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Residential Location and Daily Travel Distances: The Influence of Trip Purpose

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Abstract

This paper investigates the extent to which residential location influences daily distance travelled if travel purposes are differentiated. Statistical multilevel models are applied to Swedish National Travel Survey data from 2005–2006. Travel purposes are categorized by considering time–spatial constraints and hypothesized factors of personal freedom of choice. Results indicate that the influence of residential location on daily distance travelled is highly conditional on trip purpose in a nationwide Swedish context. Although statistically significant proportions of the variation in daily distance travelled to work, on service errands, and on weekdays were dependent on residential location, daily travel distances for leisure activities and on weekends varied greatly among people living in the same neighbourhood. From a policy perspective, these results suggest that measures intended to alter the built environment to reduce the volume of travel will be most efficient as regards work trips, while trips taken during free time are unlikely to be much affected. In addition, the multilevel models applied reveal several important interactions between the variation in travel distances across residential locations and individual characteristics of which researchers should be aware, especially when examining service trips.

1. Introduction

Studies in the academic field of travel behaviour often consider the extent to which spatial circumstances relative to individual characteristics explain daily travel demand. Some scholars emphasize spatial patterns, the friction of distance, and proximity to various amenities as important determinants of travel choices (see, e.g., Ewing and Cervero, 2010; Newman and Kenworthy, 1999). Others find that individual attributes and activities have a decisive effect on spatial behaviour in today’s society (e.g., Kitamura et al., 1997; Weber and Kwan, 2003). It is often argued that contradictory empirical results are caused by variations in geographical settings or research designs, or by differences in the dimensions of travelling behaviour being considered (Van Acker and Witlox, 2011). Although such factors may be significant, there is still a lack of knowledge of how and why study results vary (Boarnet and Crane, 2001; Pontes de Aquino and Timmermans, 2010). Still, both policymakers (CEC, 2001; CNU, 1998) and scholars (Ewing and Cervero, 2010; Newman and Kenworthy, 1999) often express a strong belief that travel behaviour can generally be influenced by adjusting the built environment through urban planning and design. This paper contributes to these discussions by investigating whether residential location has a greater influence on some travel purposes than others in a nationwide Swedish context using a unique combination of micro-level datasets. In this study, trip purpose was elaborated from a time–space–fixity perspective.

According to the human activity approach (Fox, 1995; Jones, 1983), travel behaviour is a strategy by which individuals fulfil their needs and wishes by performing activities at various locations. Different activities are characterised by different degrees of choice and spatiotemporal constraints, depending on what needs the activity is intended to fulfil (Hägerstrand, 1970; Ås, 1978). A plausible hypothesis is that the relative importance of spatial circumstances and individual choice to travelling behaviour is conditional on the type of activity being performed. For example, a common way of categorizing activities is by differentiating between mandatory and discretionary activities. Trips carried out to perform discretionary activities can reasonably be expected to have a more flexible relationship with space and location than do more compulsory activities, such as work or grocery shopping. Individuals can generally choose more freely where and when to perform discretionary activities based on their own preferences, while wage labour generally must be performed at particular workplaces. Though such hypotheses were proposed decades ago (Hägerstrand, 1970; Jones, 1983), there are still surprisingly few direct and thorough empirical explorations of the associations between the spatial-fixity levels of various activities and travel (Schwanen et al., 2008) and no studies of which the author is aware that examine the extent to which residential location influences travel behaviour if trip purposes are differentiated in a nationwide Swedish context.

The aim of this paper is to examine whether residential location relative to individual attributes affects daily distance travelled when individuals travel for different purposes. To explore these matters, statistical multilevel models are applied combining geo-coded micro-level data from two sources: data from the Swedish National Travel Survey (RES) conducted in 2005–2006, which capture individual travel behaviour, and Swedish register data for the Swedish population, which capture geographical contexts. Separate models are fitted to examine the extent to which everyday travel distances to various activities vary among individuals who share residential locations.

This paper addresses previous research suggestions concerning the need to apply more complex models to advance the exploration of individual and spatial effects on travelling (Mercado and Páez, 2009; Shuttleworth and Gould, 2010; Snellen et al., 2002). Previous studies often ignore the hierarchical nature and spatial clustering of travel data, and problems of cross-level inference could occur if individuals and neighbourhoods are treated at the same data level. This study takes account of possible biases by using multilevel modelling and hierarchical data structures, allowing the effects of variables to be explored at different data levels (Goldstein, 2011). Another contribution concerns the fact that the processes underlying spatial behaviour and organization have developed rapidly (Kwan and Weber, 2003; Miller, 2007), so it is reasonable to believe that the relationships between everyday travel, individual characteristics, and locational premises have changed in recent decades (Elldér, 2013; Susilo and Maat, 2007). This fact calls for empirical reconsideration of currently accepted associations between the spatial-fixity levels of activities and travel, and the extent to which the influence of location on daily travel distances is conditional on trip purpose. Most previous studies have been limited to single metropolitan areas, mainly in the USA or the Netherlands. Sweden provides a new and interesting case, when unique nationwide micro-level data with high spatial resolution are accessed to analyse the relative importance to travelling behaviour of spatial circumstances versus individual choice.

Section 2 reviews research related to the aim of the paper, after which section 3 presents the data, methods, and variable definitions. Results and analyses are discussed in section 4, while section 5 reviews the main findings and presents the conclusions.

2. Literature review

2.1. Diverse time–spatial constraints when travelling to perform various activities

All human activities have temporal and spatial attributes that impose various constraints on the individual's ability to perform them (Hägerstrand, 1970). Space–time constraints that influence travelling to activities have been the subject of several empirical studies (see, e.g., Cullen and Godson, 1975; Doherty, 2006; Næss, 2006, 2013; Schwanen and Dijst, 2003; Schwanen et al., 2008; Vilhelmson, 1999), suggesting that the level of spatial-fixity varies significantly among everyday activities. The fact that some activities are more time and space bound than others could be elaborated on with reference to Ås's (1978) categorization of time use. Ås differentiates activities based on their hypothesized degree of association with personal freedom of choice and time constraints, dividing them into four time-use categories: 1. necessary, 2. contracted, 3. committed, and 4. free.

Necessary time is required to fulfil basic physical needs (e.g., sleeping and eating) and is characterized by very little flexibility. Most necessary time is fixed in the home, making it the place that most shapes daily activity patterns and constitutes the main "pocket of local order" (Ellegård and Vilhelmson, 2004). *Contracted time* refers mainly to wage labour. Activities allocated to contracted time are also characterized by the fact that, once they have been decided on, they remain relatively unaffected by personal choices. Most people have to earn a daily living and the time–spatial premises (e.g., working hours and location) associated with doing so are determined mainly by the employer (Breedveld, 1998).[1] Activities associated with *committed time* are linked predominantly to household work, such as grocery shopping and raising children. These activities also must be carried out regularly, but are expected to be associated with more individual flexibility concerning when or where they are performed than are activities performed during contracted time. People have greater opportunities both to postpone such activities and to make decisions concerning where to perform them in relation to their own premises. For example, several researchers have demonstrated that individuals often do not choose the nearest service facility (e.g., Handy and Clifton, 2001; Næss, 2013). In a Swedish context, the distance travelled to access services increased between 1995 and 2005–2006, even though Swedes lived closer to service amenities in 2005–2006 than in 1995 (Haugen and Vilhelmson, 2013). Other factors, such as socioeconomic status, preferences, attitudes, and lifestyles, greatly influence service destination choices.

All other activities are performed in people's *free time*; these activities are expected to be the most flexible in time and space and, consequently, to be the products mostly of personal preferences and resources. For example, Naess (2013), examining the mobility of residents of

[1] High-status occupations, however, are generally associated with more time–spatial autonomy.

Hangzhou, China, found that individual socio-cultural factors are central to explaining the rationales of travel to leisure activities.

2.2. Empirical explorations of how the relative significance of locational and individual attributes varies with trip purpose

Several studies gauge the relative significance of the spatial attributes of residential location and individual characteristics for everyday travelling (see, e.g., Kitamura et al., 1997; Schwanen et al., 2004; Shuttleworth and Gould, 2010; Zhou and Kockelman, 2008). Research designs, data, and geographical contexts, however, differ substantially in the literature. For example, both Shuttleworth and Gould (2010) and Schwanen et al. (2004) used multilevel models to explore the extent to which distance travelled to work varies among workers versus across neighbourhoods, but their analyses are conducted in different geographical contexts, i.e., Northern Ireland and the Netherlands. Schwanen et al. (2004) found that the residential location has a very small effect, while Shuttleworth and Gould (2010) found that a large share of variance in distance travelled to work can be explained by residential location.[2] It is therefore risky to use these studies to draw general conclusions about how the relationships between residential locations, individual attributes, and travel demand vary with trip purpose.

However, some empirical research, conducted mainly in the Netherlands, applies identical research designs to examining different trip purposes. Meurs and Haaijer (2001) considered four trip purposes when examining the extent to which spatial structure can explain the number of trips people make during a week. The only trip purpose explained primarily by the locational characteristics of the residence was that of shopping. The number of commuting trips was

[2] One possible explanation is that the Netherlands is far more densely built-up than is Northern Ireland, which implies that people generally have many options for where to work, which should relax the relationships between residential location and commuting behaviour.

explained almost exclusively by personal characteristics.[3] Spatial and individual determinants were similar in importance for explaining trip frequency to school or for social and recreational purposes. Dieleman et al. (2002) fitted separate models for work, shopping, and leisure trips, measuring both modal choice and distance travelled. The effect of residential environment was strongest when modelling the distance travelled for work, and was moderately stronger for shopping than for leisure. Snellen et al. (2002) measured the share of motorized kilometres and number of trips and kilometres travelled using separate models for work, grocery shopping, other shopping, and leisure trips. The model measuring the share of motorized trips for home-to-work travel, however, was the only one that included significant parameters for urban form.

Furthermore, Næss (2006) employed both quantitative and qualitative methods to examine what relationships between urban form and travel demand remained after considering both individual socioeconomic attributes and attitudes of people living in Copenhagen, Denmark. Næss found that the total distance travelled is much more influenced by urban structure on weekdays than on weekends (2006, pp. 104–107). The same pattern is also evident when comparing errands/shopping trips on weekdays and weekends (Næss, 2006, pp. 141–142). Furthermore, the analysis also suggested that the relationship is stronger for commuting than for other trips (Næss, 2006, pp. 145–149).

2.3. Implications for further research

Though most scholars agree that spatial circumstances causally influence travel demand (but that individual factors are of more explanatory importance) (Cao et al., 2009; Ewing and Cervero, 2001; Stead, 2001), few studies consider how and why the relative significance of individual characteristics and spatial circumstances varies with trip purpose. Outcomes of time-geographic

[3] That the number of commuting trips could not be attributed to residential location is not surprising. How often one travels to work should mostly be a product of whether one is employed and/or one's type of employment.

research suggest that constraints coupled to time, space, or a combination of the two, as well as locational–individual relationships, differ among activities. The few relevant empirical investigations also consistently found that associations between residential location, individual characteristics, and travel behaviour vary with trip purpose. Likewise, both studies of spatial fixity levels and the few empirical studies of how spatial and individual attributes relate to travelling for different activities provide clear indications that Ås's time-use categorization could be useful for understanding how these relationships interact.

3. Data, method, and variable definitions

3.1. Data

This study mainly uses data from the Swedish National Travel Survey (RES) (SIKA, 2007). RES was conducted by the Swedish Institute for Transport and Communication Analysis (SIKA) from 1 October 2005 to 31 September 2006. The survey gathered data concerning the everyday travelling of the Swedish population aged 6–84 years. RES was carried out using phone interviews (based on travel diaries) in which people responded to questions concerning all travel activities conducted on one random day. Respondents were also asked about various background conditions that may have affected their travel behaviour. The initial sample comprised 40,928 individuals and the response rate was 67.6%. Since some public administrations at the county level paid for an extended sample, it was necessary to randomly remove a predefined number of cases from the data used here to provide correct geographical stratification; this left 20,283 respondents in the database. However, respondents under 16 years old were not included, since children are assumed to make fewer travel decisions on their own. This left 17,337 respondents in the database, 14,112 of whom reported one or more trips on the measurement day. Furthermore, only respondents whose first trip originated and last trip ended at the place of residence were included in the analysis, resulting in 1742 respondents being omitted on these grounds. This was necessary since the analysis started from the residential location (discussed in section 3.3.2). This procedure also excluded many trips not made on a regular everyday basis.[4] The final database covered 12,370 individuals.

To describe and define independent variables at the residential location level, data were drawn from the GILDA database,[5] which comprises official Swedish register data for the entire Swedish population from November 2005 (SCB, 2011). Each individual is attributed variables describing demographic status, socioeconomic status, and employment, as well as geographic coordinates for home and workplace (within 100 × 100-metre cells). Workplaces are also defined in terms of industry classification and number of employees. For privacy reasons, it is impossible to identify the same individuals in GILDA and in RES; the two databases were therefore integrated using the geo-references of the residential locations. The definition of residential location is further discussed in section 3.3.2.

3.2. Empirical modelling approach

This paper applies multilevel modelling, which is an umbrella term for several statistical models that allow parameters to vary at several levels in hierarchical data structures (e.g., individuals nested in neighbourhoods). By using multilevel models, it is possible to derive the relative impacts of the various levels in a hierarchy. For more detailed descriptions of multilevel

[4] The analysis was initially also run without omitting the respondents who did not start or end their travelling at home on the measurement day. As expected, this lowered the explained variance attributed to the residential location level in all models. Many of the excluded trips (e.g., vacation trips or longer social visits) could be expected to be less constrained by the geographical context of the residential location and more a consequence of individual needs and wishes.

[5] GILDA, the Geographical Individual Longitudinal Database for Analysis, is administered by the unit for Human Geography, University of Gothenburg.

modelling, see Goldstein (2011) or Jones (1991). Several authors emphasize the applicability of this approach in mobility research (e.g., Mercado and Páez, 2009; Snellen et al., 2002).

The multilevel models used in this paper resemble standard ordinary least square regression models, the main difference being that they allow for several levels in the data. The deviation from the mean is split into more than one component. In this case there are two residuals, one for individuals and one for neighbourhoods (both assumed to follow normal distributions). This model is often referred to as a random intercept model, as the intercept of neighbourhood regression lines varies randomly across neighbourhoods[6]:

$$y_{ij} = \beta_0 + \beta_{1j} X_{1ij} + \beta_{2j} X_{2j} + u_j + e_{ij}$$

$$u_j \sim N(0, \sigma_u^2) \qquad (1)$$

$$e_{ij} \sim N(0, \sigma_e^2)$$

where

y_{ij} is the dependent variable,

e_{ij} is the residual for individuals (with variance σ_e^2),

[6] Note that a random intercept model assumes that the relationships between the daily travel distance and the independent individual variables are equal in each residential area. There are, however, reasons to believe that this assumption is violated in some cases. Schwanen et al. (2004), for example, found that the women living in residential areas located in monocentric regions were more likely to commute by car than were women living in polycentric regions. Furthermore, in the Swedish case, the effect of car access could be expected to be more important in more sparsely populated areas than, for example, in Stockholm and Göteborg. To analyse whether or not the effects of personal and household characteristics on travel distance for specific trip purposes vary systematically across residential contexts, random slope models were initially also fitted. However, allowing the effect of the individual variables to be random across SAMS in the models made few significant contributions. Note, however, that the null results could potentially be explained by the nature of the data. Three main aspects should be considered when determining sample sizes for a multilevel study: the number of level 1 and 2 units and the number of level 1 units in each level 2 unit (i.e., the cluster size). The sample size at the highest level is the main limiting characteristic of a multilevel design (Scherbaum and Ferreter, 2009; Snijders, 2005); i.e., it is considerably more informative to have a small cluster size and a high number of level 2 units than the reverse. However, if the average cluster size is small, there is less power for testing random slopes (Scherbaum and Ferreter, 2009; Snijders, 2005), which is the case in the present dataset (i.e., a high number of level 2 units but a small cluster size). Therefore, the conclusion was that random slope models have insufficient scope to permit reliable conclusions to be drawn.

u_j is the residual for neighbourhoods (with variance σ_u^2),

β_0 is the overall mean of the dependent variable,

$\beta_{1j} X_{1ij}$ is the effect of an independent variable, *x*, on individual *i* residing in area *j*, and

$\beta_{2j} X_{2j}$ is the effect of an independent variable, *x*, on area *j*.

Furthermore, the total variance around the mean distance travelled for both residuals is divided into two components: across residential area variance and within residential area variance (i.e., between individuals). These values allow estimating how much of the total variance in distance travelled is due to variation across residential areas. This figure is referred to as the variance partition coefficient (VPC) and is calculated by dividing the area variance, σ_u^2, by the total variance, $\sigma_u^2 + \sigma_e^2$:

$$\mathbf{VPC} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \quad (2)$$

By this logic, if all individuals living in the same neighbourhood travel the same daily distance, all explained variance could be derived from the residential location. Variance partition coefficients are key estimates used here to derive the significance of residential location. The variance components, in combination with the independent variables, are also used to evaluate possible biases due to cross-level inference. Observed associations between travel behaviour and the spatial attributes of a neighbourhood could, for example, instead be a product of the individual characteristics of neighbourhood residents (Kitamura et al., 1997); i.e., the distribution of X_{ij} is clustered to certain residential areas. This is controlled for by observing whether σ_u^2 changes when X_{ij} is introduced.

Finally, to test whether adding residential location as an extra level or an independent variable has any significant effect, likelihood ratio tests were employed (see McCullagh and Nelder, 1989, as cited by Goldstein, 2011, pp. 40–41). This involves measuring the difference between the log-likelihoods of the model before and after adding new terms. The result is then compared with a chi-squared distribution on x degrees of freedom. The MLwiN software (Rasbash et al., 2011) was used for all model estimations.

3.3. Variable definitions

3.3.1. Dependent variable

The dependent variables in the models are defined as the total distance travelled for various purposes on the day of the survey (specified in kilometres). Following Ås's categorization discussed above, three main categories of trip purposes are modelled: trips to activities performed on *contracted time* (includes work trips), *committed time* (includes service trips to the grocery store, health care clinic, post office, bank, and childcare centre), and *free time* (includes leisure trips for hobbies, study circles, music practice, courses, restaurants/cafes, exercise, outdoor activities, entertainment and culture, vacation trips, religious practice, and visiting friends and relatives). Note that trips are categorized based on their main purpose and may therefore include stops for other activities (i.e., trip chaining). Furthermore, Vilhelmson (1999) found that trips characterized by high time–spatial flexibility are considerably more common on weekends than on weekdays in Sweden; similar indications were also found by Næss (2006). Therefore, the total numbers of trips carried out on weekdays and weekends were also modelled separately. Table 1 presents descriptive statistics for the dependent variables. Note that the logarithms of the dependent variables were used when fitting the models, in order to comply with normal distribution assumptions.

[Table 1 about here]

On the measurement day, 12,370 of the respondents in the final dataset were engaged in some form of travel (Table 1). One quarter of the respondents commuted to work, one fifth carried out some form of service errand, and 30% travelled to leisure activities on the day of the survey. Note that many respondents made several trips for different purposes, and could be included in more than one of the models measuring work, service, or leisure trips.

3.3.2. Residential location level

How to identify location and define the spatial level of analysis are critical methodological considerations when applying the model. First, a link must be established between each individual and a specific location, and then a spatial level must be defined for that location. Two main preconditions should be fulfilled when defining a location from which to start the analysis: a large share of trips must originate from the location, and the location must be equally important to all individuals. As regards the total population, the place of residence is the only location that fulfils these requirements (Ellegård and Vilhelmson, 2004). How to define a spatial level around the residence, however, is not uncontested.

It is well known that the results of statistical analysis could be sensitive to the area configuration of the data analysed (Kwan and Weber, 2008; Openshaw, 1984). The modifiable areal unit problem (MAUP) pays attention to the fact that results could differ when the same analysis is applied to identical data but with different geographical aggregations (Openshaw, 1984). In this case, the data design constrains the opportunities to just a few options. In RES, the highest geographical resolution of the respondents' residential location is defined in so-called SAMS areas. SAMS are statistical areas defined by Statistics Sweden to represent homogeneous residential areas (SCB, 2005). There are approximately 9200 SAMS in Sweden, each including an average of approximately 1000 inhabitants. The SAMS are generally geographically larger in sparsely populated areas than in densely populated urban areas. There are 5186 SAMS in the studied dataset with 2.33 respondents on average in each (min = 1, max = 31), constituting a relatively small cluster size but a very large number of level 2 units. As discussed in section 3.2, this meets the requirements for estimations of random intercept models, while fitting random slope models is questionable (Scherbaum and Ferreter, 2009; Snijders, 2005).

The validity of the SAMS as the geographical unit of analysis in this case (as with most area definitions in geographical research) is open to question. A common suggestion for handling possible MAUP issues is to use spatial units that are theoretically meaningful for the aim of the analysis (Kwan and Weber, 2008; Openshaw, 1984). Since the purpose of this study is to evaluate the extent to which the residential location affects the daily travel distance, it is desirable that the definition of residential area be geographically homogeneous in terms of the locational characteristics that theoretically can be expected to influence travel behaviour. In an ideal situation, the geographical units of analysis should therefore be constructed based on a careful review of previous research into land use–travel interactions. In this sense, the SAMS are well equipped in comparison with the alternatives that the present dataset provides in municipalities. Swedish municipalities are geographically large and often include both large cities and sparsely populated areas. Furthermore, previous evaluations of MAUP problems in travel behavioural research have come to different conclusions. For example, Kwan and Weber (2008) found the effects of various individual and spatial variables to be scale-invariant on space–time accessibility measures, while Horner and Murray (2002) found that spatial unit definitions can have important impacts on measures of excess commuting. In summary, though there are few options to make careful evaluations of potential MAUP problems in this case, the SAMS – considering their homogeneity and relatively small size – could theoretically be expected not to significantly bias the results.

Furthermore, previous research demonstrates that, in general, people living in densely populated areas, located near a mix of amenities, travel less than do those living in more sparsely populated neighbourhoods, farther from city centres and amenities (Boarnet and Crane, 2001; Ewing and Cervero, 2010). In a Swedish context, Vilhelmson (2005), however, found a nonlinear relationship between city size and travel distances, inhabitants of medium-sized cities being found to travel shorter distances in general than did people living in the largest Swedish cities. The present study specifies three independent variables on the SAMS, or residential location, level: regional location, jobs-to-worker ratio (JWR), and a variable specifying whether or not the neighbourhood is located in an urban area with more than 10,000 inhabitants (with separate categories for the three largest cities in Sweden and for cities with 10,000–25,000 and 25,000–125,000 inhabitants). Further details can be found in Table 2.

[Table 2 about here]

3.3.3. Individual level

In the Swedish context, several individual demographic and socioeconomic factors have been found to influence daily mobility patterns. Gender (e.g., Gil Sola and Vilhelmson, 2012), income (e.g., Swärdh, 2009), education (e.g., Sandow, 2011), car access (e.g., Vilhelmson, 2007), household composition, and life course (e.g., Fransson, 1991) are important determinants that are controlled for here (see Table 3 for further description). Note that several other individual factors, not considered here due to the content of the data, are also important determinants, such as social networks (Dugundji et al., 2012; Tilahun and Levinson, 2011), the fact that people to some extent choose their place of residence based on their travel rationales (Cao et al., 2009), and attitudes (Kitamura et al., 1997). These considerations are to some extent captured in the demographic and socioeconomic variables.

[Table 3 about here]

4. Results and analysis

The departure point of this study was the question of whether residential location influences daily distance travelled differently when trip purpose is added as an analytical consideration. The results of running the simplest multilevel models – without independent variables – clearly suggest that this is the case (Table 4). Adding the neighbourhood level has a highly significant effect when modelling daily distance travelled to work and service activities as well as on weekdays; i.e., those who live in the same residential location also, to various extents, travel similar distances every day. How far people travel to work daily is most reflective of their residential location, explaining 18.29% of the variance. Residential location is also an important determinant of the daily distance travelled for service errands, explaining 12.38% of the total variance. However, adding the residential location level for leisure trips and weekend travelling has no significant effects. This indicates that there is very large variation in daily travel distances for leisure activities and on weekends among people who share residential locations. These results confirm the utility of Ås's (1978) framework for classifying activities in accordance with their level of temporal flexibility in this context. As hypothesized, of the activities modelled here, daily distance travelled to work (i.e., contracted time) is evidently the least individually flexible activity in terms of where people live. There is some spatial-fixity associated with travelling to activities performed on committed time, here operationalized as trips to access services. Furthermore, how far people in Sweden travel to free-time activities is subject to very little spatial fixity. This study also confirms Vilhelmson's (1999) finding, based on time-use data, that travelling on weekends is less spatially bounded than is weekday travelling.

[Table 4 about here]

Independent, individual-level variables are introduced in the models in Table 5. Since no significant effect resulted from including residential location as an additional level for leisure trips and weekend travelling, these are not further modelled. To capture possible cross-level interactions between the individual residential location levels, the following procedure was applied. First, each independent variable was individually added to the model to evaluate the data level at which the effect works. This was done by measuring how the unexplained variance changes at each level. If the unexplained variance changes at the residential location level, the outcomes of the models presented in Table 4 could be biased (i.e., the variation derived from residential location could instead be due to the characteristics of neighbourhood residents). In the next step, a ratio test was used to evaluate whether each variable still contributed to the model when the other variables were controlled for. The only variable that did not contribute was gender in the service trips model, so it was excluded.

Examining the results of adding the independent variables at the individual level, it is evident that the individual and residential location levels interact. The unexplained variance at the residential location level has been more than halved in the models measuring all trips, service errands, and travelling during on weekdays compared with the two-level null models in Table 4. The decrease is considerably lower for work trips (only 10%). The reduction of unexplained variance is larger at the individual level in all models except the service trip model. The residential location-level variance has been reduced by 0.149, while the individual-level variance decreased by only 0.054 for distance travelled to access services.

What individual variables contribute to these effects? Except for gender and education, all variables included have an explanatory effect at the residential location level, but there is variation depending on the type of trips considered. As expected, the strongest effect comes from introducing car access in the models. Car access, alone, lowers the unexplained variance at the residential location level by 0.053 for all trips, 0.026 for work trips, 0.121 for service trips, and 0.055 for weekday travelling. Individual car access in Sweden displays a clear spatial pattern, being more common in rural than urban areas. Many Swedes live in car-dependent, sparsely populated areas with poor access to public transport and where amenities are located far away. Life course also significantly affects the residential location variance, and alone it lowered the variance by 0.035 for all trips, 0.028 for work trips, 0.078 for service trips, and 0.043 for weekday trips. This is also expected in light of the common housing careers of many Swedes (Borggren, 2011). For example, younger people are overrepresented in cities (where the demand for daily mobility is relatively low), while many middle-aged couples with children move to the suburbs (farther from amenities, which increases mobility demand). Adding the income variable reduces the spatial variance by 0.020 for all trips, 0.038 for service trips, and 0.029 for trips on weekdays, but has no effect on work trips.

Though introducing the independent variables reduces the importance of residential location for daily distance travelled compared with the first models, the clear differences between trip purposes are still present. In addition, since the variance in distance travelled between home and work attributed to the residential location level remains relatively unaffected, this strengthens the hypothesis that work trips are considerably more spatially bounded than are trips for other purposes. In contrast, how far people travel for service activities is apparently subject to extensive spatial–individual interactions. One possible explanation concerns individual car access and its implications for the spatial-fixity constraints of service access combined with the clustering of car use to certain neighbourhoods. The possibility of driving a car greatly enlarges the potential geographical extension of an individual’s daily activity space. Since people have considerably more options for when and where to perform service errands than work travel, the effect of car access in this context should be noticeable. Haugen and Vilhelmson’s (2013) finding that large supplies of service amenities on the regional scale in Sweden, combined with car access, are related to longer daily travel distances to services supports this explanation.

[Table 5 about here]

Independent variables at the residential location level are introduced in the final models in Table 6. To further evaluate potential cross-level interactions, these variables control for parts of the unexplained variance at the residential location level being due to effects coupled to the residential location, and not being products of other individual effects that cannot be controlled for (e.g., attitudes and lifestyles). Considering the large deviance, the independent variables at the residential location level contribute significantly to all models. Introducing the spatial variables also greatly reduces the unexplained variance at the residential area level in the models that measure total trips, work trips, and weekday travelling, while the individual-level variance remains fairly intact. The results for the service model, however, are different. Here, the unexplained variance is reduced at both levels, and the effect at the residential location level is not as large as in the other models. One probable explanation is that the variables used tend not to capture the spatial patterns of the service amenities to which people travel.[7] In addition, as discussed, interactions between car access and the spatial variables are at work here. However, it is evident that the same variations in the reflection of residential location in travel distances due to trip purpose hold after controlling for the spatial variables.

As expected, in all models, JWR has a strong negative effect while distance from the residential location to the closest regional centre has a highly significant positive effect: people living in areas with higher JWR (i.e., higher job accessibility and more diverse land use) generally travel shorter distances daily, while living far from the regional centre will increase one's daily travel distances. Furthermore, in all models, people living in urban areas with populations between 10,000 and 125,000 generally travel shorter distances daily than do those not living in an urban area with more than 10,000 inhabitants. Likewise, people living in Stockholm and Malmö generally travel shorter distances to access services, which is also in line with previous research noting that denser city regions reduce travel. However, there are no significant differences in travel distance for all trip purposes or on weekdays between those living in one of the three largest cities in Sweden and those not living in an urban area with more than 10,000 inhabitants. In addition, living in Gothenburg increases the distance travelled to work, but living in a SAMS located in Malmö or Stockholm has no significant effect on this distance. These results are in line with previous research into the Swedish case (Vilhelmson, 2005). When cities become too large, the distance between people and the activities that they wish to reach increase compared with the comparable distances in medium-sized cities.

[7] Attempts were made to define variables describing the distance between service amenities and each residential area, but they did not explain significant proportions of the variance in distance travelled. A probable explanation lies in the broad definition of service trips used here, including grocery shopping, picking up children, and dental appointments.

[Table 6 about here]

5. Conclusions

The distances people travel daily have important repercussions, for example, for urban life and integration, urban form and density, energy use, and pollution levels. Factors affecting distance travelled in various geographical settings therefore merit scrutiny. In principle, in order to fully understand why and how far people travel for various trip purposes, one must consider all the opportunities and constraints constituting the complexity of everyday life – for example, the relationships between various individual internal capacities and external factors, including the spatial patterns of the built environment, the daily scheduling of activities and trips, other household members activity patterns, residential self-selection, and attitudes – which are important determinants of the travel decision making process. The empirical approach used here is more limited and is based on the premises that travelling predominantly arises from a need to perform activities at diverse locations in time and space, and that different activities are coupled to various degrees of freedom of choice and to constraints partly dependent on the needs the activities aim to fulfil. Hence, it was hypothesized that the influence of residential location on daily distance travelled differs when individuals travel for the purpose of performing diverse activities. The results of running multilevel models on Swedish National Travel Survey data verify this suggestion. There is great variation in how far people in Sweden travel for leisure activities and on weekends, even if they live in the same neighbourhood. In contrast, statistically significant proportions of the variation in daily distance travelled to work and for service errands were derived from the residential location level.

This analysis has confirmed the importance of considering the time–spatial constraints of activities when examining the relationship between location, individual characteristics, and travel behaviour. Ås's (1978) categorization of activities in accordance with their flexibility in time provided a useful general framework for doing so. However, there are likely to be variations within these activity categories. The spatial-fixity levels of service trips could, for example, be expected to vary with the degree of specialization (and the spatial supply) of service facilities. It would be interesting for future studies to include a more detailed activity categorization to test such hypotheses. An additional interesting subject for further research would be to test the effect of ICT practices on the relative significance of residential location for travel behaviour. High ICT use is often said to relax the relationship between physical location and travel (Kwan and Weber, 2003). For example, an increase in telework could erode the strong connection between work trips and residential location. Furthermore, the analysis demonstrates that there are clear interactions between several of the individual characteristics controlled for and the variation in distance travelled across residential locations, especially for service trips. As expected, car access seems to be the main source of these interactions. An important task for future research is to apply more complex multilevel models to further investigate cross-level interactions between individual and spatial variables. For example, random slope models could be used to evaluate whether the effect of car access varies systematically across residential contexts.

This study helps clarify some of the variations in research results regarding the extent to which spatial versus individual attributes explain daily travel demand. An overall conclusion is that studies of trips carried out to perform activities in contracted time are more likely to find that spatial effects are explanatory than are those focusing on trips for activities in committed or free time. From a policy perspective, these results suggest that the success of measures to alter the built environment (e.g., creating more compact urban regions with more mixed land use) to reduce the volume of travel will be most efficient when considering work trips, while trips taken in people's spare time would likely be little affected by such measures. Therefore, measures to alter the built environment are necessary but not sufficient to reduce travel distances overall. Such measures need to be combined with ones more directly targeting individual factors related to travel behaviour and destination choice (e.g., road taxes and information campaigns). Still, measures that increase land use diversity and density and reduce travel needs are important in planning for more resilient and robust urban regions and cities.

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Table 1
Descriptive statistics of the dependent variables (n = 12370).

Variable	n	Mean daily distance (km)	Std. dev.
All purposes	12097*	41.82	89.07
Work	4589	32.30	42.21
Service	3871	18.94	40.51
Leisure	5568	23.53	51.65
Weekdays	9053	43.36	94.89
Weekends	3044	37.27	68.71

* 273 respondents did not report how far they travelled.

Table 2
Description of independent variables at the residential area level.

Variable	Description	Mean	Std. dev.	Freq.
Jobs-to-worker ratio (JWR)	The number of job opportunities relative to the number of gainfully employed residents within a 10-km radius of each residential area's centre point; measures job accessibility and is a proxy for the spatial mix of activities.	1.04	0.33	
Regional location	The natural logarithm of the Euclidian distance in 10 km from each area's centre point to the centre point of the largest city in the central municipality of the local labour market region (LA region*) where the area is located.	2.14	1.31	
Larger urban area				
Stockholm	The area's centre point is located in Stockholm.			12.4%
Göteborg	The area's centre point is located in Göteborg.			5.0%
Malmö	The area's centre point is located in Malmö.			2.4%
Larger urban area	The area's centre point is located in a city with more than 25,000 inhabitants and not in Stockholm, Göteborg, or Malmö.			22.8%
Medium-sized urban area	The area's centre point is located in a city with 10,000–25,000 inhabitants.			11.7%
Not within an urban area with >10,000 population	The area's centre point is not located in a city with more than 10,000 inhabitants.			45.7%

* Swedish official functional regions based on commuting flows between municipalities.

Table 3
Description of independent variables at the individual level.

Variable	Frequency					
	All	Work	Service	Leisure	Weekdays	Weekends
Gender						
Male	6125 (49.5%)	2403 (52.4%)	1789 (46.2%)	2720 (48.9%)	4547 (50.2%)	1484 (48.8%)
Female	6245 (50.5%)	2186 (47.6%)	2082 (53.8%)	2848 (51.1%)	4506 (49.8%)	1560 (51.2%)
Car access*						
Yes	9265 (74.9%)	3871 (84.4%)	2918 (75.4%)	4216 (75.7%)	6816 (75.3%)	2314 (76.0%)
No	3079 (24.9%)	713 (15.5%)	950 (24.5%)	1342 (24.1%)	2222 (24.5%)	723 (23.8%)
Missing	26 (0.2%)	5 (0.1%)	3 (0.1%)	10 (0.2%)	15 (0.2%)	7 (0.2%)
Income**						
<140	2512 (20.3%)	259 (5.6%)	851 (22.0%)	1265 (22.7%)	1842 (20.3%)	601 (19.7%)
140–220	2868 (23.2%)	1018 (22.2%)	1012 (26.1%)	1324 (23.8%)	2096 (23.2%)	721 (23.7%)
221–300	3450 (27.9%)	1797 (39.2%)	1004 (25.9%)	1499 (26.9%)	2528 (27.9%)	862 (28.3%)
>300	2094 (16.9%)	1148 (25.0%)	565 (14.6%)	883 (15.9%)	1543 (17.0%)	531 (17.4%)
Missing	1446 (11.7%)	367 (8%)	439 (11.3%)	597 (10.7%)	1044 (11.5%)	329 (10.8%)
Education						
<Upper secondary school	2407 (19.4%)	681 (14.8%)	719 (18.6%)	1101 (19.8%)	1803 (19.9%)	529 (17.4%)
Upper secondary school	5149 (41.6%)	2197 (47.9%)	1623 (41.9%)	2209 (39.7%)	3809 (42.1%)	1257 (41.3%)
Higher education <2 yrs	729 (5.9%)	276 (6.0%)	239 (6.2%)	335 (6.0%)	498 (5.5%)	217 (7.1%)
Higher education ≥2 yrs	3071 (24.8%)	1391 (30.3%)	921 (23.8%)	1406 (25.3%)	2213 (24.4%)	798 (26.2%)
Missing	1014 (8.2%)	44 (1%)	369 (9.5%)	517 (9.3%)	730 (8.1%)	243 (8.0%)
Life course						
Single, 16–40 y.o.	1110 (9.0%)	480 (10.5%)	272 (7.0%)	465 (8.4%)	822 (9.1%)	264 (8.7%)
Single, 41–64 y.o.	934 (7.6%)	427 (9.3%)	296 (7.6%)	395 (7.1%)	695 (7.7%)	216 (7.1%)
Single, w. children	455 (3.7%)	205 (4.5%)	151 (3.9%)	176 (3.2%)	344 (3.8%)	99 (3.3%)
Partnered, 16–40 y.o.	913 (7.4%)	451 (9.8%)	229 (5.9%)	413 (7.4%)	657 (7.3%)	239 (7.9%)
Partnered, 41–64 y.o.	2402 (19.4%)	1136 (24.8%)	692 (17.9%)	1034 (18.6%)	1791 (19.8%)	577 (19.0%)
Partnered, w. children	3483 (28.2%)	1649 (35.9%)	1089 (28.1%)	1443 (25.9%)	2521 (27.8%)	910 (29.9%)
Senior citizen	2063 (16.7%)	53 (1.2%)	979 (25.3%)	1145 (20.6%)	1448 (16.0%)	543 (17.8%)
Residing with parent	912 (7.4%)	145 (3.2%)	143 (3.7%)	469 (8.4%)	709 (7.8%)	174 (5.7%)
Missing	98 (0.8%)	43 (0.9%)	20 (0.5%)	28 (0.5%)	66 (0.7%)	22 (0.7%)

* Specifies whether the respondent holds a driver's license and has access to a car.
** Annual income specified in SEK thousands.

Table 4
Random intercept models of daily distance travelled without independent variables.

	All	Work	Service	Leisure	Weekdays	Weekends
B_0 (intercept)	2.827(0.014)	2.761(0.021)	1.833(0.026)	1.951(0.021)	2.887 (0.016)	2.637(0.028)
–2 log-likelihood	43190.097	15517.370	14328.934	20131.519	31977.993	11126.928
Deviance (from one-level null model)	61.381	70.563	27.290	2.195	65.595	0.156
Area-level random part						
Intercept variance, σ^2_{u0}	0.142(0.020)	0.324(0.042)	0.298(0.063)	0.053(0.037)	0.197(0.026)	0.027(0.067)
VPC residential area	6.73%	18.29%	12.38%	Not sig.	9.67%	Not sig.
Individual-level random part						
Intercept variance, σ^2_e	1.969(0.031)	1.447(0.046)	2.109(0.074)	2.147(0.054)	1.841(0.035)	2.260(0.088)

Table 5
Random intercept models with individual independent variables.

	All	Work	Service	Weekdays
Individual-level fixed part				
Gender			-	
Male (ref)	-	-	-	-
Female	–0.168**(0.030)	–0.256**(0.043)	-	–0.214**(0.033)
Car access				
Yes (ref)	-	-	-	-
No	–0.697**(0.039)	–0.458**(0.062)	–0.841**(0.073)	–0.697**(0.044)
Income				
<140 (ref)	-	-	-	-
140–220	0.147**(0.045)	0.061(0.094)	–0.040(0.079)	0.171**(0.050)
221–300	0.282**(0.046)	0.135(0.093)	–0.032(0.082)	0.273**(0.052)
>300	0.453**(0.053)	0.359**(0.100)	–0.017(0.095)	0.513**(0.060)
Education				
<Upper secondary school	0.032(0.041)	–0.017(0.063)	0.154*(0.076)	0.056(0.045)
Upper secondary school (ref)	-	-	-	-
Higher education, <2 years	–0.022(0.058)	0.004(0.086)	–0.250*(0.109)	0.052(0.067)
Higher education, ≥2 years	–0.040(0.035)	0.048(0.049)	–0.188**(0.067)	–0.023(0.039)
Life-course				
Single, 16–40 y.o.	–0.102(0.054)	–0.208**(0.073)	–0.457**(0.113)	–0.077(0.061)
Single, 41–64 y.o.	–0.153**(0.055)	–0.158*(0.074)	–0.193(0.103)	–0.198**(0.061)
Single, w. children	–0.085(0.073)	–0.143(0.100)	–0.264*(0.134)	–0.130(0.081)
Partnered, 16–40 y.o.	0.018(0.055)	–0.100(0.072)	–0.287*(0.114)	0.014(0.062)
Partnered, 41–64 y.o.	–0.057(0.039)	–0.112*(0.052)	0.051(0.077)	–0.052(0.044)
Partnered, w. children (ref)	-	-	-	-
Senior citizen	–0.472**(0.050)	–0.390*(0.192)	–0.197*(0.083)	–0.565**(0.057)
Residing with parent	0.306**(0.076)	–0.114(0.135)	–0.177(0.175)	0.243**(0.083)
Model statistics				
B_0 (intercept)	2.981(0.052)	2.870(0.099)	2.199(0.084)	3.055(0.059)
–2 log-likelihood	34148.290	13800.714	11310.340	24995.097
Deviance (from two-level null model)	9041.807	1716.656	3018.594	6982.896
Residential area-level random part				
Intercept variance, σ^2_{u0}	0.057(0.019)	0.291(0.042)	0.149(0.067)	0.085(0.024)
VPC residential area	3.05%	17.59%	6.76%	4.86%
Individual-level random part				
Intercept variance, σ^2_e	1.813(0.031)	1.363(0.046)	2.055(0.082)	1.665(0.035)

* $p < 0.05$; ** $p < 0.01$. The independent variable estimates are divided by their standard error (specified in the parentheses following each estimate) to test the statistical significance. The critical value is 1.96 at the 5% significance level and 2.58 at the 1% level.

Table 6

Random intercept models with individual and residential location independent variables.

	All	Work	Service	Weekdays
Individual-level fixed part				
Gender			-	
Male (ref)	-	-	-	-
Female	–0.163**(0.030)	–0.246**(0.041)	-	–0.203**(0.033)
Car access				
Yes (ref)	-	-	-	-
No	–0.617**(0.040)	–0.360**(0.060)	–0.684**(0.075)	–0.601**(0.044)
Income				
<140 (ref)	-	-	-	-
140–220	0.152**(0.044)	0.048(0.090)	–0.028(0.077)	0.182**(0.049)
221–300	0.309**(0.045)	0.147(0.089)	0.013(0.080)	0.304**(0.051)
>300	0.485**(0.053)	0.388**(0.096)	0.046(0.094)	0.568**(0.059)
Education				
<Upper secondary school	0.004(0.040)	–0.052(0.060)	0.096(0.075)	0.021(0.044)
Upper secondary school (ref)	-	-	-	-
Higher education,<2 years	0.018(0.057)	0.047(0.082)	–0.191(0.107)	0.084(0.066)
Higher education, ≥2 years	–0.002(0.035)	0.101(0.047)	–0.124(0.066)	0.017(0.038)
Life-course				
Single, 16–40 y.o.	–0.011(0.054)	–0.101(0.070)	–0.365**(0.112)	0.034(0.060)
Single, 41–64 y.o.	–0.098(0.054)	–0.078(0.071)	–0.112(0.102)	–0.132*(0.060)
Single, w. children	–0.053(0.072)	–0.108(0.095)	–0.210(0.132)	–0.097(0.079)
Partnered, 16–40 y.o.	0.102(0.055)	0.017(0.070)	–0.167(0.113)	0.114(0.061)
Partnered, 41–64 y.o.	–0.063(0.038)	–0.107*(0.050)	0.056(0.076)	–0.057(0.043)
Partnered, w. children (ref)	-	-	-	-
Senior citizen	–0.440**(0.050)	–0.377*(0.184)	–0.138(0.082)	–0.523**(0.056)
Residing with parent	0.323**(0.075)	–0.129(0.129)	–0.153(0.172)	0.254**(0.081)
Residential location fixed part				
Jobs-to-worker ratio (JWR)	–0.270**(0.053)	–0.585**(0.077)	–0.327**(0.102)	–0.346**(0.058)
Regional location	0.086**(0.013)	0.157**(0.019)	0.059*(0.024)	0.108**(0.014)
Urban area				
Stockholm	–0.034(0.052)	0.146(0.075)	–0.287**(0.105)	–0.055(0.058)
Gothenburg	–0.033(0.071)	0.203*(0.095)	–0.045(0.141)	0.004(0.077)
Malmö	–0.125(0.098)	0.041(0.148)	–0.773**(0.180)	–0.187(0.109)
Larger urban area	–0.222**(0.042)	–0.281**(0.060)	–0.373**(0.081)	–0.218**(0.047)
Medium-sized urban area	–0.245**(0.047)	–0.453**(0.096)	–0.452**(0.088)	–0.298**(0.052)
Not in an urban area with >10,000 population (ref)	-	-	-	-
Model statistics				
B_0 (intercept)	3.088(0.085)	3.152(0.136)	2.506(0.153)	3.183(0.093)
–2 log-likelihood	33869.019	13392.973	11182.619	24670.283
Deviance (from two-level null model)	9321.078	2124.397	3146.315	7307.81
Residential area-level random part				
Intercept variance, σ^2_{u0}	0.017(0.017)	0.129(0.035)	0.121(0.063)	0.023(0.021)
VPC residential area	0.94%	8.70%	5.72%	1.38%
Individual-level random part				
Intercept variance, σ^2_e	1.800(0.030)	1.353(0.043)	1.993(0.079)	1.648(0.034)

* $p < 0.05$; ** $p < 0.01$.