Temporal relationships in the dynamics of residential, employment and car ownership decisions

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Background

Residential choice, job/employment choice and travel choice are highly interrelated not only in terms of causality but also in terms of time-dependency.

However, integration is limited in existing models.

1. Few researches focused on limited dimensions, e.g. residential choice and travel choices (Pinjari et al. 2007; Cao et al. 2009) or work and residential location (Waddell et al. 2007).
2. Another limitation is the common use of discrete choice frameworks. A drawback of such discrete choice frameworks is the prior specification of the interdependency in the model structure, which is not derived from data.
3. Finally, most existing studies are static in nature.

An emerging body of studies of the dynamics in household and mobility decisions suggests that relationships between decisions on different dimensions may stretch across multiple years (Oakil, et al. 2011; Feijten and Mulder 2002; Beige and Axhausen 2008).

In addition, life course and life cycle analyses provide a better understanding of the underlying processes (Lanzendorf 2003; van der Waerden 2003; Verhoeven, Arentze et al. 2005).

Contribution of the paper

First, it will look into interdependence among residential, job and car ownership decisions.

Second, it will investigate dynamics regarding these decisions explicitly by looking into changes such as moving to a larger dwelling type (moving up), moving to a smaller dwelling type (moving down) and moving to a similar dwelling type (no-change move), employer change, car acquisition and car disposal.

Third, time dependency is also recognized, i.e. relations may go both forward (responding to a change in household, residential, work or mobility situation as lagged response) and/or backward (anticipating a planned or expected change on these dimensions as lead response).

Finally, it will use a flexible way of determining such dynamic influences, without a priori determining the causality and direction of the relationships.

Methodology

Analytical framework

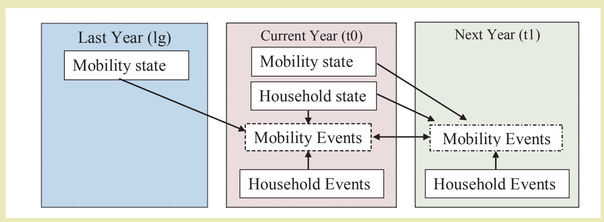


FIGURE 1
Analytical framework of data analysis

Method of data analysis

Bayesian Belief Network (BBN) is an attractive framework
- It does not require defining causal relationships a priori and
- It is capable of representing complex causal structures with direct and indirect effects.

The calibration of BBNs on a data set takes place in a two-step process:

1) Structure learning
Two groups of algorithms have emerged: 1) scoring-based learning methods, and 2) constraints-based learning methods (Cheng et al. 2002). In this study, we will use a constraints-based method, which is based on the concept of mutual information and conditional independence test.

2) Parameter learning
The estimation procedure determines observed conditional frequencies for each child node given its parent nodes in the data. A decision tree induction is introduced here to generate the conditional probability table.

Data collection

- The survey was a traditional paper and pencil questionnaire survey.
- The survey was conducted in the Utrecht region in the Netherlands.
- It included both state and event variables for every calendar year starting from 1990 to 2010.
- Historical data was collected for the following aspects:
  a) Income and work status of the respondent and his/her partner.
  b) Household events such as marriage, childbirth, children leaving the family home, divorce etc.
  c) Residential characteristics (i.e. the year one moved in, location, residential cost per month, number of rooms, age of the dwelling , garden and parking facility).
  d) Work location of the respondent and his/her partner.
  e) Number of cars per household and car availability, commuting mode and commuting time for both the respondent and his/her partner.
- In addition to the historical data, information on households' plan or target with respect to residential relocation, job change, car ownership, household formation and commuting behaviour were asked.

Sample description

- 478 questionnaires were returned (out of 1200).
- The sample size for the present analysis is 2279 person-years after the consideration of the following factors.
  i) The missing values due to no-response to important questions; and
  ii) As mentioned earlier, the consideration of lead and lagged effects means an inclusion of 2 years information simultaneously in one case and thus to avoid double counting of the mobility events, alternating years are considered. To use data economically, odd calendar years are used as it yields more cases (2279) than even calendar years (2055).
- The sample has an over-representation of dual working families (54.7%) and high income households (48.7%).

Results

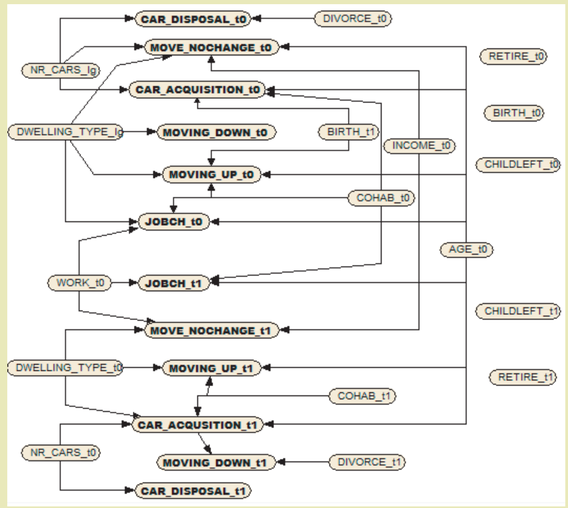
Temporal dependence between variables

- Start of cohabitation shows a lagged effect on employer change in the next year and
- Birth of the first child of the next year shows lead effect on both car acquisition and moving up.
- Mostly, mobility decisions are taken immediately in response to household events.

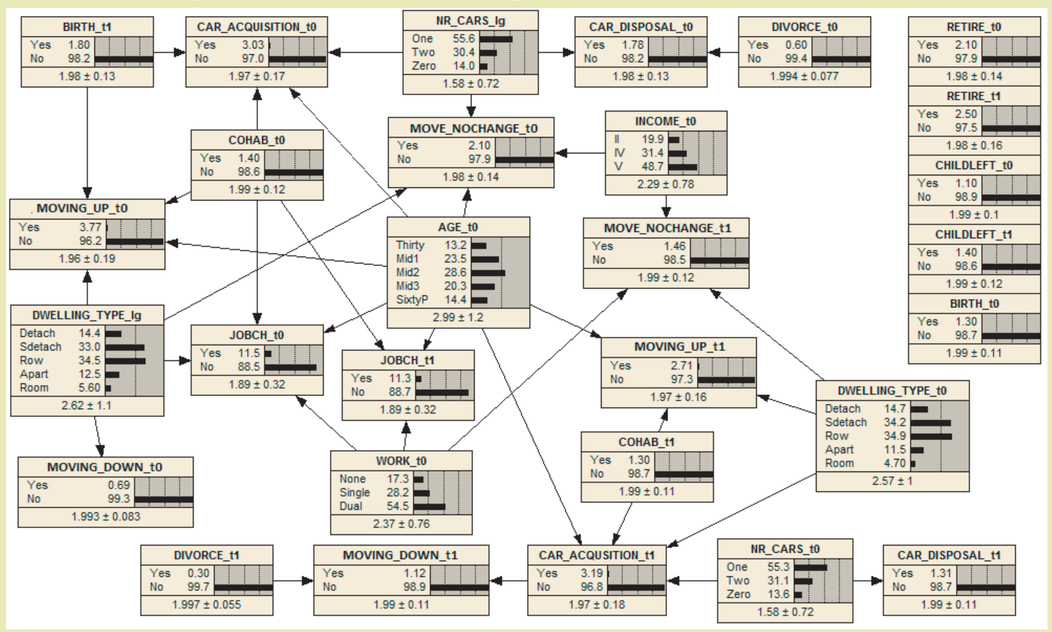
Interdependencies

- The analysis shows limited interdependency among residential relocation, car ownership change and employer change.
- However, car acquisition in the next year shows a concurrent effect on moving down in the next year. However, it is difficult to explain the reason.

Structure learning:
Causal relationship among mobility decisions, household situation and events.



Parameter learning: Results of parameter learning in BBN



Example: Probability of acquiring a car in the current (t1) year

	Number of car/s in the household			
Household events	Without evidence of cars	None	One	More than one
Start of cohabitation (Current year)	28.1	28.1	28.1	28.1
Birth of the first child (Next year)	17.6	17.6	17.6	17.6
Both of the above events	28.1	28.1	28.1	28.1
Without evidence of household events	3.03	4.87	3.47	1.38
No event (Cohabitation or birth of the first child) occurred	2.40	4.30	2.85	0.70

Conclusion

- The analysis shows that long-term mobility decisions based on cross-sectional data will be biased.
- The consideration of lagged, concurrent and lead effects improves understanding of the timing of mobility decisions..
- Mobility decisions regarding car ownership, residence and job are found to be limitedly interrelated when modelled simultaneously with other household decisions. .
- However, explanation of causal relationships is not always evident.

Geo sciences

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