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Using a Realistic Social Network to Improve Leisure Destination Choice Simulation

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Abstract

In developed countries, in the last years, a continuous increase of the share of trips that are performed for leisure purposes could be observed. Various data sources further indicate that the most important motivation behind out-of-home leisure activities is *social contact*.

On the other side, leisure remains very hard to model in simulation models, mainly because it depends highly on characteristics that are difficult to observe, such as heterogeneity of taste and the characteristics of leisure locations. As such, the best such models can do is to calibrate the level of noise added on top of classical distance and cost based utility of travel, such that simulated travel distances fit the data adequately.

This paper makes a first step in using the social nature of leisure travel to decrease the level of noise needed to simulate leisure travel. Using a realistic synthetic population with a realistic social network for Switzerland, it implements a simple model where agents have individual preferences over activity locations and social contacts, and shows how this can help reproduce the observed travel distances. In particular, the traveled distances for visiting social contacts, one of the most important leisure types in Switzerland, are pretty insensitive to the scale of the error terms and come out of the structure of the social network.

INTRODUCTION

In developed countries, a continuous increase of the share of trips that are performed for leisure purposes could be observed during the last dozens of years *(1, 2)*. This represents a challenge for travel behavior modeling, as those trips are much more difficult to capture than commuting trips: they are performed more sporadically, and data about those trips is much more difficult to collect. Understanding better how destinations for leisure trips are chosen is therefore essential to improve the accuracy of those forecasts. This increase in leisure travel has been anticipated early, and the social nature of such travel already hypothesized, for instance by Salomon *(3)*, who stated that *"one particular type of travel, that for* recreational *and* social *purpose, may increase when more leisure time is available"*. This forecast was later confirmed, for instance by Stauffacher et al. *(4)*, who analyzed the motives behind leisure activities, using the results of a Swiss 12 weeks leisure travel diary survey. They found social contact to be the most important, and that in addition respondents traveled with social contacts for more than 70% of leisure activities. This fact, among others, generated a growing interest in the social dimension of travel, and how travel decisions are influenced not only by the global state of the transportation system, but also by joint decisions and interactions with social contacts — a clear sign for this interest being the regular workshops organized on this theme *(5–9)*.

Interest in the relationship between mobility, social contacts and leisure behavior is not new *(10, 11)*, but enjoyed a renewed interest in recent years. Previous studies have been conducted with the idea that an important factor in leisure trip destination choice, or activity duration choice, is the ability to meet social contacts. Examples of empirical work include Carrasco and Habib *(12)*, Habib and Carrasco *(13)* or Moore et al. *(14)*. All those studies show a significant influence of social contacts on the spatial and temporal distribution of activities. In addition, the influence of the social nature of human beings was shown to generate paradoxical effects. For instance, Harvey and Taylor *(15)* show that persons working from home tend to travel *further* for leisure purpose, in order to fulfill their need for social contact, that they cannot fulfill at their workplace. A model ignoring such effects might thus substantially underestimate the traveled distances for such individuals.

Typically, co-participants in activities are classified in household and other contacts. Srinivasan and Bhat *(16)* analyzed the American Time Use Survey to search for interaction patterns with household members and other contacts. They found that a significant proportion of activities of all types, be it during the week or the week end, are performed jointly. There are however systematic patterns that can be identified in the data: joint (out of home) activities during the week tend to be performed with non-household members, the opposite being true on the week-end. In addition, activities with household and family members tend to be longer than activities with friends. Kemperman et al. *(17)* observed the same kind of effect between week-end and week day in the Netherlands.

Households are a typical unit of analysis in economics and transportation, and much work has been conducted on modeling the co-dependence of the mobility behavior of different household members. Those studies often use the classical random utility framework extended to group decision making, such as Zhang et al. *(18, 19)*, Kato and Matsumoto *(20)*, Bradley and Vovsha *(21)*, Gliebe and Koppelman *(22, 23)*, Ho and Mulley *(24)*, or Vovsha and Gupta *(25)*. Other techniques were however also used, such as structural equation models (*26*, *27*), specification of the plan as a classical optimisation problem to be solved by standard solvers (*28–30*), genetic algorithms (*31*) or shortest path algorithms in a generalized supernetwork (*32*), or more rule-based approaches (*33*, *34*).

Another field of empirical research studies the spatial characteristics of social networks. For instance, Carrasco et al. *(35)* studied the relationship between individual's socioeconomic

characteristics and the spatial distribution of their social contacts. This kind of empirical work allows to specify and estimate models able to generate synthetic social networks, given sociodemographic attributes and home location. Another kind of data collection is the one of Kowald *(36)*, that uses the technique of *snowball sampling*, where random individuals are asked to list social contacts, that are in turn contacted and asked the same set of questions. Based on this data, Arentze et al. *(37)* and Dubernet *(38)* estimated models capable of synthetizing social networks with realistic geographical and topological properties. This kind of model is essential if one wants to include social network interactions in microsimulation models. In particular, the algorithm of Dubernet *(38)*, that is able to reproduce non-trivial topological and spatial structures (the distribution of the size of cliques and of the socio-spatial distance between all members of the clique), that are of prime importance for mobility behavior, is used later in this paper.

This integration of social networks in multiagent simulation frameworks has already been attempted by other authors. Due to their disaggregated description of the world, such models are particularly well suited to the representation of complex social topologies. Han et al. *(39)* present experiments of using social networks to guide activity location choice set formation in the FEATHERS multiagent simulation framework. Using a simple scenario with 6 agents forming a *clique*, they consider the influence of various processes like information exchange and adaptation to the behavior of social contacts to increase the probability of an encounter. They do not, however, represent *joint decisions*, such as the scheduling of a joint activity. The same kind of processes have been investigated by Hackney *(40)*, using more complex network topologies, within the MATSim framework. Ronald et al. *(41)* and Ma et al. *(42, 43)* present agent based systems which do integrate joint decision making mechanisms, based on rule based simulations of a bargaining processes. Frei and Axhausen *(44)* demonstrate a simple joint planning model, where (a) social contacts decide to perform a joint activity if it improves the utility of all co-participants, and (b) location of a joint activity is chosen to maximise a group utility. They are not yet integrated into any operational mobility simulation platform.

Of course, due to the high share of leisure trips in industrialized countries, there has been a large number of studies aimed at understanding the determinants of those trips, outside of the more specific topic of social travel. Those analyses can be rather detailed: for instance, Grigolon et al. *(45)* study complementarity and substitution effects between several types of leisure activities, and find for instance that though outdoor leisure is a substitute with sport and hobby-courses, it tends to complement shopping-as-leisure and going out. Preferences and constraints are sometimes difficult to disentangle: evidence for instance shows that low income individuals tend to be less active *(46)*, or that going out and cultural activities occur more frequently in urban areas *(47)* — which are most probably structural effects, or even endogenous in the last case (living in a city because one wants to have the possibility to go out). Other researchers have looked at the specification of models of the choice of a *type* of recreational activity, depending on the decision maker's characteristics *(48, 49)*. Such models would be necessary for an operational model of leisure destination choice that would take into account the characteristics of the location. Other work has taken a more long-term view, looking at issues of "loyalty" to a location or activity type *(50)*.

However, in practical large-scale simulation models, modeling of destination choice tends to be pretty coarse. Bowman et al. *(51)*, for instance, only consider the distinction between "primary", "maintenance" and "discretionary" activities, and only use distance as a choice determinant for the location. Bradley et al. *(52)* or Pozsgay and Bhat *(53)*, on the other hand, use many more variables; however, they all come from aggregate zonal statistics, such as employment density for different sectors — mainly due to the difficulty to collect data on the characteristics

of any possible activity location. Other typical (American) activity-based models follow the same pattern *(54)*.

There is, of course, a limit to the complexity of a leisure destination choice model for simulation. Indeed, the list of characteristics of activity locations is close to infinite, and even assuming one would have a perfect model able to predict accurately the chosen location given the decision maker's characteristics, it is highly unlikely that one is able to collect data on all desired attributes for any possible leisure location. As noted by Horni *(55)*, this makes it impossible in practice to model destination choice without explicitly simulating error terms of significant magnitude. In crude terms, the only way we know to represent those decisions in an operational model is to add noise until one reproduces aggregated statistics from the measured data.

The idea behind this paper is the following: given the fact that getting data on any possible leisure location is so hard, but that generating a reasonable social network with the method from Dubernet *(38)* is comparatively easy, how much can the desire to meet social contacts explain traveled distance?

Of course, the aim of this paper is not to diminish the relevance of all this work, nor to claim that the simple approach described here could replace models considering a variety of alternative characteristics and deeply grounded in data. Rather, by abstracting the decision to engage in leisure activities to a few schematic components, it attempts to evaluate *how much* explicitly considering social interactions in leisure location choice might matter in practical applications.

METHOD

The aim of this paper is to test the possibility to use social contacts, and their spatial distribution, to drive the leisure location choice of agents to realistic outcomes with a lower random component.

To this end a simplified simulation framework is developed. This framework uses an equilibrium assumption, compatible with equilibrium-based frameworks, such as MATSim *(56)*. MATSim is a multi-agent, activity-based framework, that uses a co-evolutionary algorithm to find a user equilibrium on *daily plans*. This evolutionary formulation allows to avoid exploring the full choice set of agents, while still reaching states akin to an equilibrium. This, however, also makes analysis difficult. For this reason, the work presented here does not use iterations nor evolution. However, all the elements used here are implemented using the MATSim framework, and can be used as part of the co-evolutionary process.

The characteristics of this simulation framework are the following:

- agents choose one leisure location from a personal choice set, in order to maximize a utility function,
- the utility function depends on the leisure location *and* of the party composition,
- the standard Nash equilibrium criterion is extended to be applicable to *joint decisions*.

The typical Nash equilibrium criterion states that a state is a Nash equilibrium if no agent can *unilaterally* improve its utility by changing its behavior. This is not well suited for joint activities, as they require coordination. The concept of "Absence of Blocking Coalition", used in the classical House Allocation Problem *(57)*, is better suited here. This concept defines a stable state as a state without "blocking coalition", where a blocking coalition is a group of players that can all be better off by changing their strategy simultaneously. In our case here, a group of agents represents a blocking coalition for a given allocation of strategies to agents if:

1. they form a *clique*, that is, there exist social ties between any two agents in the group, and
2. they can *all be better off* by switching their strategies simultaneously.

Item 1 ensures synchronization only happens between social contacts. Item 2 defines the joint decision process, where agents can negotiate with groups of friends, the decision being accepted only if everybody in the group has an interest in it. In the case where no ties exist in the social network, this is equivalent to a Nash equilibrium. In the present paper, strategies are the location of a leisure activity and the identity of the co-participants. This can however easily be extended to more general categories, such as daily plans.

Each agent has an "awareness" set of locations it can perform leisure in. This set contains the home location of the agent, which is not special in any other way than being at distance 0. The choice set of the agents is composed of:

- performing leisure alone at one of the locations in the awareness set of the agent, or
- performing leisure with a clique of friends (friends who are all friends with each other) at any location in the awareness sets of the clique.

The choice of agents is constrained to feasible allocations, in the sense that an agent A_1 can choose to perform leisure with participants $\{A_1, \cdots, A_n\}$ at location L only if every agent in $\{A_2, \cdots, A_n\}$ also chooses to perform leisure at L with group $\{A_1, \cdots, A_n\}$.

The preferences are defined by the following simple utility function:

$$U(e, l, \mathcal{A}) = -d_{e,l} + \varepsilon_{e,l} + \sum_{a \in \mathcal{A}} (\alpha + \eta_{e,a}) \tag{1}$$

where $d_{e,l}$ is the distance between the home of agent e and location l, $\varepsilon_{e,l} \sim \mathcal{N}(0, \sigma)$ is a normally distributed random utility for location l for agent e, and $\alpha + \eta_{e,a}$ is the utility of alter a in the set $\mathcal{A}$ of co-participants, consisting of a constant part α and a normally distributed random couple-dependent part $\eta_{e,a} = \eta_{a,e} \sim \mathcal{N}(0, \vartheta)$. All random variables are independent, and generated as needed using the *quenched randomness* framework proposed by Horni *(55)*. The utility function is expressed in kilometers.

Given those choice sets and utility function, an algorithm to find a state without blocking coalition was developed. In the following, we call "individual" and activity that is performed alone, and "joint" an activity that is performed in a group of at least two agents. A group of agents $\mathcal{G}$ constitutes a blocking coalition for a given allocation $\mathcal{A}$ (a mapping of agents to elements of their choice set) if they can all be better off by *simultaneously* changing plans. Apart from trivial cases, where agents can switch to better individual solutions or where $\mathcal{G}$ is composed of smaller blocking coalitions, $\mathcal{G}$ is a blocking coalition if, in the choice set, there exists an activity with participants $\mathcal{G}$ for which individual scores for all agents in $\mathcal{G}$ are better compared to their plans in allocation $\mathcal{A}$.

This kind of allocation is found using an algorithm inspired by the classical "top trading cycle" algorithm for the house allocation problem (*57*), presented in Figure 1. The idea behind the algorithm is to let agents *point* to their preferred activity. If the activity is individual, it is immediately allocated to the agent. If the activity is joint, it is allocated to its participants if they all point towards it. If an agent is allocated to an activity, all other joint activities to which it participates are marked as *unfeasible*, and agents that might have pointed to them point to their next preferred *feasible* activity. The process is iterated until no agent remains without an activity. Note that there may be a variety of such allocations; in which case, the algorithm returns only one of them. Cases where several allocations without improving coalition are feasible lead to conflicts in the process of Figure 1, that is, states where all agents point to joint activites, but no joint activity is pointed to by all its participants. To solve those conflicts, heuristic deletion

of joint plans have to be used, represented by the `solveConflicts` function in Figure 1. In the application below, this heuristic is the following: first, all joint activities are ordered by the fraction of their participants pointing at them. Then, for all activities corresponding to the highest fraction of participants pointing, the activity pointed by the participants not pointing this activity is removed.

```
Data: persons, the group of persons for whom the allocation is computed. The persons
      always "point" to their preferred feasible activity. An activity is feasible if it is
      individual or joint with agents that do not yet have an activity allocated
Data: solveConflicts, a function that attempts to resolve conflictual allocations
Result: An allocation of activities to agents
while ( persons) > 0 do
    didSomething := false;
    for currentPerson ∈ persons do
        if currentPerson points to a feasible plan pointed by all participants then
            allocate this plan to currentPerson and its co-participants;
            remove currentPerson and co-participants from persons;
            didSomething := true;
    if ¬ didSomething then
        solveConflicts ( persons);
return the resulting activity allocation;
```

FIGURE 1 Selector without improving coalition.

Simulation

The simulations presented here take as an input a 1% synthetic population as presented by Bösch et al. *(58)*, enriched by a social network generated using the algorithm presented by Dubernet *(38)*, that puts the emphasis on reproducing a realistic *clique structure*. The awareness set of the agents consists of a set of 30 randomly sampled locations in a radius of 30km around home, plus home. Groups of co-participants are all cliques up to 3 agents — mainly to keep the computation tractable. An operational implementation would have use heuristics to avoid considering the full choice set of co-participating groups, which we avoid here to avoid considerations on the quality of the approximation.

This process is run for all possible combinations of the following values:

- $\alpha \in \{0\,\text{km}, 5\,\text{km}, 10\,\text{km}\}$
- $\vartheta \in \{0\,\text{km}, 1\,\text{km}, 5\,\text{km}, 10\,\text{km}\}$
- $\sigma \in \{0\,\text{km}, 1\,\text{km}, 5\,\text{km}, 10\,\text{km}\}$

Those values are arbitrary, and aim at covering a range of behaviors in terms of desire to meet contacts and preference variation.

Expected Outcomes

This experimental setup contains two mechanisms to entice agents out of their home: random preferences and desire for social contact. The random error term associated with each ego-alter pair is there to represent various effects that might make one prefer to meet one particular

contact over another: time elapsed since the last meeting, actual personal preference, common preference for a given activity. Due to its grounding on a realistic social network, the structural constraints (number of possible cliques and conflicts between several groups, ego-alter distances) are realistic.

The experiments are designed to explore the range from pure random location choice in the vein of Horni *(55)* to pure desire to meet contacts, independent of the location characteristics.

The experiments aim at looking at how much one can reproduce traveled distances using a preference for social contact, in comparison to random preferences for locations. If the assumption behind this work is verified, that social contacts indeed can explain leisure travel, one should be able to reproduce travel distributions with a much lower level of added noise when one introduces the desire for sociality.

RESULTS

Basic Statistics About Daily Leisure Travel in Switzerland

To give a point of reference when analyzing the experiments below, we detail here basic statistics about daily leisure travel in Switzerland, from the public results of the Swiss National Travel Survey 2010 *(59)*.

Table 1 lists the shares of the 4 most important leisure activity types, as a share of all leisure activities, per day of the week. Those 4 types represent almost three quarter of all leisure trips, and are thus a good set to focus on. From the context of social activities, those types are interesting:

- going to the restaurant is a typical way to socialize, particularly in the evening;
- non-sportive outdoor activities includes solitary activities, such as taking the dog for a walk, but might also include social encounters, such as young parents going to meet other parents at the playground to chat while the children play together. Research has in particular been conducted for the specific sub-type of visiting green spaces, and its effect on the ability of aging residents to maintain a satisfying social network *(60)*. This type is difficult from the perspective of destination choice, as anywhere can be a potential "destination";
- visits are obviously social;
- sports might mostly correspond to what Kemperman et al. *(17)* term *"institutionalized"* social activities, where an important motive is social contact, but the choice of time and place is fixed by an external entity (*e.g.* the football club).

Table 2 shows the typical trip distances for those four purposes. Trips to the restaurant tend to be pretty short, probably because the data also includes travel to lunch. Outdoor non-sportive activities also tend to be short, with half the trips being less than 2 km, and more than 90% less than 10 km. This makes the sampling for potential destinations of such trips less problematic, as their influence on the transport system is small (amplified by the fact that more than 80% of those trips are performed by non-motorized modes). Visits show a higher share of long trips than the previous purposes, with around 30% of trips longer than 10 km. This makes this kind of activity potentially interesting for transport planning, in particular given the fact that almost 60% of those trips are performed using individual motorized transport.

TABLE 1 Share of Activity Types (as % of All Leisure Activities)

Activity Type	Day of the Week			
	Mon. – Fri.	Sat.	Sun.	All
Restaurants	24.8	20.7	13.5	22.2
Outdoor (non sport)	19.2	17.2	26.0	20.0
Visits	17.7	21.5	22.4	19.2
Sports	13.0	8.6	8.8	11.5
Total	74.7	68.0	70.7	72.9

Source: *59*, Table 5.7.1

TABLE 2 Travel Distance by Leisure Activity Type (% of Purpose-Specific Trips)

Activity Type	Distance (km)			
	≤ 2	]2, 10]	]10, 20]	> 20
Restaurants	53.1	27.6	8.1	11.2
Outdoor (non sport)	49.9	42.8	4.1	3.2
Visits	36.7	32.5	12.8	17.9
Sports	34.2	42.5	12.1	11.2

Source: *59*, Table 5.7.2

Results of the Simulation

Figure 2 shows the share of each activity type for each parameter value combinations. Visits unrealistically dominate travel purpose (excluding alone at home and hosts, who do not travel), which might point to a missing phenomenon in the simplistic model, such as the cost of receiving somebody at home. Increasing desire to meet contacts (α) drives agents to increase the probability to perform a visit substantially. It also increases the share of out-of-home social activities, but does not influence that much the overall share of out-of-home activities (or even makes the overall number decrease, replacing them by visits). Variability in terms of location preferences (σ) has a much stronger influence on the share of out-of-home activities: as long as agents do not differentiate between home and other locations, it is easier to meet at home. Thus, without differentiating explicitly visits and out-of-home joint activities, it is difficult to represent the hypothesis that the influence of social activity location choice could improve simulation forecasts by making agents meet "in the middle" *(61)* or in some "fair place" *(62)*.

Figure 3 shows the distance distributions for out of home and visitor activities, as well as all activities (which includes both previous types plus alone at home and host), for all parameter value combinations. In general, an increasing base utility of meeting a social contact α increases traveled distances for all types. Overall, this is also the effect of increasing the variability of social contact preferences ϑ. However, the effect of the variability of location preferences σ is non-trivial: for high enough values of ϑ and α, traveled distances for Out of Home activities globally *decrease* with increasing σ, with a notable decrease when going from 0 to 5, followed by an increase when going from 5 to 10. This has to do with conflicting preferences: for $\sigma = 0$, the only factor pushing out of home is to meet friends, and only distance matters: finding a proper place is relatively easy. For intermediate σ, finding a place is harder, but the random preferences do not create a strong willingness to travel. With $\sigma = 10$, traveling to more remote

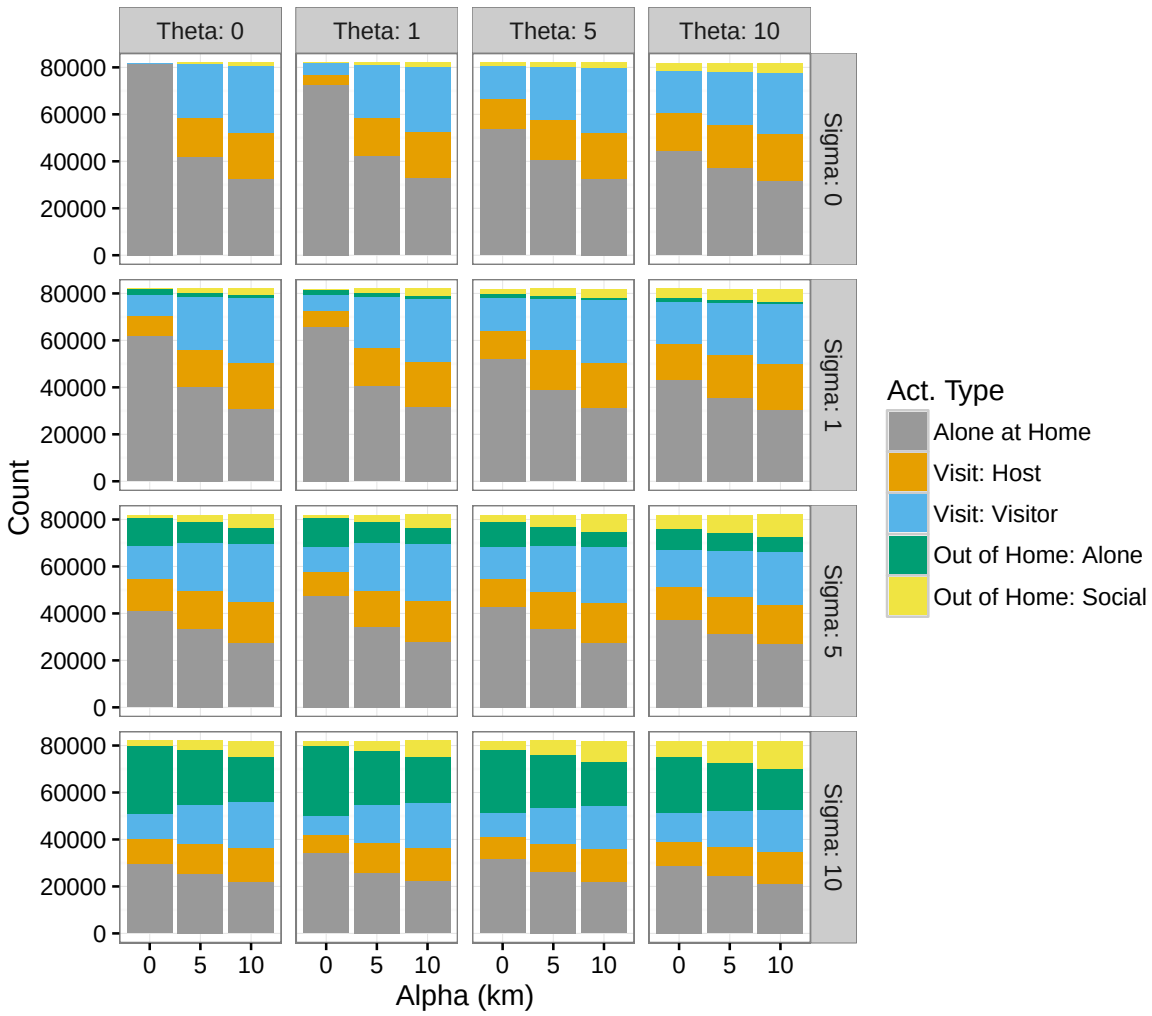

FIGURE 2 Proportion of activity types.

places starts to give a high enough utility for those trips to be undertaken.

Figure 4 represents the traveled distance distribution, for out of home activities, per group size, with the highest willingness to meet social contact ($\alpha = 10$). The parameter values for the two error terms have only moderate influence on the traveled distances of joint activities. The traveled distance distribution for out-of-home activities performed alone, on the opposite, show a strong variation. This probably comes from the fact that the choice for joint activities is much more constrained. In particular, more taste variability will not necessarily push friends to travel further, as this also makes it more difficult to find a agreement.

Figure 5 and Figure 6 shows the same kind of information for visits, for the two extreme values of the desire to meet social contacts α. Hosts (who never have to travel) are removed from the analysis. For high α, distributions are pretty stable under variations of ϑ and σ. Only in the case of relative indifference to social contacts and places ($\alpha = 0$, $\vartheta \leq 1$ and $\sigma \leq 1$) is it possible to see another pattern. A higher value of α does tend to push agents further. This "robustness" of the results vis-à-vis the scale of the error term is an argument in favor of introducing explicit joint activities in the prediction of leisure activities: the social network constrains the range of possibilities so much that it removes the need to "add noise until one fits the data".

Of course, this very constrained behavior is a good thing only if the resulting outcome is

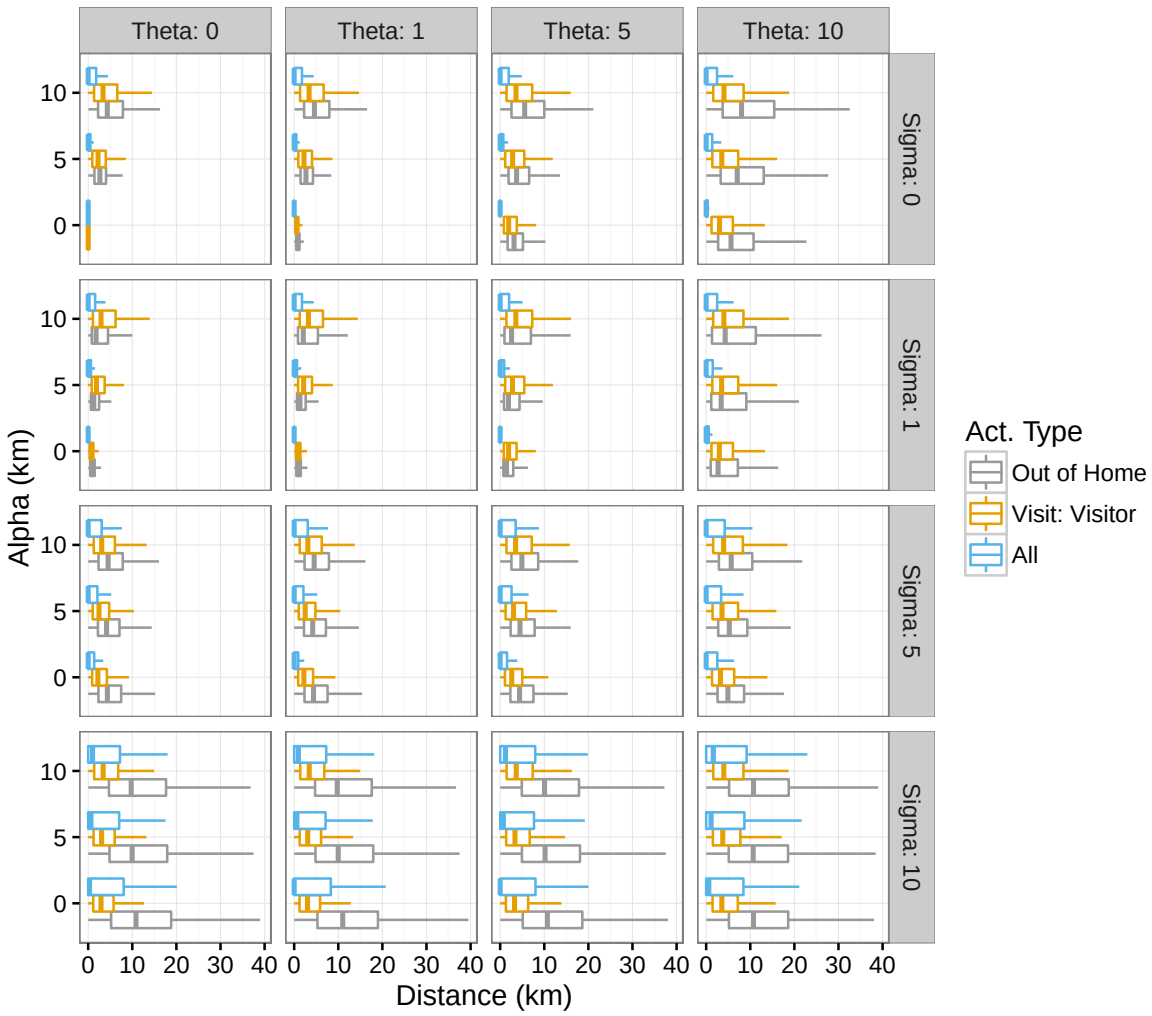

FIGURE 3 Distance distributions, per activity type (no outliers).

realistic. Figure 7 shows a comparison of distance traveled for visit purpose in the national travel survey and the simulation with parameters $\alpha = 10$, $\vartheta = 5$ and $\sigma = 1$. The distributions look satisfyingly similar, in particular given the absence of careful calibration of the three parameters. The simulated distribution is more compact, with both less low and high distances. The lack of shorter trips might simply be an artifact of using a 1% sample, for which too few short ties are present (for details, see the scalability analysis of the generated social networks in Dubernet *(38)*). The lack of longer trips might come from the absence of careful parameter calibration.

Figure 7 shows a comparison of distance traveled for "gastronomy" purpose in the national travel survey, on week-ends, and the same simulation. The purpose "Gastronomy" is taken both because it is the most represented leisure purpose in the survey, and because it is a typical way to socialize with friends. Unfortunately, the national travel survey does not contain information about the number of co-participants, so that it is impossible to filter out solitary activities from the data. Thus, weekdays are filtered out to remove the possible lunch breaks and dinner at the corner restaurant to avoid cooking: week-end trips to the restaurant are much more likely to be real leisure, and undertaken with social contacts. In the simulation, agents meeting friends travel a bit further than the individuals of the travel survey, but the few agents traveling alone due to the low preference variability make the overall distribution pretty close to the actual observed

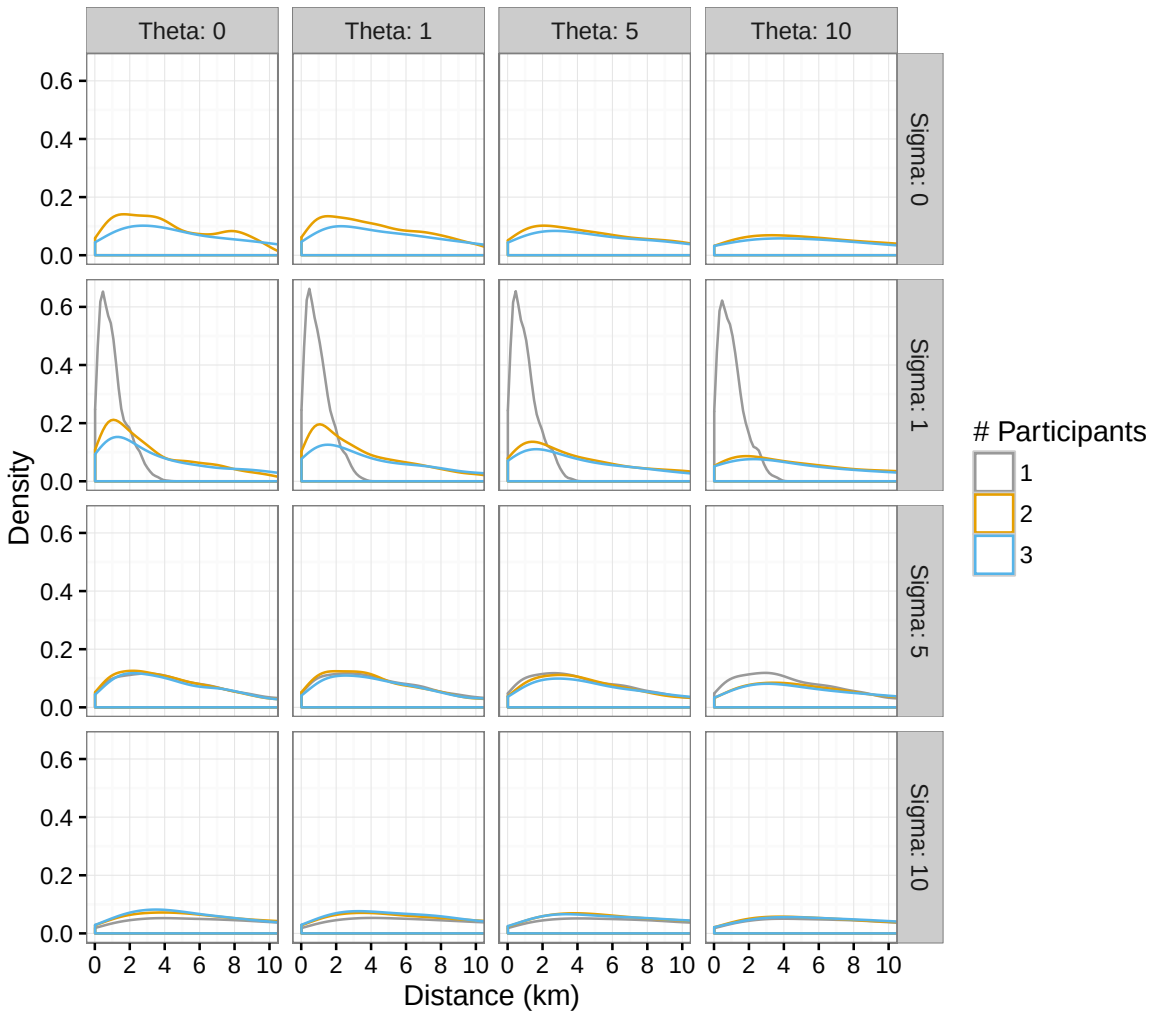

FIGURE 4 Distance distributions, per group size: out-of-home activities, $\alpha = 10$.

distribution.

CONCLUSIONS

The simple joint location choice presented here was performed outside of an iterative equilibration of transport demand and supply, such as MATSim, to remove potential confounding factors, in particular convergence considerations. It is, however, easy to generalize to such a setting, and is actually implemented mostly by combining elements of the generalization of MATSim to social decisions presented in Dubernet *(38)*. The results revealed that the process of jointly choosing a leisure location with friends is much more robust to random error terms than individual location choice. This allows the simulation to reproduce traveled distances quite accurately both for visit purpose, which represent around 20% of leisure travel, and for the "gastronomy" purpose, which is the most frequent type of leisure overall in the national travel survey. The simulated travel distances are much more sensitive to characteristics of the social network than to simulation parameters. This makes it both more behaviorally grounded and easier to calibrate than to adjust a level of noise to fit the data — calibration being a computationally expensive and error-prone process. As distances traveled for joint purpose are relatively stable, calibration should mainly consist in getting the share of social and individual activities right.

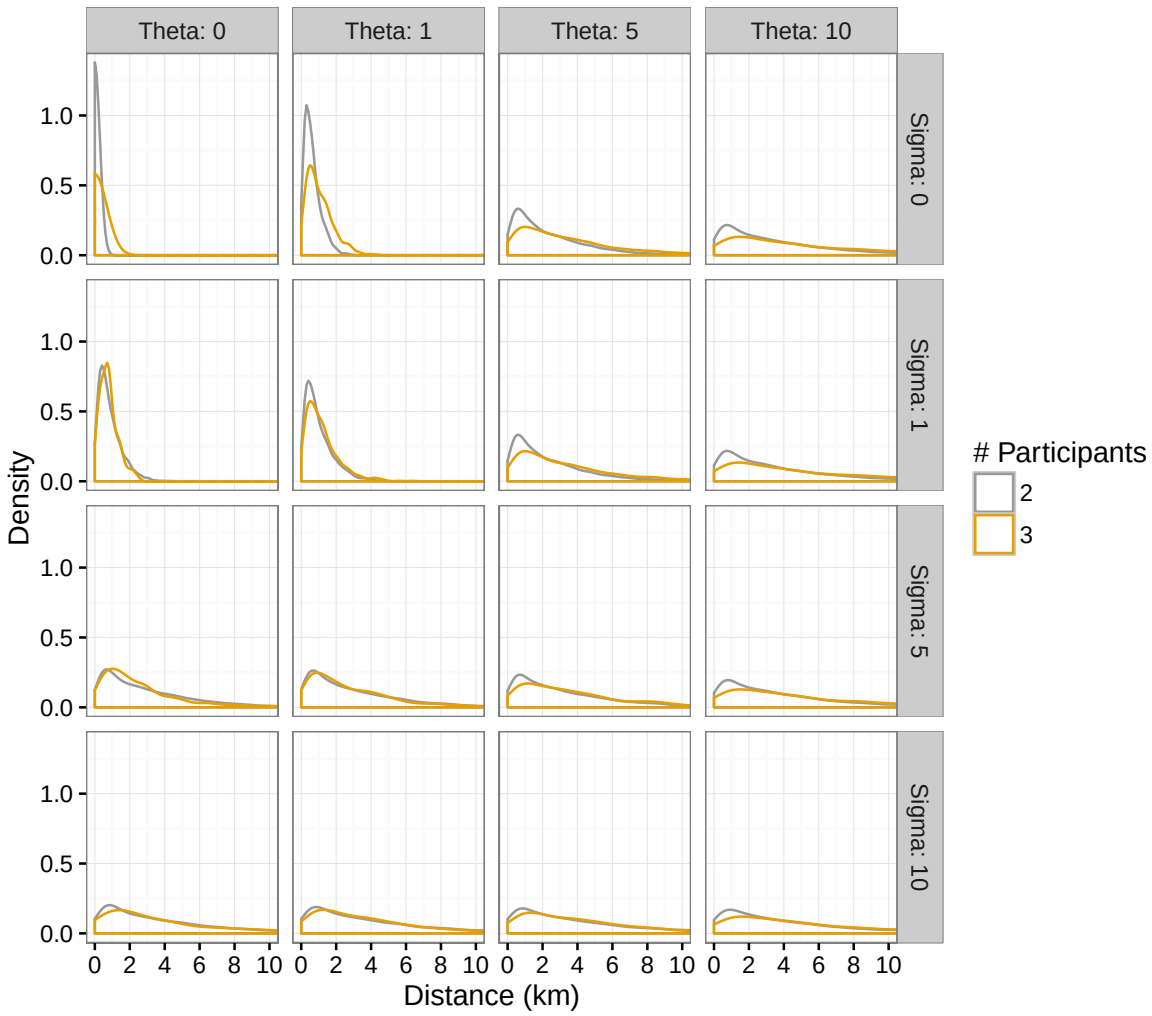

FIGURE 5 Distance distributions, per group size: visit activities, $\alpha = 0$.

The fact that the simulations exhibit very high share of visits compared to out-of-home activities shows that the intuitive "meet in the middle" solution is not the only stable solution, and that additional parameters, such as a cost to receive friends at home, have to be included in the model.

The inclusion in the MATSim loop is the obvious next step. To this end, the appropriate *evolutionary operators* have to be defined. As exemplified by Horni *(55)* for individual location choice, the sheer size of the problem forces to make strong design decisions. Limiting the choice set is a way to simplify the problem, that we already used here, and was also experimented with by Ordóñez Medina *(63)*. The other important aspect is the selection of *who* performs leisure *with whom*. Though the *with whom* can emerge from the process presented here, the *who*, *including correlation with social contacts*, remains open.

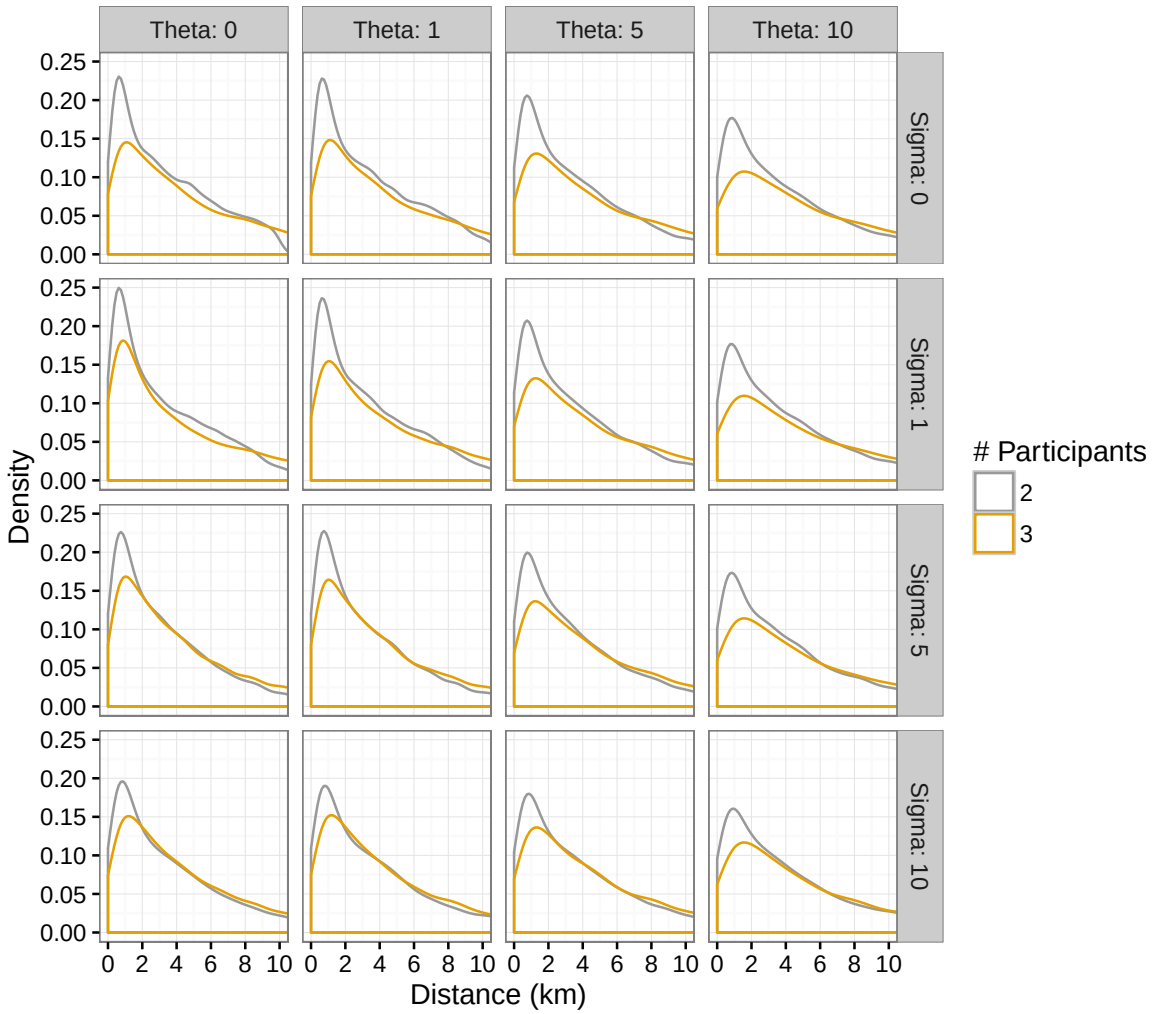

FIGURE 6 Distance distributions, per group size: visit activities, $\alpha = 10$.

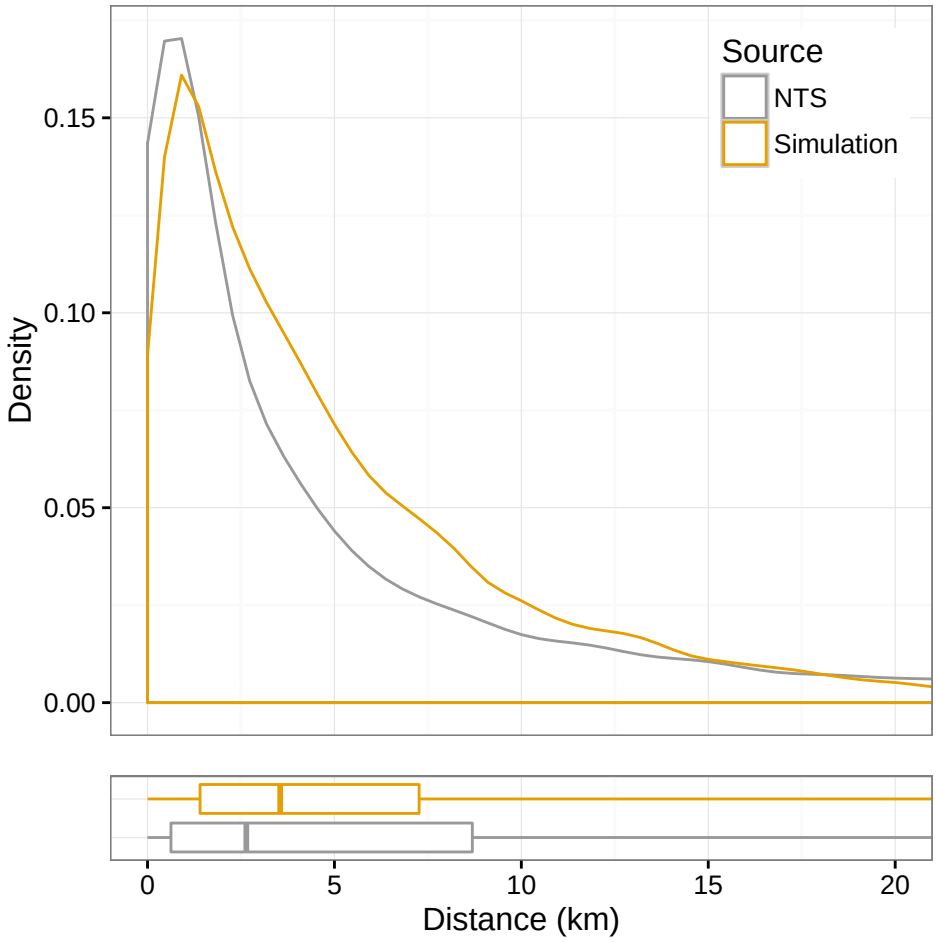

FIGURE 7 Comparison of the traveled distance distribution, for visit purpose, between the national travel survey and the simulation with $\alpha = 10$, $\vartheta = 5$ and $\sigma = 1$.

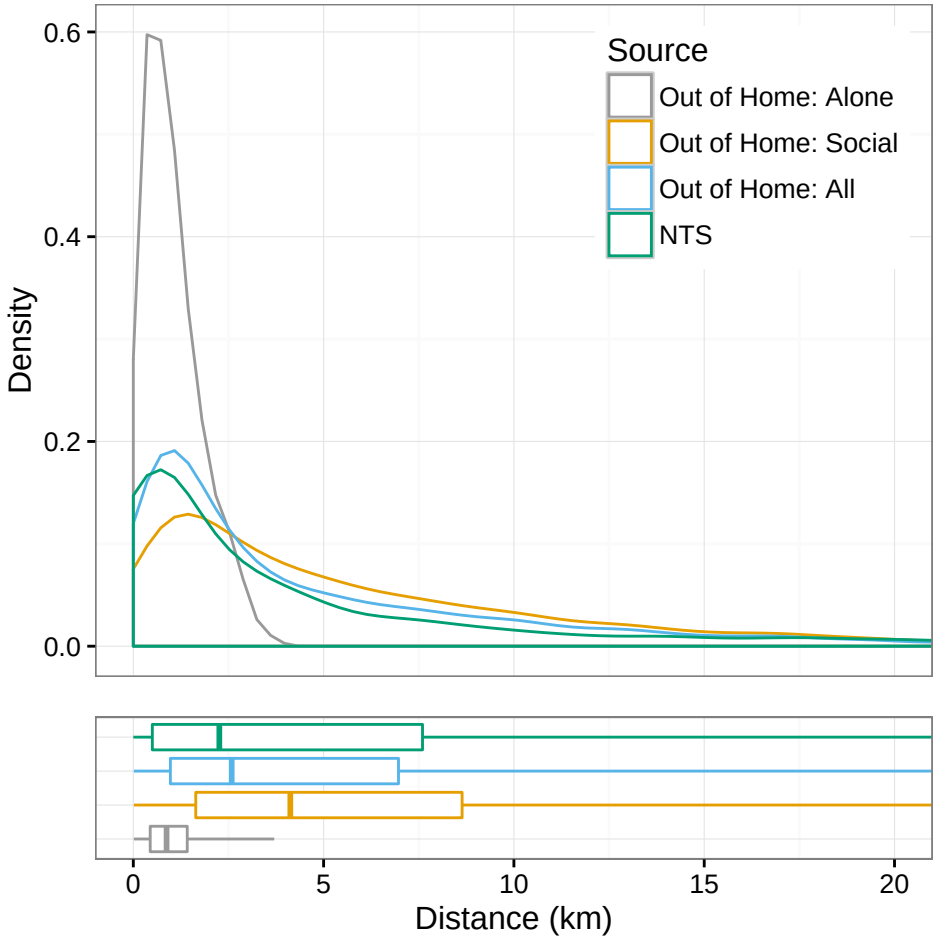

FIGURE 8 Comparison of the traveled distance distribution, for gastronomy purpose, between the national travel survey and the simulation with $\alpha = 10$, $\vartheta = 5$ and $\sigma = 1$.

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