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Commuting Choices and Residential Built Environments in Sweden, 1990-2010: A Multilevel Analysis

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Scholars argue that everyday travel behavior is related less to location than to individual characteristics, due to the space–time convergence evident with increasing individual mobility. Yet very few studies have empirically measured trends in the relative significance of location for travel habits over time. This paper uses multilevel models based on official Swedish register data covering the total Swedish working population to explore how home–work distance varied among workers and across residential areas between 1990 and 2010. The results indicate growing variation in home–work distance for workers living in the same residential neighborhoods and that the significance of residential location for the home–work distance decreased throughout the studied period. The results may suggest that there is less scope now than in the early nineties for shaping commuting behavior by altering the built environment in Sweden.

Keywords: Home–work distance, Residential location, Multilevel modeling, Register data, Sweden

Introduction

In 1996, Ewing, DeAnna and Li (1996, p. 1) proclaimed that "almost 40 years of land use and travel studies leave us with more questions than answers." They were referring to research illustrating how everyday travel is linked to various aspects of the built environment. Everyday travel could both increase and decrease with similar land use proxies and was

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sometimes found to be independent of location after controlling for individual and household characteristics. Although the association between the built environment and travel demand is currently the most-researched theme in urban planning (Ewing & Cervero, 2010), the extent to which locational characteristics relative to individual characteristics shape everyday travel is still disputed (Cao, Mokhtarian & Handy, 2009; Maat, Van Wee & Stead., 2005; Næss, 2005; Pontes de Aquino & Timmermans, 2010; Van Acker & Witlox, 2011). This is indeed troublesome considering that policymakers often emphasize the notion that travel demand can be shaped by changing the built environment. Examples are found in the New Urbanism movement in the United States (Congress for the New Urbanism, 1998) and the notion of the "compact city" in Europe (Commission of the European Communities, 2001), as well as in the traditionally location- and distance-based orientations of urban and transport forecasting methods (Maat et al., 2005).

Some scholars emphasize that everyday travel behavior is becoming less location based and increasingly dependent on individual choice. This is in line with current changes in the processes underlying the spatial formation of contemporary society (Kwan & Weber, 2003; Miller, 2007). Increasing and more heterogeneous individual mobility reduces the importance of location and distance for travel behavior. Miller (2007) argues that a place-based fallacy (i.e. when individual attributes are incorrectly attributed to places) is more likely to arise when increasing space–time convergence creates more complex relationships between individuals, locations, and travel behavior. People living in the same neighborhood may display highly heterogeneous daily travel behavior. However, few studies adopt a dynamic approach and attempt to quantify how or in what direction the relative significance of the factors *location* and *individual* for everyday travelling has developed in recent decades. Consequently, one key question is whether updated and alternative approaches based on more detailed micro-level datasets (which emphasize person-based aspects) are the main reason why individual effects are becoming increasingly prominent in the literature. Alternately, is there indeed a trend whereby location is of decreasing importance when it comes to daily travel?

In this paper I therefore analyze trends in the relative significance of residential location for home–work distance in Sweden, 1990–2010. The analysis has two aims: first, to evaluate to what extent workers who live in the same residential area had similar home–work distances during the studied period and, second, to evaluate whether there has been any change in the effect of individual and spatial characteristics on the home–work distance. Multilevel models based on unique geo-coded micro-level data covering the total employed population in Sweden are used to explore to what extent home–work distance varied within and between residential areas during this period.

This article contributes to the literature in three main ways. First, and most importantly, it is rare to quantify trends over time in the significance of location considering the extensive literature searching for explanations of travel behavior. Second, previous studies often ignore the hierarchical nature of data (e.g. individuals nested within neighborhoods) when measuring spatial behavior, which could lead to fallacious results. Multilevel modeling is designed to estimate associations between effects observed at various levels of hierarchical data structures. Three, the nationwide context of Sweden provides an interesting case due to the availability of micro-level data covering the total Swedish population and spanning several decades with high spatial resolution. Most previous studies are delimited to single metropolitan areas, many in the USA or the Netherlands, at a given point in time.

The paper is structured as follows. This introduction is followed by a review of the related literature. The third section briefly describes overall Swedish mobility trends, data, and methods. The selection and definition of variables are presented in the fourth section. The fifth section presents the multilevel modeling results and analysis. Finally, the paper is rounded off with conclusions and recommendations for further study.

Literature review: to what extent is travel behavior reflective of residential location relative to individual characteristics?

Daily travel, particularly commuting, is fundamental to contemporary society and labor market functioning, but is also strongly linked to several of today's most troublesome social and ecological problems. Since travel aims to overcome distance, the possibility of shaping travel behavior by altering land use is attractive to policymakers and planners, as is clear from the academic literature (for reviews, see Boarnet & Crane, 2001; Ewing & Cervero, 2010; Handy, 1996). Inferences are then drawn from significant associations found between the location patterns of the built environment and travel behavior. The main significant features of the built environment have been framed as the "three D's," originally density, diversity, and design (Cervero & Kockelman, 1997), later complemented with additional characteristics, including destination accessibility (Ewing & Cervero, 2001). The general observation is that compact neighborhoods with a mix of activities, workplaces, and housing (i.e. higher destination accessibility, denser, and more diversified) are associated with less intensity of everyday auto-related travel and commuting (Ewing & Cervero, 2010).

The causality and assumptions linked to these observations, however, have been questioned from various perspectives in recent decades (Giuliano, 1989; Hanson, 1982; Kitamura, Mokhtarian & Laidet, 1997; Kwan & Weber, 2003; Maat et al., 2005; Miller, 2007; Pontes de Aquino & Timmermans, 2010). Kwan and Weber (2003) argue that significant changes in the processes that shape urban form are in motion with large implications for the relationships between urban structure, mobility, and individual accessibility. Representations of such relationships have traditionally been based on the friction of distance, which emphasizes spatial behavior and the location of firms and individuals as a product of their proximity to facilities. Increasing mobility, however, is fracturing such inferences. Likewise, Miller (2007) stresses the increasing role of space–time convergence when arguing for the need to go beyond location- and distance-based perspectives and instead emphasize actor-based perspectives. Individuals have greater opportunities to choose where to perform activities when access to individual mobility resources increases. The rapid increase in the use of information and communications technology is also an important confounding factor that reinforces this development by further relaxing constraints in time and space.

Green, Hogarth and Shackleton (1999) emphasize structural changes in the labor market that may contribute to making workers' residential locations more spatially heterogeneous in terms of commuting distance. For example, the labor market has developed to include a higher proportion of non-manual jobs, dual-earner households, and workers engaged in flexible occupations.

Several efforts have been made to explore the relative importance of locational and individual effects for travel behavior on given occasions using cross-sectional data, leading to somewhat opposing conclusions (Boarnet & Crane, 2001; Ewing et al., 1996; Van Acker & Witlox, 2011). Kitamura et al. (1997) studied the effects of socio-demographic, attitudinal, and neighborhood variables on travel behavior based on a survey of residents in five areas of the San Francisco Bay Area. Attitudinal effects were found to explain most of the variance in travel. Næss (2005) employed data from qualitative interviews, travel diaries, and a survey to explore travel behavior in the Copenhagen metropolitan area. Residential location and urban structure were found to have an important influence on distance travelled and mode choice after controlling for socio-economic, demographic, and attitudinal characteristics of the respondents. Recent studies have found that significant proportions of the total variance in everyday travel demand are due to residential self-selection after controlling for aspects of the built environment (Cao et al., 2009). Cao et al. (2009) suggest that the effects of the built environment are generally small in relation to socio-demographic factors. They refer to Ewing and Cervero (2001) who derived weighted average elasticities from several studies. The built environment, however, was found to be more important than was self-selection in most of the studies reviewed by Cao et al. (2009).

Though most of the later built environment–travel studies control for individual variables (Ewing & Cervero, 2010), there are other statistical reasons why such studies could be misleading (Pontes de Aquino & Timmermans, 2010; Schwanen, Dieleman & Dijst, 2004; Snellen, Borgers & Timmermans, 2002). Most studies reviewed by Ewing and Cervero (2010) applied standard logistic or ordinary least squares (OLS) regressions. These models cannot take into account grouping effects (e.g. individuals nested in residential neighborhoods) in the data. Using such models to compare neighborhood effects with individual effects will result in exaggerated significance tests at the neighborhood level, since neighborhoods are not only related to other neighborhoods but also to individuals. Furthermore, the basic assumptions of independent measurements are violated (i.e. spatial autocorrelation). Individuals living in the same neighborhood share locational effects and are generally more like each other than to individuals living in other neighborhoods, indicating that the process of deciding where to live or work is generally not random. Multilevel modeling is designed to neutralize such potential problems of cross-level inference by simultaneously estimating variations within groups (e.g. between workers) and between groups (e.g. across residential neighborhoods) (Goldstein, 2011).

Therefore, several travel-behavioral studies apply multilevel modeling to control for locational and individual aspects simultaneously. Snellen et al. (2002) used household travel diaries to explore mode choice as well as trip frequency and length. Schwanen and Dijst (2002) used data from the Dutch National Travel Survey to analyze the relationship between commuting time and workplace visit duration, on one hand, and travel time ratios, on the other. Both studies found that urban form had very modest effects. In a later paper, Schwanen et al. (2004) analyzed the impact of metropolitan structure on commuting behavior. Again, a large proportion (around 90%) of the total variance in commuting time and distance was related to the individual level while a very small proportion was attributable to the spatial level. Furthermore, Weber & Kwan (2003) also found the influence of geographic context to be very weak when analyzing individual accessibility in Portland, Oregon.

Multilevel modeling has become more common lately, and has been applied in a range of travel behavioral inquiries into, for example, whether the commuting gender gap is constant across cities (Zolnik, 2010), how urban sprawl is associated with the duration and length of private vehicle commutes (Zolnik, 2011), the mobility of working couples in Hong Kong (Loo & Lam, 2011), and the determinants of distance travelled by the elderly in Hamilton CMA, Canada (Mercado & Páez, 2009). In most of these studies, most of the explained variance in travelling behavior was attributed to the individual level. However, there are exceptions. Shuttleworth and Gould (2010) found that only 26.5% of the total variance could be attributed to individuals while residential location was as the greatest source of variance when considering commuting distance in Northern Ireland. In Loo and Lam's (2011) Hong Kong study, the neighborhood level did not explain as much of the variance (12.8%), but this was considerably more than in the Dutch studies.

It is important to point out that these different research results are not necessarily due to inaccuracy. Variations between inquiries due to different research designs, geographical settings, and data are to be expected. For example, studies analyzing commuting behavior in more sparsely populated areas (as in Shuttleworth & Gould, 2010) are likely to find location-based effects to be more important than in metropolitan areas since there are fewer possible job locations for workers to choose from. Travel, like all human behavior, is highly complex and involves countless factors, making “true” disentanglement of locational effects from individual effects extremely complicated. People may, for instance, select their place of residence based on their travel needs, but as Næss (2009) has pointed out, it is also the spatial structure that allows households to make that choice. Although self-selection alone does not seem to be more important than the built environment (Cao et al., 2009), many of those who quantify the relative significance of location- versus person-based factors conclude that individual characteristics more strongly affect travel behavior than does location in modern society (Ewing & Cervero, 2001). Most, however, agree that locational and individual aspects jointly shape daily travelling, and that there are several risks if either is excluded from analysis.

It is important to note, not least from a spatial planning perspective, that studies quantifying how relationships between locations, individuals, and travel behavior develop over time are very scarce. Susilo and Maat (2007) made one of the few attempts to empirically measure trends in the influence of urban form on commuting trips. They undertook their study in the Netherlands between 1995 and 2005, and their analysis demonstrated that the influence of various spatial aspects changed during the studied period. There were different trends for different aspects of the commuting journey, but no apparent patterns when modeling commuting distance. Furthermore, Kwan and Weber (2003) and Miller (2007) argue theoretically that individual aspects are becoming more important relative to location over time. Likewise, there is increased interest in exploring how individual characteristics are reflected in travel behavior, which may partially be due to improved modeling techniques and data that allow for more complex inquiries. An important research question is therefore whether we are witnessing a decreasing trend in the importance of location? We may have simply learned to measure travel behavior better.

The asserted reduced significance of location over time calls for further empirical examination using appropriate data and statistical models. The results might have implications for how to view the role of spatial structure in the forming of everyday travel, and for the extent to which and under what conditions physical planning policies (e.g. favoring denser and more compact cities) could promote sustainable mobility (e.g. reduced travel distances and volumes).

Context, data, and methods

Daily mobility trends in Sweden

As in other modernized countries, daily mobility and the spatial dispersion of everyday activities in Sweden have increased in recent decades (Vilhelmson, 2007). The average trip length for all purposes increased by 50.5% between 1978 and 2006, and the length of work trips increased by 54.6% (Frändberg & Vilhelmson, 2011). Important determinants of individual variations in commuting in Sweden are gender, income, education, employment sector, and family situation (Öhman & Lindgren, 2003; Sandow, 2011). Some efforts have been made to study how such variations have developed over time. Frändberg and Vilhelmson (2011) noted a convergence between men’s and women’s distance travelled, as well as reductions in the distance travelled by younger age cohorts. Though car access and use have recently decreased in younger age cohorts in Sweden (Frändberg & Vilhelmson, 2011), they have increased among those who travel to work. The average distance commuted by car increased by 27% for men and 31% for women between 1995 and 2011. During the same period, the proportion of people who drive to work increased from 44% to 50% for women but remained relatively stable at approximately 64% for men (Gil Sola, 2013, pp. 112–114).[1] Vilhelmson (2005) explored the spatial characteristics of mobility trends in Sweden, comparing everyday mobility in built-up areas of different sizes in 1978 and 1996–

1997. Residents of smaller villages were found to travel the farthest; people in the largest cities travel 5–10 km per day less than do residents of smaller villages, while inhabitants of medium-sized towns had the smallest daily activity space. The study of changes in the Swedish population's accessibility to amenities between 1995 and 2005 by Haugen, Holm, Strömgren, Vilhelmson and Westin (2012) is of special interest in light of the aim of the present paper. In general, both travel distances and accessibility (proximity) were found to increase during the studied period. Mobility enables people to ignore location-bound factors such as proximity and instead choose more freely based on their own preferences. These results indicate that individual choice has become more important in recent decades in Sweden. Furthermore, urbanization continued throughout the study period in Sweden. In 1990, 83.4% of the population was living in built-up areas, compared with 85.1% in 2010 (SCB, 2010). Meanwhile, the proportion of Swedes living in the three largest urban regions increased from 31.4% to 35.6%.

Data

The data used here were extracted from the Geographical Individual Longitudinal Database for Analysis (GILDA) database, which comprises the Swedish official register of geocoded micro-data updated annually between 1990 and 2010. It contains data for every individual in Sweden and includes demographic and socio-economic variables such as education, income, family situation, and current employment. Individual geographical coordinates (within 100 × 100 meter cells) of residence and work allow for calculation of Euclidian home–work distances. This dataset is unique in many ways. It contains longitudinal data covering the total Swedish population, and is thus free from survey deficits such as sampling errors and incorrect answers and from spatial and temporal limitations. However, it is not a perfect match for the purposes of this study, principally since it does not include information about how workers actually travel to work. Hence, certain biases (Amcoff, 2009) may occur that need to be addressed. For example, there may be weekly commuters who reside in temporary housing nearer work during the week, and part-time workers such as students working during their holidays. These biases can produce large outliers (e.g. according to the register, some workers live hundreds of kilometers from their workplaces) that distort model outcomes. Since the interest here is in everyday commuting, two measures were adopted to minimize such biases.[2] First, workers registered as living more than 200 km from their workplaces were excluded, as these workers are likely not daily commuters. Second, annual wage income was used as a proxy to remove part-time workers by excluding the 10% of workers with the lowest income each year. Finally, to ensure that the models were robust in significance tests, a random sample of five percent of the total data was used for each year. This was also necessary due to computational power limitations when fitting multilevel models with several parameters.

Statistical modeling approach

The main rationales for applying multilevel modeling to measure travel behavior were presented in the literature review and have also been discussed by others (see e.g. Mercado & Páez, 2009; Pontes de Aquino & Timmermans, 2010; Snellen et al., 2002).

The simplest two-level model can be written as follows:

$$y_{ij} = \beta_{0j} + u_{0j} + e_{ij}$$
$$u_{0j} \sim N(0, \sigma_{u0}^2)$$
$$e_{ij} \sim N(0, \sigma_e^2)$$

This model is quite similar to a standard OLS regression model, though it allows for two levels within the data as individuals (*i*) are nested within residential areas (*j*). The departure from the mean home–work distance (y_{ij}) is split into two components, one residual for individuals (e_{ij}) and one residual for residential areas (u_{0j}). These are assumed to follow normal distributions, i.e. $u_{0j} \sim N(0, \sigma_{u0}^2)$ and $e_{ij} \sim N(0, \sigma_e^2)$. β_{0j} is the overall mean of the home–work distance. Hence, the mean home–work distance for workers within residential area *j* is β_{0j} + u_j and the residential area residual is the difference between the mean of area *j* and the grand mean across all *j*. The individual worker residual is the differences between the home–work distance of worker *i* and the mean home–work distance of that worker's residential area. Independent variables at both levels are later added based on the variable selection described in the next section. An independent variable at the worker level is denoted $\beta_{1j}X_{1ij}$ (the effect of variable *x* for worker *i* residing in area *j*). $\beta_{2j}X_{2j}$ denotes the effect of an independent variable *x* for area *j*. Independent variables were centered around their grand mean.

To test whether adding residential location and the independent variables has any significant effect, a likelihood ratio test is employed (see McCullagh & Nelder, 1989, as cited by Goldstein, 2011, pp. 40–41). This involves measuring the difference between the log-likelihoods of a single-level and a two-level model; the result is then compared to a chi-squared distribution with two degrees of freedom.

Furthermore, the total variance around the mean home–work distance of both residuals is divided into two components: the variance across residential areas (σ_{u0}^2) and the variance within residential areas (σ_e^2) (i.e. between workers). These values allow for estimation of the proportion of the total variance in home–work distance that is due to variations across areas by dividing the area variance by the total variance, i.e. the variance partition coefficient (VPC):

$$\text{VPC} = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_e^2}$$

VPC values are key estimates in deriving the significance of residential location for home–work distances, since they estimate the similarity of the home–work distances of individuals sharing a single residential neighborhood. If, for instance, all variance is derived from the residential area level, this implies that workers within one residential area have identical home–work distances. The variance components – combined with the independent variables – are also used to control for potential cross-level inferences (e.g. that the variance attributed to neighborhoods is instead due to the individual characteristics of residents within neighborhoods). If, for example, σ_{u0}^2 changes when X_{ij} is introduced, there are associations between the mean of X and Y within residential areas, implying that the distribution of X_{ij} is clustered to certain residential areas.

A more detailed explanation of multilevel modeling can be found in Goldstein (2011) or, in geographical research in particular, Jones (1991). MLwiN software (Rasbash, Charlton, Browne, Healy and Cameron, 2011) was used for all model estimations.

4 Selection and definition of variables and residential areas

Dependent variable

The Euclidian home–work distance is used as dependent variable, which in itself is not unproblematic. Since transportation networks are disproportionately distributed across space, different geographical distance constructions can result in different outcomes. Though network distance is not obtainable in this case, Euclidian distance has previously been found to be strongly correlated with actual travel distance or time using the road network.[3] There are also other potential biases associated with using network distance, since large proportions of the Swedish population use other means of transport than the car for their work trips.[4] Ideally, though, models explaining actual travel behavior, such as time and distance travelled or mode choice, should also be used. Previous studies in Sweden using National Travel

Surveys (e.g. Frändberg & Vilhelmson, 2011) and the same official register data used here (e.g. Eliasson, Westerlund & Åström, 2007; Swärdh, 2009), however, identify similar overall mobility trends over time. Considering the extensive data and that the main interest here is the macro trends, it is difficult to see that significant biases exist in overall trends.

Table 1 includes descriptive statistics for the dependent variable, home–work distance, for each year. A continuous trend of increasing home–work distances is evident throughout the studied period. The mean distance for the total population increased by 33.9% between 1990 and 2010.

TABLE 1

Like many other variables of spatial interaction, home–work distance is highly positively skewed. The empirical models used here assume the variables to be normally distributed around their means. Home–work distances were therefore transformed using natural logarithms to produce a normal distribution before running the models.

Individual independent variables

Variables were selected based on what previous research found to be important determinants of everyday commuting behavior in Sweden. Five independent variables were specified at the individual worker level: gender, income, education level, life course, and employment sector. Descriptive statistics and definitions can be found in Table 2.

TABLE 2

As in other countries, gender has been found to be an important aspect when analyzing commuting distance in Sweden (Gil Sola, 2013; Sandow, 2011). Due to the unequal division of unpaid work in the home and gendered labor markets in which women are overrepresented in low-paid sectors, men have been found to commute farther to work. In the Swedish context, income has been found to be positively related to commuting distance (Swärdh, 2009), as a higher salary provides a larger incentive to accept longer commutes. Income is also a proxy for car use, which is one of the most important explanatory factors.[5] Previous research demonstrated that, in Sweden, a higher education level makes workers more willing to commute longer distances (Öhman & Lindgren, 2003; Sandow, 2011). More highly educated workers are more specialized than are workers with less education; hence, those with higher education often have to search for jobs in a larger geographical area to find employment that matches their skills. For similar reasons, the employment sector has also been found to be an important determinant of commuting behavior (Öhman & Lindgren, 2003; Sandow, 2011). Finally, life course and household composition also affect the distance that workers can commute on a daily basis in various ways (Fransson, 1991; Öhman & Lindgren, 2003). For instance, a worker who resides with a partner and children is more spatially attached to their place of residence, as moving closer to work might result in the spouse having to change jobs or the children having to change schools. On the other hand, workers who live with their children also have less time to spend commuting to work. In Sweden, car access is also considerably lower among young adults than among middle-aged and older workers (Frändberg & Vilhelmson, 2011).

Residential area definition and independent variables

To compare locational and individual characteristics, the data need to be structured hierarchically; that is, workers must be situated in the spatial context of their residence.[6] This is a crucial process, since the relative significance of locational and individual aspects in the model relies on the precise definition of the spatial areas used. Kwan and Weber (2008), however, found relationships between locational and individual characteristics to be scale independent when using multilevel models. The high spatial resolution of these data also allows for testing of different area definitions. Several model variations were initially fitted to evaluate potential problems, administrative areas (i.e. municipalities, post-code areas, SAMS[7] areas, and parishes) and 1- and 5-km squares both being used. As expected, when using considerably larger areas (e.g. municipalities), the explained variance attributed to the area level decreased. Model results, however, were similar in terms of their development over time. Three-level models were also fitted, with region added as another level in the hierarchy, to further explore possible issues. The regional level, however, explained only a minor share of the variance already attributed to the residential-area level. Finally, models based on SAMS areas are presented. SAMS areas are standard statistical units commonly used in Swedish research and policy. A standard recommendation for handling possible biases due to area definitions (i.e. the modifiable areal unit problem) is to use areas that are theoretically meaningful for the analysis (Openshaw, 1984). In this case, such areas would be homogeneous in terms of the characteristics expected to influence home–work distances. The use of SAMS areas is appropriate since they, unlike administrative areas, were constructed by Statistics Sweden for the explicit purpose of representing homogeneous residential areas (SCB, 2005).

Three independent variables were specified at the residential area level[8]: the job-to-worker ratio (JWR), regional location, and a variable capturing whether or not the residential area is located in an urban area with >10,000 inhabitants (see Table 3 for further description). JWR captures the spatial balance of workers/housing and jobs, and is a proxy for geographical job accessibility. JWR has been found to be an important characteristic of the built environment in explaining commuting distance (Cervero, 1996). A JWR higher than 1 indicates higher job accessibility and is expected to result in shorter average commutes. Regional location, in terms of distance to the closest larger city center, was the main spatial variable in Næss's (2005) study of how residential location affects travel behavior. Næss noted that workers residing in areas located farther from the city center generally commute farther than do those living within or near the center. This effect also remained after controlling for individual effects. Likewise, workers living in a larger urban area are expected to commute shorter distances than those who do not.

TABLE 3

Analysis

This section presents and analyzes the results from running multilevel models. The first model (Model 1 in Table 4) is a one-level null model that measures only the variance around the mean home–work distance for all workers. This model is used to test whether adding the additional level of residential areas in Model 2 (Table 4) has any significant effect. The large reductions in deviance (–2 log-likelihood) when comparing models 2 and 1 indicates that adding the additional level has a highly significant effect; that is, there are statistically significant locational effects in all years. Having ensured statistical significance, the key statistics of interest here are the intercept variance values of Model 2. Hypothetically, if all variance were due to variations across residential areas (i.e. all workers living in each area have the same home–work distance), the intercept variance of the worker-level random part would be zero. However, the individual variance is considerably larger than the residential area level variance in all years, explaining more than 75% of the variance in home–work distance. Similar results are evident in most previous studies that applied multilevel models to similar inquiries, although a higher proportion of variance is attributed to the individual level in most studies. This may be explained by the considerably more diverse and larger study area of Sweden (in terms of land use and geography) compared with the areas studied in previous research.

TABLE 4

The VPC estimates, however, are not constant over time. The proportion of variance attributable to variations between residential areas decreased from 24.86% in 1990 to 18.47% in 2010. This implies growing variation in the home–work distance for workers who share residential location during the studied period. These results somewhat agree with the arguments of Kwan and Weber (2003) and Miller (2007). The distance people commute to work every day is reflected less in their residential location in 2010 than in 1990. However, there does not seem to be any strict linear relationship between increasing home–work distances overall and the declining importance of residential location. Although average home–work distances continued to increase between 2005 and 2010, only a very small increase in the proportion of variance was attributable to the individual-worker level during the same period. These results, however, need to be confirmed after controlling for individual effects. Hypothetically, if workers with similar individual characteristics live in the same residential area, the unexplained variance at the residential area level in Model 2 could be due to those workers' individual characteristics instead of the spatial characteristics of that residential area.

Independent variables at the individual-worker level were introduced in Model 3 (Table 5). The reduction in deviance between models 3 and 2 confirms that introducing worker-level variables significantly contributed to the ability to explain variations in home–work distances. Adding worker-level individual variables to the model also slightly reduced the worker-level variance in all models, while the variance at the residential area level did not change notably. The reduction in unexplained individual variance implies that the added variables help explain the variation in home–work distance among workers. However, the decrease is unexpectedly moderate, which suggests that the individual-level variables introduced only help explain a smaller part of the variance among individuals. The small decrease suggests that other more important individual effects (e.g. attitudes) are not picked up by the model. However, the trend of decreasing importance of residential location remained largely intact after the worker-level independent variables were introduced. Furthermore, since the unexplained variance at the residential area level has not changed notably, there are no significant biases in the VPC estimates in Model 2 due to spatial clustering of the workers' individual characteristics controlled for.

TABLE 5

An interesting observation is that most individual variables remain consistent over time in terms of their direction and the proportions of variation in home–work distance they explain, but with some variations in strength. Second, men commute farther than do women in all years studied. There are, however, signs of convergence throughout the studied period similar to the observations of Frändberg and Vilhelmson (2011), as women increased their home–work distance at a faster rate than did men. Somewhat unexpectedly, there was a negative effect that grew stronger over time comparing workers in the second income quintile with those in the lowest quintile. One explanation could be the housing market and the gentrification processes evident in the largest Swedish cities, where low-income groups cannot afford to live in centrally located housing and are forced to move to the semi-periphery of the city (Elldér, Gil Sola & Larsson, 2012). However, and as expected, workers in the upper income quintiles commute significantly farther than do low-income workers.

Variations in commuting distance due to education level are also consistent with those found in previous research, and in all years being more educated has a significant positive effect. The difference between workers with three or more years of higher education and workers with the least education, however, increased between 1990 and 2010. One reason could be that the labor market has become more knowledge intensive and that highly educated workers are more specialized, and therefore have to search for jobs in a larger geographical area. This factor could also help explain the trend of decreasing importance of residential location.

There are significant effects due to worker phase of life, but no apparent trends over time. In most years, workers younger than 45 years and single, or who reside with a partner or their parents, are more likely to commute longer distances than are workers who reside with a partner and children. On the other hand, workers living with a partner and children generally commute less than do those who are single but living with children or those who are 45 years or older and not living with children. The branch of industry in which the worker is employed is also a significant factor in explaining the variance in home–work distance. Workers employed in the second knowledge-intensive service category (e.g. in education, public administration, health care, and social services) are more likely to commute shorter distances than are those in all other sectors (besides those employed in capital-intensive industries). These effects did not, however, display any particular trend over time.

Independent variables at the residential area level were introduced in the fourth model (table 6). Again, comparing models 4 and 3, there is a large reduction in deviance, which indicates that the spatial variables contributed significantly to explaining home–work distances. The individual variable estimates as well as the unexplained variance at the worker level did not change notably; that is, there are no substantial interaction effects between independent variables at the residential area level and worker level. Adding area-level variables, however, considerably lowered the area-level variance. The area-level variance is 0.470–0.364 in Model 3 compared with 0.229–0.141 in Model 4. This large reduction implies that the explanatory variables specified at the area level contributed greatly to explaining the variance in home–work distance. Although the area-level variance is more than halved in Model 4, the trend of the diminishing importance of residential location is as evident as in the previous models. Between 1990 and 2010 the area-level variance decreased from 13.56% to 8.55% in Model 4.

TABLE 6

The estimates of the spatial variables are also consistent with previous research. The job-to-worker ratio had a strong negative effect of in all years. Workers living in areas with more jobs than workers are more likely to commute a shorter distance to work than are workers living in areas dominated by housing. As expected, regional location also has positive effects when comparing workers who do not reside in cities with over 10,000 inhabitants with workers who do. Workers living farther from their regional employment center and in more densely populated areas generally travel farther to work. The spatial variables displayed no particular trends over time in terms of strength or explained variance.

Concluding discussion

This paper set out to investigate trends in the significance of residential location for home–work distances in Sweden between 1990 and 2010. The VPC outcomes indicate growing variation in the home–work distance for workers who lived in the same residential neighborhood during the studied period. In 1990, 24.86% of the variance was attributable to variations across areas compared with only 18.47% in 2010. These results are interesting in relation to previous research for two main reasons. First, the individual-level variance is low compared with that found elsewhere. One explanation is that most previous studies were based on single metropolitan areas that are largely geographically homogeneous and generally include a greater choice of possible job locations than does the nationwide Swedish case, which also includes small towns and sparsely populated areas. Second, the results suggest that the relative importance of residential location for the home–work distance has decreased throughout the studied period. Most previous studies of the relationships between individuals, locations, and travel behavior did not measure possible variations over time. Results indicate that such relationships could indeed change over a few years, which has possible implications for planning and policy. For example, the results suggest that there may have been less scope for shaping commuting behavior by altering the built environment during the studied period in Sweden. This would mean that the volume of commuting is difficult to influence by spatial planning measures alone as long as individual mobility capacities (e.g. car access and use) are increasing. Hence, strategies promoting compacter and denser city regions, in order to reduce congestion and promote sustainability, are likely to be necessary though insufficient measures to reduce travel distances. Another contrasting possibility in the Swedish case is that planning and policy measures themselves may have contributed to the increasing and more spatially heterogeneous home–work distances. Transport planning in recent decades in Sweden has focused strongly on regional enlargement strategies, and large infrastructure investments have been made to create larger functional labor markets to increase economic growth potential (Amcoff, 2009).

Furthermore, the effects of individual and spatial variables were essentially as expected. The spatial variables explained much of the variation in the home–work distance and were robust over time. Except for gender, which displayed signs of convergence, most of the individual effects did not change notably over time either. Much of the individual-level variance also remained unexplained throughout the studied period, in contrast to the hypothesis that the individual variables would explain more of the variation in home–work distance over time as the variance attributed to the worker level increased. This was not the case here, however. Other individual effects (e.g. attitudes and lifestyles) not captured by register data could underlie this. People can use their increasing mobility to fulfill their own needs and wishes. The decrease in VPC, however, is in line with the theoretical suggestions of Kwan and Weber (2003) and Miller (2007): as the average distance travelled to work increases, a concurrent trend of decreasing importance of residential location is evident. Residential location, however, still plays a crucial role in shaping everyday commutes and is also likely to do so in the future. This is true not only because the trend leveled out over the last five-year period, but also in light of the saturation of everyday travel noted recently in several countries (Metz, 2010), including Sweden (Frändberg & Vilhelmson, 2011). However, future research has the important task of empirically explaining in greater detail the decreasing importance of residential location in order to improve predictions of future trends. For instance, in the case of commuting, Green et al. (1999) discussed the restructuring of the labor market as an important contributor. Another possible contributor is the continuing urbanization in Sweden: more people living in large urban regions with better overall job accessibility (i.e. more possible job locations to choose from) combined with increasing mobility could be expected to generate increasingly more spatially diverse commuting.

A key limitation of this study is that it measures the physical home–work distance instead of actual trip length. Although overall trends of increasing home–work distances and variations due to individual variables are similar to those found by other studies based on the Swedish National Travel Survey, it is important that further research confirm these findings using behavioral data. Work trips involve several other key policy aspects (e.g. mode choice and vehicle miles travelled) that are not fully captured by Euclidian distance. Furthermore, there is also the possibility that the relationship between Euclidian distance and actual distance travelled does not remain constant when travel distances increase; for example, greater home–work distances generally include more detours (e.g. for grocery shopping) (McGuckin, Zmud & Nakamoto, 2005). Since the mean distance to work increased over the study period, this could have resulted in more complex work trips (more closely related to individual needs) not captured by the Euclidian distances. Another important issue for future research is to apply more complex multilevel models to make more robust comparisons of the effects of independent variables over time. Multilevel models can be used to analyze repeated-measures data and extended to include interactions between time and specific independent variables (Goldstein, 2011). Furthermore, location has here been reduced to residential location, though workplace location has also been found to be important (Shuttleworth & Gould, 2011). Though initial model testing identified residential location as more important in the nationwide Swedish context, there are possible settings where the workplace end might be more significant. For example, in sparsely populated areas where access to everyday destinations is poor, the location of the workplace in relation to services might be more important. Specifying cross-classified multilevel models in which workers are nested in both residential and workplace areas would also be an interesting task for future studies. This study is also limited to workers and work trips, whereas trips related to non-work activities constitute an increasing share of Swedes' daily travel (Frändberg & Vilhelmson, 2011). Studies of the Swedish case indicate large variations in the extent to which residential location influences daily distance travelled when travel purposes are differentiated (Elldér, 2014).

In a sense, this study has only scratched the surface of the increasingly complex relationships between individuals, locations, and spatial behavior. The relatively small decrease in unexplained variance at the worker level after introducing independent variables testifies to the presumably large number of confounding individual effects not captured here. The central conclusion is that locations are evidently more individually dynamic now in terms of distance travelled to work than they were in the early nineties. Miller's (2007) warning of the growing risk of "place-based fallacies" is thus important for scholars and policymakers to heed.

Notes

[1] The author has complemented Gil Sola's (2013) findings with calculations from the Swedish National Travel Survey 2011.

[2] Sandow (2011) and Swärdh (2009) are examples of studies that apply similar measures.

[3] Apparicio, Abdelmajid, Riva and Shearmur (2008) compared differences in results regarding geographical accessibility to health care services computed using various distance types, including Euclidian distance. All four distance constructs were strongly correlated with each other, but with some local variations in more densely populated suburban areas. In a similar study, Sparks, Bania and Leete (2011) found that Euclidean distances were generally 35–38% larger than street network distances, though highly correlated with them. In a Swedish context, Reneland (1998) found that the Euclidian distance can be multiplied by 1.3 to produce the network distance.

[4] 39 %, according to the Swedish National Travel Survey, 2005–2006 (SIKA, 2007).

[5] Unfortunately, neither car ownership nor possessing a driving license is included in the dataset.

[6] Since work location was earlier also found to influence the home–work distance (Shuttleworth & Gould, 2011), models were initially tested with workers nested in workplace areas. The results suggested that the workplace end also provided a source of variation in the home–work distance, but indicated residential location to be the main source. Furthermore, trends in workplace VPCs over time were similar to the VPCs from residential neighborhoods.

[7] Small area market statistics (SAMS) areas are based on classifications made by Statistics Sweden; there are 9200 SAMS areas in Sweden with an average of approximately 1000 inhabitants each.

[8] Several variables at the residential location level were initially tested. The final setup of variables presented in the models is the one that explained the most variation in home–work distance. Previously found important variables, such as various population density measures, were not significant after controlling for the present variables.

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Table 1. Descriptive Statistics for the Dependent Variable Home–Work Distance.

	1990	**1995**	**2000**	**2005**	**2010**
n	144,741	140,531	160,569	167,669	171,859
Mean (KM)	10.68	11.41	12.44	13.22	14.34
Std. deviation	18.28	18.93	20.47	21.31	23.18
Mean (lnKM)	1.52	1.59	1.68	1.74	1.82
Std. deviation	1.36	1.36	1.37	1.37	1.37

Table 2. Description of Independent Variables at the Individual Worker Level (Numbers Describe Frequencies in Percent).

Variable	**Description**	**1990**	**1995**	**2000**	**2005**	**2010**
Gender						
Male		51.4	51.6	52.3	52.0	51.5
Female		48.6	48.4	47.7	48.0	48.5
Income	Annual wage income					
Lower quintile	Lowest paid quintile	20.0	20.0	20.0	20.0	20.0
2nd quintile		20.0	20.0	20.0	20.0	20.0
3rd quintile		20.0	20.0	20.0	20.0	20.0
4th quintile		20.0	20.0	20.0	20.0	20.0
Upper quintile	Highest paid quintile	20.0	20.0	20.0	20.0	20.0
Education						
<Upper secondary school	No diploma from upper secondary school	62.0	55.7	47.5	40.9	34.8
Upper secondary school	Diploma from upper secondary school	13.3	14.7	19.5	22.1	24.2
<3 years higher education	Higher education, less than three years	12.7	15.5	14.6	14.8	14.9
≥3 years higher education	Higher education, three years or more	12.0	14.2	18.0	21.9	25.6
Life course						
Partner, ≤45 years old	45 years old or younger and living with a partner but no children	4.8	3.7	2.9	2.6	2.9
Partner, >45 years old	Older than 45 years and living with a partner but no children	18.1	20.6	19.8	20.2	20.0
Partner and children	Living with a partner and at least one child younger than 18 years old	35.4	35.8	34.2	34.1	34.0
Single, ≤45 years old	45 years old or younger, no registered partner or children	21.6	20.6	22.4	21.0	20.1
Single, >45 years old	Older than 45 years, no registered partner or children	8.3	10.3	11.2	12.4	13.6
Single with children	No registered partner and living with at least one child younger than 18 years old	4.0	4.3	4.7	4.9	4.5
Residing with parent	Residing with at least one parent	7.9	4.6	4.7	4.7	5.0
Branch of industry[a]						
Knowledge-intensive industry	e.g. manufacturing of chemicals and electronic devices	11.6	11.7	11.3	9.6	8.5
Capital-intensive industry	e.g. manufacturing of refined petroleum, paper products, and metals	2.1	2.4	2.3	2.2	1.8
Labor-intensive industry	e.g. manufacturing of food, textiles, and plastic	8.6	7.8	7.7	7.1	5.9
Knowledge-intensive services 1	e.g. financial activities, research and development, and business services	8.8	9.7	12.5	11.7	13.6
Knowledge-intensive services 2	e.g. education, public administration, health care, and social services	35.4	37.5	36.4	38.3	38.3
Capital-intensive services	e.g. logistics and real estate	9.4	8.8	8.4	8.2	8.0
Labor-intensive services	e.g. construction, hotels, restaurants, and retail	21.8	19.8	19.7	21.0	22.1
Capital-intensive, other	e.g. agriculture, fishing, mining, electricity, gas, and water supply	2.2	2.1	1.7	1.8	1.8

[a] The classification, developed by the Swedish Agency for Economic and Regional Growth (NUTEK, 2000), is carried out in two steps. First, all capital-intensive sectors are identified by selecting those sectors in which the relative consumption of the fixed-capital share of value-added at factor cost is at least 25%. Second, knowledge-intensive sectors, if not already identified as capital intensive, are identified. A knowledge-intensive industry is here defined as an industry in which employees with three or more years of higher education constitute more than 5% of the workforce; remaining sectors are categorized as labor intensive.

Table 3. Description of Independent Variables at Residential Area Level (Mean and Standard Deviation for Continuous Variables and Frequencies for Categorical Variables).

Variable	**Description**	**1990**	**1995**	**2000**	**2005**	**2010**
Job-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 center point.	1.05 (0.37)	1.04 (0.35)	1.04 (0.34)	1.04 (0.33)	1.04 (0.33)
Regional location	The natural logarithm of the Euclidian distance 10 km from each area center point to the center point of the largest city in the central municipality of the local labour market region (LA-region[a]) the area falls within.	2.11 (1.31)	2.15 (1.30)	2.15 (1.31)	2.14 (1.31)	2.12 (1.31)
Urban area (year 2000 version)						
Urban area, pop. >10,000	The area's center point is located in a city with over 10,000 inhabitants.	41.7%	43.7%	43.2%	43.4%	42.4%
Not within an urban area, pop. >10,000	The area's center point is not located in a city with over 10,000 inhabitants	58.3%	56.3%	56.8%	56.6%	57.6%

[a] Swedish official functional regions based on commuting flows between municipalities (1998 version).

Table 4. Models 1 and 2.

	1990	1995	2000	2005	2010
Model 1					
B_0 (intercept)	1.519	1.593	1.676	1.739	1.816
–2 log-likelihood	499371.656	485401.397	556287.893	582217.958	596396.518
Worker-level random part					
Intercept variance, σ_e^2	1.845	1.852	1.871	1.886	1.882
Model 2					
B_0 (intercept)	1.658	1.703	1.776	1.839	1.913
–2 log-likelihood	476446.890	466696.895	536693.995	563276.437	576998.686
Residential-area-level random part					
Intercept variance, σ_{u0}^2	0.476	0.418	0.381	0.360	0.355
VPC residential area	24.86%	21.93%	19.89%	18.67%	18.47%
Worker-level random part					
Intercept variance, σ_e^2	1.439	1.488	1.535	1.568	1.567

Table 5. Model 3.

	1990	1995	2000	2005	2010
Individual-level fixed part					
Gender (ref = Male)					
Female	–0.224**	–0.197**	–0.180**	–0.177**	–0.174**
Income (ref = Lower quintile)					
2nd quintile	–0.001	–0.021*	–0.020*	–0.048**	–0.050**
3rd quintile	0.017	0.025*	0.051**	0.014	–0.014
4th quintile	0.138**	0.085**	0.134**	0.132**	0.106**
Upper quintile	0.213**	0.236**	0.267**	0.250**	0.236**
Education (ref = <Upper secondary school)					
Upper secondary school	0.118**	0.108**	0.104**	0.084**	0.086**
<3 years higher education	0.155**	0.166**	0.149**	0.165**	0.148**
≥3 years higher education	0.161**	0.185**	0.221**	0.263**	0.247**
Life course (ref = Partner and children)					
Partner, ≤45 years old	0.073**	0.051**	0.055**	0.096**	0.049**
Partner, >45 years old	–0.152**	–0.123**	–0.076**	–0.069**	–0.078**
Single, ≤45 years old	0.046**	0.025*	0.023**	0.042**	0.014
Single, >45 years old	–0.085**	–0.073**	–0.038**	–0.037**	–0.058**
Single and children	–0.020	–0.067**	–0.069**	–0.071**	–0.072**
Residing with parent	0.180**	0.132**	0.158**	0.114**	0.103**
Branch of industry (ref = Knowledge-intensive services 2)					
Knowledge-intensive industry	0.172**	0.185**	0.174**	0.212**	0.183**
Capital-intensive industry	–0.066**	–0.048*	–0.019	–0.031	–0.032
Labour-intensive industry	0.022	0.034*	0.057**	0.099**	0.056**
Knowledge-intensive services 1	0.286**	0.269**	0.297**	0.290**	0.257**
Capital-intensive services	0.171**	0.256**	0.332**	0.342**	0.309**
Labour-intensive services	0.174**	0.196**	0.228**	0.230**	0.212**
Capital-intensive, other	0.198**	0.170**	0.186**	0.282**	0.296**
Model statistics					
B_0 (intercept)	1.552	1.586	1.582	1.634	1.740
–2 log-likelihood	470078.897	461087.705	528083.782	554341.623	568158.938
Residential-area-level random part					
Intercept variance, σ_{u0}^2	0.470	0.416	0.387	0.372	0.364
VPC residential area	25.42%	22.55%	20.82%	19.87%	19.42%
Worker-level random part					
Intercept variance, σ_e^2	1.379	1.429	1.472	1.500	1.510

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

Table 6. Model 4.

	1990	1995	2000	2005	2010
Residential-area-level fixed part					
Job-to-worker ratio	–0.404**	–0.515**	–0.467**	–0.539**	–0.435**
Regional location	0.197**	0.170**	0.179**	0.171**	0.181**
Urban area (ref= Urban area, pop. >10,000)					
Not within urban area, pop. >10,000	0.388**	0.332**	0.349**	0.344**	0.373**
Individual-level fixed part					
Gender (ref = Male)					
Female	–0.219**	–0.192**	–0.176**	–0.173**	–0.174**
Income (ref = Lower quintile)					
2nd quintile	–0.002	–0.020*	–0.020*	–0.050**	–0.054**
3rd quintile	0.018*	0.029**	0.053**	0.014	–0.014
4th quintile	0.141**	0.093**	0.140**	0.135**	0.106**
Upper quintile	0.221**	0.250**	0.281**	0.264**	0.245**
Education (ref = <Upper secondary school)					
Upper secondary school	0.133**	0.122**	0.116**	0.094**	0.092**
<3 years higher education	0.174**	0.185**	0.168**	0.187**	0.169**
≥3 years higher education	0.186**	0.212**	0.250**	0.294**	0.275**
Life course (ref = Partner and children)					
Partner, ≤45 years old	0.081**	0.064**	0.066**	0.114**	0.063**
Partner, >45 years old	–0.142**	–0.120**	–0.077**	–0.071**	–0.082**
Single, ≤45 years old	0.071**	0.055**	0.052**	0.070**	0.040**
Single, >45 years old	–0.063**	–0.049**	–0.021*	–0.022*	–0.047**
Single and children	–0.007	–0.052**	–0.057**	–0.061**	–0.063**
Residing with parent	0.182**	0.131**	0.158**	0.111**	0.106**
Branch of industry (ref = Knowledge-intensive services 2)					
Knowledge-intensive industry	0.177**	0.190**	0.175**	0.213**	0.181**
Capital-intensive industry	–0.097**	–0.080**	–0.053*	–0.065**	–0.066**
Labour-intensive industry	–0.003	0.007	0.025	0.068**	0.021
Knowledge-intensive services 1	0.306**	0.286**	0.315**	0.308**	0.273**
Capital-intensive services	0.182**	0.269**	0.342**	0.354**	0.316**
Labour-intensive services	0.180**	0.203**	0.235**	0.237**	0.215**
Capital-intensive, other	0.162**	0.135**	0.147**	0.245**	0.255**
Model statistics					
B_0 (intercept)	1.248	1.319	1.308	1.359	1.460
–2 log-likelihood	465833.943	456964.910	523474.401	549249.778	563097.177
Residential-area-level random part					
Intercept variance, σ^2_{u0}	0.229	0.203	0.172	0.150	0.141
VPC residential area	13.56%	12.45%	10.48%	9.10%	8.55%
Worker-level random part					
Intercept variance, σ^2_{e}	1.376	1.427	1.469	1.498	1.509

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