

**MODELING POPULATION-WIDE PERSONAL NETWORK DYNAMICS USING  
A TWO WAVE DATA COLLECTION METHOD AND AN ORIGIN-  
DESTINATION SURVEY**

Fariya Sharmeen  
Eindhoven University of Technology  
P.O. Box 513, Vertigo 8.09  
5600 MB Eindhoven  
The Netherlands  
Telephone: +31 40 247 4814  
Email: f.sharmeen@tue.nl

Óscar Chávez  
Department of Civil Engineering  
Universidad de Concepción  
P.O. Box 160-C, Concepción, Chile  
Telephone number: + 56 41 220 3603  
Email: oscarchavez@udec.cl

Juan-Antonio Carrasco\*  
Department of Civil Engineering  
Universidad de Concepción  
P.O. Box 160-C, Concepción, Chile  
Telephone number: + 56 41 220 3603  
Email: j.carrasco@udec.cl

Theo Arentze  
Eindhoven University of Technology  
P.O. Box 513, Vertigo 8.16  
5600 MB Eindhoven  
The Netherlands  
Telephone: +31 40 247 2861  
Email: T.A.Arentze@tue.nl

Alejandro Tudela  
Department of Civil Engineering  
Universidad de Concepción  
P.O. Box 160-C, Concepción, Chile  
Telephone number: + 56 41 220 3601  
Email: atudela@udec.cl

\*) Corresponding author

## **ABSTRACT**

This paper presents a tie dynamics model that can be used to simulate personal network evolution for broader modeling systems. Drawing from a theoretical and methodological framework previously applied to life course events in the Dutch context, this study adds empirical evidence for the case of a two wave personal networks panel, collected in a four timeframe period. Using an Origin-Destination survey to account for non-existing ties, the dataset provides the support to model an initial phase (tie formation) and an adaptation phase (tie evolution), with a population wide scope.

The model results add empirical evidence about the relevance of the role of homophily (similarity between social contacts) in aspects such as age, gender, and similar occupation, especially in the initial phase. In contrast, the adaptation phase is strongly related with heterophily, possibly reflecting variety seeking behavior. Other factors, such as the evolving role of geographical distance and personal network size, also illustrate further aspects that need to be taken into account on these processes.

## 1. INTRODUCTION

The last ten years, the travel behavior literature have experience and increasing thread of literature devoted to understand and modeling social interactions and social influence (1). This is motivated in part since recreational and social trips are increasingly relevant purposes in the last years, and that there is a still an important gap on understanding this important part of daily mobility (2). The focus on these purposes is partly driven by the need of better forecasting future travel demand, especially if the broader traveler's context wants to be taken into account through activity-based approaches (3; 4). The interest is not only confined on demand outputs, but also on assessing the broader impact of transport on quality of life, where socializing is an important part, not only because people' basic need to interact with others, but also due to the relevance of social support exchange, both material and emotional (5; 6).

Social networks have been a central focus on the study of social activities with the hypothesis that good understanding and modeling of these purposes need to take into account explicitly the characteristics of those people with whom travelers interact (7). Starting from experiences in Sociology and other related fields, these studies have improved our knowledge in a broad range of aspects, such as data collection methods (8), simulation models (9), and the role of key variables such as distance (10; 11), frequency of interaction (12; 13), activity scheduling and time use (14), and information and communication technologies (15; 16).

All this research has been recently expanded towards the need of understanding and modeling the embedded dynamic processes for example in personal network formation and maintenance. From a behavioral perspective, the role of transport in aspects such as social interaction, network capital, and accessibility to people are part of processes that are difficult to grasp without dynamics (17). From a modeling perspective, dynamics are crucial aspect when moving to activity-based approaches, which require incorporating aspects such as learning and stress (18), as well as focusing on long-term, life-course processes (19). In this latter aspect, recent efforts on modeling social network dynamics for travel behavior require to build a "proof of principle" about their feasibility and possibility to be expanded and applicable to useful modeling systems that focus of transport related questions. A key element on this regard, it is the ability of mimicking population wide processes that expand the scope from sample based analysis and models.

With that motivation in mind, and building from recent theories and methodologies developed in the field, the objective of this paper is to present a model that illustrates a method to study personal network dynamics at a population wide level. The analysis uses data from a dedicated personal network collection as well as population wide data. Personal network data was empirically collected in a dedicated two year panel whereas population wide data comes from a representative Origin-Destination survey collected in the study area. The model focuses on the changes in people's social networks in a four year period, assessing the most relevant aspects that influence maintaining, incorporating or losing a social contact.

The study uses an egocentric or personal networks perspective, consisting on the specific social contacts (known as *alters*) with whom a specific person interacts (known as *ego*). Personal networks concentrate on “core” social contacts, that is, those people that have certain emotionally close level with the ego, excluding acquaintances. Thus, the study focuses on the evolution of social activity-travel with these most relevant, “core” social contacts. This study sets an arbitrary time frame (four years) without pre-imposing specific conditions, but looking at change in a somewhat medium to short period of time, contrasting with recent research that focus on social interaction dynamics when key lifecycle events occur (20). In this way, this paper complements Sharmeen *et al.* (21-24) insights on social networks dynamics, by looking at people who did not have necessarily important cycle events on the period of time studied.

In this sense, this study also adds empirical experience on using data that incorporate explicit tie dynamic information, as well as population wide information, adding empirical experience on the usefulness of fusion methods to understand social activity-travel. In addition, the paper serves as an illustration and contrast with the empirical framework developed by Arentze (9) to simulate personal network dynamics. Finally, this paper serves as useful comparative point with results obtained in the Netherlands with the same framework, but focusing on specific events rather than an arbitrary timeframe, which enables the analysis to understand social interaction dynamics that occur in other, more routinely situations.

The article is structured in five sections. The next section corresponds to a brief conceptual overview regarding the study of social network dynamics in the context of social activity-travel. The third section consists of a brief description of the data and methods used in the study. The fourth section describes the results obtained from the models, followed by final section of summary and conclusions.

## 2. CONCEPTUAL OVERVIEW

Social network dynamics has been studied explicitly in the Sociological literature from the 1990s. Suitor *et al.* (25), for example, discuss four key aspects that are important when studying network dynamics, remarking the importance of core ties, social support, ego’s characteristics (e.g., marital status, geographical area, age, and gender) and the broader cultural context on network turnover. Empirically, there is a broader set of results in the Social Networks literature that constitute an important background for this research; some examples are provided here. In their study in Toronto, Wellman *et al.* (26) analyzed the change on personal networks in a ten year interval, and the influence of personal circumstances – such as occupational status and residential location – and the role of the ties (family versus friends). Their results show that constant telephone interaction and social support affect positively tie maintenance over time. On the other hand, marital status – especially on women – involves changes on network ties, especially losing friendship ties. Interestingly, they report a strong turnover in personal networks, with a very small, core kin network as a stable component. Similarly, studies among young French (27) also show dramatic changes as they become adults, identifying end of studies, new employment, and going into a relationship as factors for reducing ties; and remaining single or having

specific jobs as factors for increasing ties. Using data from two waves of 2-3 years in between, Bowling *et al.* found complementary trends for elderly people (28), especially in terms of the tendency of losing ties as ages progresses, and the need of other informal support as family members change due to aging. Finally, studies in the context of Kenya (29; 30) add further evidence in terms of the low levels of stability over short periods of time and the intrinsic measurement bias that these panels have, in terms of people recalling alters who were mentioned on the previous wave.

In the travel behavior field, interest on dynamics has been a subject of interest for some time, in terms of data collection and modeling methods, as well as the behavioral insights that they can provide (31). Indirectly, dynamics has also been part of the discussion regarding understanding mobility geographies and life-course events (32). However, only the very recent work by Sharmeen and colleagues has focused more specifically on social network dynamics and travel behavior, by using a retrospective, lifecycle event data driven collection process (21-23). In the first study of their series (21), they analyze how life events influence travel behavior, including as endogenous variable the individual's personal network size, finding that the most important variable that influences changes in size is the change in marital status. In fact, they find that a marital status change involves a diminishing on personal network size. In another study, Sharmeen *et al.* (22) concentrate more explicitly on social network dynamics and lifecycle events, showing that people younger than 20 years old and men tend to create new ties after an event. Similarly, a high educational level and larger original network sizes also influences a higher probability of building new ties. Finally, in a third study of their series, Sharmeen *et al.* (23) discuss the role of the geographic context on the dynamics of face-to-face interaction and – implicitly – on the social interaction and tie dynamics.

The interest in the travel behavior field is not only on understanding the embedded processes, but on providing theoretical and empirical background that could be useful for simulation models that could be fed into activity-based approaches (9). A key guiding principle from the Social Sciences literature on these processes is *homophily*, that is, the tendency of people to have relationships with other with similar characteristics (33). In the modeling framework presented next, this homophily principle is combined with two aspects. First, the models incorporate key socio-demographics available on the datasets, such as age, gender and occupation. Second, the framework also considers distance as an important factor, still determinant for social network dynamics in the current information age (34). Next section concentrates on the data and methods used for those purposes.

### **3. DATA AND METHODS**

#### **3.1. Data description**

##### ***3.1.1. Two year panel personal networks data collection***

The main dataset comes from two collection efforts performed in the years 2008 and 2012, in the city of Concepción, Chile. The city is located 500 km south from Chile's capital, Santiago. The Greater Concepcion Area has a population of around one million people,

being the second largest city in the country. The 2008 data were collected in semi guided interviews with 240 people. Respondents were chosen by a random and socio-demographic quota based procedure. The study included questions regarding the respondent's socio-demographics, their personal networks (alters's characteristics, spatial location, frequency of interaction, and social support exchange), and a two-day retrospective activity-travel survey. More details about this dataset can be found in Carrasco *et al.* (35). In 2013, the previous participants were approached again, and 105 were successfully re-contacted; other 135 people served as the refreshment sample.

The 105 re-contacted respondents correspond to the core dataset used for the descriptive analysis presented on this paper, which is merged with population-wide survey, as later explained. The 2012 data collection effort included the same core socio-demographic and social network related questions as in 2008, as well as other travel aspects, out of the scope of this paper. Although the 2008 and 2012 instruments have differences on some modules, the core questions used for the analysis in this paper are the same. In particular, personal network members were elicited using the same name generator described by Carrasco *et al.* (8), who defined two types of social contacts: very close and somewhat close. Very close alters consist of "people with whom you discuss important matters with, or regularly keep in touch with, or they are for you if you need help". Somewhat alters consisted of "more than just casual acquaintances, but not very close". These definitions mark the personal network boundary with respect to the overall respondent's social network, and thus the scope of the analysis of this paper, that is, "core" emotional members rather than acquaintances.

In this way, these dataset captures dynamics at the tie level as ego-alter relationships can i) "appear" in 2012, ii) be "lost" between 2008 and 2012, or iii) be "maintained" between 2008 and 2012. As discussed later in more detail, the model studied in this paper will not concentrate on ties that are maintained. The dynamic on each was identified using a manual matching procedure was performed by comparing the 2008 and 2012 names, and recording those that repeated, disappeared or appeared. Other key matching variables were used in a second phase, most notably gender, age, and role, as well as possible misspellings and other issues. Home locations were also matched for the remainder alters in order to explore other potential remaining matches. Finally, audio records from both instruments were also consulted, in case of doubts. Participants did not contrast directly the 2008 and 2012 alters.

Table 1 presents selected descriptive statistics from the sample, both for egos and their alters. The results show a decrease in the average number of ties by network, ranging from 16.8 alters in 2008 to 12.4 alters in 2012. In order to investigate this change and assess possible biases on the analysis presented on this paper, we compared the re-contacted and new respondents in 2014 without observing significant changes between them. We also performed qualitative interviews to selected respondents from the sample for the third time without finding evidence of a systematic biases towards the aspects studied on this paper (36). These findings are also backed up by literature that reports some cognitive issues in the repetitive collection of personal networks with no great influence on the assessment of tie variables (29; 30). Despite this result, there is a high level of dynamics on all directions (gaining and loosing ties), and one quarter of the respondents actually increase their absolute network size. In addition, tie dynamics in terms of roles follow an expected and

intuitive pattern, where family members are more stable than other roles (see Figure 1). It is important to remark that, even in the case of direct family members, it is expected that some ties could disappear in the networks since the name generator criteria in terms of emotional support and frequent interaction do not force necessarily the respondents to mention direct family members. Other interesting descriptive statistics from Table 2 suggest the relevance of emotional closeness for tie maintenance, and the lack of importance of gender homophily. Next section presents the multilevel model, which controls the multivariate nature of the phenomenon studied.

### 3.1.2. Adding non-existing ties

Given that the objective is to be able to model at dynamics at the population wide level, the previous dataset is insufficient since it does not include “negative” ties, that is, alters that were not tied to respondents both in 2008 and 2012. With this objective, we draw the latest Concepción’s Origin-Destination survey, which is the best available resource for a reasonable probability distribution of sociodemographic attributes.

The data fusion process between the main dataset and the O-D survey individuals is illustrated in Figure 1. For each respondent, 100 negative ties are randomly added from the O-D data; this number appears to be sufficient to lead estimation results, according to previous experiences (24). We also note that different random samples were taken for each ego and that no synthetic network was repeated throughout the 105 egos. Finally, although ties were drawn randomly, we constrained the synthetic ties to keep key socio-demographic attributes observed in the population wide dataset, in terms of distance, gender, and income level.

As a consequence, the merged dataset involves the following tie dynamic process, with two phases: and *initial* process and an *adaptation* process. The initial process (year 2008) involves two possibilities positive (existing) and negative (non-existing) ties. The adaptation process involve four possibilities: ties that appeared in 2012, ties that disappeared in 2012, ties that “never” appeared, and ties that were maintained between the two years. Given that the number of observations in the maintained ties is limited, the model does not include them. Next section describes the modeling approach taken to model the tie dynamic process.

## 3.2. Modeling approach

The model is adopted from the dynamic tie formation model developed by Sharmeen et al (24) based on a utility-based tie formation function introduced by Arentze et al. (9, 37). The model was developed and applied to predict the formation of a tie between two random individuals of the population. The model applies a random utility maximization approach. The utility is defined by three structural utility components related to respectively homophily, transitivity and geographical distance, as follows:

$$U_{ij} = V_{ij}^Q + V_{ij}^D + V_{ij}^C + \varepsilon_{ij} \quad (1)$$

where  $U_{ij}$  is the utility of forming a tie between individual  $i$  and individual  $j$  and  $V_{ij}^Q, V_{ij}^D$  and  $V_{ij}^C$  are structural utility components related to homophily, geographical distance and transitivity (common friends), respectively, and  $\varepsilon_{ij}$  is an error term. Homophily refers to the notion that individuals prefer to form a tie based on the degree of similarity, transitivity accommodates the existence of common friends and geographical distance adjusts the effect of distance in formation of ties. The model therefore states that a tie between two individuals is more probable if the persons are similar in attributes, live nearby and have common friends. In this study, we leave the transitivity component out of consideration since we do not have relevant data and only look at the homophily and geographical distance effects on tie formation.

As a general assumption of the model, friendship ties are reciprocal. In other words, if person  $i$  is a friend of person  $j$  then person  $j$  must also be a friend of person  $i$ . Of course, preferences may vary, but for the sake of simplicity at this stage, the model assumes that  $U_{ij}$  is equal to  $U_{ji}$ .

To account for the opportunity of meeting a person and/or the costs (time, money) associated with maintaining a tie, the model includes a threshold utility. The threshold values may differ between persons depending on the time they are willing or able to invest in maintaining social ties and possibly other constraints. A tie is worthwhile to make or maintain when the largest value of the threshold utility is met:

$$P(i \leftrightarrow j) = \Pr(U_{ij} > \max[u_{ij}, u_{ji}]) \quad (2)$$

where  $u_{ij}, u_{ji}$  are the threshold utility values for individual  $i$  and individual  $j$ .

The model is extended to incorporate the evolution of personal social networks (24). To incorporate the time dynamics of tie formation, the decisions of tie formation were calculated in two phases, viz. initial and adaptation phase. The attribute parameters were estimated in the initial phase and re-evaluated in the adaptation phase to cater for any changes. Contrasting with Sharmeen et al (24), who assume that changes are triggered by key life cycle events, here we assume changes over time, specifically in the course of the four years of the sample. The utility function can be defined in operational terms as follows:

$$U_{ijg} = \mu_g [V_{ijg}^Q + V_{ijg}^D + Z_{ig}] + \alpha_g + \eta_i + \varepsilon_{ij} \quad (3)$$

where  $g$  is an added index of existing condition,  $\alpha_g$  is a condition specific constant,  $\eta_i$  is a random error component related to agent  $i$ ,  $Z_{ig}$  is an additional term that captures the influence of the existing network on the utility of a tie ( $Z_{ig} = 0$  in the initial phase),  $\mu_g$  is a condition-specific scaling factor and  $\varepsilon_{ij}$  is a random error term as before. In the initial phase,  $g = 0$  by definition and in the adaptation phase  $g = 1$ . Thus, in the  $g = 0$  and  $g = 1$  case the utility of forming a new tie in the initial and adaptation phase respectively. In this equation, the constant,  $\alpha_g$ , captures the threshold utility of forming a new tie ( $g = 0, 1$ ). The structural utility terms,  $V$ , on the right-hand side of the equations are operationalized for the

different conditions as follows. First, in the initial phase where no tie exists ( $g = 0$ ), the attribute-similarity utility is specified in a straightforward way as:

$$V_{ij0}^Q = \sum_k \beta_{ik} X_{ijk} \quad (4a)$$

where  $X_{ijk}$  is a homophily characteristic between person  $i$  and  $j$  regarding attribute  $k$  and  $\beta$  are parameters to be estimated. For the adaptation phase the term is extended to account for a possible re-evaluation of the same attributes in the adaptation phase ( $g = 1$ ):

$$V_{ij1}^Q = \sum_k (\beta_{ik} X_{ijk} + \beta_k^\Delta X_{ijk}) \quad (4b)$$

where  $\beta^\Delta$  parameters represent adaptations of the evaluations. The distance related utility term is specified in the similar way, for the initial and adaptation phases ( $g = 0$  or  $g = 1$ ), as follows:

$$V_{ij0}^D = \theta_i \ln(D_{ij}) \quad (5a)$$

$$V_{ij1}^D = \theta_i \ln(D_{ij}) + \theta^\Delta \ln(D_{ij}) \quad (5b)$$

where,  $D_{ij}$  is geographical distance between persons  $i$  and  $j$  and  $\theta$  and  $\theta^\Delta$  are related parameters. The log transformation of distance ( $\ln D_{ij}$ ) is implemented to take decreasing marginal utility of distance into account, which generally is assumed to be the case in tie formation models. Finally, the influence of the existing network is defined as:

$$Z_{i0} = \lambda N_i \quad (6a)$$

$$Z_{i1} = \lambda N_i + \lambda^\Delta N_i \quad (6b)$$

where  $N_i$  is the size of the existing social network of person  $i$  and  $\lambda$  and  $\lambda^\Delta$  are parameters to be estimated. To account for taste heterogeneity, the core parameters are included as random parameters in this model:

$$\beta_{ik} = \beta_k + \gamma_{ik} \quad (7)$$

$$\theta_i = \theta + \chi_i \quad (8)$$

where  $\gamma_{ik}$  and  $\chi_i$  are agent-specific error terms regarding attribute similarity and distance parameters, respectively.

The parameters have the following interpretation:  $\beta^\Delta$  parameters represent the effects of being in the adaptation phase on the way similarity is valued on the various attributes ( $k$ );  $\lambda$  represents the effect of the current size of the network in the adaptation phase on the utility of a relationship and  $\mu$  takes into account a possible scale effect on how attributes and distance are valued under the different conditions.

In sum, the above equations (3) – (8) define the model of tie formation decisions in the initial phase and adaptation phase taking the time dynamics into account. The model takes

into account taste-heterogeneity across agents (ego's) in terms of homophily, geographical distance and base utility (threshold) for formation of ties.

#### 4. FINDINGS

The model was estimated using a mixed-logit framework to account for the panel-structure of the data, i.e. multiple observations for the egos of the sample. The estimation was conducted in two steps. At first the scale parameter,  $\mu$  (in Eq. 3), was estimated in a multinomial specification of the model. Then the data were rescaled accordingly and the model was estimated using the final mixed logit estimation with the scale parameter omitted (given that the data have been rescaled and hence the scale difference is solved). The best fitting model was obtained after evaluating random effect variations in constant, same age group, same gender and distance parameters. The log likelihood estimates and Rho square statistics display that the model has a good fit compared to a null model.

The constant is negative for the initial phase showing the all else being equal, the probability of formation of a tie is unlikely. However the constant is positive for the adaptation phase reflecting on a reverse probability. Given that parameters of the adaptation phase are to be interpreted as effects on those of the initial phase (Eq. 4b, 5b, 6b), the overall effect remains negative. This means that formation of a tie would still be unlikely in the adaptation phase, with somewhat lower intensity.

Strong homophily effects are observed for tie formation at the initial phase, in line with the concept of homophily, that individuals form ties based on the degree of similarity between them. Similar findings were also reported in the Dutch research (24).

On the other hand, heterophily effects dominate the adaptation phase, showing that ties could be formed regardless to the degree of similarity between the actors. The opposite effects in the adaptation phase may cater to the existence of a strong and steady personal social network. Sensitivity to homophily effects minimizes after one has a strong support network, in line with the findings of Sharmeen et al. (24). However, while the findings of the Dutch research showed a declining tendency towards homophily only, in this study, we have found a clear dominance towards heterophily (note the remarkably strong parameters of same age group, same gender and same occupation level in part B of table 1). However, it is to note that a direct comparison is unrealistic since, unlike this study, the life cycle approach was applied in the Dutch research.

Geographical distance has negative effects on the formation of ties in both phases. The effects minimize in the adaptation phase though. Thus geographical distance matters in ego-centric social networks, as expected, and reported by scholars in earlier research (23, 24, 34).

Although not significant in the initial phase, size of social networks (barely) positively influences the formation of ties. The effects were found to be insignificant in the Dutch research. The findings suggest that homophily, geographical distance and the size of social network are important aspects in defining the formation and evolution of ego-centric social

networks. The effects vary with time, possibly explaining the sensitivity of the existence (or absence thereof) of a stable social network.

## 5. CONCLUSIONS

This paper has presented more empirical evidence to illustrate the feasibility of modeling personal network dynamics (tie formation), results that can be used for an activity-based, microsimulation system, for example. The interpretation of the modeling framework – which was originally defined for event based tie formation – was slightly extended in order to incorporate a two wave personal network survey that occurs in an ad-hoc time frame (four years) and where only respondents had specific major life events. These data were merged with an Origin-Destination survey in order to incorporate characteristics of “negative ties”, that is, alters who are not linked with egos in both points in time, and that are obviously not observed on the two wave, dedicated dataset. In this way, the modeling framework now have a population wide scope.

The model results present several similarities and some differences with those found in the Dutch context. In fact, homophily in age, gender, and occupation level, plays different roles, depending on the modeling phase. In fact, for the initial phase (tie formation), ego-alter homophily makes a tie more likely to exist; in the adaptation phase, heterophily is the dominant force for tie dynamics. In that regard, variety seeking is a process that becomes increasingly important as time evolves. This result found in the Chilean context goes in line with the Dutch counterpart, although a decline in homophily was the predominant force in the adaptation phase rather than heterophily. Although a plausible hypothesis is that this contrast is due to the different nature of the dynamics modeled (i.e., routine change versus event based), more research is needed to disentangle the possible effects due to the different national contexts studied. This variety seeking process can also be found in the role of distance, which has a negative effect in the initial phase, but a positive role in the adaptation phase, result that is similar with the Dutch context. It is important to note, though, that the role of distance is highly heterogeneous, judging by the relative high standard deviation effect. Finally, personal network size also plays a positive role in the adaptation phase, possibly due to the likelihood of engaging with other alters and its consequences for the overall network stability.

Overall, this study illustrates the feasibility of modeling tie dynamics using a dedicated and a population wide data collection, and the conceptual insights that it can provide, especially in terms of the role of homophily on the evolution of personal networks. Further research should also incorporate tie maintenance (not analyzed here due to small sample sizes), and possibly exploring the role other contextual variables that could potentially influence these processes.

## ACKNOWLEDGEMENTS

Data collection and merging process was funded by the Complex Engineering Systems Institute (CONICYT: FB016).

## REFERENCES

- [1] Carrasco, J.A. and S. Farber (2014), "Selected papers on the study of the social context of travel behavior," special issue for *Transportation Research Part A*, 68, 1-2.
- [2] Axhausen, K. W. Social networks and travel: Some hypotheses. In *Social Aspects of Sustainable Transport: Transatlantic Perspectives*, Ashgate, Aldershot, 2005.
- [3] Archer, M., R. Paleti, K. Konduri, R. Pendyala, and C. Bhat. Modeling the Connection between Activity-Travel Patterns and Subjective Well-Being. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2382, 2013, pp. 102-111.
- [4] Buliung, R., and P. Kanaroglou. Activity-travel behaviour research: conceptual issues, state of the art, and emerging perspectives for behavioural analysis and simulation modelling. *Transport Reviews*, Vol. 27, No. 2, 2007, pp. 151 - 187.
- [5] Deutsch, K., and K. Goulias. Understanding Place Through Use of Mixed-Method Approach. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2323, No. -1, 2012, pp. 1-9.
- [6] Carrasco, J. A., and B. Cid-Aguayo. Network capital, social networks and travel: An empirical illustration from Concepcion, Chile. *Environment and Planning Part A*, Vol. 44, No. 5, 2012, pp. 1066-1084.
- [7] Carrasco, J. A., and E. J. Miller. Exploring the propensity to perform social activities: A social networks approach. *Transportation*, Vol. 33, No. 5, 2006, pp. 463-480.
- [8] Carrasco, J. A., B. Hogan, B. Wellman, and E. J. Miller. Collecting social network data to study social activity-travel behavior: an egocentric approach. *Environment and Planning B-Planning & Design*, Vol. 35, No. 6, 2008, pp. 961-980.
- [9] Arentze, T. A., M. Kowald, and K. W. Axhausen. An agent-based random-utility-maximization model to generate social networks with transitivity in geographic space. *Social Networks*, Vol. 35, No. 3, 2013, pp. 451-459.
- [10] Kowald, M., P. van den Berg, A. Frei, J.-A. Carrasco, T. Arentze, K. Axhausen, D. Mok, H. Timmermans, and B. Wellman. Distance patterns of personal networks in four countries: a comparative study. *Journal of Transport Geography*, Vol. 31, 2013, pp. 236-248.
- [11] van den Berg, P., T. Arentze, and H. Timmermans. Size and composition of ego-centered social networks and their effect on geographic distance and contact frequency. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2135, 2009, pp. 1-9.
- [12] Carrasco, J.-A., and E. J. Miller. The social dimension in action: A multilevel, personal networks model of social activity frequency between individuals. *Transportation Research Part a-Policy and Practice*, Vol. 43, No. 1, 2009, pp. 90-104.
- [13] van den Berg, P., T. Arentze, and H. Timmermans. A multilevel path analysis of contact frequency between social network members. *Journal of Geographical Systems*, 2010, pp. 1-17.
- [14] Moore, J., J.-A. Carrasco, and A. Tudela. Exploring the links between personal networks, time use, and the spatial distribution of social contacts. *Transportation*, Vol. 40, No. 4, 2013, pp. 773-788.
- [15] Carrasco, J. A. Personal network maintenance, face to face interaction, and distance: Studying the role of ICT availability and use. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2231, 2011, pp. 120-128.

- [16] van den Berg, P. E. W., T. A. Arentze, and H. J. P. Timmermans. A path analysis of social networks, telecommunication and social activity-travel patterns. *Transportation Research Part C*, Vol. 26, 2013, pp. 256-268.
- [17] Ettema, D., and T. Schwanen. A relational approach to analysing leisure travel. *Journal of Transport Geography*, Vol. 24, No. 0, 2012, pp. 173-181.
- [18] Psarra, I., F. Liao, T. Arentze, and H. Timmermans. Modeling Context-Sensitive, Dynamic Activity-Travel Behavior, by Linking Short and Long-Term Responses to accumulated Stress: Results of Numerical Simulations. *Transportation Research Record: Journal of the Transportation Research Board*, 2014, p. forthcoming.
- [19] Scheiner, J., and C. Holz-Rau. A comprehensive study of life course, cohort, and period effects on changes in travel mode use. *Transportation Research Part A: Policy and Practice*, Vol. 47, 2013, pp. 167-181.
- [20] Sharmeen, F. A., T. Timmermans, H. An analysis of the dynamics of activity and travel needs in response to social network evolution and life-cycle events: A structural equation model. *Transportation Research Part A: Policy and Practice*, Vol. 59, 2014, pp. 159-171.
- [21] Sharmeen, F., T. A. Arentze, and H. J. P. Timmermans. A multilevel path analysis of social network dynamics and the mutual interdependencies between face-to-face and ICT modes of social interaction in the context of life-cycle events. In *Travel Behaviour Research: Current Foundations, Future Prospects*, Lulu Publishers, Toronto, 2013. pp. 411-432.
- [22] Sharmeen, F., T. Arentze, and H. Timmermans. An analysis of the dynamics of activity and travel needs in response to social network evolution and life-cycle events: A structural equation model. *Transportation Research Part A: Policy and Practice*, Vol. 59, 2014, pp. 159-171.
- [23] Sharmeen, F., T. Arentze, and H. Timmermans. Dynamics of face-to-face social interaction frequency: role of accessibility, urbanization, changes in geographical distance and path dependence. *Journal of Transport Geography*, Vol. 34, 2014, pp. 211-220.
- [24] Sharmeen, F., T. Arentze, and H.J.P. Timmermans, Predicting the Evolution of Social Networks with Life Cycle Events. *Transportation*, forthcoming.
- [25] Suitor, J. J., B. Wellman, and D. L. Morgan. It's about time: How, why, and when networks change. *Social Networks*, Vol. 19, No. 1, 1997, pp. 1-7.
- [26] Wellman, B., R. Y.-L. Wong, D. Tindall, and N. Nazer. A decade of network change: turnover, persistence and stability in personal communities. *Social Networks*, Vol. 19, 1997, pp. 27-50.
- [27] Degenne, A., and M.-O. Lebeaux. The dynamics of personal networks at the time of entry into adult life. *Social Networks*, Vol. 27, No. 4, 2005, pp. 337-358.
- [28] Bowling, A., M. Farquhar, and E. Grundy. Changes in network composition among older people living in inner London and Essex. *Health & Place*, Vol. 1, No. 3, 1995, pp. 149-166.
- [29] White, K., and S. C. Watkins. Accuracy, stability and reciprocity in informal conversational networks in rural Kenya. *Social Networks*, Vol. 22, No. 4, 2000, pp. 337-355.
- [30] Bignami-Van Assche, S. Network stability in longitudinal data: A case study from rural Malawi. *Social Networks*, Vol. 27, No. 3, 2005, pp. 231-247.
- [31] Golob, T., R. Kitamura, and L. Long. *Panels for Transportation Planning*. Kuwer Academic Publishers, USA, 1997.

- [32] Lanzendorf, M. Mobility biographies. A new perspective for understanding travel behaviour. In 10th International Conference on Travel Behaviour Research, Lucerne, 10-15 August 2003, 2003.
- [33] McPherson, M., L. Smith-Lovin, and J. Cook. Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, Vol. 27, 2001, pp. 415-444.
- [34] Mok, D., B. Wellman, and J. Carrasco, Does distance matter in the age of the Internet? *Urban Studies*, 2010. 47(13): p. 2747-2783.
- [35] Carrasco, J. A., C. Bustos, and B. Cid-Aguayo. Affective personal networks versus daily contacts: Analyzing different name generators in a social activity-travel behaviour context. In *Transport Survey Methods: Best Practice for Decision Making*, Emerald Press, London, 2013.
- [36] Carrasco, J. A., S. Salazar, D. Sandoval, O. Chávez, and B. Cid-Aguayo. Spatial and temporal dynamics on personal networks: Some methodological and theoretical challenges to study their embedded social travel behavior In 10th International Conference on Transport Survey Methods, Leura, Australia, 2014.
- [37] Arentze, T., P. van den Berg, and H. Timmermans, Modeling social networks in geographic space: approach and empirical application. *Environment and Planning A*, 2012. 44(5): 1101-1120

**TABLES AND FIGURES**

**Table 1: Selected descriptive statistics main dataset**

<b>Egos (105 cases)</b>	
Women	60%
In a relationship in 2008	68%
Occupational status: working	66%
Age in 2012: younger than 25 years old	10%
Age in 2012: between 25 and 39 years old	31%
Age in 2012: between 40 and 60 years old	34%
Age in 2012: older than 60 years old	25%
Car ownership in 2008 (at least one car)	50%
Engages in a relationship between 2008 and 2012	14%
Maintain income	31%
Diminishes income	19%
Increases income	50%
<b>Network level variables (1,765 in 2008 / 1,304 in 2012)</b>	
<i>New ties</i>	
Have the same gender	61%
Have the same occupation	53%
<i>Lost ties</i>	
Have the same gender	62%
Have the same occupation	23%

**Table 2: Binary mixed logit model of social ties formation (population wide prediction)**

Dependent variable: tie present or absent

<b>Parameter Estimates</b>	<b><math>\beta</math></b>	<b>t-stat</b>
<b>A. Initial (wave:2008) phase</b>		
Constant	-11.60	-17.68
Same age group	1.21	13.04
Same gender	0.126	1.61
Same occupation level	2.05	20.58
Log of distance in km	-2.04	-33.30
Size of social network (close ties?)	0.009	1.43
<b>B. Adaptation (wave:2012) phase</b>		
	<b>Effects on <math>\beta</math></b>	<b>t-stat</b>
Constant	7.64	14.67
Same age group	-9.18	-10.84
Same gender	-0.661	-3.13
Same occupation level	-6.03	-7.92
Log of distance in km	1.69	8.91
Personal network size	0.0586	5.22
<b>Std Dev Random Effects</b>		
	$\chi_i$ and $\gamma_{ik}$	<b>t-stat</b>
Constant	0.0196	0.36
Same age group	0.637	7.22
Same gender	0.407	5.06
Distance	-0.123	-4.39

Model goodness-of-fit:

Initial log-likelihood: -9993.796. Final log-likelihood: -4125.034. Rho-square: 0.587

# Halton draws: 200. # observations: 14418

**Figure 1: Schematic overview of data fusion process**

