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The impact of metropolitan structure on commute behavior in the Netherlands

a multilevel approach

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Abstract

This paper investigates the impact of metropolitan structure on commute behavior of urban residents in the Netherlands. It not only analyzes the impact of mono- versus polycentrism, but also looks at the influence of metropolitan density and size as well as the ratio of employment to population and growth of the population and employment. Further, it uses data at a variety of levels ranging from the individual worker to the metropolitan region instead of drawing on aggregate-level statistics only. Multilevel regression modeling is applied to take account of the interdependencies among these levels of aggregation. Regarding mode choice, the results indicate that the probability of commuting as a car driver is lower in employment-rich metropolitan regions and higher as the number of jobs per resident has grown. Further, women in most polycentric regions are less likely to commute as a car driver. Commute distances and times for car drivers are, ceteris paribus, larger in most polycentric regions than they are in monocentric urban areas. In addition, commute time as a car driver rises with metropolitan size, whereas distance depends on employment density and growth of the number of jobs per resident. Our analysis does not support the claim that car dependence is higher in polycentric regions, a result that may be related to historic urbanization patterns and the extensive regulation of the land and housing markets in the Netherlands. On the other hand, metropolitan structure explains only a small part of the variation in commute behavior.

Keywords:

commuting, metropolitan structure, polycentrism, car use, multilevel models, the Netherlands

1. Introduction

The role of the automobile in shaping current metropolitan settlement patterns is well recognized. Along with rising affluence and structural economic changes, such as de-industrialization, the increase in auto ownership after World War II was one of the major forces in the deconcentration of land uses (Anas *et al*., 1998). In both the USA and Western Europe metropolitan settlement patterns have changed from *monocentric* – a situation with a concentration of most functions in the urban core with residences clustered around this core in declining densities – to *polycentric*. In such regions urban functions have decentralized from the core area across urban space, many of which relocated to suburban nodes of development or edge cities (Forstall and Greene, 1997).

Notwithstanding this acknowledgment, the literature about the impact of polycentrism on commuting by private car is not unequivocal. Consider commute time, for example. Some US researchers have found that car commute times tend to be lower in polycentric than in monocentric metropolitan regions (e.g. Gordon *et al*., 1991). In a way this makes sense, because the rise of polycentric urban areas is at least partly the result of households' and firms' preference for less congested locations. Others have, however, questioned this (e.g. Cervero and Wu, 1998). Regarding mode choice, many studies found that a development towards polycentrism was accompanied by a decline in the importance of mass transit and bicycling and walking (Schwanen *et al*., 2001). Again, this is hardly surprising, since the rise of polycentrism is due to increased auto ownership. Nevertheless, some empirical investigations suggest that polycentrism need not by definition result in larger auto dependence. In addition, the evidence about the effect of polycentrism on mode choice is rather fragmentary; few systematic analyses have been carried out that rigorously compare mode choice across metropolitan regions.

Although previous work has made a substantial contribution to the understanding of variation in commute patterns, several gaps in the existing literature can be identified. For example, most investigations of commute time or distance draw from US data; evidence from European contexts is scarcer. In addition, researchers have easily attributed variations in commute patterns to changes or differences in the spatial distribution of employment relative to residences, that is, whether a metropolitan region has a mono- or polycentric character. Despite their potential importance to commuting, other factors that may differ among regions, such as differences in prosperity and employment growth, have often not been taken into account. Moreover, many previous papers relied on aggregate-level statistics and do not account for micro-level variation in commute behavior.

This paper compares commute patterns of workers in 26 urban areas in the Netherlands. Using data from the 1998 Netherlands National Travel Survey, we try to explain differences in commute behavior among metropolitan regions by linking them not only to a classification of mono- and polycentric structures but also to a range of other variables at the metropolitan level. Examples are the number of jobs per hectare or per inhabitant and developments in the number of jobs during the boom period of the second half of the 1990s. In addition, we make use of travel data and explanatory variables at more than one level of aggregation. Instead of using metropolitan-wide statistics, we also incorporate data at the level of the individual worker, the household and the residential zone within the metropolitan region. Multilevel regression modeling is applied to account the fact that explanatory variables are measured at various levels of aggregation.

The remainder of the paper starts with a brief discussion of the existing literature about the impact of polycentrism on commute behavior. Section 3 describes the data and research methods used for the empirical analysis. The results for the analysis of mode choice are presented in section 4, and those pertaining to commute distance and time in section 5. The last section concludes the paper.

2. Study background

In the literature about the impact of metropolitan structure on commuting a central position is taken by the *co-location hypothesis*, originally formulated by Peter Gordon and colleagues (e.g. Gordon and Wong, 1985; Gordon *et al*., 1989a, 1989b, 1991). They argue that individual households seek ways to avoid the time penalties caused by the extensive congestion in monocentric urban areas by periodically changing their workplace or residence. This allows them to travel shorter distances and/or to make use of less congested routes. Employers also attempt to escape the disadvantages of high-density locations – traffic congestion, poor accessibility to the suburban labor force, high land prices and limited opportunities for spatial extension – and find new locations in less-congested areas. In the aggregate, the result is a dispersal of activities across urban space and the rise of polycentric urban areas with lower average commute times. Thus, when workers are assumed to minimize travel time, it can be expected that commute times tend to lower in polycentric than in monocentric areas. The same may be true for commute distance.[1] A series of empirical studies have been published that support these notions, for example Gordon *et al.* (1989a, 1989b and 1991) and Levinson and Kumar (1994). Schwanen *et al*. (2001, 2002a and 2002b) provide a detailed description of this literature.

Yet, other empirical studies have drawn opposite conclusions. Cervero and Wu (1998), for instance, indicated that in the San Francisco Bay Area commute times and distances have risen after an increase in the degree of polycentrism. Several phenomena may account for the longer commute in polycentric regions. Constraints on spatial choice behavior may prevent a minimization of commute time or distance. Examples are the presence of multiple workers in a household (Clark *et al*., 2002; Giulano and Small, 1993), lags in housing developments near suburban employment concentrations (Cervero and Wu, 1997), or zoning measures to create green belts around urban nodes (Jun and Bae, 2000). Further, the mechanisms underlying the co-location may not be valid for all people at all times. Salomon and Mokhtarian (1997) point out that employment or residential relocation may serve as means for households to escape congestion, but often function as last resorts when other strategies have proven inadequate. The reason for this is that the costs for of changing job and particularly the place of residence are quite large, not only for the workers themselves but also for other household members. In addition, the assumption of travel minimization may be challenged; traveling has an intrinsic value of its own (Mokhtarian and Salomon, 2001).

A transition from monocentrism to polycentrism may also affect mode choice. A shift from transit use to solo driving has been observed in many spatial contexts (Schwanen *et al*., 2001). The spatially diffuse commute patterns that characterize polycentric urban areas make it more difficult for transit providers to compete with the ubiquity of the private car. Only with massive investments in public transportation networks or when the decentralization of land

[1] In this case, the relationship is less straightforward. If travel speeds have risen because of less congestion or a change in commute mode choice, commute distance may have become larger even when commute time has decreased.

uses can be channeled along public transport infrastructure might this impact of decentralization be offset, as the advocates of strong planning interference like to make us believe (e.g. Newman and Kenworthy, 2000). Bolotte (1991) provides some empirical support for this. He showed that, in the Paris region, the market share of public transit remained at a stable level of 31% in the period 1971-1989. In addition, Schwanen *et al.* (2001) found that in some polycentric regions in the Netherlands the use of public transport as well as walking and bicycling is relatively high, whereas the opposite was true for other polycentric regions. Thus, polycentrism may not always be associated with larger car dependence.

This short review of previous empirical studies serves to illustrate that the effects of metropolitan structure on commute behavior are not undisputed. Drawing conclusions about the impact of metropolitan structure on basis of previous empirical work is, however, not without problems for at least two reasons: the role of many potentially important explanatory factors has often been neglected and the application of different research methods.

Previously, researchers have been confident to relate differences in metropolitan commute patterns across time and space merely to changes or variation in the distribution of employment relative to that of the population. Thus, much earlier work – including our own – has limited the influence of metropolitan structure on commuting to the impact of mono- and polycentrism; it has sometimes downplayed or even ignored the role of other dimensions of metropolitan spatial structure. This seems a little surprising given that, among others, the literature on excess commuting[2] has long asserted that observed commute behavior cannot be explained by the distribution of housing and jobs alone (Giuliano and Small, 1993; Scott *et al.*, 1997). Of course, there are some exceptions. Gordon *et al.* (1989a), for example, analyze the impact of factors such as metropolitan size and density on commute times in addition to the effect of the degree of polycentrism. However, their analysis is limited to commute time and does not consider commute distance or mode choice.

Having asserted that the difference between mono- and polycentrism is not the only relevant factor, we now turn to a brief discussion of other differences among metropolitan regions that should be considered. Metropolitan-wide *population and employment densities* may be a first potentially important dimension of metropolitan structure. Higher densities can be expected to be associated with lower car use and shorter commute distances (e.g. Newman and Kenworthy, 2000). Because higher densities also lead to higher levels of congestion, the effect on commute time is questionable (Levinson and Kumar, 1997). The *size of a metropolitan area* may also be relevant. Although some US research found little or no effect of metropolitan size on commute distance or time (Gordon *et al.*, 1989b; Levinson and Kumar, 1997), some evidence exists that, in Europe, average commute distance or time rises as urban areas become larger (Coombes and Raybould, 2001; Schwanen, 2002).

Some factors that are less directly related to the spatial location of employment and population should also be taken into account. For example, the *ratio of total employment to the labor force* in an urban area may be important. If the number of jobs per worker is low competition for employment is fierce. If workers seek for employment from their homes, it may be harder for them to find a suitable job near their residential location (e.g. Levinson,

[2] The term excess or wasteful commuting has been used to denote the difference between the average *observed* commute for a metropolitan area and the average required commute that would result from travel-minimizing behavior given the spatial distribution of residential and employment locations (e.g. Scott *et al.*, 1997). Estimates of the amount of excess commuting vary widely depending on the method used and characteristics of the metropolitan region considered (Buliung and Kanaroglou, 2002).

1998). In the aggregate, this may result in a larger average commute distance and time and, related to this, lower shares of the bicycle and walking in the mode split for commuting.

Cross-sectional comparisons of metropolitan commute patterns should also attempt to incorporate some of the *dynamics over time in the number of workers and employment* in urban areas. Of course, the relative distributions of employment and population at a single point in time are the spatial outcomes of such developments. In the short term, however, disequilibria may occur between residential and employment locations. Firms and households do not immediately respond to changes in their environment, which is, among others, due to the high costs of relocation. When individual households have not yet balanced residential and employment locations, they may experience longer commute times or distances than they prefer. During the second half of the 1990s, such a disequilibrium situation may have existed for many households in the Netherlands. The economy was booming and net incomes rose for all segments of the population. Particularly the 'new' economic sectors grew, such as business and financial services and companies in information and communication technologies. Many but not all firms belonging to these sectors have a preference for locations on the urban fringe or along highways that are highly accessible by private car (e.g. Atzema, 2001). As a result, a further decentralization of employment took place. Since these economic sectors are relatively overrepresented in regions located in the northern part of the Randstad Holland, such as Amsterdam, Utrecht and Amersfoort (Lambooy, 1998), we may expect the impact of employment growth to be relatively large in these regions.

A second difficulty with previous empirical studies that compared metropolitan commute patterns across time or space is that they have applied different research methodologies. Many researchers have relied solely on aggregate data for comparing commute patterns taking some spatial unit as the unit of analysis. Yet, disaggregate data at the individual worker level ought to be used to account for worker heterogeneity and because it is the individual who acts instead of some spatial unit. To reflect that an individual's opportunities for behavior depend, among others, on his or her socioeconomic position and role within the household, such personal and household attributes should be incorporated in the analysis.[3] Moreover, when analyzing the role of variables at the metropolitan level, we should also pay attention to locational characteristics at lower geographical levels. Many studies have addressed the reasons for *intra*-urban variations in commute behavior and have shown that local residential density and distance to the CBD or suburban employment centers are important variables that explain differences in commuting within metropolitan areas (e.g. Levinson, 1998; Levinson and Kumar, 1997; Shen, 2000; Wang, 2000). Thus, to take account of the fact that the influence of the urban context on commuting is not restricted to a single geographical level, we should link spatial variables at multiple geographical scales to commute patterns. As a result, we can conceptualize commute behavior as being influences by characteristics of workers, their households, their residential environment and the DUS they live in. The interdependencies among these levels of analysis can be handled with multilevel statistical models (see below).

The analysis of commute behavior in Netherlands urban areas presented in this paper attempts to address the issues raised so far. Rather than limiting metropolitan structure to the distribution of employment relative to population, that is, differences between mono- and polycentric structures, we examine the role of a range of factors that differ between metropolitan regions. In particular, the paper focuses on the impact of metropolitan-wide

[3] Recent reviews of the literature about the impact of personal and household attributes on commute behavior are presented, for example, in McQuaid and Greig (2001), Schwanen *et al.* (2002b); Stead *et al.* (2000).

employment and population densities, metropolitan size, the ratio of jobs to residents and population and employment growth in addition to the effect of polycentrism. This is done not only for commute distance and time, but also for commute mode choice. Further, we use data at the individual-worker level data derived from the 1998 Netherlands National Travel Survey instead of metropolitan-wide or zonal averages and incorporate characteristics of individuals, households and residential zones in the analysis. It is assumed that the behavior of individuals depends on characteristics of the worker, her/his household, the residential zone within the urban area, and the DUS in which s/he resides (Table 1). We use multilevel regression techniques to deal with the interdependencies and violations of assumptions underlying conventional regression modeling this conceptualization creates. The next section describes the data set and presents some basic information about multilevel modeling.

3. Research design

3.1 Data

The 1998 Netherlands National Travel Survey (NTS) is used for the empirical analysis. Initiated in 1978, this survey is a continuous inquiry into the travel behavior of Dutch households. Every year, approximately 70,000 households are asked to participate in the survey. It yields data on the travel behavior of some 130,000 individuals including children over the age of four. Respondents are asked to provide information about personal and household attributes as well as to complete a trip diary for a single day. For each trip undertaken, they have to report the purpose, the mode chosen, the distance traveled, the start and end time, and the origin and destination (Statistics Netherlands, 1999).

Heads of households and their partners if present, residing in one of the 26 metropolitan regions and making at least one commute trip on the day of inquiry were selected for the empirical analysis. Only individuals whose out-of-home activity pattern starts and ends at the home location have been included in the analysis. Further, for all commute trips in the activity pattern the main travel mode and the distance covered should be known. In total, data from 14,590 workers have been used in the empirical analysis. Based on the information they reported we have constructed three commute variables. For all 14,590 workers, a binary *commute mode choice* variable has been created that distinguishes between those who used the car-driver mode to commute and those who commuted by any other means of transport. 7,996 persons (54.8%) indicated they made at least one commute trip as a car driver. For the7,996 car drivers, we have summed up the distance they traveled and the time they spent for all their commute trips and created the variables total daily commute *distance and time as a car driver*. The analysis of commute distance and time is limited to car drivers to control for the confounding effects of mode choice and because much of the literature and US studies in particular focus on car travel.

The NTS provides information about a range of personal and household attributes, which has been used to create a set of variables at the individual-worker and household level to be considered in the empirical analysis (Table 1). A variable indicating the municipality of residence is also available; this has been used as a proxy for the residential zone. Based in part on the STATLINE database of Statistics Netherlands, the following context data have been created: three density measures, a zonal size indicator and dummy variables for core cities and growth centers. The core city variable indicates the central part of each metropolitan region where the largest employment concentration is located; it serves as a proxy indicator for distance from the center of the region. Growth centers were the centerpiece of Netherlands national spatial planning of the 1970s and early 1980s. In an attempt to influence the massive suburbanization after the increase in car ownership in the 1960s and 1970s, national government designated a number of settlements that had to curb the relocating households and firms. These new towns had to become self-contained, but turned into dormitory towns. Eventually, they attracted substantial employment; however, a mismatch between residents and workers has remained. Many people working in the growth centers commute from elsewhere, whereas does residing in the new towns tend to work in other employment centers (Van der Laan, 1998).

Similarly, data at the level of the metropolitan region or *Daily Urban System* (DUS) have been drawn from Van der Laan (1998) and Louter *et al*. (2001). The latter source provided the input for a range of potentially explanatory variables: metropolitan size and density indicators as well of the number of jobs per resident and three measures of employment and population growth (Table 1). In addition, while many researchers have acknowledged that mono- and polycentrism are the extremes of a continuum, they generally do not pay explicit attention to distinct differences among polycentric regions (Schwanen *et al*., 2002a). A categorization of DUSs developed by Van der Laan (1998) does incorporate variation among polycentric forms and is therefore used for the present research. Four types of DUSs have been defined (Figure 1):

1. *Centralized*: this type of DUS resembles the traditional, monocentric urban region. Home-to-work commutes are mainly oriented toward the core city.
2. *Decentralized*: a very large share of employment is located in suburban areas; many central-city residents commute to the suburbs in the morning and many suburbanites commute to work located in other suburbs.
3. *Cross-commuting*: many suburban residents work in the suburbs and many central-city workers are locally employed. This urban region consists of relatively independent, substitutable, and self-contained nodes. This archetypal polycentric region develops when workers minimize travel expenditure (Schwanen *et al*., 2002a).
4. *Exchange-commuting*: reciprocal relationships exist between suburbs and core area with many suburbanites working in the central city and many urbanites traveling to work in the suburbs. The level of self-containment is low; employment centers are complementary to each other rather than substitutable (Schwanen *et al*., 2002a).

The spatial distribution of these types of DUSs across the Netherlands shows a clear pattern (Figure 2). Decentralized regions are mainly located in the Western part of the country, the Randstad Holland, whereas centralized systems tend to be concentrated in the North, East, and South. This can be explained by referring to differences in regional economic structure (Van der Laan, 1998). While services dominate economic structure all over the country, agricultural and traditional industrial employment, such as food-processing (North and East) and heavy and (petro)chemical industry (e.g. the regions of Enschede, Arnhem and Geleen-Sittard) are still more important in the North, East and South than in the West of the Netherlands. As a consequence, more traditional urbanization patterns tend to prevail outside the Randstad Holland. In contrast, in the western part of the Netherlands, employment is more concentrated in modern manufacturing, logistics and service-related sectors, and urban regions have evolved into metropolitan areas with complex interaction patterns between lower-level spatial units.

3.2 Multilevel regression analysis

Every regression model consists of a fixed and a random part. The *fixed* part represents the systematic relationship between the dependent variable and the explanatory factors; it consists of the intercept and regression or slope coefficients. The *random* part allows for variation around this fixed part (Bullen *et al*., 1998). Ordinary Least Squares (OLS) regression models are based on the assumption that the random variation around the fixed parameters is constant and does not depend on the explanatory variables – the homoscedasticity assumption. Because all observations are assumed to be independent from each other, residual variance can be summarized by a single random term. In this paper, however, we assume that commute behavior depends on characteristics of workers within household within residential zones within metropolitan regions. This nested conceptualization clearly violates the assumptions of independence of observations and homoscedasticity; the application of OLS regression may result in biased results. Multilevel regression modeling has been proposed to handle the clustering or nesting of data through extension of the random part of the regression equation (Goldstein, 1995; Snijders and Bosker, 1999). The basic four-level model can be written as:

$$\mathrm{Y}_{ijkl} = \hat{a}_{0ijkl} + \hat{a}_1 \mathrm{X}_{ijkl} + e_{ijkl} \qquad (1)$$

where Y_{ijkl} is a continuous dependent variable – commute time, for instance – reported by person i (level 1) in household j (level 2) residing in municipality k (level 3) that is located in DUS l (level 4). The variable X_{ijkl} is an explanatory variable at the individual-worker level and $\hat{a}_1$ is the estimated regression coefficient for X_{ijkl}. The random term e_{ijkl} is the usual error term capturing the random variation among individuals, with $\mathrm{E}(e_{ijkl}) = 0$ and $\mathrm{var}(e_{ijkl}) = \acute{o}^2_e$. $\hat{a}_{0ijkl}$ has a fixed mean, $\tilde{a}_0$, the intercept; the variation around this mean among households is captured by the random variable u_{0jkl} with $\mathrm{E}(u_{0jkl}) = 0$ and $\mathrm{var}(u_{0jkl}) = \acute{o}^2_{u0}$. Similarly, the variation around the fixed intercept among residential municipalities is reflected by the random variable v_{0kl} and the variation among DUSs by f_{0l}, which are also assumed to be normally distributed with a mean of zero and can be summarized by their variances. Thus, $\hat{a}_{0ijkl}$ can be written as:

$$\hat{a}_{0ijkl} = \tilde{a}_0 + u_{0jkl} + v_{0kl} + f_{0l} \qquad (2)$$

When the multilevel model only accommodates random variation around the intercept, it is called an *intercept-only model*. However, random variation may also be allowed around the other elements of the fixed part of the regression equation – the coefficient(s) for explanatory variables. In such *random-slope models*, the estimated regression coefficient $\hat{a}_1$ is turned into a set of random variables:

$$\hat{a}_{1ijkl} = \tilde{a}_1 + e_{1jkl} + u_{1jkl} + v_{1kl} + f_{1l} \qquad (3)$$

the terms of which have the same meaning as before: $\tilde{a}_1$ is the fixed mean and u_{1jkl}, v_{1kl} and f_{1l} capture the random variation around this mean among household, residential municipalities and DUSs, respectively. Again, all random terms are assumed to be normally distributed, have a mean of zero and can be summarized by their variances. In addition, they may be correlated with other random variables at the same level of analysis, but are assumed to be independent from terms at other levels. The correlation between random terms at the same level of analysis – u_{0jkl} and u_{1jkl} for example – is captured by a covariance term – $\mathrm{cov}(u_{0jkl}, u_{1jkl}) = \acute{o}_{u01}$. In (3), an additional random term e_{1jkl} is specified for the individual-worker level. This is done because the random variation among individual workers may not be constant. By specifying an additional variance term e_{1jkl}, we can incorporate such effects into our models. A covariance term with the error term at level 1, cov(e_{0jkl}, e_{1jkl}) = $ó_{e01}$, indicates how the variance varies with an increase in the value of the explanatory variable: a positive covariance term implies that the variance around the mean effect of income becomes larger with an increase in the independent variable, a negative term that the variance decreases.

Over time, multilevel modeling has been extended in such ways that, among others, discrete rather than continuous dependent variables can be analyzed and that multiple dependent variables can be considered simultaneously. If the dependent variable is *discrete* as with mode choice, a generalized linear model is specified consisting of a set of linear predictors as in (1) and a non-linear link function, which is typically a logit function in the case of a binary response variable. The resulting model is the multilevel equivalent to the traditional logistic regression model. The main difference with multilevel models with a continuous dependent variable is that all variance terms at the lowest level are constrained to one for a number of technical reasons (Snijders and Bosker, 1999).

Because of their strong interdependence, estimating a model with both commute distance and time as dependent variables is statistically more efficient and may provide additional insights. A specific type of multilevel models has been developed to handle more than one dependent variable – *multivariate* multilevel models (Goldstein, 1995). In these models another level of analysis is added to define the multivariate structure. The resulting model with an explanatory variable at the worker level X_{jklm} can be expressed as:

$$Y_{ijklm} = \hat{a}_{01}Z_{1ijklm} + \hat{a}_{02}Z_{2ijklm} + \hat{a}_{11}Z_{1ijklm}X_{jklm} + \hat{a}_{12}Z_{2ijklm}X_{jklm} + u_{1jklm}Z_{1ijklm} + u_{2jklm}Z_{2ijklm} \quad (4)$$

with Z_{1ijklm} = 1 for commute distance, Z_{1ijklm} = 0 for commute time, and Z_{2ijklm} = 1 - Z_{1ijklm}. Note that compared with (1) the subscripts have changed because the lowest level i is now used to distinguish commute distance and time. For this reason, the terms u_{1jklm} and u_{2jklm} now indicate the between-individuals variation in commute distance and time, respectively. As with the univariate model, the terms $\hat{a}_{01}$ and $\hat{a}_{02}$ can be expanded to include random variations around the intercept among households, residential municipalities and DUSs; the same is true for the slope coefficients $\hat{a}_{11}$ and $\hat{a}_{12}$ (see eq. 2 and 3). All multilevel models presented in the remainder of the paper have been estimated with the MLwiN software (Rasbash *et al.*, 2000).

4. Mode choice

Polycentrism may have led to higher levels of automobile dependence, as we argued in the introductory parts of this paper. One of the manifestations of this would be larger probabilities of choosing the car-driver mode to get to work. To see to what extent this is true for the Netherlands, we have conducted a multilevel analysis with the binary choice between commuting as a car driver (1) or commuting by any other means of transportation (0). Two models are presented: an intercept-only model and the final model containing a range of fixed explanatory variables (Table 2).

Focusing on the intercept-only model, we see that the estimated constant is positive, indicating that the majority of the sample commutes by car. The random variables in the model show that the contribution of the residential-zone level to the variation in car use is fairly large. In contrast, the role of the DUS level is much more limited; the estimated variance of the random variable for this level is strictly speaking not significant at the 5% or

10% confidence level. We kept it in the model specification, however, for the variation between DUSs is a main topic of interest of this paper. The coefficient estimated for the household level turned out to be zero; it was therefore omitted from the model specification. This probably reflects that the number of households with two instead of one commuter in the sample on which the model is estimated is relatively small (11.2 percent of all households).

To illustrate how the probability of commuting as a car driver varies between the 26 DUSs in the Netherlands, we used the intercept-only model to estimate residuals or deviations from the fixed intercept for each metropolitan region.[4] Figure 3 displays these residuals in rank order for the 26 DUSs in the Netherlands; the bars indicate the 95% confidence interval for the estimates. The intercept estimated for a DUS is significantly different from the Netherlands average if the 95% confidence interval does not intersect with the dotted line. Figure 3 shows that the intercepts for Amsterdam and The Hague are significantly below the Dutch average, while those for Groningen and Vlissingen/Middelburg tend to be lower as well. On the other hand, the regions of Geleen/Sittard and Hilversum are the most car dependent, followed by Heerlen and Tilburg.

In an attempt to explain these variations among metropolitan regions, we estimated a full model. Only variables with a statistically significant effect have been included in the final model specification shown in Table 2. The results are consistent with our hypotheses and previous studies. The probability of driving a car to work is higher, as the level of car availability and/or the personal income is higher. Higher-educated workers are less likely to commute by car, which is consistent with previous findings that these people are most likely to commute by train (Schwanen *et al*., 2002b). This may reflect that many higher educated both live and work in more urbanized areas where commuting by train is relatively fast and convenient. In addition, the likelihood to commute by car is lower for older people as well as for single workers and to a lesser extent persons in two-worker families.

In general, women are generally less likely to drive a car to work than men. During the model-building process, it became clear, however, that the effect of gender is not uniform and differs between households. Therefore we included several interaction variables of gender with household types in the model. These indicate that the gender difference in the probability of driving to work is much smaller in households comprising children and one worker; in single-worker households no difference exists between men and women. Moreover, women are more likely to commute by car than men in two-worker families. Having a working partner and children, these women often face high levels of time pressure, since they have to combine working with household maintenance tasks. Obviously, they value the efficiency and flexibility the private car offers.

The importance of the residential-municipality level is borne out in the results of the final model. The probability of commuting as a car driver is lower in municipalities with a higher residential density as well as at short distances from the most important employment concentration, in the core areas of the DUS. Car use may be less attractive in high-density zones and/or at short distances from the urban core of the region due to congestion and parking problems and because the supply of public transportation is usually larger there, making transit a more attractive alternative to the automobile (Schwanen *et al*., 2002b). The bicycle may also be a more viable choice alternative, for in high-density areas more jobs can often be reached within an acceptable commute tolerance.

[4] see Rasbash *et al*. (2000) and appendix 2.2 in Goldstein (1995) for details

At the metropolitan level, two employment indicators are related to mode choice. The ratio of jobs to residents is negatively correlated with the probability of commuting by car, indicating that fewer resident workers commute by car in areas with many jobs per resident. Since more jobs are available for workers there, it may be easier for them to find suitable employment relatively close to home. This makes other modes of transport, such as the bicycle, more attractive (Schwanen *et al*., 2002b). Another explanation may be that employment-rich areas attract much inward commuting from people that reside in other DUSs or in municipalities outside metropolitan regions. This may on the one hand worsen congestion on the road network within the DIS and on the other create opportunities for spatially and temporally more extended transit networks. The first explanation may apply for example to the relatively low car use in the region of Groningen (Figure 3), whereas the latter may be more valid to the regions of Amsterdam and Utrecht.

Further, car use is higher for workers living in urban areas with a large growth of the ratio of jobs to residents during the period 1994-1999. Three explanations may be given for this result. First, a strong growth of the number of jobs serves as an indication of economic prosperity; this empirical result may indicate that car use tends to be higher in more prosperous regions. Second, the growth of the number of jobs during the period of economic well-being was particularly strong in the upper segments of the labor markets. People that were attracted to such employment may be more likely to commute by car. Third, the increase in the number of jobs differed across space; it was relatively strong in urban fringe and suburban areas as well as along highways. These employment locations are strongly car oriented and usually not served well by mass transit.

All else equal, the influence of the difference between mono- and polycentrism on mode choice is rather limited. No statistically significant effects were found for the whole sample. Experimentation with the model indicated, however, that for women the spatial distribution of employment vis-a-vis population does matter. This seems to reflect that women are generally more dependent on the local and regional labor markets than men as indicated by their shorter commute distances (see below). The analysis reveals that women residing in decentralized and exchange-commuting DUSs are less likely to commute as a car driver. This is consistent with our expectations in the sense that the probability of commuting by car is relatively high in the archetypal polycentric region – the cross-commuting DUS. Thus, it seems that the relatively high car use in the regions of Hilversum and Geleen-Sittard (Figure 3) is mainly attributable to the spatial distribution of employment and population. However, the fact that women in centralized DUSs are more likely to commute by car than females in most polycentric regions is at odds with our expectations. This paradox can be explained by the fact that most decentralized regions and the largest exchange-commuting region – Utrecht – are located in the Randstad Holland (Figure 2), where the supply of public transport is of a higher standard and the road networks are more congested than elsewhere in the Netherlands. In sum, it seems that polycentrism itself need not result in higher car dependence. A variety of factors determine the level of car dependence for commuting at the metropolitan level. Other factors seem to be more important and may overrule the proposed effects of polycentrism on mode choice.

5. Commute distance and time as a car driver

The correlation between commute time and distance is usually quite large. Moreover, most factors that influence commute distance also affect commute time and vice versa. For the people who drove to work, we have therefore estimated a multivariate multilevel model with two dependent variables – total daily commute distance as a car driver and total daily commute time as a car driver. To make estimated coefficients of explanatory variables comparable across the dependent variables, we first took the natural log of commute distance and time and then standardized them to be normally distributed. As with mode choice, an intercepts-only model is presented together with estimated residuals for the 26 DUSs, followed by a final model containing significant predictor variables relating to the individual worker, his/her household, the residential municipality and the DUS.

Because the dependent variables are standardized, the fixed intercepts in the intercepts-only model are very close to zero (Table 3). A first conclusion that can be drawn from the random terms in the model is that the correlation between commute distance and time as a car driver is high irrespective of the level of aggregation. The random variance and covariance terms can be used to calculate correlation coefficients between the two dependent variables at a given level of analysis.[5] At the individual worker level the correlation is 0.89, while it is 0.87 and 0.94 for the residential-zone and DUS level, respectively. Thus, commute distance and time are indeed strongly dependent on each other. Yet, this does not imply that the impact of personal, household or locational attributes is identical for both dimensions of commute behavior.

A second main conclusion is that by far the largest part of the variation in both commute distance and time is to be explained at the level of the individual workers. The between-municipality and between-DUS variation is very small. No more than 3% of the variation in either commute distance or time is due to the spatial context. Nevertheless, the variation among spatial contexts – be they municipalities or DUSs – is larger for commute distance than for time. The dominance of the individual worker level should not be a surprise. There are much more individuals (7,996) than municipalities (210) or DUSs (26). Further, it is at the individual worker level that the most extreme values are recorded; in area-wide average indicators of commuting the effects of individual extremes are neutralized. Nevertheless, the results clearly indicate that the variation in commute distance and time as a car driver among workers *within* geographical units is much larger than the variation *among* residential zones and metropolitan regions.

The intercept-only model also reveals that the share of variation to be explained at the household level differs considerably between commute distance and time (Table 3). The estimated variance term was far from statistically significant for distance. We therefore constrained this term to be zero in the final intercepts-only model. In contrast, the household level is rather important for the temporal dimension of commute behavior; it explains about 10% of the total variance in commute time. In other words, the commute times of the two partners in two-worker households are related to each other. This might be interpreted as indicating that decisions regarding a worker's commute time as a car driver are not made independent of the partner's commute time, perhaps to ensure that the share of the household's time budget that is spent on car commuting does not exceed some unobserved threshold level.

[5] For a given level of analysis, the estimated covariance term is divided by the square root of the product of the variance terms, e.g. $\acute{o}_{u01} / \quad (\acute{o}^{2}_{u0} * \acute{o}^{2}_{u0})$.

Like we did for mode choice, we have used the intercepts-only model to estimate residuals or deviations from the fixed intercept for the 26 metropolitan regions for both commute distance and time (Figure 4). A comparison of these residuals again shows that the variation among DUSs is larger for the commute distance as a car driver than for time, as indicated by the numbers on the y-axis. In addition, the number of DUSs that has an intercept that significantly differs from the Netherlands average is larger for commute distance than for time: six versus three. The rank orders of the 26 DUSs are rather different; only four regions occupy exactly the same position on both dimensions. However, the extremes on the low and high ends are roughly the same: both commute distance and time are highest in the regions of Utrecht, Amersfoort and Amsterdam and considerably below the average in the Heerlen area. The Hague is an interesting case: while commute distances are second shortest of all DUSs, it occupies a mere eighth position when commute times are considered. The short distances may be attributed to the compactness of the region, squeezed together between the North Sea coast and Green Hart.[6] On the other hand, the combination of compactness and limited opportunities for spatial extension seems to have led to relatively high congestion levels that have decreased commute speeds. In contrast, fairly large commute distances are combined with somewhat shorter commute times in the centrally located region of 's Hertogenbosch. This region has been going through a period of considerable growth in the number of jobs and the ratio of jobs to workers since the mid-1990s (Louter *et al.*, 2001). This might have led to larger commute distances but also to somewhat higher travel speeds implying a smaller rise, if any, in commute times.

Turning to the full model containing statistically significant explanatory variables (Table 4), we see that, with the exception of age, all personal and household attributes that influence commute distance also affect commute time; however, the relative importance in the explanation of commute distance or time varies for most variables. The socioeconomic indicators of car availability, personal income and education are all positively associated with both commute distance and time. As the number of cars per driver, the monetary reward form paid labor, and the educational attainment increase, commute distance and time by car become longer. The impact on distance is, however, stronger. Moreover, the influence of education is non-linear, especially for commute time. For the car availability index, the homoscedasticity assumption is violated. This means that for both commute distance and time the magnitude of the random variation around the fixed coefficient is unequal for different levels of car availability. The negative covariance terms with the intercepts – ó$_{u1101}$ and ó$_{u1202}$ – indicate that the random variance around the fixed regression coefficient is lower when the level of car availability is higher. This probably reflects that few workers have more than one car at their disposal; the commutes of those who have so are relatively similar in terms of distance and time.

As said before, age is only related to commute distance; older people tend to commute fewer miles than younger workers. The general or main effects of household structure are small; ceteris paribus, single workers commute less than those with a partner do. If singles have children, they commute much less. The impact of these variables is somewhat larger for commute time than for distance, suggesting that they are proxy indicators for the amount of time pressure workers in these household categories experience.

[6] The Green Hart is the core area of the Randstad Holland. Since World War II, government policy has quite successfully attempted to preserve this area as open space by severely restricting the number of residences and other urban functions that could be developed in this area (Dieleman *et al.*, 1999).

Consistent with previous studies, the difference between men in women in commute time is smaller than in distance (Hanson and Johnston, 1985; Turner and Niemeier, 1997). Also in line with expectations and the literature on the *household responsibility hypothesis* (e.g. Turner and Niemeier, 1997) is that women in households with children commute not only much less than males, but also considerably less than other females and than females with a working partner but no children in particular. Because mothers are still primarily responsible for childcare and household maintenance in the Netherlands (Schwanen *et al*., 2002b), they are often part-time employed and work close to home, which offers them more spatiotemporal flexibility. Interestingly, the impact of the interaction terms of gender and living in a household with children is larger for time than for distance, indicating that women in these households want to economize on commute time rather than distance. The time that is saved in this way can be allocated to other activities, such as maintenance or leisure. In contrast, women in couples without children can devote more time to paid labor and may be more career-oriented. As a result, they are prepared to commute more.

At the residential-zone level only one variable is significantly related to commute distance and time, revealing that people living in growth centers tend to commute more. It seems that the relatively strong mismatch between supply and demand for labor in these communities (Van der Laan, 1998) means that their residents have to commute longer than workers elsewhere in metropolitan regions.

The factors at the DUS level that influence commute distance and time as a car driver are not identical. Commute distance for driving to and from work tends to decrease, as the number of jobs per hectare rises. This is consistent with a priori expectations: as employment density is higher, more jobs are in theory located within a certain range from any residential location in a DUS and workers are more likely to find suitable employment at a relatively small distance from home. That commute time is not impacted by employment density may reflect that density measures also act as proxy indicators for levels of congestion (Churchman, 1999); the shorter car commute distances may be offset by lower travel speeds.

Commute distance is also affected by the degree of change in the ratio of employment to residents. It tends to be higher in DUSs that have undergone a strong growth of the number of jobs per resident during 1994-1999. At first sight, this is somewhat contradictory with the previous result. As argued before, however, it takes some time before households respond to changes in the macro-environment, resulting in a temporal disequilibrium between residential and employment location. Further, a growth of the number of jobs also serves as an indication of economic prosperity. Thus, this result may also indicate that DUSs with a high growth tend to be the more prosperous regions, where commute distances are usually larger. Interestingly, commute time is not dependent on this growth indicator. Perhaps this is related to the spatial distribution of the additional jobs. As said before, growth was highest in locations that are highly accessible by private car, for example on the urban fringe or along highways. Thus, the bulk of the new employment is located in less congested areas and larger commute distances may be offset by higher travel speeds.

In contrast, commute time as a car driver rises with the size (in km^2) of DUSs, reflecting that in spatially extended areas large distances are possible between employment concentrations and residential locations. This leaves the question why commute distance is not directly related to urban size in the model. It seems that this effect is included in the employment-density variable.

Although the impact on distance is larger, the distribution of employment relative to residences across the metropolitan region is the only dimension of metropolitan structure that influences both commute distance and time as a car driver. Workers living in decentralized and exchange-commuting regions commute longer than residents of centralized and cross-commuting DUSs. The fact that people in cross-commuting areas commute less than workers in other DUSs is consistent with our expectations. The spatial constellation of this type of regions resembles the archetypal polycentric region consisting of relatively independent, self-contained and substitutable nodes of development. This is the type of region that would come into existence if minimization of commute times would be the main impetus for changing the job and/or residential location (Schwanen *et al*., 2002a). However, the fact that car drivers in cross-commuting DUSs commute approximately as much as those in the more monocentric, centralized regions is in sharp contradiction with the *co-location hypothesis*. Thus we find only very partial evidence for the claim that car drivers in polycentric regions commute less than residents of monocentric regions in the Netherlands.

The spatial variables included in the full model succeed in explaining the bulk of variation among residential zones and metropolitan regions in commute distance and especially commute time as a car driver. This can be illustrated by a comparison of the random variance terms at these levels of analysis – σ^2_{f01}, σ^2_{f02}, σ^2_{g01} and σ^2_{g02} – in the intercept-only model (Table 3) with those in the full model (Table 4). Compared with Table 3, the terms for distance – σ^2_{f01} and σ^2_{g01} – have been greatly reduced in size in Table 4. The random variables for time – σ^2_{f02} and σ^2_{g02} – are lacking in Table 4; they were omitted from the final model specification, because they were far from significantly different from zero. We have thus been able to explain (almost) all variation among DUSs and residential zones for commute time as a car driver. In contrast, at the levels of the individual worker and his/her household our model performs much worse.[7] Sociodemographic variables alone are insufficient to explain the variation among individuals and workers. Additional variables should have been included, such as job characteristics and attitudes towards toward commuting. Unfortunately, such factors are not available in the NTS data.

6. Discussion

This paper has compared the commute behavior of resident workers of urban areas in the Netherlands to see to what extent metropolitan structure affects commute patterns. Unlike some previous work, we have not only considered the distribution of employment vis-a-vis population, i.e. the difference between mono- and polycentrism. A broader definition of metropolitan structure is used that also encompasses employment and population density, metropolitan size, the ratio of jobs to residents and growth of employment and the population. In addition, we have used data at multiple levels of analysis ranging from the individual worker to the metropolitan region instead of drawing conclusions from aggregate-level statistics only. Three dimensions of commute behavior have been considered – mode choice, total daily commute distance by private car, and total commute time by private car.

[7] Compared with the intercepts-only model in Table 3, the variance terms for commute distance and time at the individual worker and the household level have increased in size. This is, however, due to the inclusion of to the of the variance terms for car availability. In a model where all random terms involving car availability are constrained to zero, the variance and covariance terms for commute distance and time at the worker and household levels are smaller than in the intercepts-only model. Yet, they are still large; the proportional reduction due to the inclusion of the independent sociodemographic variables is limited.

For all dimensions of commute behavior, the variation among geographical units – be they residential zones or Daily Urban Systems (DUSs) – is much smaller than among individual workers. More specifically, only 3% of the total variation in both commute distance and time as a car driver is to be explained by the levels of the residential zone and the DUS together. In other words, the variation among individual workers *within* residential zones and DUSs is much larger than the variation *between* such geographical units. Further, the analysis has revealed that the differences among residential zones within DUSs are larger than the variation among DUSs for commute mode choice. The opposite is true for commute distance and time as a car driver: the contribution of the DUS level is larger than that by the residential zone level.

Like numerous other studies we have found that socioeconomic status and gender are important explanatory factors at the individual worker-level and that gender differences in commute behavior depend on household structure. At the residential zone level, the expected relationships have also been established. In high-density environments and core cities, the probability of driving a car to work is lower than elsewhere in metropolitan areas. Further, commute distance and time tends to be higher in growth centers, indicating a qualitative mismatch between labor demand and supply in these settlements.

A range of variables at the metropolitan level affect individuals' commute behavior. The probability of driving a car to work is lower as the number of jobs per resident is higher and commute distance by car decreases with the number of jobs per hectare. In addition, if the number of jobs per resident has grown during the second half of the 1990s, workers are not only more likely to commute by car but may also cover larger distances. Interestingly, commute time is affected by different factors at the DUS level than distance; only the spatial extension of the DUS is relevant to the explanation of variation in this dimension of commute behavior.

Further, the analysis has shown that, ceteris paribus, the relative distributions of employment and population influences commute behavior. For mode choice no effects have been detected for the whole sample. Nevertheless, the probability of commuting as a car driver is lower in the majority of the polycentric DUSs for working females. It thus seems that polycentrism does not by definition result in larger probabilities for driving a car to work, especially if urban areas are served by well-developed transit networks. This conclusion may sound encouraging for policy makers who prefer to cope with decentralization by stimulating transit-oriented developments. However, it is unclear to what extent the circumstances in the Netherlands can be replicated elsewhere. One should not forget that population densities have always been high and transit networks well developed in the Netherlands and in the Randstad Holland in particular.

Regarding commute distance and time for car drivers, we found evidence of considerable variation between the types of metropolitan regions distinguished. In the majority of polycentric regions, commute distances and times as a car driver are significantly longer than in the monocentric-oriented, centralized DUSs. Only in one specific type of polycentric region – the cross-commuting region consisting of relatively self-contained nodes of development – do car drivers commute equal distances and spend similar amounts of time on traveling between home and work as their counterparts in the monocentric DUSs do. By and large, polycentrism has not resulted in less commuting by car in the Netherlands. This conclusion is at odds with a number of US empirical studies arguing that polycentrism results in more efficient travel patterns. At least three factors may explain this difference (Schwanen *et al*., 2002a). First, the majority of the polycentric regions are located in close proximity of each other within the Randstad Holland (Figure 2). As a consequence, the number of commuters that work and live in different DUSs is larger in polycentric than in monocentric regions. This clearly influences the results. Second, the role of spatial policy should be mentioned. The strict regulation of the housing and land markets may very well have hampered the co-location of residences and jobs in close proximity and created imbalances in the locations of housing and employment. The impact of spatial planning is direct through the imposition of greenbelts and other restrictions on building as well as indirect. Land and housing have become scarce goods, which has increased their prices and made buying a residence close to work virtually impossible for many households. Third, while constraints on spatial choice processes may be more severe in the Netherlands than in the USA, it is not unlikely that preferences also vary between these countries. Perhaps the Dutch are less inclined to move house in response to employment changes than their American counterparts.

In sum, the analysis has revealed that the distributions of employment and population across the metropolitan region are not the only factor at the DUS level that matters to the explanation of commute behavior. Other differences between metropolitan regions are also important for commute distance and time as well as for mode choice. Although the contribution of the residential zone and DUS level in the total variation in commute behavior is small, we have been able to explain the bulk of this variation in commute mode choice, distance as a car driver and particularly time as a car driver with a rather limited set of spatial variables. In contrast, the largest part of the variation at the individual-worker level remains unexplained. This poses an important challenge for future inquiries into commute behavior.

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TABLE 1.
Potential explanatory variables

Level of analysis	Variable name	Description
Worker	Car availability index	Ratio of the number of cars to the number of household members with a valid driver's license; set to zero if person has no driver's license
	Personal income	A worker's annual net income (*10,000 gld.)
	Education	Low; medium; high
	Age	In 10 years
	Gender	Male; Female
Household	Household type	Single worker; Two-worker couple; One-worker couple, Two-worker family (youngest child <12 yr.); One-worker family (youngest child <12 yr.); Single-parent family (youngest child <12 yr.); Other household
Residential municipality	Population density	Number of residents per hectare
	Residential density	Number of residences per hectare
	Employment density	Number of jobs per hectare
	Area municipality	Size of municipality in km^2
	Core city	Main settlement within DUS
	Growth center	Suburban settlement designed to accommodate population and employment relocating from the core cities; centerpiece of Netherlands national spatial planning policy in the 1970s and 1980s (Schwanen *et al*., 2002b)
Metropolitan region (DUS)	DUS type	Centralized; Decentralized; Cross-commuting; Exchange-commuting
	Area DUS	Size of DUS in km^2
	Number of residents	In 1,000 residents
	Number of jobs	In 1,000 jobs
	Population density	Number of residents per hectare
	Employment density	Number of jobs per hectare
	Ratio of jobs to residents	Number of jobs per resident
	Growth of number of residents	Average annual growth (in %) of the number of residents in a DUS in the period 1994-1999
	Growth of number of jobs	Average annual growth (in %) of the number of jobs in a DUS in the period 1994-1999
	Growth of ratio of jobs to residents	Average annual growth (in %) of the number of jobs per resident in a DUS in the period 1994-1999

TABLE 2.
Multilevel logistic regression model for the likelihood of commuting as a car driver

	Intercept-only model		Full model	
	coefficient	T statistic	coefficient	T statistic
Fixed part				
Intercept ($\tilde{a}_0$)	0.340	7.44	-0.455	-1.25
Car availability index			3.212	46.82
Personal income (* 10,000 gld.)			0.114	8.03
Low education			0.235	4.37
Medium education			0.234	4.85
LN(age (yr.))			-0.296	-3.58
Female			-0.414	-6.17
Female single worker			0.440	3.42
Female in two-worker family			0.648	6.25
Female in one-worker family			0.325	2.25
Single worker			-0.640	-7.37
Two-worker family			-0.189	-2.91
Residential density (municipality)			-0.104	-2.53
Core city			-0.231	-4.21
Ratio of jobs to residents (DUS)			-0.014	-2.68
Growth of the ratio of to residents (DUS)			0.084	1.65
Female in decentralized DUS			-0.297	-3.83
Female in exchange-commuting DUS			-0.235	-2.11
Random part				
level 1 – worker				
Variance intercept ($\acute{o}^2_{e01}$)	1.000		1.000	
level 2 – residential municipality				
Variance intercept ($\acute{o}^2_{u01}$)	0.132	5.73	0.019	1.94
level 3 – DUS				
Variance intercept ($\acute{o}^2_{v01}$)	0.021	1.42	0.006	1.03

N cases = 14,590

TABLE 3.
Multilevel regression model of commute distance and time containing only fixed intercepts

	estimated coefficient	T statistic
Fixed part		
Intercept distance (ã$_{01}$)	-0.017	0.58
Intercept time (ã$_{02}$)	-0.019	0.80
Random part		
Level 1 – individual worker		
variance intercept distance (ó$^{2}_{u01}$)	0.976	62.61
variance intercept time (ó$^{2}_{u02}$)	0.899	33.31
covariance intercept distance & intercept time (ó$_{u0201}$)	0.835	44.57
Level 2 – household		
variance intercept distance (ó$^{2}_{v01}$)	0.000	
variance intercept time (ó$^{2}_{v02}$)	0.091	3.90
covariance intercept distance & intercept time (ó$_{v0201}$)	0.028	2.24
Level 3 – residential municipality		
variance intercept distance (ó$^{2}_{f01}$)	0.008	2.14
variance intercept time (ó$^{2}_{f02}$)	0.006	1.67
covariance intercept distance & intercept time (ó$^{2}_{f0201}$)	0.006	1.77
Level 4 – DUS		
variance intercept distance (ó$^{2}_{g01}$)	0.016	2.64
variance intercept time (ó$^{2}_{g02}$)	0.010	2.31
covariance intercept distance & intercept time (ó$^{2}_{g0201}$)	0.012	2.42

Log likelihood = -16,078.6; N cases = 15,003

TABLE 4.
Multivariate multilevel regression model for total daily commute distance and time by the car-driver mode

	Distance		Time	
Fixed part	coefficient	T	coefficient	T
Intercept (ã$_0$)	-0.026	0.35	0.163	4.30
Car availability index	0.227	6.29	0.163	4.30
Annual year income (*10,000 gld.)	0.060	8.16	0.049	6.48
Low education	-0.133	-4.54	-0.114	3.78
Medium education	-0.110	-4.77	-0.113	4.20
Age (*10 yr.)	-0.062	10.58		
Female	-0.362	10.43	-0.264	7.38
Single worker	-0.071	1.99	-0.102	2.73
Single worker with children	-0.405	3.10	-0.421	3.09
Female in two-worker couple	0.111	2.40	0.085	1.80
Female in two-worker family	-0.214	4.18	-0.240	4.54
Female in one-worker family	-0.150	1.56	-0.171	1.79
Growth center	0.117	2.92	0.109	2.85
Decentralized DUS	0.114	3.58	0.079	3.24
Exchange-commuting DUS	0.159	3.52	0.138	3.82
Job density (DUS)	-0.021	3.62		
Area DUS (*1,000 km^2)			0.607	3.82
Growth of ratio of jobs to residents (DUS)	0.031	1.89		

Random part	coefficient	T statistic
Level 1 – worker		
Var. intercept distance (ó$^{2}_{u01}$)	1.051	13.69
Var. intercept time (ó$^{2}_{u02}$)	0.973	11.82
Cov. intercept dist. & intercept time (ó$_{u0201}$)	0.883	11.91
Var. car availability dist. (ó$^{2}_{u11}$)	0.227	2.87
Cov. car availability dist. & intercept dist. (ó$_{u1101}$)	-0.233	-3.13
Cov. car availability dist. & intercept time (ó$_{u1102}$)	-0.389	-2.67
Var. car availability time (ó$^{2}_{u12}$)	0.250	2.79
Cov. car availability dist. & car availability time (ó$_{u1203}$)	0.208	2.66
Cov. car availability time & intercept time (ó$_{u1202}$)	-0.218	2.65
Level 2 – household		
Var. intercept dist. (ó$^{2}_{v01}$)	0.059	1.89
Var. intercept time (ó$^{2}_{v02}$)	0.132	4.03
Cov. intercept dist. & intercept time (ó$_{v0201}$)	0.080	2.69
Level 3 – residential municipality		
Var. intercept dist. (ó$^{2}_{f01}$)	0.002	2.47
Level 4 – DUS		
Var. intercept distance (ó$^{2}_{q01}$)	0.002	1.86

N cases = 15,003; Log likelihood = -15,666.5; Model improvement ÷^{2} = 824.3

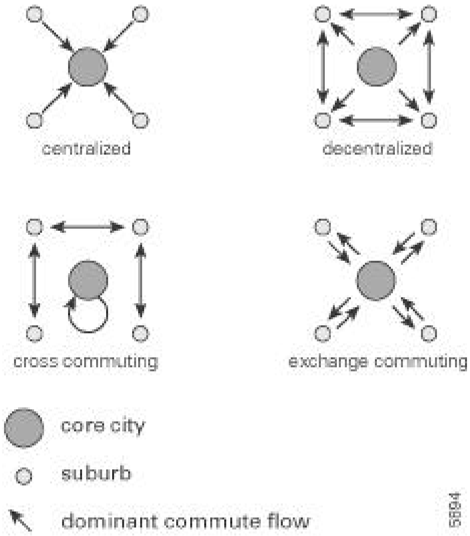

FIGURE 1. Schematic representation of types of DUSs

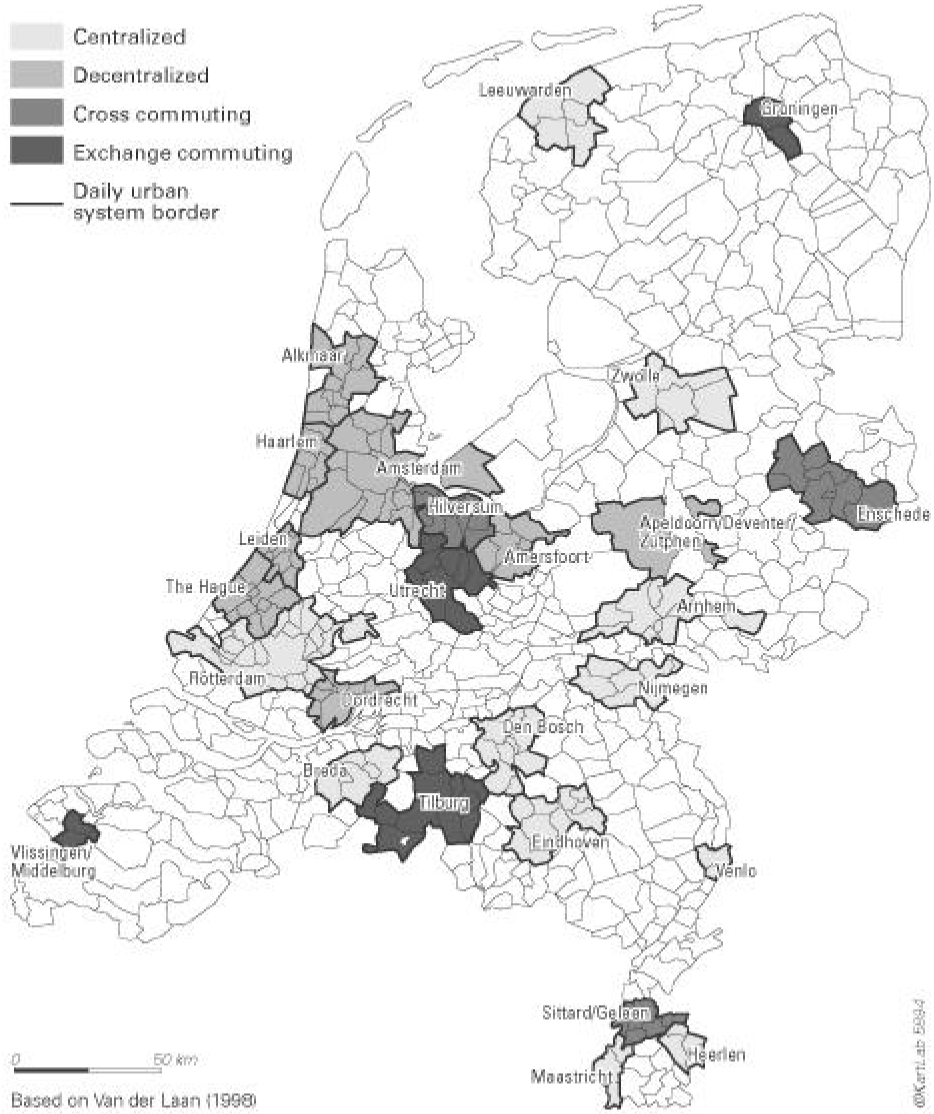

FIGURE 2. Spatial distribution of DUSs across the Netherlands

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FIGURE 3. Estimated residuals for the 26 DUSs in the intercept-only model for mode choice

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FIGURE 4. Estimated residuals for the 26 DUSs in the intercept-only model for the regression model for commute distance and time