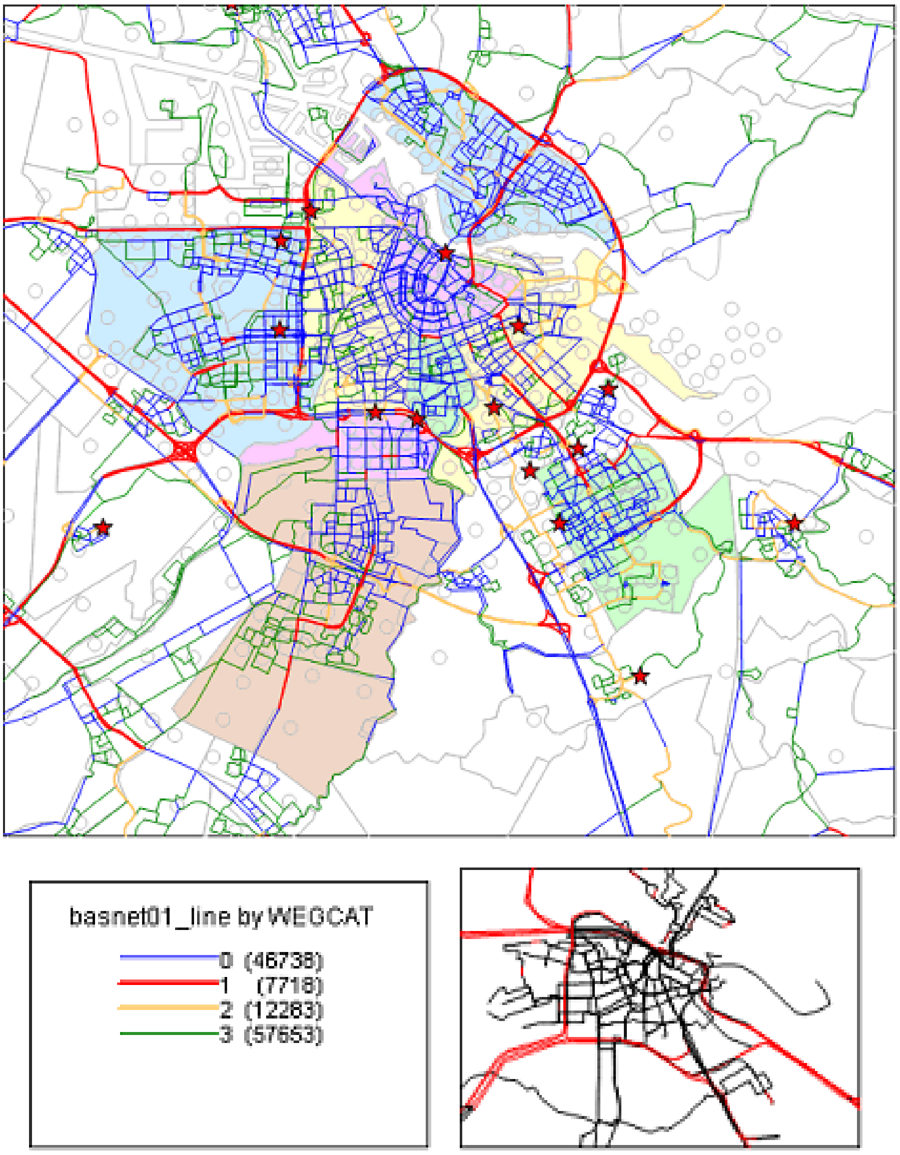


Figure 7.1: Primary residential locations (known to precision of a TAZ centroid) of respondents sampled by the dIVV in the period 1992-1997 making direct home-work or direct work-home trips – indicated with commuter mode choice. The polygons indicate boundaries of national 4-digit postcode regions. The orange colored area shows roughly the 4-digit postcode regions of residential locations sampled in 1992; yellow shows roughly 1994; green shows roughly 1995; blue shows roughly 1996; purple shows roughly 1997. The pale grey circles indicate centroids of traffic analysis zones in Amsterdam (361 TAZs) and in Amstelveen (48 TAZs). Red dots represent the primary residential location of (clusters of) direct-commuting respondents choosing public transit; green diamonds indicate bicycle or moped/motorcycle users; blue circles indicate (clusters of) car drivers; pink squares indicate (clusters of) car passengers.



(b) (c)

Figure 7.2: Transportation network in Amsterdam and immediate environs. The national railway lines are not shown in the main diagram, but its stations are indicated with red stars. The TAZ centroids and 4-digit postcode regions are shown in gray and the sampled region is shown in the background to guide the eye, using the same coloring scheme as Figure 7.1. Inset (b) indicates roadway category and number of such road segments in the Netherlands. Inset (c) shows national railway lines and local bus/tram/metro lines.

7.2.2 *Considerations*

This case study reports on the development of a transportation mode choice model. The central questions which this case study aims to answer is:

> To what extent can a respondent's mode choice be explained by his or her neighbors' mode choices and those choices made by a respondent's socioeconomic peers, after controlling for travel mode attributes such as travel time, as well as sociodemographic characteristics?

Note however, that causality will not be addressed, that is, the question of whether a respondent chooses a residential location a priori based on a certain travel mode lifestyle of the residents in a neighborhood, or whether after having moved to a location a respondent is then a posteriori influenced by the travel behavior of his or her neighbors.

Given the above described data set, there are several considerations that come to mind immediately:

(1) First, the samples are stratified by residential location. For a residential choice model to be estimated at later date, we will thus have the case of choice based sampling. Since it cannot be assumed that sampling fractions in each of the strata have been chosen a priori to equal the population shares, if we want to estimate any model other than a simple multinomial model (with a full set of $J-1$ alternative specific constants, where J is the number of alternatives), we will need to consider appropriate estimation procedure options. One possibility may be weighted exogenous sample maximum likelihood (WESML), as described in Ben-Akiva and Lerman (1985, pp. 238-239). The WESML estimator is computationally tractable and consistent under very general conditions, but not in general asymptotically efficient (Manski and Lerman, 1977; Lerman and Manski, 1979). Another possibility may be to address the sample likelihood of a general stratified sample with nonoverlapping strata described in Ben-Akiva and Lerman (1985, pp. 235-236) via simulation. Fortunately, with the travel mode choice model at hand, we have an exogenously stratified sample and the usual estimation procedure for a simple random sample applies.

(2) Presumably there may be a bias in commuter mode choice incurred by only having direct home-work and direct work-home trips in this particular subset of the database. For example, we might hypothesize that there is a potential flexibility afforded by the car in carrying out complex trip chains. If so, the proportion of car users might be under-represented in the data set as compared to the population share of all commuters, as the car users may be disproportionately excluded in the set of commuters making stops on the way to and

from work. It is isn't clear at this stage how to adjust for such a potential bias. At this point, we proceed under the assumption that any extensions to population shares are only made for shares of direct work-home or direct home-work trips, and not for population shares of all commute trips.

(3) To test for a temporal year effect and/or geographical residential location effect, there are several possibilities. First, we might want try including a limited set of dummy variables for year or district directly in the specification the utility function. Second, a market segmentation test for taste variations might be entirely appropriate. Third, we might want to try a random coefficients model, where coefficients for records from the same year or district differ from the population mean by the same unobserved amount.

(4) The same approach as outlined in (3) might also be interesting to apply for the purpose of the trip at the non-home location in understanding if there is any distinction between the two classifications "work" versus "business".

(5) Presumably the best residential location choice model possible here to be estimated at later date, would be one at the TAZ centroid level, that is, the smallest scale available, and thus most homogeneous within the unit of analysis. However, there may be several trade-offs to be considered. Since there are 381 TAZs in Amsterdam plus 48 TAZs in Amstelveen, for a total of 429 possible TAZs, a model estimation procedure using sampling of alternatives for a residential location choice might be a computationally tractable option, using the approach proposed by Guevara (2010). There are two caviats. First, in order to flexibly account for spatial correlation between end alternatives, it may be interesting to experiment with a *mixed* cross-nested logit structure as described in Bhat and Guo (2003). Without results for sampling of alternatives for such structures, it could mean at least in the short term, that it might be necessary to apply the "brute force" method of compiling attributes, and calculating utilities and individual choice probabilities for all realistically possible TAZ for each respondent. This may be computationally prohibitive as well as logistically impractical due to run time constraints, with such a number of end alternatives for combined residential location choice and mode choice. Second, corrections for aggregation of elemental alternatives (residences) within a zone would need to be applied, as described in Ben-Akiva and Lerman (1985). The number of residences per zone is known at the level of a centroid of a 6-digit postcode. Although x,y-coordinates of the centroids are available for import into a GIS package, it is not immediately clear how to carry out a mapping of data from the 6-digit postcode centroid to a TAZ centroid. Much more straightforward would be if it were possible to obtain access to a GIS file with the traffic analysis zone boundaries, then it would be simple matter to aggregate data from the 6-digit postcode centroids within

the TAZ boundaries. If such a file does exist, it may not be possible to obtain access to it for various reasons. On the other hand, it is a straighforward matter to aggregate data from the 6-digit postcode centroids with the 4-digit postcode boundaries using data immediately at hand.

(6) Development of a tour based model is beyond the scope of this case study. Furthermore, gaps in the available data as described in the subsection 7.2.1 "Overview of the data" due to having only direct home-work and direct work-home trips and thus incomplete and/or ambiguous tour information poses additional challenges. Thus, a simple trip based model is considered here. However, because one of the central research questions to be answered is concerned with the explanatory power of the average choice behavior in residential neighborhood on a given respondent's commute mode choice, having multiple trips over the course of the day for one individual in the sample could bias results and confound decision making, correlation and constraints of mode choice of trips at the tour level and respondent level, with the research question. It was therefore decided to include only one trip per person in the sample. In practice, the one trip per person was selected on the basis of being the first trip in the day for which there was data for a given respondent. While not a perfect solution (particularly if a respondent happened to travel by different modes on an outward versus return journey), compared to the corrections necessary when including multiple trips per person and treatment of ambiguous information due to having only direct trips, the chosen approach seems the most straightforward. Additionally, reducing the sample size from on the order of 5368 trips to on the order 2925 trips gives computational advantages with respect to memory constraints and estimation time.

7.2.3 *Sample Preparation*

The sample is reduced from 5368 trips to 2925 trips, that is, from multiple trips per respondent to one trip per respondent, as described above in the subsection 7.2.2 "Considerations." In doing so, however, we create several additional variables for potential future reference summarizing some of the lost information, in accordance with points identified in the subsection 7.2.1 "Overview of the data."

- Number of direct home-work and work-home trips made per respondent in their day sequence
- Inferred day tour sequence type
- Whether the respondent has indicated an alternate residence, that is, returning "home" or starting from "home" that is not their primary residential address, among any of their trips (not just the one trip selected for inclusion in the sample)

- Whether the respondent has indicated going to more than 1 work location in their day sequence
- Whether the respondent switches modes in their day sequence

Frequencies for these created variables are given in Tables 7.4 to 7.8.

Table 7.4: Direct commute trips per respondent

DIRECT COMMUTE TRIPS	FREQUENCY	PERCENT
1	772	26.4
2	1994	68.2
3	47	1.6
4	103	3.5
5	3	0.1
6	5	0.2
10	1	0.0
Total	2925	100.0

Table 7.5: Inferred tour sequence

INFERRED TOUR SEQUENCE	FREQUENCY	PERCENT
Direct outward commute only	606	20.7
Direct return commute only	166	5.7
Direct commute with no trips between	1577	53.9
Direct commute with work based trips	235	8.0
Direct open jaw commute tour	170	5.8
Two direct commute tours	103	3.5
Other sequence	68	2.3
Total	2925	100.0

Table 7.6: More than 1 home location in day sequence

> 1 HOME LOCATION	FREQUENCY	PERCENT
No	2843	97.2
Yes	82	2.8
Total	2925	100.0

At this stage three brief points are nonetheless worth noting:

Table 7.7: More than 1 work location in day sequence

> 1 WORK LOCATION	FREQUENCY	PERCENT
No	2653	90.7
Yes	272	9.3
Total	2925	100.0

Table 7.8: More than 1 transport mode in day sequence

> 1 TRANSPORT MODE	FREQUENCY	PERCENT
No	2820	96.4
Yes	105	3.6
Total	2925	100.0

(1) More than half of the respondents (53.9%) have a direct commute with no other trips in between their direct outward journey from home-to-work and their direct return journey from work-to-home. We may like to know if these respondents have structurally different preferences than respondents with more complex day commute tour sequences. It might be interesting to carry out a simple market segmentation at later stage to test for taste variation for the set of respondents with the single direct commute tour versus respondents with other inferred day sequence types.

(2) Only 3.6% of respondents indicate having different direct commute travel modes for different direct commute trips during the course of the day. Thus there appears to be a very high correlation for direct commute mode choice among these trips for a given respondent, and concerns hypothesized earlier in this regard are upheld. Likewise, any bias to be incurred with regard to any neighborhood feedback effect, due to considering the mode choice of the one selected trip in the day sequence as representative of a general choice behavior for direct commute trips of a respondent, might be hypothesized to be not so serious. A stability analysis of the contributions of these few respondents in the preference structure of the sample might be interesting to carry out at later stage by repeating the final analysis when replacing the selected trip with instead one of the trips by the same respondent with an alternate mode for inclusion in the sample.

(3) Fairly few persons indicate having more than 1 work location (9.3%) and even less indicate having more than 1 "home" location (2.8%) in their day tour sequence. We may like to know if having a more complex geographical pattern in the day sequence affects mode preference. These might be interesting dummy variables to experi-

ment with including in the model. Also, as similarly just mentioned in (2) with respect to mode choice, it may interesting to carry out a stability analysis of final results when replacing the primary residential location with instead the alternate residential location for the few respondents with more than 1 "home" location with regard to our study of neighborhood feedback.

Until now we have discussed aspects of correlation and decision making among trips in a tour and tours in a day sequence, and reduced the research problem to one of direct commute mode choice behavior at the respondent level. We will soon address a hypothesized relation between individual choice behavior and average choice behavior of neighbors and socioeconomic peers. But what about the intermediate level of decision making within a household? There are many possible approaches to this question, most of which are beyond the scope of this case study. For example, we might imagine a nested preference structure where one household member's choice is conditional on another household member's choice. Another approach might be imagining a structure where we treat the data set effectively as panel data where different household members' choices from the same household are treated as repeated observations. A very simple approach might be including a dummy indicator variable in the utility specification for a given respondent if another member of the household chooses a particular mode. A fourth approach might involve estimating separate models with market segmentation by household composition. Of course, combinations of these approaches are also possible.

The travel surveys administered by the Municipality of Amsterdam dIVV during the period 1992-1997 have been carried out among all persons in a household above the age of 12. In principle, this gives a very rich database for investigating the approaches to the modeling of correlation and decision making within a household. Unfortunately, as the available subset of this database contains only direct home-work and direct work-home trips, much of the information about household composition and mode choice behavior of individuals within a household is lost. Nonetheless due to the coding of the records not only by trip sequentially within a day, and by respondent, but also by household, it is possible to infer some information. For example, it is not possible to differentiate whether a household with only one respondent is the data subset is indeed a single person household, or a single worker household, or in fact actually a multiple worker household but only one worker of which makes a direct commute with no stops to or from work on the survey day. It is however possible to conclude definitively that a household does have more than one direct-commuting worker, and not only one. Thus we create a dummy indicator variable as follows:

Table 7.9: More than 1 direct commuter per household

> 1 DIRECT COMMUTER	FREQUENCY	PERCENT
No	1763	60.3
Yes	1162	39.7
Total	2925	100.0

- Whether a respondent resides in a household where there is definitively at least one other person with a direct home-work or direct work-home commute

The frequency for this created variable is given in Table 7.9. More than one-third of respondents (39.7%) can be definitively concluded to belong to a multiple worker household where at least of these workers make direct home-work and/or direct work-home trips. Recognizing that the number of actual multiple worker households might be greater than this, nonetheless, as described above it might interesting to carry out a market segmentation test on this variable. In doing so, we test for taste variations in respondents where there might be correlation or constraints in decision making among multiple direct-commuting members of a household, versus respondents from other households.

7.2.4 *The Choice Dimension, Availability of Alternatives and Exclusion of Records*

Next we consider the choice dimension and availability of alternatives. There are two variables in the dIVV database specifically indicating for each respondent the availability of a car and the availability of a bicycle. A three-way cross tabulation of the these two variables by the primary mode choice described in the subsection 7.2.1 "Overview of the data" is presented in Table 7.10.

Several observations in this regard:

- There are 22 car drivers plus 64 car passengers, that is, 86 respondents total traveling by car mode, for whom travel by car is unavailable according to the dummy indicator variable for car availability.

- There are 13 respondents traveling by bicycle for whom travel by bicycle is unavailable according to the dummy indicator variable for bicycle availability.

- There 21 respondents traveling by external public transit and 150 traveling by internal public transit, that is 171 public transit

Table 7.10: Car availability by bicycle availability by primary transportation mode

PRIMARY MODE	CAR:	BICYCLE: No	BICYCLE: Yes	TOTAL
External public transit	No	21	101	122
	Yes	7	72	79
	Total	28	173	201
Internal public transit	No	150	183	333
	Yes	43	119	162
	Total	193	302	495
Car driver	No	9	13	22
	Yes	282	995	1277
	Total	291	1008	1299
Car passenger	No	15	49	64
	Yes	14	67	81
	Total	29	116	145
Moped/motorcycle	No	0	21	21
	Yes	1	12	13
	Total	1	33	34
Bicycle	No	8	383	391
	Yes	5	355	360
	Total	13	738	751

users, who according to the car and bicycle availability dummies actually had no choice.

First, due to the number of logical inconsistencies in the data, the accuracy of the two availability variables is called into question. Second, the proportion of transit users whose records would be excluded from the data set, that is, 171 respondents with "no choice" divided by 201 plus 495 external and internal public transit users, or about one-fourth (!), is rather high. By outright excluding these records, we lose valuable information about the behavior of these individuals and lose statistical power in estimating coefficients for the transit mode. Furthermore, it is precisely the public transit attributes which could be important for policy forecasting in terms of being variables which might be most likely to be in the control of the dIVV to adjust. On the other hand, not including any variables to indicate the availability of alternatives could bias results.

Table 7.11: Driver's licence by car availability

DRIVER'S LICENSE	CAR: No	CAR: Yes	TOTAL
No	639	0	639
Yes	314	1972	2286
Total	953	1972	2925

Taking these points into consideration, we look for an alternative. In keeping with the spirit of the case study to understand a general choice behavior at a respondent level and in particular any explanatory power of neighborhood feedback, one possibility is to consider instead the availability of a mode at the level of a longer time horizon, rather than availability at a given day. The decision to buy – or particularly to borrow or to rent – a bicycle even if a bicycle is not immediately "available" on a given day, might be assumed to be one with not such high threshhold or fixed costs so as to outright exclude travel by bicycle in general.

Similarly, even the decision to buy – or particularly to borrow or to rent – a car even if a car is not immediately "available" on a given day, might be considered to be one with not such a high threshhold or fixed costs so as to outright exclude travel by car in general. This last case is all the more relevant with the appearance of highly flexible, on-demand car rental services in Amsterdam and environs such as "Greenwheels," where cars can be picked up and dropped off at a multitude of locations. On the other hand, obtaining a driver's license is not something to be arranged immediately on-demand and places a substantial, effective barrier with a longer time horizon. In fact, in the Netherlands, even repeated attempts at the driving test before ultimately obtaining a license is not uncommon.

By way of exploratory consideration of the usefulness of the possession of a driver's license as an indicator variable for availability of travel by the car mode, we perform a cross tabulation of this against the original "car availability" dummy variable. Results are presented in Table 7.11. Indeed every respondent who is indicated to have a car available according to the original dummy variable (1972 respondents) also a driver's license. On the other hand, there are 314 additional respondents who do have a driver's license who theoretically couldn't travel by car mode according to the original availability variable. There remain 639 respondents with neither a car available according to the original indicator variable nor a license. The lowering of the barrier for which car mode is excluded is thus achieved and is at the same time logically consistent with the original variable.

Using possession of a drivers' license as an indicator for availability of travel by car is also consistent with the approach taken in numerous other studies. There is one important outstanding fact however, namely that this particular dataset includes car passenger as a mode choice not only car driver – although car passenger is indeed the second smallest mode choice category (145 respondents) after moped/-motorcycle (34 respondents) and followed by external public transit (201 respondents). All other mode choices have on the order of 500 respondents or more, and the car driver category in particular has almost an order of magnitude more respondents (1299 respondents) than the car passenger category. At this point we adopt the analysis practice of the dIVV by merging the external and internal public transit categories to one public transit category and by merging the bicycle with moped/motorcycle category to one two-wheeled mode category (referred to from here forward simply as "bicycle" following dIVV convention). Merging of the car driver and car passenger category is now also considered.

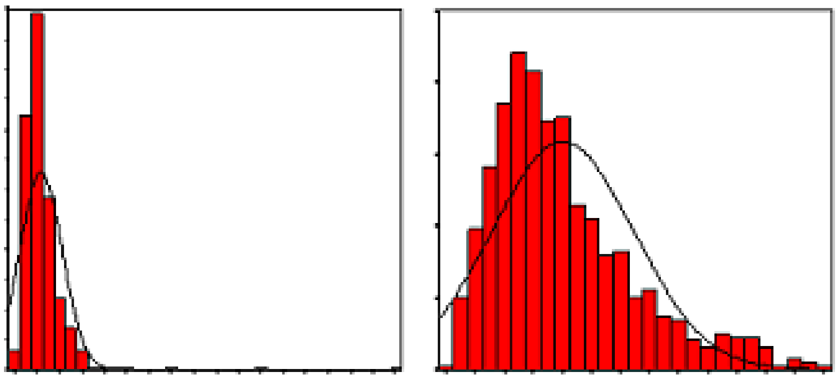
Presumably a car passenger could just as well be a car driver provided the respondent in question is in possession of a driver's license. A car passenger without a driver's license is more problematic, as their mode choice is unavoidably contingent on the choice behavior of the driver, and potentially also activity and scheduling constraints, in order to choose this mode. Establishing conditions for the availability of travel by car without possession of a driver's license for the respondents who in fact chose to travel by public transit or by bicycle is beyond the scope of this study. Furthermore, while the full dIVV database involving all trips in a day, for all members of a household above the age of 12, presents interesting and rich modeling possibilities for developing such activity based and time-of-day based conditions, the available data containing only the direct home-work and work-home trips hardly supports such an approach.

A cross tabulation of primary mode choice for direct home-work and direct work-home trips by possession of a driver's license is given in Table 7.12. The number of car drivers without a license is 10 and the number of car passengers without a license is 53. Rather than exclude records these records from the sample, it is decided to use car ownership as an explanatory variable in the model and from this point forward, the remaining car drivers and car passengers are merged into one category.

Next, we consider a procedure applied by the dIVV of excluding records for respondents traveling by bicycle who have a travel time greater than 75 minutes. We would like to know if these records can be considered exceptional in the context of our sample. Figure 7.3 shows histograms of travel time by bicycle for the set of respondents who choose travel by bicycle or moped/motorcycle for their direct commute.

Table 7.12: Primary transportation mode by driver's license

PRIMARY MODE	LICENSE: No	LICENSE: Yes	TOTAL
Bicycle/moped/motorcycle	266	519	785
Public transit	310	386	696
Car driver	10	1289	1299
Car passenger	53	92	145
Total	639	2286	2925



(a) (b)

Figure 7.3: Histograms of total travel time by bicycle for direct-commuting respondents choosing bicycle or moped/motorcycle. Inset (a) with no respondents excluded, has mean 23.6, and standard deviation 19.0. Inset (b) with 6 respondents in the right tail of the original distribution having travel time greater than 75 minutes excluded, has mean 22.5, and standard deviation 12.2.

Indeed there are only 6 respondents of 785 respondents total choosing bicycle or moped/motorcycle in the sample, or less than 0.8%. Of these, the most extreme record is more than 16 standard deviations away from the mean. Excluding these records likewise reduces the mean by more than one minute and reduces the standard deviation by more than 8 minutes. Thus, the procedure applied by the dIVV is accepted for this dataset, as these very few records seem have an exceptional influence on the distribution. Out of curiosity, we might wonder if this situation occurred due these 6 records being disproportionately moped/motorcycle users, that is, respondents with in fact a motorized means of transport, rather than unusually avid cyclers. A cross tabulation of travel time by bicycle by primary mode in Table 7.13 shows that only 1 of these records is from the moped/motorcycle category, and the most extreme case is indeed a bicycle user.

Table 7.13: Reported travel time by primary transportation mode for respondents traveling by bicycle/moped/motorcycle with travel time greater than 75 minutes

TRAVEL TIME	MOPED/MOTORCYCLE	BICYCLE	TOTAL
75.2	0	1	1
93.6	0	1	1
100.8	0	1	1
136.1	0	1	1
219.7	1	0	1
342.9	0	1	1
Total	1	5	6

Table 7.14: Reported travel time by dummy variable 'More than 1 transport mode in day sequence' for respondents traveling by bicycle/-moped/motorcycle with travel time greater than 75 minutes

TRAVEL TIME	>1 MODE: No	>1 MODE: Yes	TOTAL
75.2	1	0	1
93.6	1	0	1
100.8	1	0	1
136.1	1	0	1
219.7	1	0	1
342.9	1	0	1
Total	6	0	6

We now take a moment to assess the records excluded until now. There are 6 records excluded on the basis of being exceptionally avid two-wheeled mode users. While for purposes of consistency in procedure we uphold the exclusion of these records, we might still like to have an idea whether the respondents in the excluded records might have made other trips by an alternate mode among the trips that were not selected for inclusion in the sample in the subsection 7.2.3 "Sample Preparation." A cross tabulation of travel time by bicycle for the 6 excluded records with travel time greater than 75 minutes by the dummy variable created in the previous subsection for whether the respondent switches modes in their day sequence, shows that none of these traveled by an alternate mode. See Table 7.14. Thus even if we do a stability analysis at later stage as proposed in the subsection 7.2.3 "Sample Preparation" point 2, these records will remain excluded.

Finally, we consider availability of the public transit mode. We would like to know if there are any respondents for whom travel by public transit is networkwise inconsistent with respect to the location of their residence relative to their work location. That is, we would like to know whether there are trips such that upon the respondent's arrival to the nearest public transit stop by their access mode, the respondent can more efficiently continue from the same stop by their egress mode, without actually traveling by the primary public transit mode at all. Such a scenario would arise for example as follows. Suppose there is a geometry of points along a line in order A – B – C – /... / – D. Point A is the location of the respondent's residence. Points B and D are immediately sequential public transit stops with no other public transit stops in between. Point C is the work location, and point C is closer in time and distance by the egress mode to point B than it is to point D.

To identify whether there are indeed any respondents in the sample with networkwise inconsistent public transit alternatives, first we filter the sample for records with travel cost by public transit equal to zero, and then we compute the descriptive statistics for all travel attributes for the public transit mode. See Table 7.15. Indeed there are 62 such records in the sample, and all 62 records show that the total travel time and total travel distance for the public transit alternative is comprised solely of travel time and travel distance for access and egress with no actual travel by the public transit mode itself (local bus, express bus, external express bus, tram, express tram, metro, local train, regional train, intercity train). An availability dummy variable for public transit is created as follows:

- Whether the respondent has a trip with in-vehicle travel time for the public transit alternative greater than zero

Since the travel attributes for the public transit mode are generated from zone-by-zone network skims, there may in fact be some respondents who actually chose public transit even though the trip is networkwise inconsistent. A cross tabulation of primary mode against the newly created public transit availability dummy shows that are indeed 6 such respondents, who are accordingly removed from the sample for reasons of consistency. See Table 7.16. Furthermore we note by way of a double check that the dummy variable defined on the basis of in-vehicle travel time for public transit gives a total of 62 respondents for whom public transit is unavailable. Since the 62 records shown earlier in Table 7.15 are all listwise valid, it is precisely the same 62 respondents who have zero travel cost by public transit as those who have zero in-vehicle travel time by public transit, and we conclude there are no further hidden inconsistencies in this regard.

As discussed earlier regarding the record exclusions on the basis of being exceptionally avid two-wheeled mode users, we might like to have an idea whether the newly excluded 6 public transit users with

Table 7.15: Descriptive statistics for records with zero public transit costs

VARIABLE	N	MIN	MAX	MEAN	SD
Waiting time public transit	62	0	0	0	0
Transfer time public transit	62	0	0	0	0
Access time public transit	62	2.08	9.80	4.51	1.90
Egress time public transit	62	2.08	8.03	4.34	1.64
In-vehicle time public transit	62	0	0	0	0
Total travel time public transit	62	4.16	17.67	8.87	3.47
Access distance public transit	62	112	1743	433	264
Egress distance public transit	62	62	1062	390	161
In-vehicle distance public transit	62	0	0	0	0
Total distance public transit	62	224	2805	824	3956
Number of transfers	62	0	0	0	0
Travel time local bus	62	0	0	0	0
Travel time express bus	62	0	0	0	0
Travel time external express bus	62	0	0	0	0
Travel time tram	62	0	0	0	0
Travel time express tram	62	0	0	0	0
Travel time metro	62	0	0	0	0
Travel time local train	62	0	0	0	0
Travel time regional train	62	0	0	0	0
Travel time intercity train	62	0	0	0	0
Distance local bus	62	0	0	0	0
Distance express bus	62	0	0	0	0
Distance external express bus	62	0	0	0	0
Distance tram	62	0	0	0	0
Distance express tram	62	0	0	0	0
Distance metro	62	0	0	0	0
Distance local train	62	0	0	0	0
Distance regional train	62	0	0	0	0
Distance intercity train	62	0	0	0	0
Cost train for external travel	62	0	0	0	0
Cost all networks except ext. train	62	0	0	0	0
Cost public transit	62	0	0	0	0

Table 7.16: Primary transportation mode (recoded) by public transit availability

PRIMARY MODE	TRANSIT: No	TRANSIT: Yes	TOTAL
Bicycle/moped/motorcycle	33	746	779
Public transit	6	690	696
Car	24	1420	1444
Total	63	2856	2925

Table 7.17: Primary transportation mode (recoded) by dummy variable 'More than 1 transport mode in day sequence' for public transit users with networkwise inconsistent trips

PRIMARY MODE	>1 MODE: No	>1 MODE: Yes	TOTAL
Public transit	6	0	6
Total	6	0	6

networkwise inconsistent trips might have made other trips by an alternate mode among the trips that were not selected for inclusion in the sample in the subsection 7.2.3 "Sample Preparation." A cross tabulation of primary mode choice by the dummy variable created in the previous subsection for whether the respondent switches modes in their day sequence, shows that none of these traveled by an alternate mode. See Table 7.17. Thus even if we do a stability analysis at later stage as proposed in the subsection 7.2.3 "Sample Preparation" point 2, these records will remain excluded.

The last point to check is whether the combination of the public transit availability dummy and the condition for travel time by bicycle/moped/motorcycle less than 75 minutes as an availability dummy leaves any respondents with only the car alternative for their mode choice, and thus in fact have no choice. Such records would also introduce bias into our results and should be excluded. A three-way cross tabulation of the two dummy variables by the primary mode choice is presented in Table 7.18. There are indeed no such respondents with "no choice".

This concludes our discussion of choice dimension, availability of alternatives and exclusion of records. The final sample has 2913 respondents. Frequencies for the primary mode choice are given in Table 7.19. The proportion of respondents during the period 1992-1997 residing in Amsterdam/Amstelveen and making direct home-work or work-home trips who are choosing public transit is slightly less

Table 7.18: Travel time less than 75 minutes for bicycle, by public transit availability by primary mode (recoded)

PRIMARY MODE	BICYCLE <75 MIN	TRANSIT: No	TRANSIT: Yes	TOTAL
Bicycle/moped /motorcycle	No	0	0	0
	Yes	33	746	779
	Total	33	746	779
Public transit	No	0	140	140
	Yes	0	550	550
	Total	0	690	690
Car	No	0	353	353
	Yes	24	1067	1091
	Total	24	1420	1444

Table 7.19: Primary transportation mode (recoded)

PRIMARY MODE	FREQUENCY	PERCENT
Bicycle/moped/motorcycle	779	26.7
Public transit	690	23.7
Car	1444	49.6
Total	2913	100

than one-quarter (23.7 %), the proportion choosing bicycle/moped motorcycle is slightly more than one-quarter (26.7 %) and the proportion choosing car is slighlty less than one-half (49.6 %).

7.3 BENCHMARK MODEL WITH GLOBAL INTERACTIONS

For the purpose of comparison in the extension from existing literature and docking of the multi-agent based simulation, we first estimate a benchmark nested logit model with a fully connected network and the only explanatory variable in the systematic utility being the field variable. Since we do not include any sociodemographic information yet about the agents, since we do not include agent-specific attributes of the home-to-work or work-to-home trips yet, since we do not take availability of transportation mode alternatives for specific agents yet into consideration, since the network is assumed here to be fully connected and since the model includes self loops, that is, each agent counts it own choice in evaluating the choices made

Table 7.20: Definition of *global* field variables for reference mode choice model, with self loops

VARIABLE	TYPE	DESCRIPTION
fullbisl	x_i, $i = bi$	Mode share of all agents in the sample choosing to commute by bicycle, motorcycle or moped
fullptsl	x_i, $i = pt$	Mode share of all agents in the sample choosing to commute by public transit (internal and/or external system)
fullcasl	x_i, $i = ca$	Mode share of all agents in the sample choosing to commute by car (either as a driver or a passenger)

by reference agents, the descriptions of the systematic utilities of the agents are therefore perfectly homogeneous. This is a case for which the steady state solutions of the sociodynamic system can be solved analytically as derived in Chapter 5.

Three global field variables are defined as in Table 7.20. The designation "sl" refers to "self loops." That is, the mode choice of a given decision making agent n is indeed included here when considering the average behavior of the reference group perceived by that agent, for the special case of a fully connected network where the reference group is the entire sample. As a consequence, there is no variation of the field variable among agents with a fully connected network. That is why it is not possible to estimate a set of alternative specific constants in this case, as mentioned earlier in Table 7.1. The field variable will be perfectly correlated with the set of alternative specific constants in the case of a global (fully connected) or uniform network.

The reason why we include self loops in this case, is because if we did not include self loops, the field variables would be a perfect predictor of choice when considering a fully connected network. Endogeneity is assumed not to be relevant here since the influence of the agent's own choice in the average over the entire sample will be negligible.

Using the notation of uppercase letters to denote estimated coefficients and the notation of lowercase letters to denote variables, the linear-in-parameters systematic utilities for the benchmark nested logit model are specified as follows for bicycle/motorcycle/moped (bi), internal/external system public transit (pt), and car driver/passenger (ca) modes:

```
V_bi = FULL*fullbisl
```

Table 7.21: Estimation results for benchmark nested logit model with fully connected network. The *t*-statistic for the utility parameter is against 0; for the scale parameter it is against 1.

ESTIMATED PARAMETERS	VALUE	STD ERR	T-STAT
Share of agents choosing each mode, with self loops, defined generically	2.7595	0.1551	17.79
Scale parameter for transit-car nest	1.0339	0.0500	0.6774
Null log likelihood (L_0)	-3200.3		
Final log likelihood	-3034.6		
Likelihood ratio test	331.4		

```
V_pt = FULL*fullptsl
V_ca = FULL*fullcasl
```

Estimation of three successive nested logit models first with public transit nested with bicycle, then with public transit nested with car, and finally with bicycle nested with car, show the second nesting structure to be indicated, namely, a transit-car nest. See Figure 7.4. Table 7.21 provides the estimation results for this benchmark nested logit model.

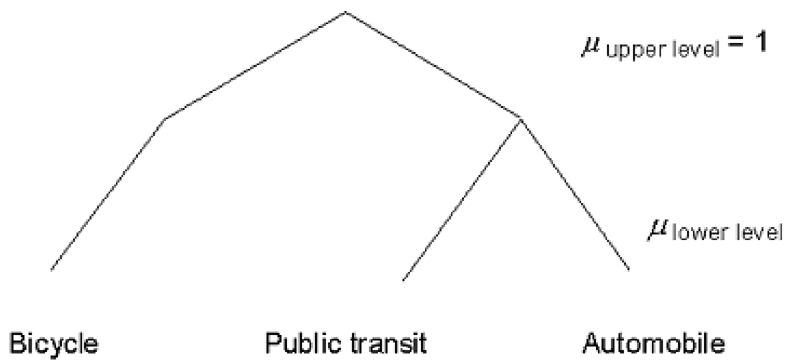


Figure 7.4: Depiction of the nesting structure of a trinary discrete choice model with unobserved heterogeneity that is shared between public transit and car driver/passenger mode alternatives. Such a shared attribute not observed in the particular subset of raw data made available for analysis might be for example crow's flight distance (above a certain threshold) between residential location and work/business location. The inclusion of travel time attributes in the systematic utilities however may be a reasonable proxy, thus a possible reason why the models estimated in sections 7.4 and 7.7 indicate a different nesting structure.

7.3.1 *Transition Dynamics: Simulated Evolution of Choice Behavior over Time*

Using the Repast multi-agent based modeling platform, we create computational versions of the model. The discrete choice estimation results controlling overall mechanisms related to individual preferences are embedded in the multi-agent based computational model. In this way, we are able to study the simulated evolution of choice behavior over time with positive feedback due to network effects. We investigate the simulated transition dynamics for the benchmark nested logit model estimated in Table 7.21 with the fully connected network and the only explanatory variable in the model being the field variable. Example time series results are shown in Figure 7.5. Each run is allowed to iterate for 600,000 time steps. This is on average 200 revisions of choices with asynchronous decision making for the sample size of roughly 3000 agents.

The temporal dynamics show a moderately slow transition to either one of two steady states. One of the emergent equilibrium solutions has a mode share for bicycle of 0.70 and mode shares for public transit and car of each 0.15. The other emergent equilibrium solutions has a mode share of approximately 0.70 for car and mode shares for public transit and bicycle of each approximately 0.15.

Note that because of the symmetry of the system where public transit and car are nested together and the agents are otherwise homogeneous in this case, at any mode share value for which there is an equilibrium solution for public transit, there should theoretically exist a dual equilibrium solution with an analogous mode share value for car, and vice versa. This implies that there should be a third equilibrium solution with a mode share of approximately 0.70 for public transit and mode shares for car and bicycle of each approximately 0.15. However given that the initial starting conditions for the sample are almost 50% for car commuters, and less than 25% for public transit users, in the computational simulations we find that this third stable solution never has a chance to emerge.

When the global field variable is the only component of the systematic utility, there are simplifications that make the steady state behavior also possible to solve analytically. In Chapter 5, five equilibrium solutions of the benchmark nested logit dynamic system are found with the particular estimated parameter values from Table 7.21. The stable steady state solutions nrs. 1 and 2 in Table 7.22 are confirmed in Figure 7.5. Solution nr. 3 is the theoretically expected solution which we don't find in practice in the computer simulations as mentioned in the previous paragraph. For Random seeds 5 and 6 in Figure 7.5 we do see the temporary appearance of the saddle node solution nr. 4 at the beginning of the time series, although as to be expected, the solution does not persist. Saddle node solution nr. 5 never has an op-

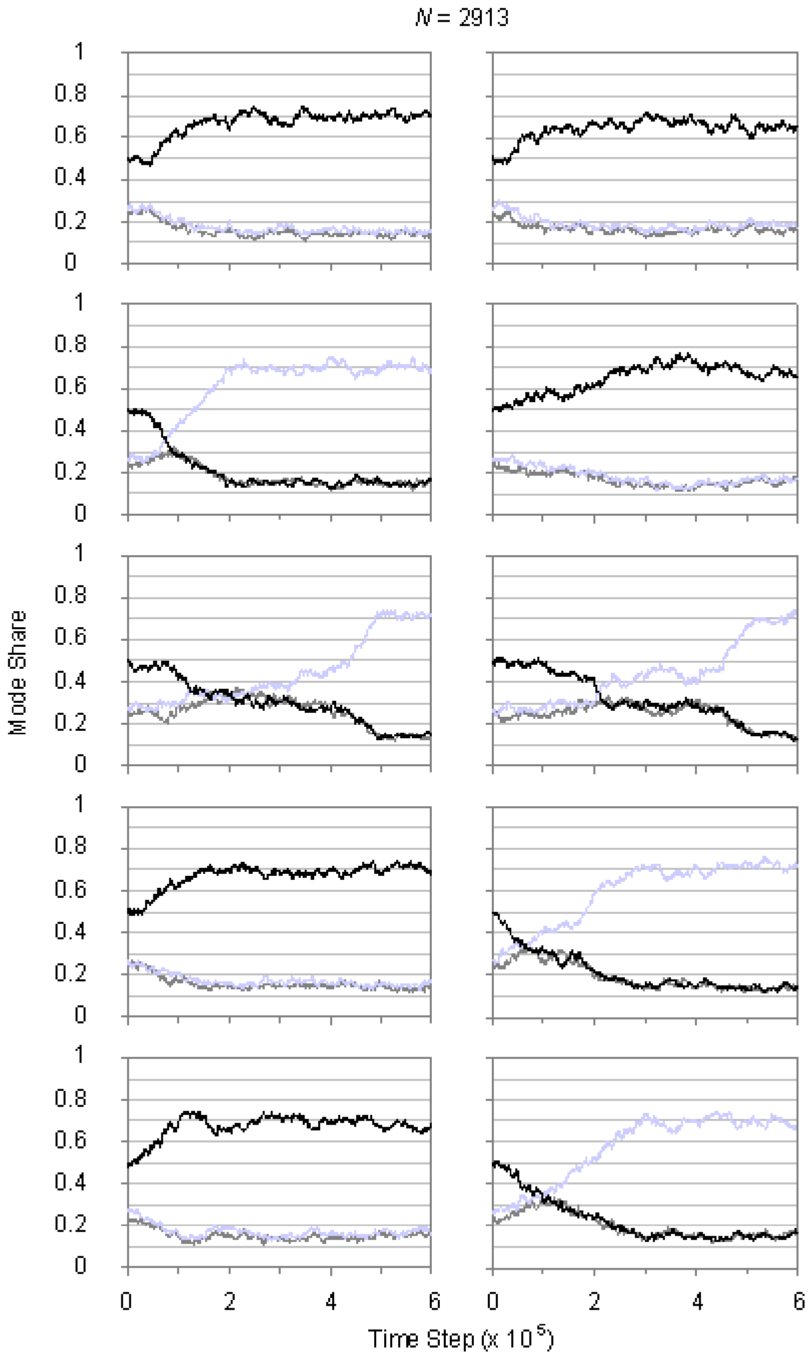


Figure 7.5: Example time series with different random seeds determining the agent decision making order for a benchmark sociodynamic trinary nested logit model with only a generic global field variable in the systematic utility for each mode

Table 7.22: Analytical equilibrium solutions for the benchmark sociodynamic nested logit model with fully connected network

NR	STABILITY	BICYCLE	TRANSIT	CAR
1	Asymptotically stable node	0.700	0.150	0.150
2	Asymptotically stable node	0.158	0.143	0.698
3	Asymptotically stable node	0.158	0.698	0.143
4	Saddle point	0.267	0.237	0.496
5	Saddle point	0.267	0.496	0.237

portunity to emerge because of the values of the initial mode shares, and would not be expected to persist anyway.

It is also instructive to note that since the scale parameter for the transit-car nest in Table 7.21 is close to unity, the emergent mode shares in the first equilibrium solution of 70% for bicycle commuters and 15% each for public transit and car commuters are analogous to the emergent equilibrium solution with a mode share of approximately 70% for car commuters and approximately 15% each for public transit and bicycle commuters. In numerical terms, the emergent mode shares are close to a perfectly symmetrical case of a trinary multinomial logit model. The significant impact however of the scale parameter for the public transit-car nest being 1.03 instead of exactly 1 however, is that the first equilibrium solution with 70% for bicycle commuters has a chance to emerge. In a pure multinomial case, while the equilibrium solution exists theoretically, the solution wouldn't emerge in practice since the initial starting conditions for the sample are almost 50% for car commuters, and less than 25% for bicycle commuters. Without the nesting to account for shared unobserved heterogeneity between public transit and car, in a perfectly homogeneous multinomial case with initial conditions of almost 50% car commuters, the positive feedback effect of the car mode in a global (fully connected) or uniform network will always "win" in practice over time over the other two modes with initial conditions of mode share of about 25%.

Although this benchmark model is too stylized to be seriously applied for policy purposes in transportation mode choice without any explanatory variables in the model except the hypothesized field variable, the exercise of estimating the benchmark model, investigating the emergent behavior over time and corroborating the computational results with analytical results is good practice in that it gives us confidence that the computational model is behaving as we expect. The exercise is also useful as a baseline in understanding corner solutions in parameter space before proceeding to more complex empirical models.

7.4 IMPACT OF AGENT HETEROGENEITY ON EMERGENT OUTCOMES

7.4.1 *Field Variables for Residential District and Socioeconomic Group*

Next we turn to the specification of the aggregate interdependence. Raw variables available for use in the model are described in Table 7.23.

We begin with the broad classification by residential district as shown in Figure 7.6. There are 9 districts represented in the sample, ranging in size from 223 sampled respondents to 461 sampled respondents. The mean size is 323 respondents with standard deviation 74, skewness 0.32 and kurtosis 0.19.

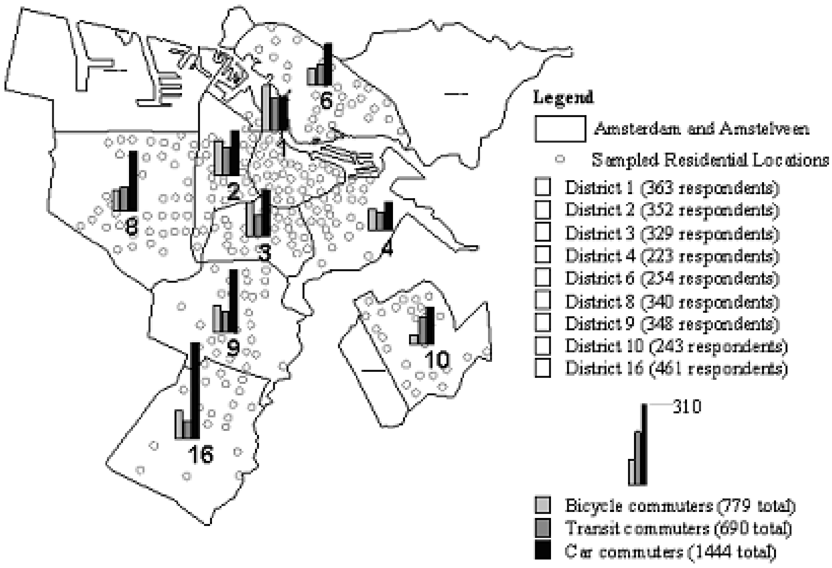


Figure 7.6: Transportation mode count for commuters in the sample grouped by residential district. Sampled residential locations are given in terms of the centroid of a traffic analysis zone, indicated in the figure with small gray circles. There are 9 sampled residential districts each with a distinctively characteristic population in part reflective of period of construction of the district. Adhering to the original numbering of districts in the raw data set these are: (1) Amsterdam Center, (2) Amsterdam West, (3) Amsterdam South, (4) Amsterdam East, (6) Amsterdam North, (8) Amsterdam Far West, (9) Amstelveen, (10) Amsterdam Southeast, (16) Far Amstelveen. The number of respondents in the sample per district is indicated in the inset. The non-sampled regions of the Municipality of Amsterdam represent the industrial harbor district to the west, the commercial office park district to the southeast, and the primarily agricultural district to the north.

Table 7.23: Description of raw variables in transportation mode choice data set

VARIABLE	TYPE	DESCRIPTION
Public transit availability	A_{in}, i = pt	1 if public transit alternative is available for agent n, 0 otherwise
Car ownership	S_n	1 if agent n owns a car, 0 otherwise
Gender	S_n	1 if agent n is female, 0 if male
Income category	S_n	Income range of agent n by governmental classification:
		0-5000 NLG; 5000-AOW; AOW-social minimum; social minimum-Zkf; Zkf+
Age category	S_n	Age range of agent n: 12-17 years; 18-29 years; 30-44 years; 45-59 years; 60+ years
Education level	S_n	Education level achieved: elementary; lower vocational; high school; post high school; other
Residential location	S_n	Residential location of agent n given by centroid of a traffic analysis zone
Travel time for bicycle mode	z_{in}, i = bi	Travel time in minutes by bicycle
Public transit in-vehicle time	z_{in}, i = pt	In-vehicle travel time in minutes by public transit
Out-of-vehicle time for transit	z_{in}, i = pt	Out-of-vehicle time for travel by public transit, in minutes
		(access, egress, waiting, transferring, etc)
Travel time for car mode	z_{in}, i = ca	Travel time in minutes by car
Parking time for car mode	z_{in}, i = ca	Time in minutes to park car

Next using the three variables age, income and education, 13 socioeconomic groups are defined. See Table 7.24. The socioeconomic groups range in size from 99 sampled respondents to 385 sample respondents. The mean size is 224 respondents with standard deviation 111, skewness 0.33, and kurtosis –1.8.

In both Figure 7.6 and Table 7.24, we find distinct clusters of agents whereby the commuter mode share per district and per socioeconomic group deviates notably from the overall modal split in the sample as a whole. For example, in district 1 (Amsterdam Center) the mode share by bicycle is highest, whereas at the periphery of the metropolitan region, in district 8 (Amsterdam Far West) and in district 16 (South Amstelveen) the mode share by car is the highest. This is intuitive with respect to the urban density in general, and concentrations of residential locations and work locations in particular. What is not immediately obvious from the geographical distributions of mode shares per district in the thematic map in Figure 7.6 is how much of the mode share is due to attributes of the transportation alternatives and characteristics of the decision makers, and how much of this may be due to social influence by neighbors and residential self-selection. For the socioeconomic group of commuters with above average incomes in Table 7.24, it is similarly intuitive that the mode share by car is higher than those groups with the same age category and same education level with lower incomes. Again what is not immediately obvious from simply studying the cross-tabulations in Table 7.24 is how much of the variation in mode shares is due to having more spending power for travel by car and how much is due to social influence to travel by car when income is a certain level and status pressures. To understand these questions we need to delve deeper. One way of doing this is by estimating various discrete choice models with different specifications.

In absence of detailed data on the exact interaction framework between identifiable decision makers at inter-household level, we turn instead to consider aggregate interactions between decision makers. We hypothesize a network of commonality between different agents in different residential districts based on common attributes in terms of social grouping between districts. This way we take into account in a general way both possible socioeconomic influences as well as possible feedback due to local neighbourhood effects. See Figure 7.7 Three field variables are defined as in Table 7.25.

The designation "`dsd`" (district sociodemographics) in Table 7.25 refers to the hypothesized network of commonality between different agents in different residential districts, based on common attributes in terms of social grouping between districts. This is to be contrasted with the designation "`full`" in Table 7.20 in the definition of a global field variable for the treatment with a fully connected or uniform network. In section 7.7 various other treatments are additionally hy-

Table 7.24: Commuter mode share and sample count by socioeconomic group, defined on the basis of age category in years, education level and income category. Education is coded: elementary education and lower vocational education (LO/LBO); high school education and other (MO/other); post high school education (HO). Income category is based on the Dutch governmental classification: zkf+ indicates above average incomes, o-zkf is all else. Where income level is not explicitly specified, respondents from all incomes falling in the given age/education group are included.

SOCIOECONOMIC GROUP	BICYCLE	TRANSIT	CAR	SAMPLE COUNT
12-29, LO/LBO	0.24	0.31	0.45	112
12-29, MO/other	0.27	0.32	0.41	385
12-29, HO	0.30	0.34	0.36	329
30-44, LO/LBO	0.20	0.24	0.55	117
30-44, MO/other, o-zkf	0.26	0.29	0.45	353
30-44, HO, o-zkf	0.41	0.21	0.37	361
30-44, MO/other, zkf+	0.11	0.17	0.72	115
30-44, HO, zkf+	0.22	0.14	0.63	338
45-up, LO/LBO	0.23	0.16	0.61	175
45-up, MO/other, o-zkf	0.27	0.21	0.52	175
45-up, HO, o-zkf	0.35	0.20	0.46	101
45-up, MO/other, zkf+	0.15	0.15	0.70	99
45-up, HO, zkf+	0.24	0.17	0.59	193
Total	779	690	1444	2913

Table 7.25: Definition of *local* field variables for transportation mode choice model, without self loops

VARIABLE	TYPE	DESCRIPTION
`dsdbinsl`	x_{in}, i = bi	Share of agent's fellow district residents and socioeconomic peers in the sample choosing to commute by bicycle
`dsdptnsl`	x_{in}, i = pt	Share of agent's fellow district residents and socioeconomic peers in the sample choosing to commute by public transit
`dsdcansl`	x_{in}, i = ca	Share of agent's fellow district residents and socioeconomic peers in the sample choosing to commute by car

pothesized and estimated. The designation "nsl" refers to "no self loops." That is, the mode choice of a given decision making agent n is not included when considering the average behavior of the reference group perceived by that agent. The reason why we do this, is to avoid endogeneity. In practice however, if the reference group is very large, the influence of the agent's own choice in the average will be negligible.

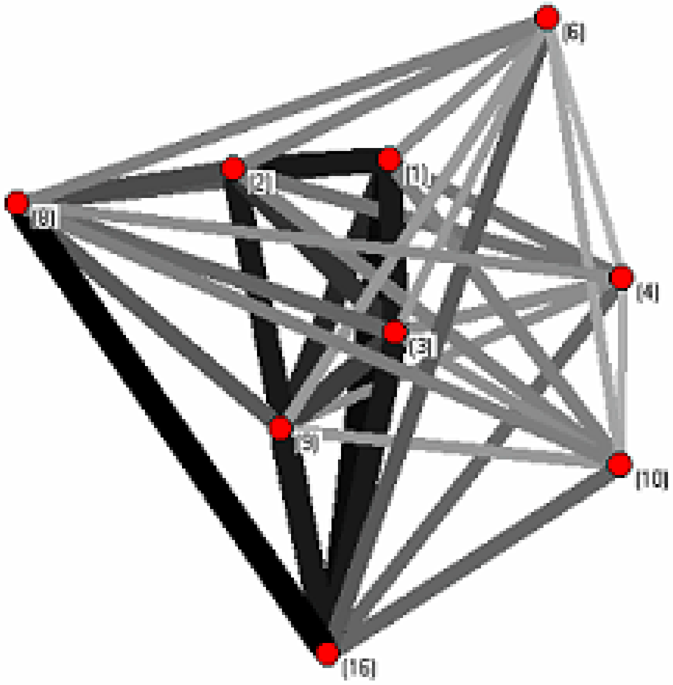


Figure 7.7: Abstract visualization of network interdependence defined by residential district plus socioeconomic group using the freely available software program Pajek developed by Batagelj and Mrvar (http://pajek.imfm.si). Red dots represent fully connected residential districts; the numbering of the districts indicated in parentheses corresponds to the same district numbering as in Figure 7.4. The darkness and width of lines gives an indication of the number of links between districts induced by socioeconomic group; this is in turn a reflection of both the number of respondents in the sample living in a given district indicated in Figure 7.4 as well as the similarity of the districts in terms of residential group stratification.

7.4.2 *Specification of Utility Functions*

Various piecewise linear specifications of all travel time related variables as well as age were tested against linear, quadratic and logarithmic forms of these variables. Similarly various generic forms

Table 7.26: Definition of constants, decision maker characteristics and trip attributes in mode choice model

VARIABLE	TYPE	DEFINITION
`ascpt`	h_i, $i = pt$	1 if alternative i is the public transit mode, 0 otherwise
`ascca`	h_i, $i = ca$	1 if alternative i is the car mode, 0 otherwise
`carown`	S_n	1 if agent n owns a car, 0 otherwise, defined in the systematic utility for car
`gender`	S_n	1 if agent n is female, 0 if male, defined alternative specifically for transit and car
`aowmin`	S_n	1 if income category AOW-social minimum, 0 otherwise, defined for bicycle
`lnage`	S_n	Natural logarithm of age in years as given by midpoint of age category, defined for transit
`age4559`	S_n	Age 45 to 59 defined piecewise continuously for public transit: max [0, min (age - 45, 15)]
`ttbi`	z_{in}, $i = bi$	Travel time in minutes by bicycle, defined in the systematic utility for bicycle
`ivtsqpt`	z_{in}, $i = pt$	In-vehicle travel time in minutes by transit, squared, defined for public transit
`ovtpt`	z_{in}, $i = pt$	Out-of-vehicle travel time by public transit in minutes, defined for public transit
`lnttca`	z_{in}, $i = ca$	Natural logarithm of travel time in minutes by car, defined for car
`parksqca`	z_{in}, $i = ca$	Time in minutes to park car, squared, defined in the systematic utility for car

of the categorical variables were tested against alternative specific forms. Considering various a priori hypotheses of behavior in the greater Amsterdam region and after statistical comparison of the alternative nonlinear specifications of variables against the linear versions thereof using loglikelihood ratio tests and non-nested tests (Ben-Akiva and Lerman 1985), the following definitions of observable characteristics Sn of the decision making agents, observable attributes z_{in} of the choice alternatives for a given decision making agent, and alternative specific constants h_i as given in Table 7.26 are ultimately used in a baseline multinomial logit model, in addition to the field variables x_{in} defined in Table 7.25.

Additionally, an availability indicator variable for the bicycle mode is defined using the raw variable for travel time for the bicycle mode, as: 1 if travel time by bicycle for decision making entity n is less than 75 minutes, 0 otherwise.

Using the notation of uppercase letters to denote estimated coefficients and the notation of lowercase letters to denote variables, the linear-in-parameters systematic utilities for the baseline model are thus specified as follows for bicycle/motorcycle/moped (bi), internal/external system public transit (pt) and car driver/passenger (ca) modes:

```
V_bi = DSD*dsdbinsl + AOWMIN_BI*aowmin + TT_BI*ttbi

V_pt = DSD*dsdptnsl + ASC_PT*ascpt + GEND_PT*gender
+ AGE4559_PT*age4559 + LNAGE_PT*lnage
+ IVTSQ_PT*ivtsqpt + OVT_PT*ovtpt

V_ca = DSD*dsdcansl + ASC_CA*ascca + GEND_CA*gender
+ CAROWN_CA*carown + LNTT_CA*lnttca
+ PARKSQ_CA*parksqca
```

After estimation of the baseline multinomial logit model, estimation of three successive nested logit models first with public transit nested with bicycle, then with public transit nested with car, and finally with bicycle nested with car, show the first nesting structure to be most significant in terms of loglikelihood ratio test and in terms of the a *t*-test on the nest coefficient. See Figure 7.8. The third nesting structure was not indicated. The nested logit model thus adds one additional parameter to the multinomial specification, namely the scale parameter μ_L for the transit-bicycle nest. Table 7.27 provides estimation results for the baseline multinomial logit and final nested logit model.

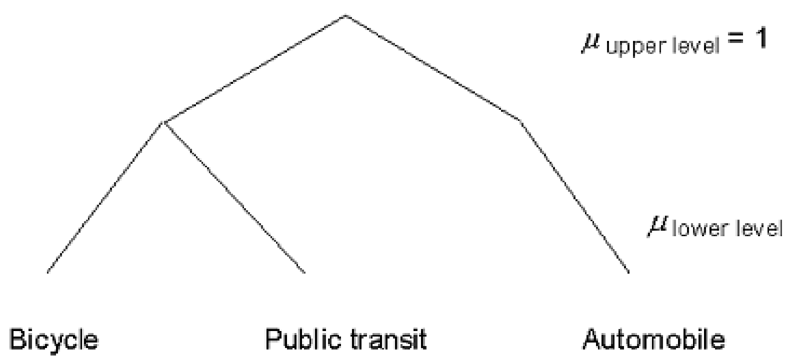


Figure 7.8: Depiction of the nesting structure of a trinary discrete choice model with unobserved heterogeneity that is shared between public transit and bicycle/motorcycle/moped mode alternatives. It is not possible to identify both the scale parameter of the upper level nest and the lower level nest(s), since what matters is only the ratio; in practice, typically the upper level nest is fixed to 1.

Note that in the case of the benchmark nested logit model with the only explanatory variable in the systematic utility being the global

Table 7.27: Estimation results for multinomial logit [MNL] and nested logit model specifications with sociogeographic network interdependence defined by residential district and socioeconomic group. All t-statistics (indicated in itallic below the estimated coefficient value) are against 0, except where noted for the scale parameter.

ESTIMATED PARAMETERS	MNL	NESTED
Share of agent's district residents and	1.91	1.93
socioeconomic peers choosing each mode	*4.54*	*5.59*
Alternative specific constant for transit	0.15	0.20
	0.18	*0.50*
Alternative specific constant for car	0.32	-1.11
	0.65	*-2.14*
Car ownership, defined for car	2.54	2.53
	24.68	*24.84*
Gender, defined for transit	0.56	0.24
	4.64	*3.12*
Gender, defined for car	0.45	0.28
	3.70	*2.46*
Low income, defined for bicycle	-0.48	-0.17
	-2.92	*-1.87*
Natural logarithm of age, for transit	-0.72	-0.30
	-3.10	-2.12
Age 45 to 59, piecewise, for transit	0.0409	0.0194
	2.13	*1.80*
Travel time for bicycle	-0.0810	-0.0375
	-14.96	*-4.38*
In-vehicle time for transit, squared	-3.95e-4	-2.90e-4
	-4.42	*-3.68*
Out-of-vehicle time for transit	-0.0252	-0.0191
	-2.87	*-3.26*
Natural logarithm of travel time for car	-1.40	-0.50
	-7.11	*-1.97*
Parking time for car, squared	-0.0117	-0.0136
	-7.51	*-8.35*
Scale parameter for transit-bicycle nest	–	2.51
(t-statistic against 1)	–	*2.48*
Null log-likelihood (L_0)	-2977	-2977
Final log-likelihood	-2063	-2055
Likelihood ratio test	1829	1844
Rho-squared (ρ^2)	0.3072	0.3096

field variable, the nesting structure in Figure 7.4 is differently indicated than in the case in Figure 7.8 with the full empirical model. The reason for this is because without other explanatory variables in definition of the systematic utilities, the nesting structure is forced to try to grossly capture the effect of all of these omitted variables as shared unobserved heterogeneity. In the case of a well-specified model, the nesting structure is able to capture any remaining shared unobserved heterogeneity at a more refined level. The fine-tuned shared unobserved heterogeneity when observed characteristics and observed attributes are properly accounted for, may have a different structure than that of the gross shared unobserved heterogeneity when there is little in the model.

It is possible to identify maximum $J-1$ alternative specific constants h_i and maximum $J-1$ alternative specific variables for each characteristic S_n of the decision making agents. For our case of a trinary mode choice model, that is a maximum of 2 in both cases. The reason why defining 3 alternative specific constants in our trinary choice case would be non-identifiable, is because all that matters is the difference between the alternative specific constants $h_j - h_i$ for elemental alternatives i, j in J. Similarly defining 3 alternative specific variables for a given characteristic S_n would be non-identifiable, because all that matters is the effect of the alternative specific variables on the relative utility between the elemental alternatives.

Most estimated coefficients in Table 7.27 for the multinomial logit versus the nested logit model are within two standard errors of each other. A noteworthy exception is the scale parameter estimated for the nested logit model (4 standard errors difference). We will see that the inclusion of shared unobserved heterogeneity in this way has a critical impact on the simulated evolution of choice behaviour over time.

7.4.3 *Transition Dynamics: Multinomial Logit Model with Empirically Defined Systematic Utility and Local Field Variable*

Using the Repast multi-agent based modeling platform, we investigate the simulated temporal dynamics over time due to the hypothesized aggregate feedback effect among agents defined by residential district and socioeconomic group. Example time series results for different random seeds are shown in Figure 7.9 for the multinomial logit case. As in Figure 7.5, the light gray time series again represent agents choosing bicycle/motorcycle/moped, the dark gray time series again represent agents choosing public transit, and the black times series again represent agents choosing car. Similarly each run is allowed to iterate for 600,000 time steps, on average 200 revisions of choices with asynchronous decision making for the sample size of roughly 3000 agents.

The temporal dynamics in Figure 7.9 show the relatively rapid emergence of only one single equilibrium solution with a mode share of approximately 60% for car commuters and approximately 25% for public transit and approximately 15% for bicycle commuters. The general picture in Figure 7.9 is thus notably different than Figure 7.5 along four different dimensions: the magnitude of the "winning" mode share; the emergence of only one steady state solution; the symmetry breaking of the "non winning" mode shares; and the speed of the transition to the steady state.

We have already noted that the simulated behavior over time of the benchmark nested logit model estimated in Table 7.21 is close to multinomial since the scale parameter on the nesting structure is only 1.03. Since the value of the coefficient on the field variable is 1.91 for the multinomial logit model in Table 7.27 as compared to the value of 2.76 in the benchmark nested logit model in Table 7.21, that is, since the coefficient is lesser in magnitude in Table 7.27, we might expect that the emergent effect on mode share of the "winning" mode is lesser in magnitude – which it indeed is.

Also since we now have a true multinomial logit model, it is understandable that the car mode always "wins" given the existing initial conditions of almost 50% car commuters; the other modes never have a chance to "win" over time over the car mode given the starting conditions – especially since the coefficient on the feedback is even less strong here than versus in section 7.3.

We see here that the symmetry of the mode share of "non-winning" modes in the emergent equilibrium solution is broken. Instead of the mode share of the "non-winning" modes in the steady state solution being each (approximately) 15% in Figure 7.5, we see that in Figure 7.9 the mode share of public transit commuters is consistently higher at a level of approximately 25% than the mode share of bicycle commuters at approximately 15%. This symmetry breaking is due to the heterogeneity of the agents in the model estimated in Table 7.27 with fully specified, empirically defined systematic utilities as compared to the homogeneous agent case in Table 7.21 with only a generic global field variable in the systematic utilities. Finally, we note that the convergence to steady state solution is relatively rapid in Figure 7.9 as compared to Figure 7.5. Since the coefficient on the field variable is less strong here than versus in section 7.3, the rapidity of the convergence would not seem to be purely due to the magnitude of the coefficient on the feedback. We hypothesize two distinct mechanisms for the rapidity of the convergence phenomenon. As with the symmetry breaking of the "non-winning" mode shares phenomenon, one hypothesis could be again the fact of the observed heterogeneity of the agents in the fully specified, empirically defined systematic utilities as compared to the homogeneous agent case. Another hypothesis could be simply the efficiency of information flow in the smaller ref-

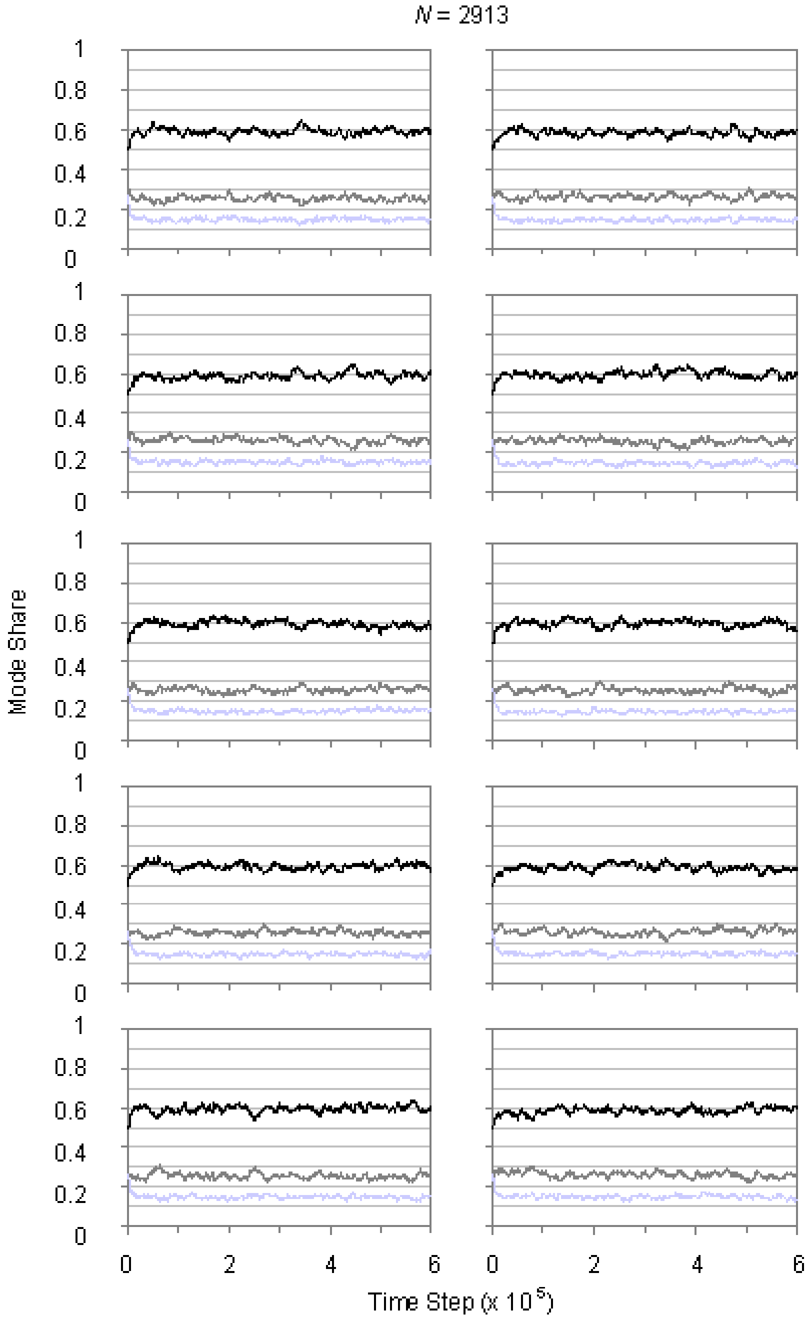


Figure 7.9: Example time series with different random seeds seeds determining the agent decision making order for a sociodynamic trinary multinomial logit model with fully specified systematic utility for each mode and empirically defined local field variable

erence group defined by residential district and socioeconomic group versus the time necessary for information flow in the entire sample. Further research is necessary to separate these two effects. Sections 7.5 through 7.7 compare the behavior over time of information flow with various hypothesized empirically-defined aggregate interaction effects.

7.4.4 *Transition Dynamics: Nested Logit Model with Empirically Defined Systematic Utility and Local Field Variable*

Finally, we investigate the simulated temporal dynamics over time due to the hypothesized aggregate feedback effect among agents defined by residential district and socioeconomic group in the nested logit case. Example time series results for different random seeds are shown in Figure 7.10. Again as in Figures 7.5 and 7.9, the light gray time series again represent agents choosing bicycle/motorcycle/-moped, the dark gray time series again represent agents choosing public transit, and the black times series represent agents choosing car. Similarly each run is allowed to iterate for 600,000 time steps, on average 200 revisions of choices with asynchronous decision making for the sample size of roughly 3000 agents.

Comparing the time series for the multinomial versus the nested logit case, we obtain yet again dramatically different results for the steady state solutions of the system. The temporal dynamics in Figure 7.10 show the rapid emergence of a perhaps surprising single equilibrium solution with a mode share of approximately 93% for public transit commuters and approximately 5% for car and approximately 2% for bicycle commuters.

Since in practice the rapid time evolution of behaviour from an initial case where almost 50% of commuters in the sample choose car to a steady state solution where 93% of commuters choose public transit is unexpected and counter-intuitive, further research is necessary to understand how this result arises. The result is particularly significant when we realize that most estimated coefficients in Table 7.27 for the multinomial logit versus the nested logit model are within two standard errors of each other. A noteworthy exception of course is the scale parameter estimated for the nested logit model (4 standard errors difference). In any case, the effect of considering shared unobserved heterogeneity through the introduction of the scale parameter, that is, the effect of common unobserved attributes of the choice alternatives in the error structure clearly cannot be ignored in an empirical application of a discrete choice model with network dynamic interactive feedback.

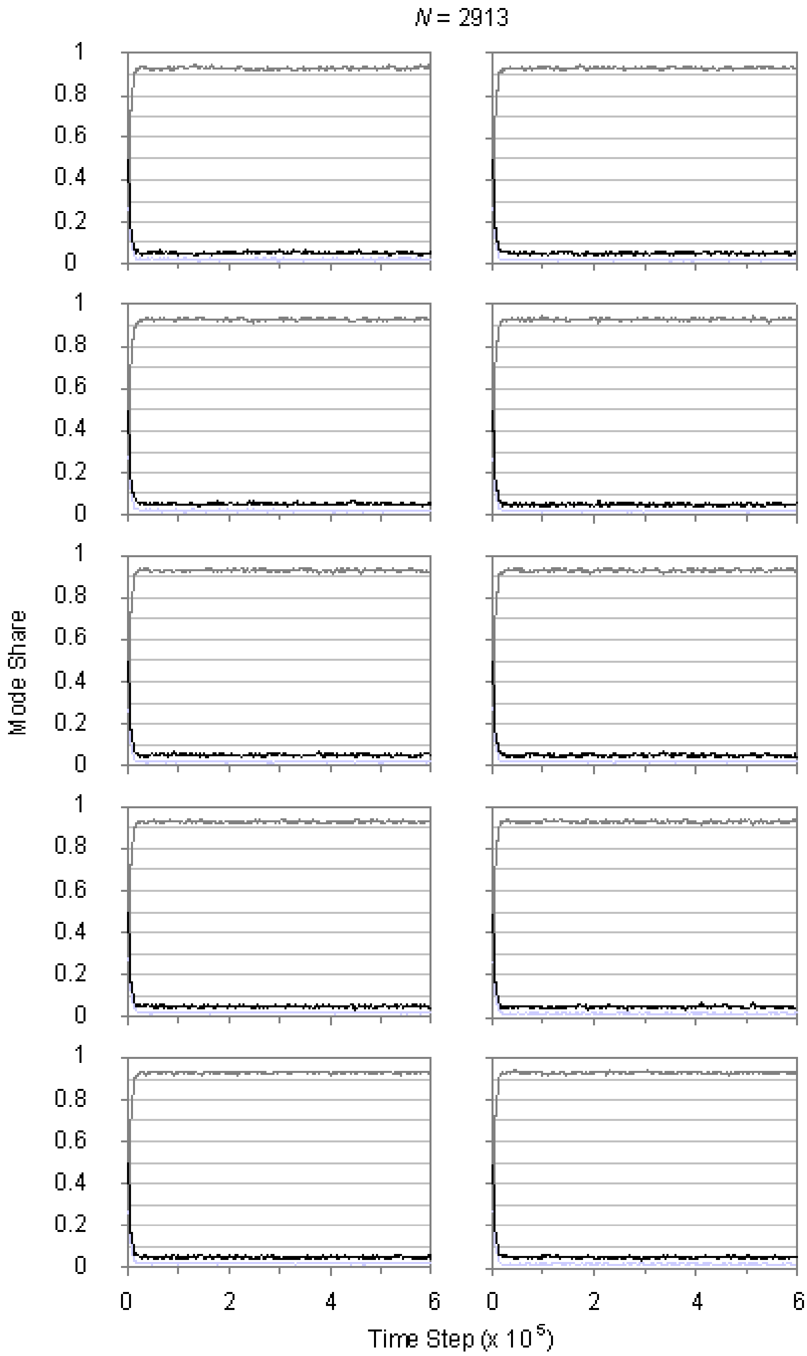


Figure 7.10: Example time series with different random seeds determining the agent decision making order for a sociodynamic trinary nested logit model with fully specified systematic utility for each mode and empirically defined local field variable

7.5 INITIAL CONDITIONS AND NETWORK SIZE IN BENCHMARK MODELS

Although we are fundamentally interested in non-global interactions, we continue our modeling endeavor by first re-visiting our fully connected network with global interactions. The reason for this is that when the model includes "self loops", that is, each agent counts it own choice in evaluating the choices made by reference agents, the steady state solutions of the sociodynamic system can be solved analytically as derived in Chapter 5, since the agents are perfectly homogenous in this special case. We have seen that such an analytical benchmark is useful for verification of our programming implementation of the multi-agent based model to confirm that we get expected results under known conditions in parameter space. Moreover, the benchmark can help us to interpret emergent outcomes as we change the parameter settings step-by-step away from the known analytical case. By studying the simulation results for the fully connected network under controlled conditions varying the initial starting mode shares and network size, it can help us gain insight in subsequently understanding the behavior of the system with hypothesized socio-geographic networks.

We thus return to the benchmark nested logit model from section 7.3 where the only observed explanatory variable in the model is the network interaction variable. Unobserved heterogeneity across the transportation mode choice alternatives is captured by nesting the alternatives that are assumed to be correlated. In a typical empirical application we would usually consider additionally other explanatory variables in the specification of the utility function, including individual-specific socioeconomic characteristics of the commuters (eg. gender) as well as individual-specific attributes of the choice alternatives (eg. travel time), and the availability of alternatives (eg. while Amsterdam and Amstelveen are well served by public transit, not everyone in the sample might be able to commute by public transit if there is no transit service at their work destination). We deliberately restrict our consideration in this section to the minimal model in order well understand the fundamental behavior of the benchmark model first before proceeding to an even more complex situation. This way we can focus on understanding the network effect in the nested logit model without confounding the contributions to the long-run results.

It is important to re-emphasize that our goal with the estimation here is not an analysis to inform policy, but rather simply to generate parameters to study the abstract behavior of a minimal nested logit model with social interactions. We will be interested in recognizing trends in the broad classification of behavior not in precise outcomes. If we were interested in precise outcomes such as for policy purposes, it would be important not only to include obvious additional explanatory variables in the model but also to apply a test, and if relevant a correction, for possible endogeneity of the network variables. Likewise we accept the fact that the scale parameter in Table 7.21 is only weakly statistically significant for this particular data set owing to the relative similarity between the bicycle mode share and the public transit mode share in the modal split, and still apply the nested model for its theoretical value.

Using the Repast (`http://repast.sourceforge.net`) modeling platform, the computational version of this model allows us to experiment with different hypothetical scenarios that can either be derived from the sample data, or tweaked by the modeler accordingly to study variation. As depicted in Figure 7.11, there are three aspects that we will consider: initial starting mode shares, network size and network connectivity. In order not to confound the effects of the utility parameters in the econometric estimation with the time-varying evolution of the mode shares, we use the estimated coefficient values in Table 7.21 for all multi-agent based simulations in this section and the next section. We defer the re-estimation of parameters based on different network structures until section 7.7.

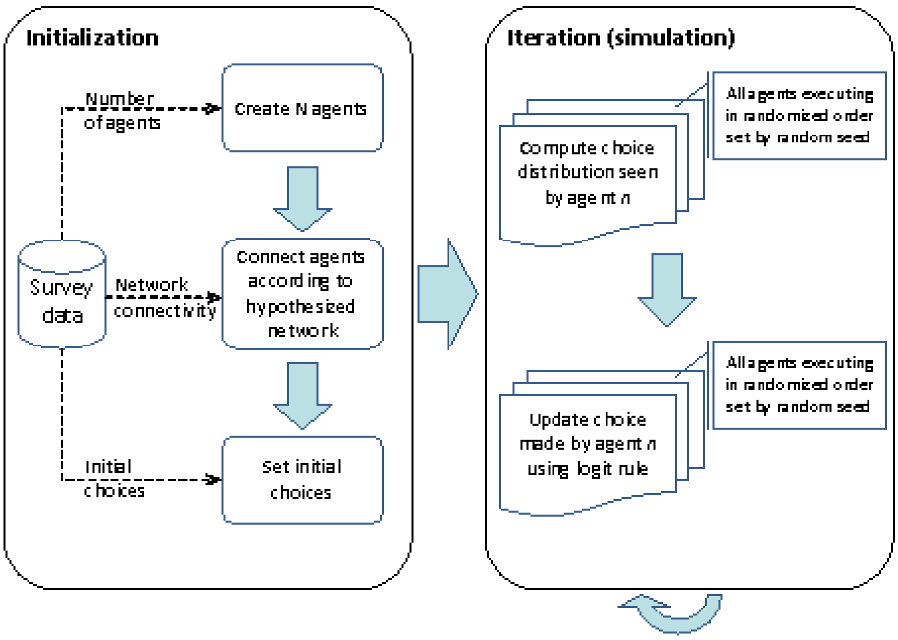


Figure 7.11: The working of a single simulation run.

7.5.1 *Benchmark Models*

Example time series results for the mode shares with a fully connected network under different scenarios are shown in Figure 7.12. Each run is allowed to iterate for 600,000 time steps. This is approximately 200 revisions of choices with asynchronous decision making for the network of 2913 agents. The light gray time series represents the proportion choosing bicycle at any given time step, the dark gray time series represent the proportion choosing public transit and the black times series represents the proportion of agents choosing car. Figure 7.13 shows observed long-run outcomes at the last time step when applying different random seeds for determining the decision making order for agents evaluating the choice distribution and updating their choice.

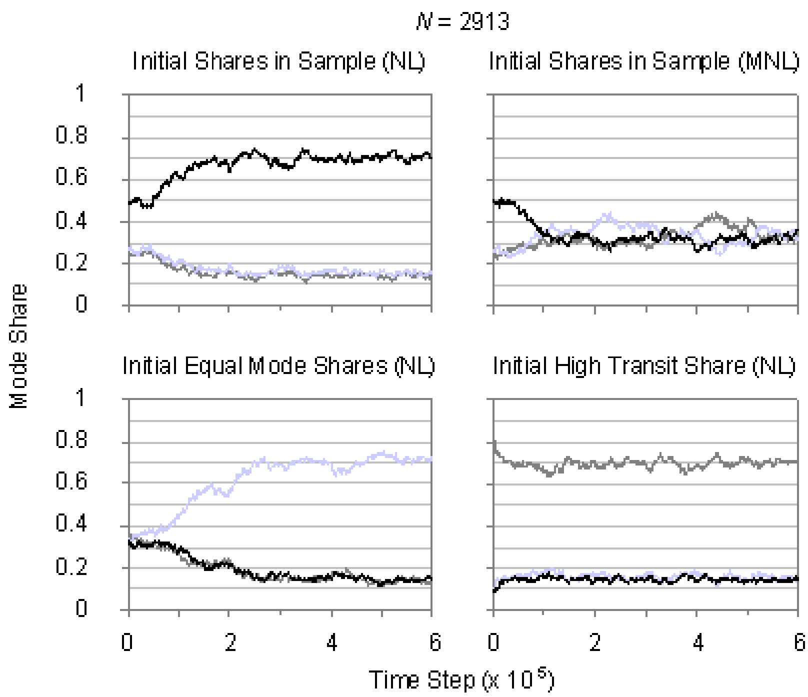


Figure 7.12: Example time series for benchmark sociodynamic nested logit (NL) and multinomial logit (MNL) models on a fully connected network, as well as the benchmark sociodynamic nested logit model under different initial conditions

Sociodynamic Trinary Nested Logit

We recall from section 7.3 that there are five equilibrium solutions for the long-run behavior of the benchmark nested logit model with sociodynamic feedback with global interactions for the particular estimated parameter values in Table 7.21. Three of these solutions are stable and two of these solutions are unstable as in Table 7.22. Due to the symmetry of the system whereby transit and car are nested together, at any mode share value for which there is a solution for transit, there will be a dual solution with an analogous mode share value for car, and vice versa.

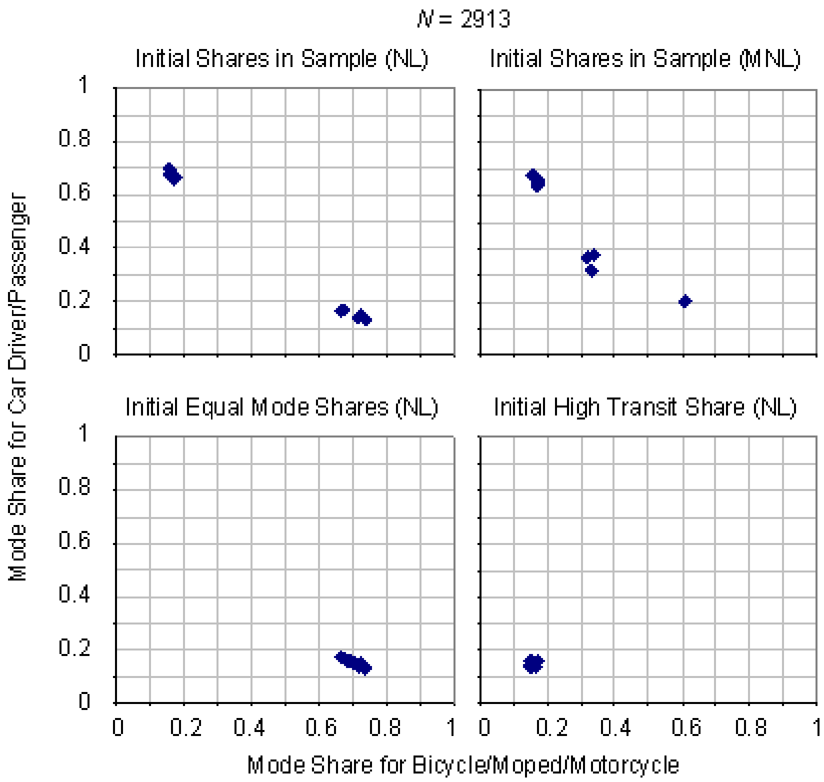


Figure 7.13: Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order for benchmark sociodynamic nested logit (NL) and multinomial logit (MNL) models on a fully connected network, as well as the benchmark sociodynamic nested logit model under different initial conditions

From Table 7.22 we know the most stable solution occurs with a mode share for bicycle of 0.700 and mode shares for transit and car of each 0.150. In practice we do not expect to see the saddle node solutions. Also, for initial starting mode shares as in the survey data with almost 50% car commuters, and less than 25% transit users, we might expect in practice that stable solution nr. 2 listed in Table 7.22 with mode share 0.698 for car and mode share 0.143 for transit will be more likely to be reached than its dual solution nr. 3 with the mode shares reversed. In the upper left panel of Figure 7.12 we see an example time series where the stable solution nr. 2 is gradually reached. In the upper left panel of Figure 7.16, over multiple runs we indeed consistently obtain the analytically predicted first two equilibrium solutions in Table 7.22.

In section 5.3 we saw that the solutions of the sociodynamic nested logit model can be visualized in terms of a so-called "potential" surface, where any stable equilibria are isolated minima, any unstable equilibria are isolated maxima, and any saddle points are points at the center of saddle-shaped forms on the surface which have minima in one direction but maxima in a crossing direction. The five solutions in Table 7.22 can be depicted in this way as in Figure 7.14. As depicted in Figure 7.4, the mode share for elemental alternative 0, the pendant in its own "nest" is given by p_0, and the mode shares for elemental alternatives 1 and 2, assumed to be correlated and thus nested together are given by p_1 and p_2. Note however that the full modal split is entirely specified given only p_0 and p_1 since the mode shares must sum to unity and thus p_2 can be calculated immediately as $p_2 = 1 - p_0 - p_1$. In the nested logit model estimated in Table 7.21, bicycle/moped/motorcycle is the pendant alternative, and public transit and car driver/passenger are the nested alternatives. We can imagine a ball rolling on the surface in the Figure 7.14 and tending to settle in one of the basins of attraction formed by the isolated minima, i.e. stable equilibria. The depth of a basin furthermore gives an indication how stable the solution is, both locally in the region around the minimum and globally with respect to any other minima. In Figure 7.14 we see three basins near the three corners of the surface with minima at the stable solutions ($p_0 = 0.7$, $p_1 = 0.15$), ($p_0 = 0.16$, $p_1 = 0.14$), and ($p_0 = 0.16$, $p_1 = 0.7$). The minimum at the solution ($p_0 = 0.7$, $p_1 = 0.15$) with leading bicycle mode share is the most stable; it is thus accordingly the lowest in Figure 7.14. If the ball comes to settle in one of the other two equilibria, in order to exit, it must roll up over a small passage at a saddle point, respectively ($p_0 = 0.27$, $p_1 = 0.24$), or ($p_0 = 0.27$, $p_1 = 0.5$). These saddles namely have minima from the curved upward sides of the surface, but importantly maxima along the direction of the trough to the basin of attraction. If the ball is stochastically able to clear the saddle point and thus escape basin of attraction, the ball would then tend to roll down the smooth incline towards the lowest, most stable equilibrium, in this case the equilibrium with leading mode share of the pendant alternative, bicycle/moped/motorcycle. We will return to the concept of stochasticity shortly.

Sociodynamic Trinary Multinomial Logit

By way of comparison, we also estimate a sociodynamic multinomial logit model with a fully connected network. See Table 7.28. According to Brock and Durlauf's general theoretical results reviewed in section 4.1.1, there exist multiple equilibria when $\beta > 3$. However, using the approach presented in Chapter 4, we compute the analytical equilibria and find that there are in fact seven equilibrium solutions even for $\beta = 2.79$. Four of these solutions are stable and three of these solutions are saddle points. See Table 7.29. In the multinomial model there is perfect three-way symmetry. At any mode share value for which there is a solution for one alternative, there will also be a solution for the other two alternatives as well. Importantly, the feedback in the system is apparently "dominant enough" to cause runaway

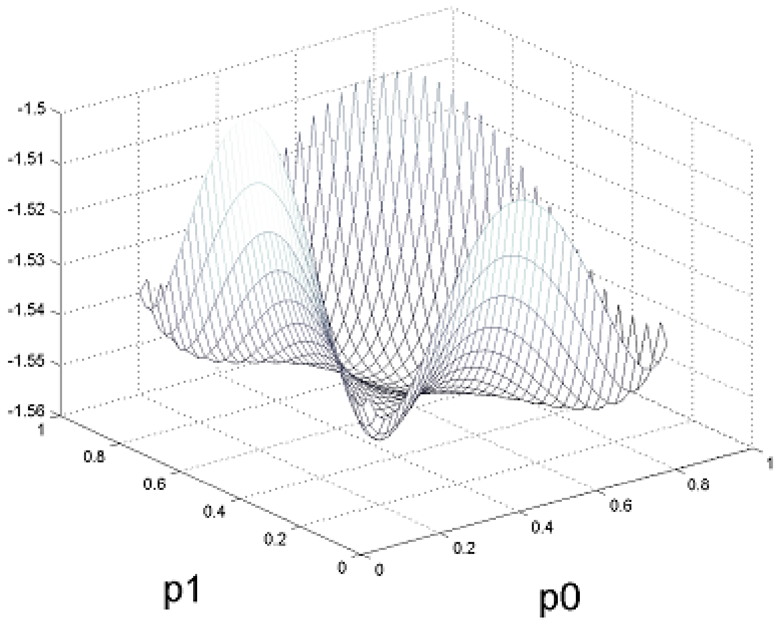


Figure 7.14: Visualization of analytical solutions of the sociodynamic nested logit model on a potential surface

flocking. Comparing the pattern of the solutions in Table 7.22 and Table 7.29, we see that with the multinomial logit model we get two extra equilibria: the missing saddle node that was lost, and a stable equilibrium where all mode shares are equal. The latter stable equilibrium is indeed predicted by Brock and Durlauf for $\beta < 3$.

It is worth noting that the initial modal split in the data described in Table 7.19 on page 241 appears back as a steady state equilibrium point in the results in Table 7.22 for the sociodynamic nested logit model (solution nr. 4, a saddle point), but not in Table 7.29 for the sociodynamic multinomial logit model. The reason for this is because the initial model split in the data set is not symmetric among

Table 7.28: Estimation results for benchmark multionomial logit model with fully connected network. The t-statistic for the utility parameter is against 0.

ESTIMATED PARAMETERS	VALUE	STD ERR	T-STAT
Share of agents choosing each mode, with self loops, defined generically	2.7885	0.1520	18.35
Null log likelihood (L_0)	-3200.3		
Final log likelihood	-3034.8		
Likelihood ratio test	330.9		

Table 7.29: Analytical equilibrium solutions for the benchmark sociodynamic multinomial logit model with fully connected network

NR	STABILITY	BICYCLE	TRANSIT	CAR
1	Asymptotically stable node	0.687	0.156	0.156
2	Asymptotically stable node	0.156	0.156	0.687
3	Asymptotically stable node	0.156	0.687	0.156
4	Asymptotically stable node	0.333	0.333	0.333
5	Saddle point	0.261	0.261	0.478
6	Saddle point	0.261	0.478	0.261
7	Saddle point	0.478	0.261	0.261

any pairs of mode shares, while the sociodynamic multinomial logit model can only have long-run, steady-state solutions where pairs of mode shares are equal as seen in Table 7.29. Brock and Durlauf (2002, 2006) discuss further the intuition underlying this phenomenon. In the nested logit model however, the symmetry of pairs of mode shares within a given modal split is broken by the nest scale parameter. In short, the scale parameter in the nested logit model allows an extra degree of freedom which permits the re-capturing of the initial modal split as one of the long-run outcomes. The fact that the initial modal split happens to be a saddle point in the example in this case study is specific to this particular data set. A different data set with different initial modal split could yield an equilibrium outcome with different stability.

From Table 7.29 we know the most stable solutions for the sociodynamic multinomial logit model with our data occur for the trio of symmetric solutions where the mode share for one of the alternatives is 0.687 and mode shares for the other alternatives are each 0.156. In addition the three-way symmetric solution with all mode shares equal to one-third is also stable. In practice we again do not expect to see the saddle node solutions. Also, for the initial modal split in the survey data with 0.267 bicycle mode share, 0.237 transit mode share and 0.496 car mode share, we might expect in practice that stable solution nr. 2 and nr. 4 listed in Table 7.29 will be more likely to be reached than the others due to their proximity to the initial starting condition. Solution nr. 3 with the mode share of 0.687 for transit will be least likely to be reached due to the mode share for transit being lowest initially. In the upper right panel of Figure 7.12 we see an example time series where the three-way symmetric stable solution nr. 4 is reached fairly quickly. Furthermore in this example the system does not manage to stochastically jump out this local basin of attraction even though it is not globally one of the most stable solutions. In the upper right panel of Figure 7.13, over multiple runs we indeed consistently obtain the predicted "nearby" solutions nr. 2 and nr. 4 in Table 7.29. In one time series the system traverses over the locally stable center solution and proceeds to onwards to the globally more solution nr. 1 in Table 7.29. Stable solution nr. 3 is not reached.

7.5.2 *Transition Dynamics: Effect of Initial Conditions*

Next, we test a hypothetical case where the initial mode shares are not determined from the survey, but are tweaked so that the starting mode shares are equal, ie. all one-third. In this initially non-biased case, we might expect the most stable equilibrium to be dominant. In the example time series in the lower left panel of Figure 7.12 we see initially ambivalent average behavior, but once the runaway effect is established, the series proceeds to the stable solution and then stays there. Over multiple runs with different random seeds determining the decision making order we find in the lower left panel of Figure 7.13 that all runs went to the dominant equilibrium.

Then, we consider a hypothetical case where the initial mode share for public transit is very high (80%). The example time series in the lower right panel of Figure 7.12 moves easily to the stable solution nr. 3 listed in Table 7.22, and stays there. Over multiple runs with different random seeds, we find in the lower right panel of Figure 7.13 that all runs are locked in at this steady state.

7.5.3 *Transition Dynamics: Network Size Effects*

Next we consider the effect of the size of the network on the long-run behavior. Since our sociographic networks with clustered groups can be expected to show the weighted average behavior of the separate clusters, it is useful to see how a separate cluster behaves. In our case study, a separate cluster is assumed by design to be a fully connected network of a subset of the total number of agents. Table 7.30 presents, for example, initial sample mode shares in the raw data by residential district.

The time series in the left panel of Figure 7.15 shows an example for District 16 (Amstelveen South) where $N = 461$. It is interesting to consider District 16 since it is the district with the largest number of respondents in the sample. Here the initial mode share for car within the district is also particularly high (66.2%). However, instead of finding a long-run lock-in at stable solution nr. 2 listed in Table 7.22, because the dynamics become more volatile with the lesser number of agents we see that the time series *stochastically cycles* between all three stable equilibria in Table 7.22, and all modes have an opportunity in turn to become dominant.

The time series in the right panel of Figure 7.15 shows an example for District 10 (Amsterdam Southeast) where $N = 243$. District 10 is

Table 7.30: Commuter mode share and sample count by residential district. Numbering of districts adheres to the original numbering in the raw data set; non-sampled regions include the west industrial harbor district, the southeast commercial office park district, and the primarily agricultural district to the north of Amsterdam.

RESIDENTIAL DISTRICT	BICYCLE	TRANSIT	CAR	SAMPLE COUNT
1: Amsterdam Center	0.408	0.287	0.306	363
2: Amsterdam West	0.324	0.264	0.412	352
3: Amsterdam South	0.334	0.216	0.450	329
4: Amsterdam East	0.314	0.269	0.417	223
6: Amsterdam North	0.220	0.260	0.520	254
8: Amsterdam Far West	0.200	0.235	0.565	340
9: Amstelveen North	0.247	0.193	0.560	348
10: Amsterdam Southeast	0.132	0.362	0.506	243
16: Amstelveen South	0.206	0.132	0.662	461
Total	779	690	1444	2913

the district with the second smallest number of respondents in the sample after District 4 (Amsterdam East). Here the initial mode share for transit within the district is relatively highest (36.2%) among all districts as seen in Table 7.30. With the smaller district size however the dynamics become even more volatile, even more easily stochastically flipping between the stable equilibria.

In Figure 7.16, when considering the behavior over multiple runs with different random seeds determining the order in which agents make decisions, we find a picture of emergent outcomes scattered across the three stable equilibria, transitioning through the region of the saddle node equilibria. Furthermore the most stable solution nr. 1 is notably dominant over all runs, despite the initial conditions of starting with high car mode share in District 16. Comparing District 10 with $N = 243$ to District 16 with $N = 461$ we see that the picture is slightly more scattered, spending relatively more time transitioning through the saddle node region and relatively less time in a stuck in a stable steady state.

The reason for the volatility with the smaller network size has to do with the assumption of each agent's choice being influenced here by the percentage of agents the reference group making each choice. Since each cluster by definition here contains only a subset of the total number of agents in the data sample, the influence of an individual agent updating a choice is larger within the fully connected cluster than when considering the entire data sample being fully connected.

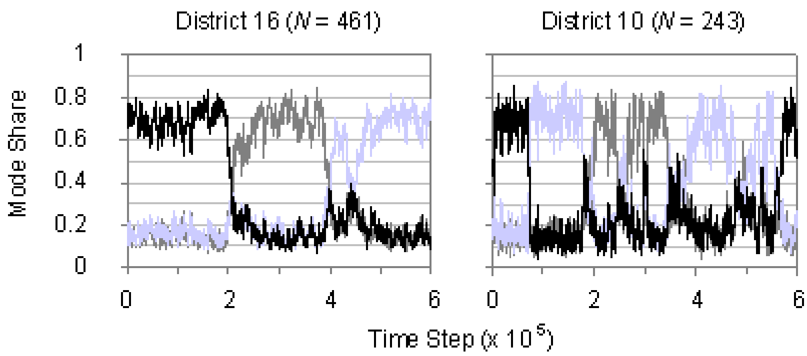


Figure 7.15: Example time series for the benchmark sociodynamic nested logit model on fully connected extracted subsets of the sample with different sizes

This relatively larger jump in mode share for a particular mode alternative as a given agent updates its choice within a smaller reference group, gives the possibility to jump out of a particular steady state and move to another one.

7.5.4 *Interim Conclusions*

In summary, thus far we have seen: 1) lock-in at the analytically predicted stable steady states, 2) manifestation of the analytically predicted most stable equilibrium being dominant, and 3) for a fully connected network with smaller size, the larger jump in mode share as an agent updates each choice per iteration breaks the lock-in that we found when the entire sample is fully connected. Given this knowledge, we now proceed to our study of sociogeographic networks.

7.6 sociogeographic networks: clusters and overlapping groups

7.6.1 *Definition of Interaction Variables*

We begin our detailed consideration of the impact of sociogeographic networks on emergent outcomes with a broad classification by residential district. The districts in the Municipality of Amsterdam are meaningful entities for the purpose of our case study since they have their own local government structures with their own directly elected representative aldermen. In the multi-party system in the Netherlands, the composition of the majority coalition in one district may be different than the majority coalition in another district reflecting the different local cultures associated with the districts. As a result the districts have the possibility to organize themselves in different ways and set different spending priorities. Residents identify themselves

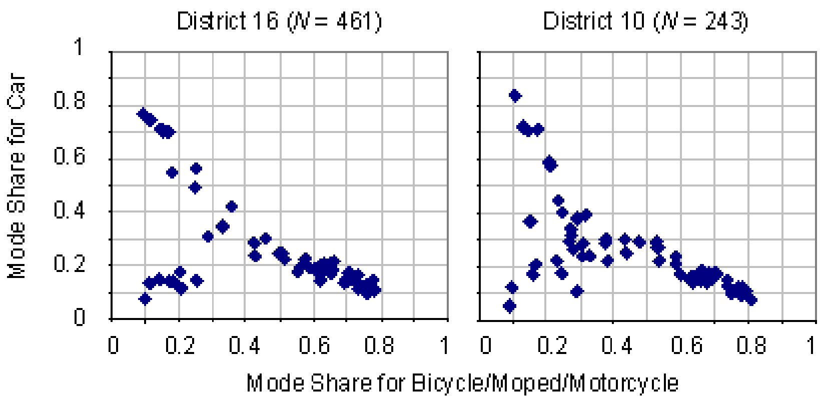


Figure 7.16: Observed mode shares by increment $t = 100,000$ until $t = 600,000$ with different random seeds determining the agent decision making order for the benchmark sociodynamic nested logit model on fully connected extracted subsets of the sample with different sizes. Compare with the upper left panel of Figure 7.13 on page 263. Initial conditions have no significant effect on long-run outcomes as sociodynamics become more volatile with smaller clusters.

with their districts and often deliberately choose to live in a particular district, and not another district. In our case study, there are 9 districts represented in the data, ranging in size from 223 sampled respondents (District 4, Amsterdam East) to 461 sampled respondents (District 16, Amstelveen South). As described earlier in section 7.4, the mean size is 323 respondents with standard deviation 74, skewness 0.32 and kurtosis 0.19.

In the urban economics literature, the phenomenon of residential self-organization was famously studied by Tiebout (1956). His focus on local variations in public expenditure and the thereby associated residential mobility of "consumer-voters" was a direct challenge to Samuelson's earlier conjecture (1954, 1955) that public goods could not be allocated efficiently when assuming public expenditures are handled solely at a central, federal government level, and Musgrave's analysis (1959) that the only mechanism for determining the level of public goods would have to be political. Initially ignored, Tiebout's model became popularized after his untimely death following Oates' empirical work (1969) on effects of property taxes and local public spending on property values. Fischel (2006) provides a 50th anniversary edited volume sampling the plethora of research exploring different facets, expansions and variations of Tiebout's seminal work now extending to social sciences beyond public economics. Tiebout's simple seven tenet hypothesis also lends itself naturally to computational modeling via multi-agent based simulation. Kollman, Miller and Page (1997) is a notable example. Gulyás and Dugundji (2006) have explored the possibility for agents to dynamically update their transportation mode choice and their residential location. In the interest of the explicit aim of simplicity in this chapter, however, and in order to avoid confounding effects, the residential location and work location are both assumed to be static. Nonetheless the visionary perspective of Tiebout in viewing a population not as a stationary one, but as one in motion, is deeply appreciated. This is an important direction for further research as noted in the Preface to this thesis and as outlined in Dugundji et al (2001).

In order to be able to test the effect of spatial scale, by way of comparison with the network interdependence defined by residential district, we also define a smaller neighborhood region of influence on the basis of 4-digit postcode. There are 67 postcode regions represented in the sample, ranging in size from 10 sampled respondents to 161 sampled respondents. The mean size is 43 with standard deviation 32, skewness 2.1 and kurtosis 4.4. As with districts, the postcode definitions are also meaningful in that they do not have arbitrary boundaries: residents know in which postcode zone they live and the postcode zones have different reputations. The postcodes in the greater Amsterdam metropolitan region are generally defined such that there is homogeneity within a zone, and heterogeneity across zones, in terms of land uses and built environment according to the period that the zone was originally developed and/or subsequently re-developed in the incremental growth of the region over the years. Our assumption is that the postcode boundaries delineate spatial peers and that agents residing within a particular postcode have similar underlying preferences and values, thus exerting a relatively stronger influence than agents who live outside the postcode.

Next, under the assumption that respondents are influenced by the choice behavior of others in their own socioeconomic class regardless of their residential location, we define 13 socioeconomic groups using the three variables age, income and education as in section 7.4. The groups range in size from 99 sampled respondents to 385 sample respondents. The mean size is 224 respondents with standard deviation 111, skewness 0.33, and kurtosis –1.8. Our assumption is that a respondent's direct friends and colleagues are likely of a similar socioeconomic status. For the purposes of the case study, we consider here a relatively dense network of overlapping groups where agents are connected by both their residential district and socioeconomic class.

Finally, since we are considering commute behavior and the work location is known in the data set, we define postcode regions for the work locations. Here again the idea is that due to urban planning policy in the Netherlands the type of work locations and their accessibility will tend to be more homogeneous within a postcode zone than across postcodes. The sociocultural and practical acceptance of traveling to work by bicycle, for example, may be likely to be higher

Table 7.31: Summary statistics for networks with clusters and networks with overlapping influence groups: Residential district clusters [DTR]; Residential postcode clusters [PC4]; Residential district and socioeconomic group [DSD]; Residential and work postcode [PWW]. Diameter, radius and average path length are defined within connected components.

NETWORK STATISTICS	DTR	PC4	DSD	PWW
Average degree	338.6	66.8	576.8	108.2
Diameter	1	1	2	5
Radius	1	1	2	3
Average path length	1	1	1.8	2.3
Network density	0.116	0.0229	0.198	0.0371
Components	9	67	1	1

in a postcode zone where many commuters already travel by bicycle. This in turn may inspire other workers who initially travel by another transportation mode, to revise their mode choice. The mechanism may occur through various different means, such as direct communication with their colleagues, financial travel re-imbursement incentives from their employers, simply being aware that colleagues commute by bicycle, or even just seeing lots of other bicycles parked outside on the street or in a bicycle parking area. Furthermore if there is a critical mass of bicycle commuters to a particular area, there is more stimulus to provide better bicycle facilities, such as covered bicycle parking and dedicated bicycle paths. Regardless of the precise underlying mechanism of the interaction, such an effect can approximately modeled in the aggregate as an agent being influenced by the proportion of other agents in their work postcode zone making a given mode choice. For the purposes of the case study, we define connectivity of interactions with an overlapping network where an agent is influenced both by the proportion of agents making a given choice in their work postcode zone and their residential postcode zone. This leads to a network which is much less dense than the scenario with overlapping residential districts and socioeconomic groups.

7.6.2 *Summary Network Statistics*

Table presents summary network statistics.

Average Degree

Average degree refers to the average number of "links" (in our case the number of "reference" decision making entities) that the agents have, with average being taken over all agents in the data set. Since the size of the residential district clusters ranges from 223 sampled respondents (District 4, Amsterdam East) to 461 sampled respondents (District 16, Amstelveen South) it is obvious that the average degree over all the residential district clusters will be a number between these extremes. Likewise the residential postcode clusters range in size from 10 sampled respondents to 161 sampled respondents and thus the average degree over all the residential postcode clusters will again be a number between these extremes. It is interesting to see how many more links are added on average when considering the overlapping groups, that is, adding the influence from social group to the residential districts and adding the influence from the work postcode to the residential district postcode. In our scenarios the overlapping groups add on average roughly 60-70% more links (reference decision makers) for a given agent as compared to the relevant clustered scenario.

Network Density

Related to the average degree is the concept of density, introduced earlier in the previous chapter in section 6.2.1. The network density is the total number of existing links in the network divided by all theoretically possible links if everyone were linked to everyone else as in the case of the fully connected network. In our scenarios, this measure is the same as the average degree divided by the number of agents. The average degree for the residential district clusters is roughly five times higher than the residential postcode clusters and thus the density is also roughly five times higher. Likewise the density for the overlapping residential district and social group is about 5.3 times higher than the overlapping residential and work postcodes.

Components

The components measure tells how many isolated groups there are in the data with no connections between them. Since there are nine districts and 67 postcodes represented in the data, this is the respective number of components for these scenarios. It is interesting to see that by adding the influence from social group to the residential districts and by adding the influence from the work postcode to the residential postcode, there becomes only one giant component where it is possible for influence to flow along links and spread throughout the entire network. In our scenarios with the overlapping groups, there are no longer any parts of the population that are not reachable from somewhere else. Influence can reach everybody along some path.

Average Path Length (within connected components)

The average path length tells how many links this takes on average to travel by the shortest way. For the district and social group this is

1.8 links, for the residential and work postcode this is 2.3 links. In the case of the clusters, the average path length is defined within the cluster. Since everybody is assumed to be connected to everyone else within the cluster, the average path length is then just 1.

Radius and Diameter (within connected components)

The radius and the diameter of the network are both computed by determining the farthest distance traveling by the shortest way between any two agents. The radius is the shortest of these farthest distances over all agents; the diameter is the farthest of these farthest distances. The diameter is thus equivalent to the longest shortest path. Similar to the average path length, for the case of the clusters, radius and diameter are defined with the clusters. Since everyone is connected to everyone within the cluster, the shortest path is always 1 within the cluster, and thus the radius and diameter are also 1. It is interesting to see that for the overlapping residential district and social group the radius and diameter are both equal to 2. That means that influence is maximum only 2 links away from anyone. By the design of the overlapping groups, this implies that influence can always travel from decision maker A with a given residential district and social group to decision maker B with another residential district and social group travelling either first through the district of A to the social group of B and then through the social group of B to the district of B, or vice versa first though the social group of A to the district of B and then through the district of B to the social group of B. With overlapping residential district and work postcode however the radius is 3 and there is variation between the radius and diameter. Statistically speaking if we were to do a crosstabulation of residential and work postcode, there will be many empty cells.

7.6.3 *Transition Dynamics: Residential Clusters and Overlapping Influence Groups*

Using our multi-agent based model, we now explore the evolution of the choice behavior of the nested logit model with feedback defined by these sociogeographic networks. By experimental design, the network of disconnected residential district clusters and the network of overlapping residential district and social group are approximately five times more dense than the network of disconnected postcode zone clusters and the network of overlapping residential and work postcode zones, respectively. Example time series for the nested logit model with sociogeographic network interaction are shown in Figure 7.17. We will be interested to compare these example time series with that of the baseline nested logit model on a fully connected network shown in Figure 7.12. As in the previous section, each run is allowed to iterate for 600,000 time steps; the light gray time series represents mode share for bicycle, dark gray represents mode share for public transit and black represents mode share for car. Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order are shown in Figure 7.18. We will be interested to compare these emergent outcomes with that of the baseline nested logit model on a fully connected network shown in Figure 7.13.

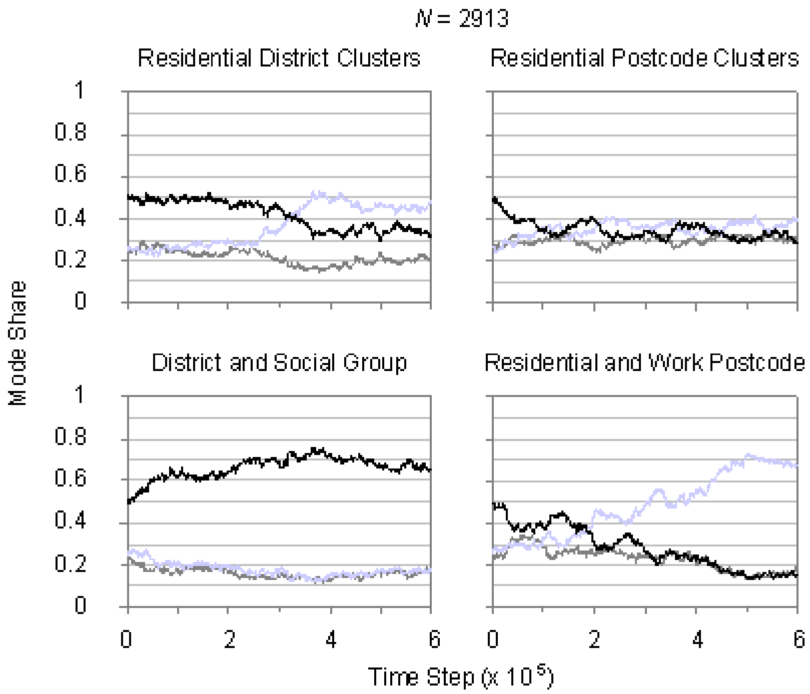


Figure 7.17: Example time series for the benchmark sociodynamic nested logit model on different sociogeographic networks

Residential Clusters

We first consider the two scenarios with a disconnected network of clustered groups. From our study of fully connected networks in section 7.5, we know that smaller network size leads to more volatile sociodynamics in our model. Since we saw evidence of this volatility already in the largest district comprising 461 agents, we might expect that all other residential districts (with the smallest having only 223 agents) and accordingly all postcode zones (ranging in size from 161 to 10 agents) can only be more volatile. Furthermore since transmission of influence is prohibited across the separate clusters, the overall time-varying behavior of the global modal split must logically be the weighted average behavior of the mode shares within the separate clusters. In the example time series in the upper left panel of Figure 7.17 we see initially persistent average behavior across the clusters with high mode share for car, but then over time the most stable equi-

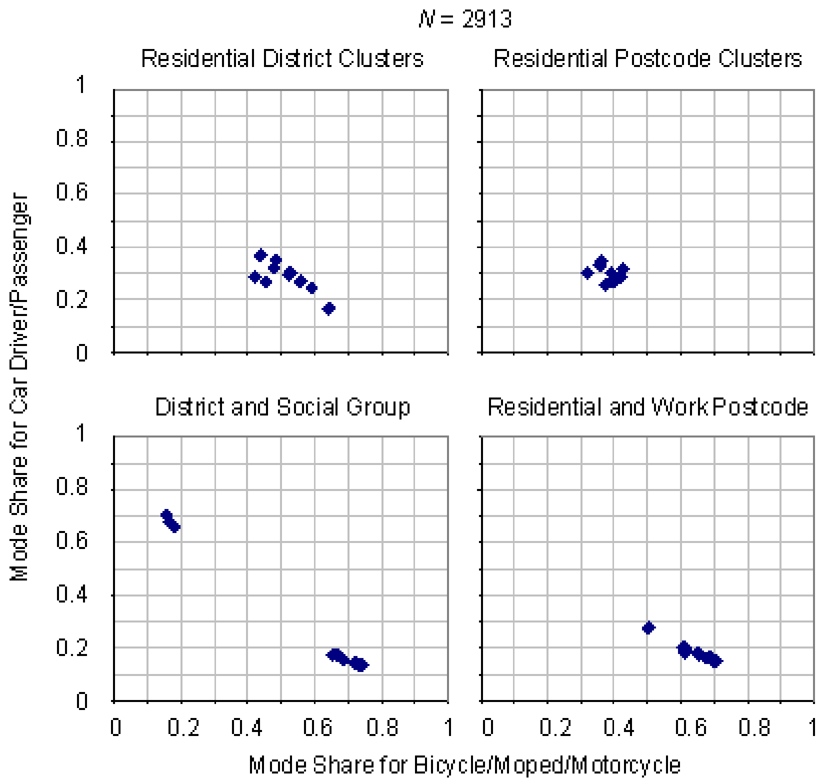


Figure 7.18: Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order for the benchmark sociodynamic nested logit model on different sociogeographic networks. In the upper panels, global behavior is weighted average behavior of separate clusters; initial conditions have no significant effect on long-term outcomes when clusters are small. In the lower panels, influence can spread throughout entire sample; initial mode shares matter, but dominant equilibrium ultimately prevails in connected, sparse network. Compare with the upper left panel of Figure 7.13 on page 263.

librium in Table 7.22 tends to become dominant. However, we see in the example time series that the overall bicycle mode hovers around 0.5 never reaches the mode share of 0.7 that it did in section 7.5 in the upper left panel of Figure 7.12, since there is no interaction mechanism in this scenario to coordinate across clusters.

With the volatility that we saw ranging from District 16 to D/istrict 10 in Figure 7.12 and given the dispersion of long-run outcomes across different seeds that we saw in Figure 7.16, we might presume that is unlikely that all 9 clusters here will happen to be in the same equilibrium at the same time. While the majority of clusters may tend to be at the most stable equilibrium in the long-run, probabilistically there will be some clusters that will be in one of the other two stable equilibria, or in the process of transitioning between equilibria.

Table 7.32: Example emergent commuter mode share outcomes by residential district, for the benchmark sociodynamic nested logit model on residential district clusters. Numbering of districts adheres to the original numbering in the raw data set; non-sampled regions include the west industrial harbor district, the southeast commercial office park district, and the primarily agricultural district to the north of Amsterdam.

RESIDENTIAL DISTRICT	BICYCLE	TRANSIT	CAR	SAMPLE COUNT
1: Amsterdam Center	0.719	0.124	0.157	363
2: Amsterdam West	0.188	0.165	0.648	352
3: Amsterdam South	0.152	0.672	0.176	329
4: Amsterdam East	0.762	0.139	0.099	223
6: Amsterdam North	0.134	0.138	0.728	254
8: Amsterdam Far West	0.653	0.176	0.171	340
9: Amstelveen North	0.167	0.161	0.672	348
10: Amsterdam Southeast	0.745	0.140	0.115	243
16: Amstelveen South	0.755	0.104	0.141	461
Total	1390	588	935	2913

Table 7.32 shows the emergent commuter mode share outcomes at $t = 600,000$ by residential district for the benchmark sociodynamic nested logit model on residential district clusters for the specific example time series in the upper left panel of Figure 7.17. Five of the nine districts (that is, District 1, 4, 8, 10 and 16) are near the most stable equilibrium where mode share for bicycle is highest (nr. 1 in Table 7.22). Three of the nine districts (that is, District 2, 6 and 9) are near the stable equilibrium where mode share for car is highest (nr. 2 in Table 7.22), and one of districts (District 3) is near the stable equilibrium where mode share for transit is highest (nr. 3 in Table 7.22).

In the example time series in the upper right panel of Figure 7.17, we find that the overall behavior across the 67 postcode clusters moves fairly rapidly to a roughly equal split of one-third for each mode. Here the volatility within the clusters is so high that no single mode ever stays dominant for very long and there are so many clusters that the average behavior statistically tends to be non-biased, with perhaps only a slight tendency towards the most stable equilibrium. Indeed the picture of the observed mode shares at $t = 600,000$ with different random seeds determining the agent decision-making order in the upper right panel of Figure 7.18 shows a concentration of outcomes near an equal modal split of one-third, one-third, one-third, just slightly tending more towards the bicycle mode.

Overlapping Influence Groups

Now, given this behavioral information within isolated clusters, we proceed to understand what happens in the empirically most relevant scenarios with overlapping groups, where we have interaction within socioeconomic and spatially defined groups but there is a possibility for transmission of influence across groups. In the example time series in the lower left panel of Figure 7.17 with interaction defined by overlapping residential district and social group, we find initial prominence of the high mode share for car as we did in the case of the network of disconnected residential district clusters, but here there is indeed the possibility for eventual coordination across clusters, with the entire sample locking-in to one of the stable equilibria in Table 7.22. In the example in Figure 7.17 we find the most stable equilibrium prevailing with high mode share for bicycle; time series with other random seeds for defining the decision making order of the agents showed stable equilibrium nr. 2 in Table 7.22 prevailing with high mode share for car. We never found transit mode prevailing, presumably due to inability to overcome the initial conditions with low transit mode share. The observed long-run outcomes at time step $t = 600,000$ when applying different random seeds thus yields a similar picture as the left panel of Figure 7.16.

The example time series in the lower right panel of Figure 7.17 with interaction defined by the relatively less dense network of overlapping residential and work postcode zones is just as interesting. With the relatively small cluster sizes in this scenario, we find initial statistical tendency towards an overall non-biased split fluctuating around one-third for each mode, similar to the case of the network of disconnected residential postcode clusters. Because of the possibility for transmission of influence across clusters here though, eventually the most stable equilibrium gradually takes over as in the case we saw with the hypothetical fully connected network with initially equal mode shares. Over multiple runs with different random seeds determining the decision making order in the lower right panel of Figure 7.18 we find that all runs indeed tended towards to the dominant equilibrium, just as on fully connected network with initially equal mode shares.

7.6.4 *Transition Dynamics: Effect of Initial Conditions with Sociogeographic Networks*

For thoroughness we now repeat the analysis for the four sociogeographic network scenarios, carrying out a sensitivity test to the effect of non-biased initial conditions. Example time series for the nested logit model with initial equal mode shares are shown in Figure 7.19. We will be interested to compare these example time series with those shown in Figure 7.17 where the initial modal split is the same as the sample. As in the previous section, each run is allowed to iterate for $600,000$ time steps; the light gray times series represents mode share for bicycle, dark gray represents mode share for public transit and black represents mode share for car. Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order are shown in Figure 7.20. We will be interested to compare these emergent outcomes with those shown in Figure 7.18.

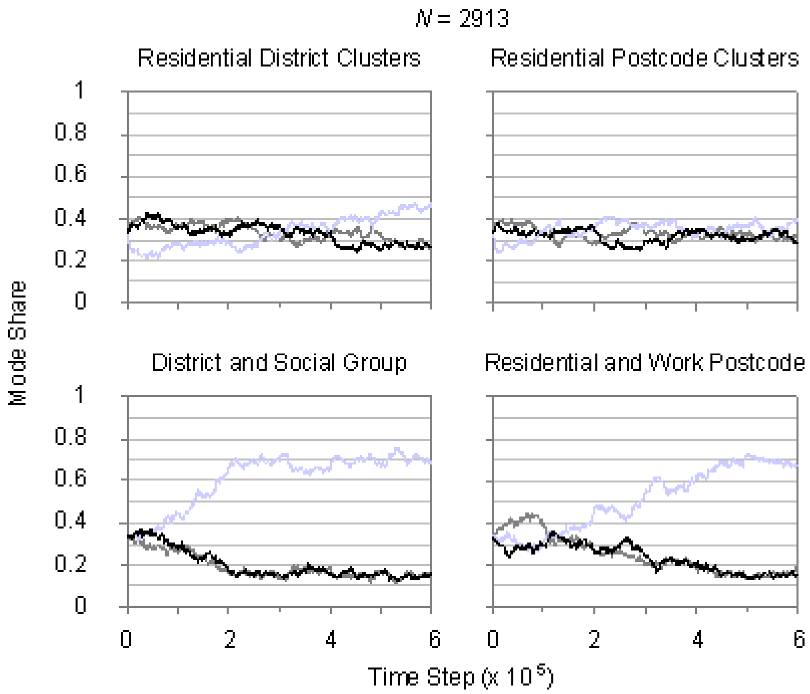


Figure 7.19: Example time series for the benchmark sociodynamic nested logit model on different sociogeographic networks with initial equal mode shares

Residential Clusters

For the case of residential district clusters we expect that the overall time-varying behavior of the global modal split will again logically be the weighted average behavior of the mode shares within the separate districts. However with an initially unbiased overall modal split, there is no longer anything to distinguish between the choice alternatives within the nest, car and transit. If the number of districts is large enough, on average we will expect the number of districts that have leading mode share for car to be the same as the number of districts that have leading mode share for transit. If the number of agents within districts are roughly similar, the overall mode shares for car and transit will then be roughly similar as well. In the example time series in the upper left panel of Figure 7.19 we indeed see the mode share for car and transit varying together. Furthermore, as

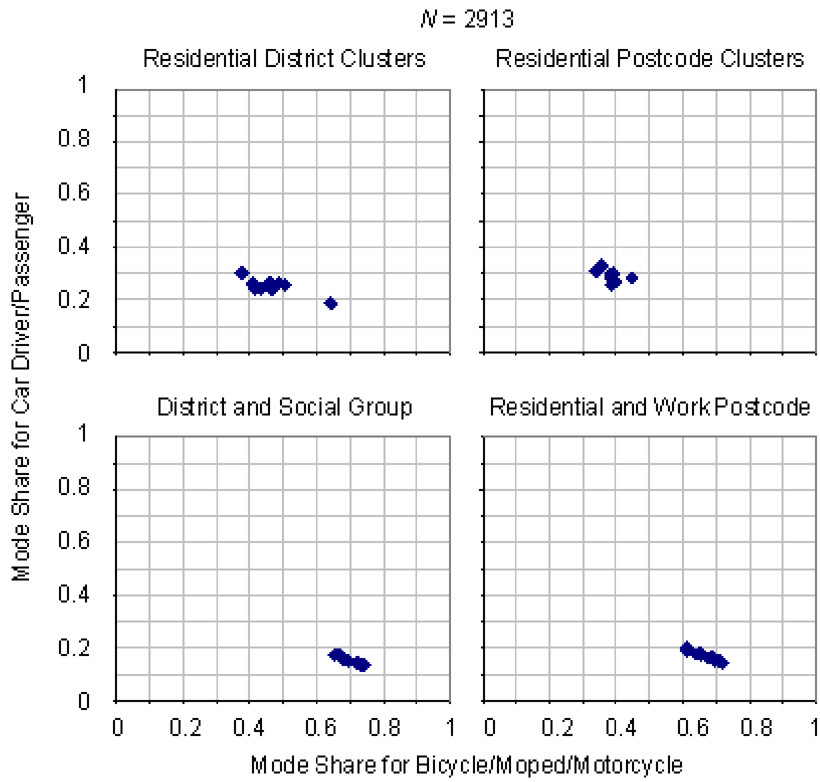


Figure 7.20: Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order for the benchmark sociodynamic nested logit model on different socio-geographic networks with initial equal mode shares. Compare with Figure 7.18 on page 276 and the lower left panel of Figure 7.13 on page 263.

before in the upper left panel of Figure 7.17, over time the most stable equilibrium in Table 7.22 with leading mode share for bicycle tends to become more dominant.

Table 7.33 shows the emergent commuter mode share outcomes at $t = 600,000$ within the residential districts for the specific example time series in the upper left panel of Figure 7.19, and confirms these insights numerically. Four of the nine districts (i.e. Districts 1 through 4) are near the most stable equilibrium where mode share for bicycle is highest (nr. 1 in Table 7.22) and one of the districts (District 9) is in the process of transitioning to that equilibrium. Two of the nine districts (i.e. Districts 6 and 8) are near the stable equilibrium where mode share for car is highest (nr. 2 in Table 7.22). One of districts (District 16) is near the stable equilibrium where mode share for transit is highest (nr. 3 in Table 7.22) and one of the districts (District 10) is at the saddle point at the entry to the basin of attraction of this stable equilibrium.

The concentration of outcomes in upper left panel of Figure 7.20 along the line $p_1 = (1 - p_0)/2$, where p_0 is the pendant alternative bi-

Table 7.33: Example emergent commuter mode share outcomes by residential district, for the benchmark sociodynamic nested logit model on residential district clusters with initial equal mode shares. Numbering of districts adheres to the original numbering in the raw data set; non-sampled regions include the west industrial harbor district, the southeast commercial office park district, and the primarily agricultural district to the north of Amsterdam.

RESIDENTIAL DISTRICT	BICYCLE	TRANSIT	CAR	SAMPLE COUNT
1: Amsterdam Center	0.719	0.124	0.157	363
2: Amsterdam West	0.659	0.190	0.151	352
3: Amsterdam South	0.684	0.158	0.158	329
4: Amsterdam East	0.762	0.139	0.099	223
6: Amsterdam North	0.134	0.138	0.728	254
8: Amsterdam Far West	0.200	0.150	0.650	340
9: Amstelveen North	0.572	0.193	0.236	348
10: Amsterdam Southeast	0.300	0.523	0.177	243
16: Amstelveen South	0.156	0.696	0.148	461
Total	1334	796	783	2913

cycle and p_1 is the nested alternative car, shows that observed mode shares at $t = 600,000$ with different random seeds confirm these insights too. This line namely reflects the relation $p_1 = p_2 = 1 - p_0 - p_1$ (i.e. equal mode shares for car and transit). Furthermore, the cluster of outcomes on this line shows the mode share for bicycle primarily between 0.4 and 0.5 being more dominant that the other modes. In comparison, the upper left panel of Figure 7.18 also shows the dominance of the bicycle mode, but the outcomes lie clearly above the line $p_1 = (1 - p_0)/2$, more towards mode share for car due to the initial modal split favoring car.

For the case of residential postcode clusters, due to the even higher volatility than the case of the districts within the smaller size postcode zones, we already saw in upper right panel of Figure 7.17 that the overall behavior across the 67 postcode clusters moves fairly rapidly to a roughly equal split of one-third for each mode. Since the modal split in upper right panel of Figure 7.19 starts at initial equal mode shares, the qualitative picture is not much different after the transient effects of the initial time steps than in the upper right panel of Figure 7.17. The outcomes of the observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order in the upper right panels of Figure 7.18 and Figure 7.20 are qualitatively identical, both showing a concentration of outcomes near an equal modal split of one-third, one-third, one-third, just slightly tending more towards the bicycle mode.

Overlapping Influence Groups

For the case of overlapping residential district and social group, we recall the ability in the lower left panel of Figure 7.17 to coordinate influence across clusters. Thus we may again expect the entire sample to lock in to one of the stable equilibria in Table 7.22. However, we also recall in the lower left panel of Figure 7.12 that for the fully connected network with initial equal mode shares, the most stable equilibrium prevailed. The transition was slow and steady and there was not enough stochasticity to escape the dominance. In terms of the imagery of system as a ball rolling on the "potential" function in Figure 7.14, the system is a big, heavy ball which has as its starting position a point on the long, smooth incline to the lowest basin of attraction. After a little stochastic nudge to get it in motion, once it gets rolling, the ball rolls all the way down the smooth incline to that basin of attraction and then can't be pushed out. With both the insights from Figure 7.17 and Figure 7.12 in mind, we might expect the time series in the lower left panel of Figure 7.19 to look quite similar to that in the lower left panel of Figure 7.12. Indeed this turns out to be true. Furthermore, all runs when applying different random seeds yield a similar picture, so that the observed long-run outcomes at time step $t = 600,000$ in the lower left panel of Figure 7.20 is qualitatively identical to the lower left panel of Figure 7.13 for the sociodynamic nested logit model on a fully connected network with initial equal mode shares.

For the case with the relatively less dense network of overlapping residential and work postcode zones, we already saw in the lower right panel of Figure 7.17 that after a period of fluctuating around one-third for each mode, the possibility for transmission of influence across clusters drives the convergence to the dominant equilibrium. Since the modal split in lower right panel of Figure 7.19 starts at initial equal mode shares, the qualitative picture is not much different after the transient effects of the initial time steps than in the lower right panel of Figure 7.17. Compared with the example time series for the sociodynamic nested logit model on the overlapping residential district and social group in the lower left panel of Figure 7.19, the runaway to the stable equilibrium takes longer to take-off with the less dense network, hovering longer around the initial equal mode shares. In terms of the imagery of system as a ball rolling on the "potential" function in Figure 7.14, the system is a big, but less heavy ball that takes a little bit more of a stochastic nudge to build up momentum. It doesn't move as fast as the big, heavy ball. Nonetheless, once it gets rolling, the ball rolls all the way down the smooth incline to the most stable basin of attraction and then can't be pushed out.

Over multiple runs with different random seeds in the lower right panel of Figure 7.20 we find that all runs for overlapping residential and work postcode zones indeed tended towards the dominant equilibrium. Compared with the lower right panel of Figure 7.18 for overlapping residential and work postcode zones with initial mode shares as in the data sample, we see there that one run was on its way towards the stable equilibrium but had not quite yet reached it due to the starting modal split there having leading mode for car and thus further to "travel" in mode share space. With the initial equal mode shares in the lower right panel of Figure 7.20 all runs did indeed squarely reach the stable equilibrium, just as in the lower left panel of Figure 7.13 on a fully connected network with initial equal mode shares, and in the lower left panel of Figure 7.20 on the overlapping residential district and social group, despite having taken longer to get there.

7.6.5 *Interim Conclusions*

In summary, we have seen: 1) global modal choice behavior in a disconnected network of clustered groups is the weighted average behavior of separate clusters; 2) smaller cluster sizes yield more volatility in our nested logit model with sociodynamic feedback and as a result, a tendency towards an overall non-biased modal split averaged over many clusters; 3) with sufficient volatility, initial conditions have no significant effect on long-term outcomes; 4) with overlapping groups, influence can spread throughout entire sample; 5) for a giant cluster with sufficient network density and sufficient average degree, the precise connectivity of the network doesn't appear to matter in the long-run, but the initial conditions of the starting mode shares do matter; the emergent distribution of outcomes for overall modal split gives the same picture as the analytically predicted outcomes for a fully connected network with the given initial conditions; 6) the analytically predicted most stable equilibrium ultimately prevails in connected, sparse network of overlapping clusters; initial conditions of the starting mode shares don't seem to matter here.

7.7 UTILITY PARAMETERS AND CONNECTIVITY IN EMPIRICAL MODELS

7.7.1 *Definition of Interaction Variables*

Now we proceed to the specification of a full empirical model. We consider a broad classification by residential district as defined earlier in section 7.4. Similarly using the three variables age, income and education, socioeconomic groups are defined. In addition, to be able to test the effect of spatial scale, we define a smaller neighborhood re-

Table 7.34: Descriptive statistics for local field variables

VARIABLE	MEAN	STD DEV	MIN	MAX
Share of agent's fellow district residents choosing:				
Bicycle/moped/motorcycle	0.268	0.080	0.132	0.409
Public transit	0.238	0.062	0.133	0.364
Car driver/passenger	0.497	0.108	0.307	0.663
Share of agent's social group peers choosing:				
Bicycle/moped/motorcycle	0.269	0.071	0.114	0.414
Public transit	0.238	0.070	0.145	0.338
Car driver/passenger	0.498	0.112	0.366	0.728
Share of agent's district residents and social group peers choosing:				
Bicycle/moped/motorcycle	0.271	0.057	0.128	0.399
Public transit	0.238	0.048	0.138	0.351
Car driver/passenger	0.493	0.082	0.339	0.664
Share of agent's postcode residents and social group peers choosing:				
Bicycle/moped/motorcycle	0.268	0.063	0.100	0.424
Public transit	0.237	0.061	0.126	0.387
Car driver/passenger	0.498	0.097	0.341	0.741

gion of influence on the basis of 4-digit postcode as in section 7.6. We may hypothesize that the smaller spatial scale network interdependence defined by postcode may be more homogeneous with regard to choice behavior than that for the variables defined on the basis of district. Thus we may expect the coefficient on these variables to be relatively stronger. Network interaction variables for four scenarios are presented in Table 7.34. Two scenarios consider clustered groups: Residential district; Social group. Two scenarios consider overlapping groups: District and social group; Postcode and social group.

The case of overlapping groups is depicted abstractly in Figure 7.21. For simplicity, the reference agents that a given agent is connected to are counted all together, without any discrimination as to which of the groups the reference agent belongs to. A reference agent is also not counted twice if the reference agent happens to belong to two of the groups that the given agent does. For example in the case of overlapping district and social group, suppose we are interested to characterize the interactions of decision maker Henk. Ingrid is in Henk's social group and they both live in Amsterdam North, Jan also lives in Amsterdam North but is not in Henk's social group, and Kees is in Henk's social group but lives in Amsterdam West. The network connections of Henk for his reference group are simply: Henk, Ingrid, Jan, Kees, counting himself, and without distinction as to social group or district, and without counting Ingrid twice. In this way, there is only one feedback effect per agent, namely the combined aggregate effect of the influence from both reference groups indiscriminately. This allows us to focus on changes in the network structure at an abstract level, rather than on the influence from particular groups. In a more detailed analysis, particularly for a policy purposes, it could indeed be natural to estimate separate coefficients for each group. This is what is done in Chapter 8 when we focus on econometric estimation of such variables. When studying the impact of multiple influences from different groups with different coefficients per group, the complexity of the envelope of possible steady state outcomes is likely to increase significantly. It is conceivable that along one dimension of influence there could be a strong feedback, but along another dimension there could be a moderate feedback, yielding different competing tendencies. Particularly the time varying trajectories of the mode shares is likely to be quite interesting and would be useful direction for further exploration.

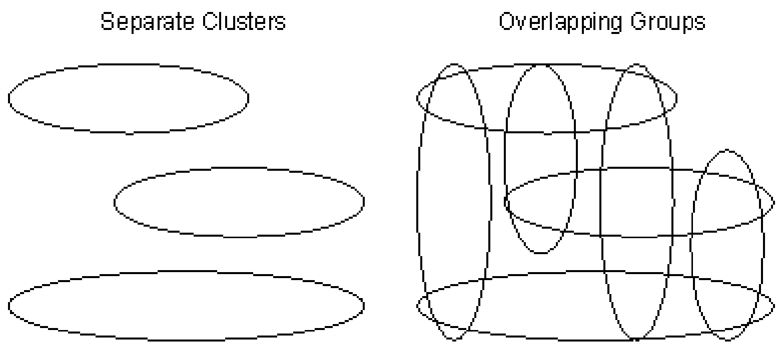


Figure 7.21: Abstract visualization of separate clustered groups and overlapping groups. With overlapping groups, influence can spread across the clusters.

7.7.2 *Specification of Utility Functions*

A trinary transportation mode choice model to work is estimated using the freely available, open source optimization toolkit Biogeme (Bierlaire, 2003. Various piecewise continuous specifications of all travel time related variables as well as age were tested against simple linear, quadratic and logarithmic forms of these variables. Considering various a priori hypotheses of behavior in the region and after statistical comparison of the alternative nonlinear specifications of variables against the linear versions thereof using loglikelihood ratio tests and non-nested tests, a baseline multinomial logit model is estimated. Estimation of three successive nested logit models first with public transit nested with bicycle, then with public transit nested with car, and finally with bicycle nested with car, show the first nesting structure to be most significant in terms of loglikelihood ratio test and in terms of the a t-test on the nest coefficient. The third nesting structure was not indicated. The nested logit model thus adds one additional parameter to the multinomial specification, namely the scale parameter for the transit-bicycle nest. The first two columns of Table 7.35 give estimation results for network interdependence defined by residential district and social group, respectively. The last two columns of Table 7.35 are treatments where social and spatial interdependence are considered jointly: agents are assumed not to distinguish between their socioeconomic peers' and their fellow district residents or neighbors when considering their choice behavior.

We conclude from t-tests on the network interaction variables, that for this particular case study and the network definitions under consideration, systematic field effects representing social and spatial network interactions between an agent and the aggregate behavior of other reference agents do indeed have explanatory power. On the basis of non-nested model specification tests in Table 7.36, we find the fit for overlapping postcode and social group is best, as expected. The fit for broad district clusters alone is worst. Interestingly, there is no there is no statistically significant gain in fit at the 0.05 level between the scenario with social group clusters versus the scenario with overlapping district and social group. In light of the latter finding, we will find that the emergent outcomes over time when these models are embedded in a multi-agent based simulation with feedback are particularly noteworthy.

For continuity in the model development process extending the original discrete choice with interactions research by Aoki (1995), Brock and Durlauf (2001a, 2002, 2006) and Blume and Durlauf (2003), a nested logit model is considered in this chapter. However, it is worth mentioning that an important econometric issue arises in the empirical estimation of discrete choice models using a nested logit specification in that, while unobserved heterogeneity is accounted for across alternatives, the Gumbel error terms are still assumed to be identically and independently distributed across decision makers. It is not obvious that this is in fact a valid assumption when we are specifically considering interdependence between decision makers' choices. We might reason that if there is a systematic dependence of each decision maker's choice on an explanatory variable that captures the aggregate choices of other decision makers who are in some way related to that decision maker, as we have done, then there might be an analogous dependence in the error structure. Otherwise said, the same unobserved effects might be likely to influence the choice made by a given decision maker as well as the choices made by those in the decision maker's reference group. The results and coefficients of such

Table 7.35: Estimation results for nested logit models with different socio-geographic networks: Residential district clusters [DTR]; Socioeconomic group clusters [SOC]; Residential postcode and socioeconomic group [PSD]. All *t*-statistics (indicated in itallic below the estimated coefficient value) are against 0, except for the scale parameter for which it is against 1. Compare with Table 7.27.

ESTIMATED PARAMETERS	DTR	SOC	PSD
Share of agent's network choosing	1.23	1.57	1.91
each mode, defined generically	*4.85*	*5.90*	*6.27*
Alternative specific constant for transit	1.02	-0.464	-0.443
	2.11	*-1.03*	*-1.05*
Alternative specific constant for car	-0.717	-0.733	-0.978
	-1.30	*-1.38*	*-1.94*
Car ownership, defined for car	2.56	2.51	2.51
	25.2	*24.6*	*24.6*
Gender, defined for transit	0.288	0.269	0.249
	3.07	*3.18*	*3.28*
Gender, defined for car	0.260	0.327	0.310
	2.26	*2.84*	*2.74*
Low income, defined for bicycle	-0.211	-0.196	-0.173
	-1.93	*-1.99*	*-1.93*
Natural log of age, defined for transit	-0.610	-0.155	-0.131
	-3.31	*-1.03*	*-0.97*
Age 45 to 59, piecewise, for transit	0.0320	0.0170	0.0146
	2.48	*1.50*	*1.39*
Travel time for bicycle	-0.0442	-0.0407	-0.0381
	-4.33	*-4.41*	*-4.70*
In-vehicle time for transit, squared	-3.16e-4	-3.14e-4	-2.98e-4
	-3.85	*-3.96*	*-3.85*
Out-of-vehicle time for transit	-0.0206	-0.0186	-0.0185
	-3.15	*-3.16*	*-3.26*
Natural log of travel time for car	-0.654	-0.623	-0.545
	-2.36	*-2.39*	*-2.24*
Parking time for car, squared	-0.0131	-0.0154	-0.0148
	-7.89	*-9.98*	*-9.53*
Scale for transit-bicycle nest	2.07	2.36	2.51
	2.05	*2.32*	*2.65*
Null log likelihood (L_0)	-2977	-2977	-2977
Final log likelihood	-2060	-2054	-2049
Likelihood ratio test	1834	1846	1856
Adjusted rho-squared ($\bar{\rho}^2$)	0.3029	0.3049	0.3066

Table 7.36: Non-nested tests of model specifications with different sociogeographic networks. The non-nested test bounds the probability of erroneously choosing the incorrect model over the true specification under the null hypothesis that model 1 with higher adjusted rho-squared is the true model.

1	2	DF	r	$s=2rL_0+\text{DF}$	$\Phi(-s^{1/2})$	COMMENTS
SOC	DTR	0	0.00202	12.04	0.00026	Don't reject
DSD	DTR	0	0.00165	9.84	0.00085	Don't reject
PSD	DTR	0	0.00370	22.06	0.00000	Don't reject
SOC	DSD	0	0.00037	2.20	0.06901	Reject
PSD	SOC	0	0.00168	10.02	0.00077	Don't reject
PSD	DSD	0	0.00205	12.22	0.00024	Don't reject

DF:	Difference in degrees of freedom between models 1 and 2
r	Difference in adjusted rho-squared between models 1 and 2
L_0	Null log likelihood
Φ	Standard normal cumulative distribution function

a model are likely to be biased (Train, 2009). Making an analogy of inter-agent causality and correlation with the more well-understood panel data approach towards time causality and correlation (Heckman, 1981a, 1981b), later in Chapter 8 we present and compare several modeling strategies to highlight some main hypothesized interaction effects using mixed generalized extreme value models with field and "panel" effects. Walker et al (2011) re-visit this application and apply a less computationally intensive multi-stage instrumental variables approach developed by Berry (1994) and Berry, Levinson and Pakes (1995, 2004) to control for endogeneity. Other applications addressing endogeneity in discrete choice estimation in the transportation literature are: Train and Winston (2007) who also use this same multi-stage approach to correct for price endogeneity in auto ownership choice; Guevara and Ben-Akiva (2006) who correct for price endogeneity in residential housing choice, using the "control function" approach developed by Hausman (1978), Heckman (1978) and Heckman and Robb (1985) applied to a logit model; Goetzke and Weinberger (2012) who apply the control function approach with a binary probit model to test the impact of contextual and endogenous social interaction effects on auto ownership, using the two-stage conditional maximum likelihood estimation technique proposed by Rivers and Vuong (1988); Goetzke (2008) and Goetzke and Andrade (2010) who account for endogeneity stemming from social network effects in a spatially autoregressive mode choice model using spatial lags as instrumental variables; and Goetzke and Rave (2011) who derive an instrument from records with excluded trip purposes to study endogenous effects of "bicycle culture" in German cities.

For the purposes of this section, we accept that the estimated values may be biased. Our goal here is simply to generate various plausible parameter values under different scenarios, in order to be able to characterize the long-run dynamics of the nested logit model with social feedback. While for an application for policy purposes precise parameter values would be crucially important, in this section the focus is more abstract. We are interested in getting an idea methodologically under what conditions a runaway effect is generated and what influences this. It is very useful to understand the dynamic behavior of a benchmark nested logit model, before proceeding to understand the dynamic behavior of models with even more complex kernels. Such an understanding built up step-by-step is important both theoretically and conceptually as well as for good practice in multi-agent based simulation.

7.7.3 *Transition Dynamics: Effect of Empirically Defined Systematic Utility with Sociogeographic Networks*

Using the Repast agent based modeling platform, we create a computational version of our nested logit models with heterogeneous agents and sociogeographic network interaction. Discrete choice estimation results controlling overall mechanisms related to individual heterogeneous preferences are embedded in the multi-agent based model to be able to observe the simulated evolution of choice behavior over time with sociodynamic feedback due to network effects. Example results for different random seeds are shown in Figure 7.22. Each run is allowed to iterate for 600,000 time steps, or roughly about 200 revisions of choices with asynchronous decision making for the sample size of 2913 agents.

There are several immediately striking features of the long-run results. First, we notice that in all scenarios, the long-run mode shares in Figure 7.22 moved significantly away from the initial overall modal split (23.7% public transit share; 26.7% bicycle or moped/motorcycle share; 49.6% auto driver or auto passenger share). Second, we notice that the long-run results are also fairly stable: there is little variation in the long-run results for a given scenario. This is true for both scenarios with overlapping groups where influence has the possibility, in principle, to spread through the entire sample. Since it is also true for both scenarios with disconnected clusters where there is no possibility for transmission of influence across groups, this implies that the modal split within the clusters was effectively the same across clusters for a given scenario. Third, we notice in all cases the auto share strongly decreased. This is especially remarkable since the auto mode had initially a share about twice as large as either of the other modes. We see that the feedback effect was thus indeed significant in dynamically hindering the auto mode in the long-run in all scenarios in a well-defined manner.

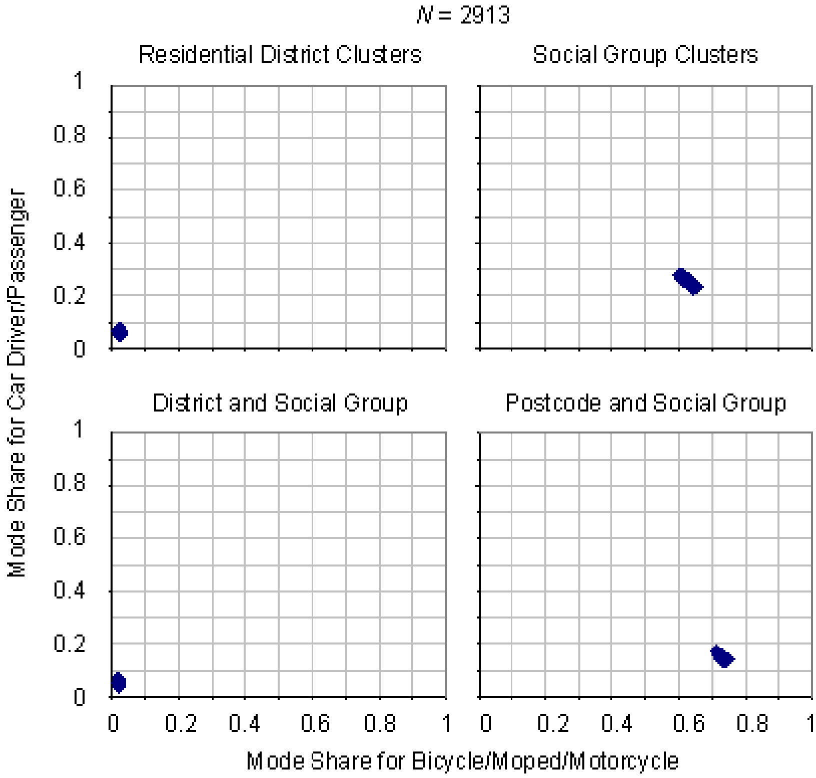


Figure 7.22: Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order for empirically defined sociodynamic nested logit models with fully specified systematic utility on different sociogeographic networks

What is curious is that the feedback effect on one hand dynamically propels the transit mode for the case of network interaction by residential district clusters, and by overlapping residential district and social group, and on the other hand dynamically propels the bicycle mode for the case of network interaction by social group clusters, and by overlapping postcode and social group. This is a dramatic difference, emphasizing how important it would be in an application for policy purposes to know in the case of clusters whether influence actually works through neighbors or though socioeconomic peers, or in the case of overlapping groups what the regional scale is of neighborhood influence. We can in any case conclude resoundingly: if a feedback effect can be assumed, the precise details of the connectivity sociographic networks matter!

It is important to recognize however that there are two stages in our process where the sociogeographic network enters. First, the network enters in the econometric estimation in determining the value of the estimated coefficients. Second, the network enters in the multi-agent based simulation in determining the course of the spread of influence when the feedback is strong enough. We may wonder then what is the driving factor of the results: is it simply the strength of the feedback effect relative to the other components of the utility? or is it the connectivity of the network during the transmission process? or both? For example, if a feedback effect can be assumed, in a campaign to promote a particular mode or new service, we would want to know whether to focus efforts on the way the mode is promoted to make the adoption most convincing, or whether to focus for example, on seeding opinion makers to try to influence the connectivity of the sociogeographic network. Concretely, if say, Twitter were used to get the word out to market a mode, is it the art of sending an enticing enough tweet to generate many re-tweets? or is it the number of followers that receive the tweet and the shape of the network? or both?

To gain some insight to the answer with regard to this particular case study, we run a hypothetical simulation experiment with sociogeographic networks swapped, while holding the utility parameters fixed. Example results for different random seeds are shown in Figure 7.23. We find that only in the case of the social group parameters did the connectivity of the network seem to have some slight effect on the outcome of the multi-agent simulation. In our particular case study, we conclude that the strength of the feedback effect relative to the other components of the utility is the dominant factor in generating the long-run results. That is, in our particular case study, the connectivity appears not to be very relevant at the transmission stage. This said, it is important to note that the networks studied here are fairly dense by definition, due to the nature of the aggregate interaction assumed within groups. Results in Chapter 6 for a binary choice model with social interactions on abstract classes of networks over a sweep of network density from a classical case of independent agents on one hand to a fully connected network on the other hand, holding utility parameters constant, indicated that sparse networks were more sensitive in the outcomes of transmission.

7.8 CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

We have extended previous work on discrete choice with social interactions in important ways. First, we present a framework for conceptualizing the interdependence of decision makers' choices, making a distinction between social versus spatial network interdependencies and between identifiable versus aggregate agent interdependencies. In our empirical application, we consider a model where an agent's choice is directly influenced by the proportions of the agent's neighbors, colleagues and/or socioeconomic peers making each choice;

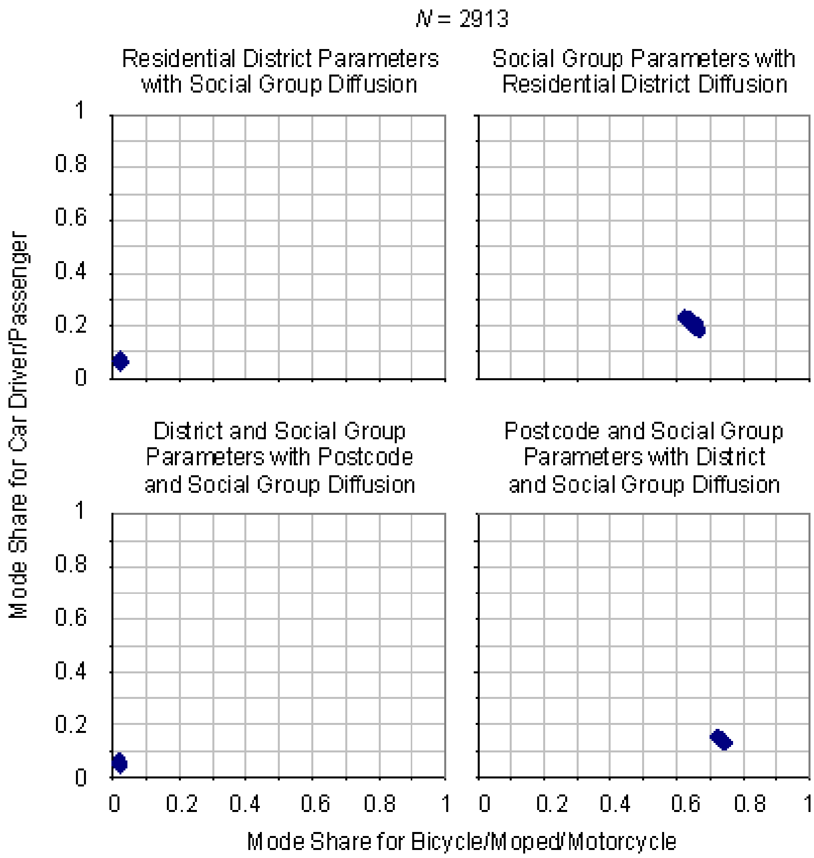


Figure 7.23: Observed mode shares at $t = 600,000$ with different random seeds determining the agent decision making order for hypothetical experiment with time evolution of sociodynamic nested logit models where estimated utility parameters and sociogeographic networks are swapped. Compare with Figure 7.22 on page 290.

given the availability of appropriate data, our approach is principle directly extendable to the identifiable agent case. We introduce additional heterogeneity in the model through different mechanisms, such as individual-specific sociodemographic characteristics of the agents, individual-specific attributes of the choice alternatives, and the availability of alternatives. Finally we introduce unobserved heterogeneity by accounting for common unobserved attributes of the choice alternatives in the error structure. We observe that these extensions generate dramatically different temporal dynamics and thus cannot be ignored in any true empirical application.

A careful specification of both observed and unobserved heterogeneity matters critically for emergent temporal outcomes when there is sociodynamic feedback in the model, even when the feedback takes the simple form of an aggregate field variable. Agent heterogeneity impacts the magnitude of the mode shares, the speed of the transition to the steady state as well as very fundamentally the number of possible observable steady state solutions. Also the detailed effect of induced heterogeneity is important to understand in different network structures, including the speed of information flow across them. Misrepresentation of the appropriate scale at which social influence occurs and of the appropriate network structure can yield strongly flawed policy implications when studying social feedback.

In order to separate out effects, more research is needed to explore systematically different model configuration treatments. In particular, the importance of observed heterogeneity (the effect of availability of alternatives, the effect of various explanatory sociodemographic agent characteristics, the effect of various agent-specific attributes of choice alternatives) relative to the importance of shared unobserved heterogeneity is interesting to understand better.

In this chapter we considered various sociogeographic network scenarios. First we depict influence within a disconnected network of clustered groups. Next we depict influence within overlapping social and spatial groups. We observe that the estimated utility parameters for different hypothetical sociogeographic network scenarios can generate dramatically different dynamics. This finding underscores the need for more empirical research to understand actual sociogeographic influence networks, including those at the population level.

Given the availability of suitable temporal data another interesting extension to this research would be to estimate a time lag coefficient, representing the importance of an agent's choice on the existing choice. We might intuitively expect that there may be a resistance to change. The introduction of such a time lag variable might result in a more intuitively expected steady state solution than the perhaps surprising result we discovered in section 7.4 for the empirical nested logit model with sociogeographic network effects.

Also very important for any policy application, particularly for transportation mode choice, would be the introduction of not only positive feedback, but also negative feedback into the model to account for congestion effects in addition to agglomeration effects. The absence of negative feedback to account for congestion effects in the model over time may also possibly be one of the reasons for some of the empiricially counterintutive results we discovered. If too many commuters travel by car, roads may become congested, and traffic jams may result. The increased travel time due to slower moving or still-standing traffic over some route segments may discourage commuters from choosing the car mode. The result in practice is that there is some maximum car mode share that roads can handle and commuters will tolerate. This will vary according to the road system of a given metropolitan region and the norms and values of a given population. On the other hand, if too many commuters travel by public transit, seats may not be available on certain route segments, which in turn may discourage certain strata of the population from traveling by public transit. Some strata of the population may be sensitive to crowded public situations in general, even regardless of whether there is a seat available or not. Furthermore, for example with the train system there is a maximum number of trains that can ride over a given shared rail system out of safety considerations. It may not be possible in practice to transport the entire commuting population over a given rail system particularly if freight transport by train runs over the same rail system as passenger trains. The result in practice is that just as with road system, there is some maximum public transit mode share that the public transit system can handle and commuters will tolerate. This too will vary according to the public transit system of a given metropolitan region and the norms and values of a given population.

Note however that norms and values of a given population may change over time. These can be represented as the global interactions between a decision maker and the aggregate actions of other decision makers in the entire population and may be addressed as the special limiting case of a fully connected or uniform network. Temporal data would be required in order to separate out a global field variable from an alternative specific constant.

In closing, an important stream of research in social network analysis on so-called stochastic "actor oriented" modeling of the co-evolution of networks and behavior is due to Snijders and colleagues. See Snijders, van de Bunt and Steglich (2010) for a tutorial introduction, and Steglich, Snijders and Pearson (2010) for a comprehensive empirical application. Other references are available at the SIENA website (`http://www.stats.ox.ac.uk/~snijders/siena/`). These models are currently intended for relatively small, closed networks up to about a thousand nodes where knowledge about the existence of links between all pairs of nodes has been collected via survey data over at least two waves. The models are not intended for simulating the projected evolution of large synthetic population-wide networks. Nevertheless recent work by Snijders, Koskinen and Schweinberger (2010) on maximum likelihood estimation for social network dynamics may provide useful insights for further exploration in the transportation land use planning domain as well, although proofs for consistency and asymptotic normality of the estimator are not yet available.