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The social aspect of residential location choice: on the trade-off between proximity to social contacts and commuting

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Abstract

Commuting has been found to be one of the least enjoyable activities. As it is a consequence of the choice of home and work location, the question arises as to how its disutility is compensated. Urban location theory suggests a compensation in the housing or the labor market. While this provides part of the explanation, individuals' personal networks may provide additional insights.

Data from a social network survey were used to investigate proximity to social contacts as a factor in residential location choice.

The results indicated that proximity to social contacts was an important factor and that it was traded off against commute time. The notion that the disutility of commuting is not compensated for may be a consequence of ignoring the effect of personal networks.

The results contribute to the understanding of residential location choice and have implications for urban planning and policies that seek to reduce commuting.

Keywords: Travel behavior, commuting, residential location choice, urban location, social network analysis

1. Introduction

Commuting has been found to be one of the least enjoyable activities in an individual's day, ranking below working and housework (Humphreys et al., 2013; Kahneman et al., 2004). This raises the question as to how commuting is compensated for. Stutzer and Frey (2008) use classical economic theory to conclude that a longer commute time and the associated additional psychological burden should either be compensated for by a more rewarding job (intrinsically or financially) or by additional welfare from a more attractive living situation (price, size, comfort etc.). Previous research provides a strong relationship between housing prices and distance to job opportunities and longer commutes are associated with higher wages (Ommeren et al., 2000). However, in terms of reported subjective well-being (SWB), Stutzer and Frey (2008) find that individuals with longer commute times are systematically worse off. Because SWB is used as a proxy for individual utility, the authors argue that this contradicts rational behavior, presenting a "commuting paradox". The notion of a commuting paradox is problematic in two ways. First, SWB may not accurately reflect utility in general, as individuals might choose to accept a suboptimal situation because it increases the prospect for a better situation in the future. Second, factors beyond the housing or the labor market may compensate for the commute. Nevertheless, the question raised by Stutzer and Frey (2008) is interesting, because it is not clear how the burden and disutility of commuting is compensated for.

Commuting is a consequence of the combined choice of home and work location. Thus, individuals trade-off between commute time and distance, the characteristics of home and work location and opportunities that arise by combining the commute with other activities (such as shopping on the way home). The effect of individual characteristics on location choice and the trade-offs can be investigated with discrete choice modelling (DCM). With the increasing availability of spatial data, a number of studies have used DCM for location choice modelling. Schirmer et al. (2014) conduct a review of these studies and find that a wide variety of variables are used in the literature. As a result, a common classification is proposed. Depending on the unit of analysis (zones or buildings), the studies include various groups of characteristics (such as the residential unit, the built environment, access and accessibility, etc.). Only a very limited number of studies consider the previous home location and personal networks. This is not surprising as data on individuals' personal networks is not readily available from national or regional statistics. As data collection is expensive, data availability most often determined the choice of the variables that were included in previous studies. This is problematic, because recent studies such as Stokenberga (2017) and Belart (2011) show that social networks are an important factor in residential location choice. If social network effects are indeed important, previous studies may not only suffer from ignoring an important factor, but may also be subject to an omitted variable bias that could lead to incorrect conclusions regarding the included variables.

In this paper, the distance to individuals' contacts as a factor in residential location choice was investigated. Proximity to social contacts is an important factor as it increases accessibility to the resources provided by social contacts (which is a part of social capital) and thus provides utility. Whether there is a trade-off between commute time and proximity to an individual's contacts was also investigated. It was proposed that individuals compensate for the disutility of commuting with the utility of the opportunities that arise by living closer to social contacts.

2. Background

2.1. The disutility of commuting and its effects

The notion that commuting is a burden and, therefore, constitutes a disutility, is a common assumption in transportation planning and research. Redmond and Mokhtarian (2001) challenge this assumption and suggest that commuting is not solely a source of disutility, but also provides benefits for some people as it can support the transition between home and work. The authors argue that there is an optimal commute time, but still find that most people perceive their commute as too long. Martin et al. (2014) propose that active commuting (i.e. walking and cycling) is associated with higher wellbeing and a reduced likelihood for certain psychological symptoms. But for drivers, the authors still observe a clear disutility.

Regarding the effect of commuting on individuals, Stutzer and Frey (2008) report that there is a negative correlation between commuting and SWB. The authors regard SWB as a proxy for individual utility and find that individuals with a longer commute systematically report lower SWB. Therefore, the authors assert that commuting is irrational from a perspective of individual utility maximization, which leads to the conclusion of a "commuting paradox". This seems too strong of a conclusion given the limited available data. Furthermore, the finding has not been confirmed by other studies.

Lorenz (2018) find no negative correlation between commuting and general satisfaction with life, though commuting is related to lower satisfaction for specific aspects, including satisfaction with family and leisure time. Morris et al. (2018) report no association between commute time and life satisfaction. Roberts et al. (2011) report commuting having a negative effect on psychological health (but only for women). The authors hypothesize that the greater sensitivity for women is due to higher commitments for household tasks, such as cleaning and child-care. Dickerson et al. (2014) find no evidence of the negative impacts of commuting and explain their findings with cultural differences between Germany and the UK and the choice of the well-being measure.

2.2. Modelling residential location choice

The origins of location theory can be traced back to the work of von Thünen (1826) who sought to determine the most profitable use for a property. Von Thünen developed the first model to explain land-use patterns relative to a central market location, using the bid-rent curve, which takes into account transportation costs. Alonso (1964), Muth (1969) and Mills (1967) developed more refined models, known collectively as the Alonso-Muth-Mills (AMM) model. The AMM model explains household location choice in a monocentric city with a central business district and a fixed population. The basic assumption is that households spend income on housing, a composite consumption good and transportation. Household location is determined by maximizing individual utility. After McFadden (1977) introduced DCM to residential location choice modelling, a number of studies using the approach followed. A clear advantage of DCM over previous modelling approaches was that various characteristics of the location, the household, and the individual could be taken into account and the trade-offs between the different characteristics could be investigated. Schirmer et al. (2014) review the existing literature and note that a wide variety of variables are used in residential location choice modelling. The variables are grouped into the following categories: a) residential unit, b) the built environment, c) the socio-economic environment, d) points of interest, e) access and accessibility, and f) previous location and social networks. The literature review reveals that only a limited number of studies take into account distance to social contacts.

2.3. Personal networks and residential location choice

A number of studies have shown that social networks play an important role in international migration flows and social network analysis (SNA) is a central component of migration analysis (Boyd, 1989). Thus, it is reasonable to assume that personal networks are also a factor in residential location choice in a more regional context (i.e. within countries or states). SNA has been used in transportation research after Axhausen (2007) proposed a number of hypotheses on the relationship between activity spaces and social networks. Mobility patterns are highly depended on the locations of home, work and activities (Schönfelder and Axhausen, 2004).

Ettema et al. (2011) discuss the effect of social influences on residential location, mobility and activity choice. The study focused on including social network effects in land-use-transportation interaction models. Social networks provide information about choices and potentially influence long-term decisions, such as the choice of home or work location. Belart (2011) used a multinomial logit model to investigate residential location choice in the greater Zurich area. Among other variables, the model included distance to work location and the average distance to participants' personal network members. Distance to personal network members was calculated as a weighted average distance with contact frequencies as weights. Personal networks significantly influence residential location choice, more so than distance to work (Belart, 2011).

Vyvere et al. (1998) included a "distance to friends and relatives" categorical variable in a DCM. The values of the variable that characterized the distance were "not nearby," "close" and "very close." The results of the final model show that study participants preferred to live close, but not too close to friends and relatives. A possible explanation for the reversal of the utility could be that potential social control exerted by these close contacts was perceived as negative. Another explanation might be the categorical nature of the variable and that the value "very close" was perceived to have a negative connotation. The significance of the variable, however, shows that distance to social contacts should be included in residential location choice models. To avoid differing interpretation by study participants, it may be better to include the actual measured distance.

In a more recent study, Stokenberga (2017) investigate the role of family networks on residential location choice. The author conducted a stated choice experiment with time to the nearest extended family member as a variable. This variable is connected to specific types of assistance the participant receive from family network members, such as childcare assistance and help in crises. The study shows that individuals exhibit a strong preference to live close to extended family and even prioritize it above accessibility to the central business district. The preference is stronger for individuals who received help from family, specifically help with childcare, which also underlines the connection to individual social capital.

To sum up, the limited number of studies reveals an apparent research gap on the effect of personal networks on household location choice. Given that that the effect of personal networks is potentially strong, future analyses on the effects of personal networks on residential location choice may improve understanding. In addition, knowledge about the trade-offs between proximity to personal network members and other factors that influence household location choice is scarce. In this paper, distance to personal network members was used as a factor in a residential location choice model. The following hypothesis was tested: a shorter overall distance to an individuals' contacts increases the choice probability of a municipality as residential location. The magnitude of the effect was compared with commute time to determine the relative importance of proximity to social contacts.

3. Methods

3.1. Data source

The main data source for the analysis was a mobility and social network survey that was conducted in June 2017 in Zurich, Switzerland (Guidon et al., 2018). The survey consisted of two parts: a mobility survey and an egocentric social network survey. The second part included coordinates of the home locations of participants' contacts and thus allowed for a calculation of distance to personal network members. The survey data was enriched with data on the municipalities of Zurich from the cantonal office of statistics (Statistisches Amt Kanton Zürich, 2017). Figure 1 shows a correlation plot of the variables from the municipality data that were considered for the residential location choice model. The variable "share of woods and agriculture" was not included in the final models because of its high negative correlation with population density. The number of full time equivalents ("FTA Number") was also not considered in the models because it is nearly perfectly related to the population count. Commute times between the municipalities were determined with the Google Maps API[1] (with municipality polygon centroids as origins/destinations). Individuals were included in the analysis if living and working in the canton of Zurich and if moved to Zurich after 2006 (in order to exclude participants that have not moved). The original data set included 1387 participants that completed the social network study and with the restrictions mentioned above, 583 individuals remained. Of these 583 participants, 323 could be used in the analysis (because not all participants provided complete information about the full list of social contacts). The choice set for each individual was composed of the 168 municipalities of the canton. The full choice set would also have included municipalities of neighboring cantons, but in this analysis, only the canton of Zurich was considered due to data availability.

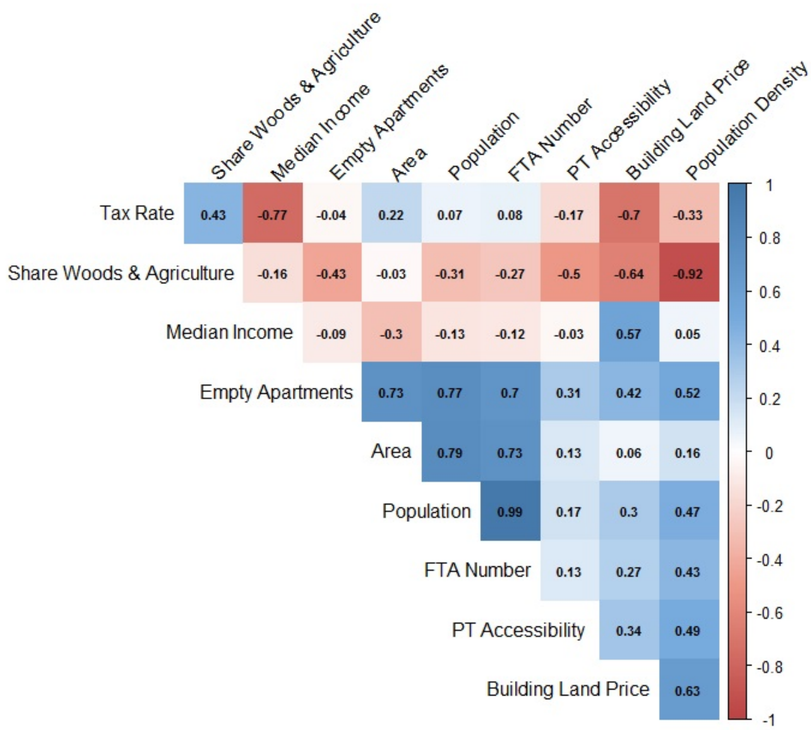

Figure 1: Correlations between variables from the cantonal municipality data.

[1]Information about the Google API: `https://developers.google.com/maps/documentation/directions`, last accessed: July 2018.

3.2. The multinomial logit model

In order to explain residential location choice in terms of the characteristics of the alternatives, the "conditional logit model" introduced by McFadden (1973) was used[2].

The modelling approach can be described as follows. U_{nj} represents the utility of alternative j for decision maker n. U_{nj} is composed of a deterministic part V_{nj} and a random error term ϵ_{nj}. U_{nj} is thus a random variable itself: $U_{nj} = V_{nj} + \epsilon_{nj}$. It was assumed that an individual will seek to maximize utility. Individuals choose an alternative i if it provides more utility than any other alternative j and thus $U_{ni} > U_{nj}, \forall\ j \neq i$. After expanding and rearranging: $V_{ni} - V_{nj} > \epsilon_{nj} - \epsilon_{ni}, \forall\ j \neq i$. The probability that decision maker n chooses alternative i is: $P_{ni} = Prob\{\epsilon_{nj} < \epsilon_{ni} + (V_{ni} - V_{nj})\}, \forall\ j \neq i$. This probability can be calculated by solving the integral $P_{ni} = \int f(\epsilon)d(\epsilon)$. Assuming independent and identically distributed (IID) error terms and a Gumbel distribution for ϵ, this integral can be solved analytically and it can be shown that $P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$.

As described by Croissant (2003), the deterministic part of the utility, V_{nj}, can include: a) an alternative specific constant α_j, b) alternative specific variables x_{ij} with a generic coefficient β, c) individual specific variables z_n with alternative specific coefficients γ_j, and d) alternative specific variables w_{ij} with alternative specific coefficients δ_j. The deterministic part can thus be written as: $V_{ij} = \alpha_j + \beta x_{ij} + \gamma_j z_n + \delta_j w_{ij}$.

In this analysis, only alternative specific variables were used with generic coefficients because there was no reason to assume that the effect of the included variables depended on the specific municipality. Individual characteristics (such as *age* and *income*) were introduced as interaction terms with variables on the characteristics of the alternatives. All models were estimated with the mlogit package for R (Croissant, 2003).

3.3. Distance to social network members

The distance of an individual n to personal network members m, D_n, was measured as the sum of the logarithms of the great circle distances

[2]As pointed out by Croissant (2003) the terminology may be misleading: in statistical literature the term "conditional logit model" is also used to describe a logit model for longitudinal data. The "conditional logit model" by McFadden is often simply refered to as "multinomial logit model" irrespective of the fact that characteristics of the alternative and not the individual are used.

between the individual and the contacts: $D_n = \sum_m log(d_{nm})$. The logarithm diminishes the effect of contacts that live far away, which are assumed to have a minor influence on location choice. Contacts that live in the same household were excluded from the analysis to avoid perfect predictions, due to cohabitation. Because residential location choice was the variable of interest, only contacts that the study participants knew prior to moving to the new location were considered in the final analysis. The mean number of contacts the included study participants provided was 14.8. 8.1 contacts remained after excluding contacts in the same household and contacts with incomplete information (i.e. the spatial information and information about the year of getting acquainted). An average of 6.9 contacts were known to the participant prior to moving to the new location and were used in the modelling process. Figure 2 shows the distribution of the distances D. The median distance in the original sample was 58.4 log(m) with a mean of 70.7 log(m) and a standard deviation of 58.9 log(m).

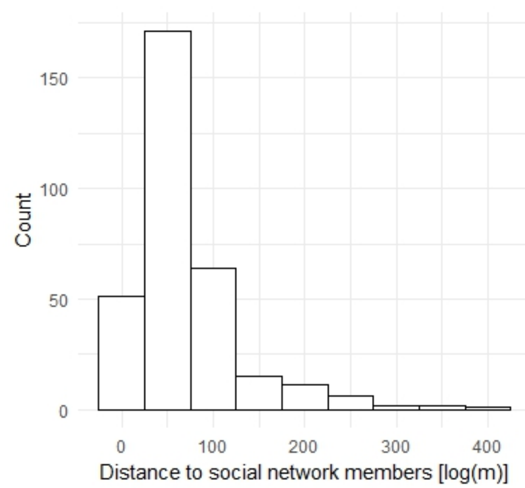

Figure 2: Distribution of distances to social network members.

3.4. Residential location choice: model specification

Table 1 provides an overview of the variables that were included in the residential location choice models and Table 2 provides an overview of the ranges of the variables. The distribution of commute times by car and public transportation is shown in Figure 3. For each individual, commute times for all 168 municipalities in the canton were determined using the Google Directions API.

Table 1: Description of variables and data source. The data sources are the Google Directions API, the social network survey conduced by Wicki et al. (2018), and open data from the cantonal office of statistics (Statistisches Amt Kanton Zürich, 2017).

Variable	Description	Data Source
commTc	Commute time car [h]	Social network survey/ Google API
commTpt	Commute time public transportation [h]	Social network survey/ Google API
distAlt	Distance to social contacts [log(m)]	Social network survey/ Google API
popDens	Population Density [pop/ha]	Cantonal statistics
landPr	Building land price [kCHF/m_2]	Cantonal statistics
ptAcc	Transit accessibility (bus or tram stop within 400 m or urban train stop within 750 m) [%]	Cantonal statistics
emAp	Number of empty apartments and houses [Num.]	Cantonal statistics
taxRate	Municipal tax rate [%]	Cantonal statistics
incM	Median income community [kCHF]	Cantonal statistics
accPc	Access to private car [0,1]	Social network survey
noAccPc	$1 - accPc$ [0,1]	Social network survey
inc	Household income [kCHF]	Social network survey
age	Age [years]	Social network survey

Table 2: Summary of variables used in residential location choice model (all alternatives). *commTc*, *commTpt* and *distAlt* vary across individuals and alternatives, the variables *popDens*,..,*taxRate* vary across alternatives, and *accPc*,...,*age* vary across individuals.

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
commTc	0.00	0.42	0.54	0.54	0.66	1.17
commTpt	0.00	0.83	1.08	1.12	1.36	2.87
distAlt	6.32	31.91	58.21	71.32	87.61	394.00
popDens	0.55	2.09	5.10	7.59	9.84	43.20
landPr	0.25	0.57	0.79	0.82	0.97	2.10
ptAcc	0.00	0.00	16.30	26.65	50.95	80.40
emAp	0.00	5.00	16.00	32.85	32.25	483.00
taxRate	75.00	97.75	108.40	106.20	116.00	124.00
accPc			82% of participants			
inc	1000	7000	11000	10870	15000	16000
age	20.00	32.00	39.00	41.26	50.00	67.00

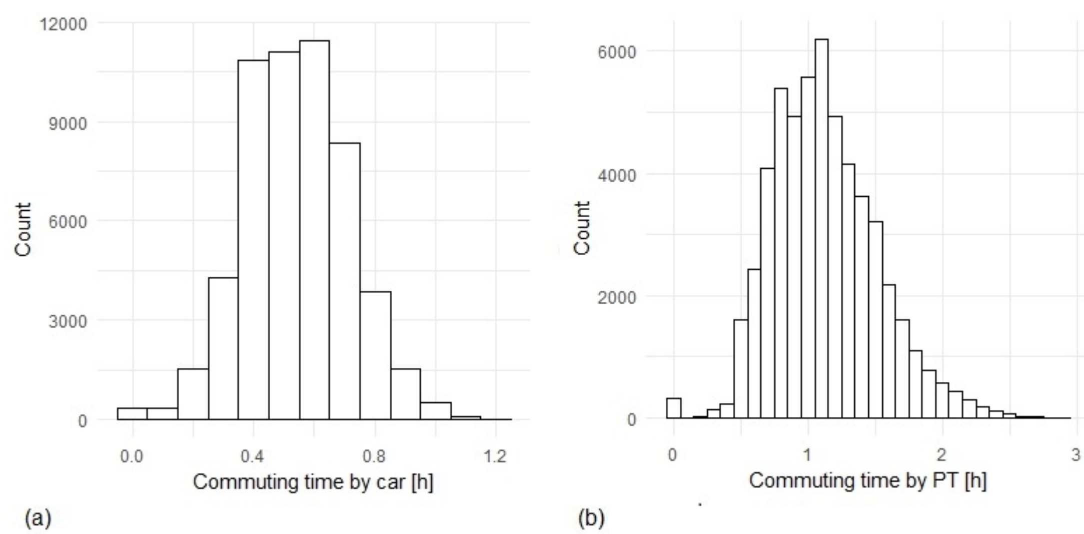

Figure 3: Distribution of commute times by (a) car and (b) public transportation (PT) for all alternatives of all individuals.

Three residential location choice models were estimated: models 1-3. Model 1 included commute time, population density (*popDens*), building land price (*landPr*), public transportation accessibility (*ptAcc*), the number of empty apartments (*emAp*) and the municipal tax rate (*taxRate*). The distance to social network members (*distAlt*) was considered in model 2. Model 3 included additional interaction terms. The interactions between commute time and distance to social contacts were added, as people have limited time budgets. Long commutes could, therefore, have a more negative effect on residential location choice if social contact members also live further away and more time is needed to visit. The interaction between population density and age reflects the observation that young people tend to prefer urban areas. The interaction between land prices and income should reflect that the effect of land prices depends on income. The systematic portion of the utility functions were as follows:

Model 1
$V_1 = \beta_{commTc} \cdot commTc \cdot accPc + \beta_{commTpt} \cdot commTpt \cdot noAccPc + \beta_{popDens} \cdot popDens + \beta_{landPr} \cdot landPr + \beta_{ptAcc} \cdot ptAcc + \beta_{emAp} \cdot emAp + \beta_{taxRate} \cdot taxRate$

Model 2
$V_2 = \beta_{commTc} \cdot commTc \cdot accPc + \beta_{commTpt} \cdot commTpt \cdot noAccPc + \beta_{popDens} \cdot popDens + \beta_{landPr} \cdot landPr + \beta_{ptAcc} \cdot ptAcc + \beta_{emAp} \cdot emAp + \beta_{taxRate} \cdot taxRate + \beta_{distAlt} \cdot distAlt$

Model 3
$V_3 = \beta_{commTc} \cdot commTc \cdot accPc + \beta_{commTpt} \cdot commTpt \cdot noAccPc + \beta_{popDens} \cdot popDens + \beta_{landPr} \cdot landPr + \beta_{ptAcc} \cdot ptAcc + \beta_{emAp} \cdot emAp + \beta_{taxRate} \cdot taxRate + \beta_{distAlt} \cdot distAlt + \beta_{commTc,distAlt} \cdot commTc \cdot distAlt + \beta_{commTpt,distAlt} \cdot commTpt \cdot distAlt + \beta_{popDens,age} \cdot popDens \cdot age + \beta_{landPr,inc} \cdot landPr \cdot inc$

4. Results

The results of the model estimations are shown in Table 3. The effects of commute time and distance to social network members (*distAlt*) were significant and negative in all models. When comparing model 2 and 1, it can be observed that including *distAlt* significantly increased the explanatory power of the model and the effect of commute time decreased. This could be due to an overestimation of the effect of commute time in model 1, which could be the result of an omitted variable bias. The number of empty apartments had a significant and positive effect on the choice probability. Including the interaction terms in model 3 further increased the explanatory power of the model. The interaction of population density with age was significant and weakly positive and the interactions between commute times and distance to social network members were not significant. The effects of the municipal tax rate and public transportation accessibility were also weak and insignificant.

The signs of the coefficients were as expected, except for the non-significant parameter *taxRate*, which was expected to be negative. Though insignificant, the interaction between commute time by train and distance to social network members was positive, which was also not expected, due to the limited time budget of individuals.

To compare the magnitudes of *distAlt* and commute time, the coefficient of *distAlt* can be divided by the coefficient of commute time to obtain the marginal rate of substitution. Using the results from model 3 for car users: $\frac{\hat{\beta}_{distAlt}}{\hat{\beta}_{commTc}} = \frac{-0.313}{-3.78} = 0.083 \; [\frac{h}{log(m)}]$. This implies that the effect of the median $altDist$ of 58.4 $log(m)$ is equal to the effect of a commute time of $0.08 \cdot 58.4 = 4.9\ h$. For individuals that rely on public transportation, the marginal rate of substitution was $0.077 \; [\frac{h}{log(m)}]$ (which is equal to a commute time of 4.5 h at the median distance to social contacts).

Table 3: Model estimates for the multinomial logit model of residential location choice.

	Model 1 Coef./(SE)	Model 2 Coef./(SE)	Model 3 Coef./(SE)
commTc · accPc	-4.58^{***}	-4.24^{***}	-3.78^{***}
	(0.36)	(0.37)	(0.51)
commTpt · noAccPc	-3.74^{***}	-3.53^{***}	-4.05^{***}
	(0.32)	(0.33)	(0.65)
popDens	0.00	-0.01	0.08^{***}
	(0.01)	(0.01)	(0.02)
landPr	-0.34	-0.39	-0.97^{*}
	(0.32)	(0.33)	(0.51)
ptAcc	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
emAp	0.01^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)
taxRate	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
distAlt	-	-0.31^{***}	-0.31^{***}
	-	(0.04)	(0.04)
commTc · accPc · distAlt	-	-	-0.01
			(0.01)
commTpt · noAccPc · distAlt	-	-	0.01
			(0.01)
popDens · age	-	-	0.00^{***}
	-	-	(0.00)
landPr · inc	-	-	0.00
	-	-	(0.00)
LR test (p-value, previous model)	-	$2.16 \cdot 10^{-9}$	$2.65 \cdot 10^{-5}$
Participants	323	323	323
LL null model	-1655	-1655	-1655
LL model	-1344	-1305	-1290
McFadden R2	0.19	0.21	0.22
AIC	2702	2625	2601

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5. Discussion

The residential location choice models showed that distance to personal network members was an important factor. Omitting the variable led to an overestimation of the effects of commute time.

The models provided no indication that the negative effect of commuting is higher for higher distances to personal network members. This was assumed to be due to the limited time budget for activities in individuals' days. However, the contact frequency and duration was not taken into account in this study. To test the hypothesis, future research could also consider contact frequency, contact duration and meeting locations. In this way, trade-offs within individuals' time budgets could be identified and an interaction between time for social activities and commuting may become apparent.

Regarding the marginal substitution rate of commute time with distance to personal network members, 4.9 h and 4.5 h were obtained at the median distance. These values were rather high for commute time, but show that distance to personal network members was weighted significantly higher than commute time. However, it might also reveal the limitations of the chosen model specifications. When individuals choose a home location, only options that do not exceed an acceptable maximum commute time are likely considered. In addition, the mean travel time by car between all municipalities of the canton of Zurich is approximately 40 min with a standard deviation of 16 min. This could, for most individuals, be below the threshold where commute time becomes an important factor for residential location choice.

Other household members most likely have a significant influence on household location choice and this could be taken into account if the data is available. In this analysis, it was assumed that the workplace location was fixed. It is more likely that individuals make a combined choice of home and work location, which is hierarchical (Lee and Waddell, 2010). Depending on the individual, either the home or the workplace location may be first selected. The other location is then chosen depending on the first choice. In addition, previous research has shown that distance to personal network members was correlated with distance to previous residential location (Schirmer et al., 2014). However, in this analysis, the previous home location was unknown and the effects could not be separated. The strong effect of distance to social contacts observed could only partly be a result of the contacts themselves and the resources provided in terms of access to individual social capital. Thus, future research could also consider place attachment and the propensity to choose residential locations that are close to the previous residential location.

6. Conclusion

Residential location choice models were estimated that considered distance to individuals' personal network members. Proximity to personal network members was an important factor in residential location choice and omitting the variable can lead to an overestimation of the effect of commute time. Only a very limited number of previous studies have taken proximity to participants' social contacts into account. This might be due to the fact that data on personal network members (including home location) is not usually collected as part of standard regional or national statistics. Nevertheless, such data is important for a better understanding of residential location choice on the individual level and has potential implications for urban planning and development. For instance, social network effects may effect the success of housing developments that are intended for a specific social group. If social network effects play a decisive role, individuals of these groups might not be willing to relocate (Stokenberga, 2017). In addition, there could also be implications for policies that seek to reduce commuting by providing housing closer to employment centers. The success of such policies could be overestimated if personal network effects are ignored.

To overcome the limitations of this analysis, future research and data collection efforts should consider all household members. In addition, data on the previous home location should be collected and included in the analysis to separate the effect of the previous home location from the proximity to personal network members. In addition, future studies should also include measures of place attachment. The unit of analysis could be changed from municipalities to individual buildings to be able to consider detailed characteristics of the house or apartment. Furthermore, in this analysis, a multinomial logit model was used to investigate the effect of proximity of personal network members. Future studies could make use of more refined hierarchical models to also account for individuals who have not moved. In addition, detailed data on workplaces and individuals' qualifications could be collected with the goal of estimating a combined home and work location choice model.

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