


How routine is a routine?

An analysis of the day-to-day variability in prism vertex location

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**How Routine Is a Routine?
An Analysis of the Day-to-Day Variability in Prism Vertex Location¹**

by

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Abstract

This study is concerned with how routine an individual's routine really can be. This question is addressed by examining the day-to-day variability of the time coordinate of the vertex of a time-space prism; in other words, by examining how the timeframe which governs the individual's daily schedule varies from day to day. When the timeframe varies, it is likely that the individual's behavior also varies. When the timeframe is stable, on the other hand, a routine can be maintained. The analysis presented in this paper attempts to determine how much of the variation in travel is due to the variation in the timeframe. The origin vertices of workers' morning prisms, which determine how early they can leave home in the morning, are examined in this study, along with the departure times of the first trips in the prisms, which are mostly supposedly routine commute trips. The results indicate that the vertices are located with a much smaller variance, but vary more systematically than do the departure times of the first trips in the prisms. This implies that a large degree of variability is introduced when a trip is made within the timeframe as determined by a prism vertex. It is also shown that the departure time varies from worker to worker according to unobserved heterogeneity—i.e., unexplained differences across individuals—much more than does the prism vertex. The study results indicate that large degrees of flexibility are associated with trip making, and suggest the presence of room for behavioral modification with respect to workers' first trips in the morning.

Introduction

Variability in travel behavior, i.e., how an individual's travel behavior varies from day to day, week to week, or season to season, has been discussed intensively by researchers to gain a better understanding of travel behavior and to acquire knowledge for better transportation planning and policy development (e.g., Hanson and Huff, 1982; Pas, 1988; Kitamura, 1988a; Keuleers et al., 2001; Schlich and Axhausen, 2003; Schlich et al. 2004). For example, one can draw a much more accurate picture of who use public transit by knowing how commuters' mode choices vary from day to day. Knowing the variation of commuters' morning departure times would offer much better insights into the nature of traffic peaking, and into the effectiveness of measures aiming at peak-spreading. Such considerations have motivated the study of day-to-day variability of travel behavior.

A "typical" daily pattern is one of the key concepts that have emerged while addressing the variability of daily travel patterns. Hanson and Huff note: "An assumption that pervades theoretical and empirical work on urban travel behaviour is that individuals' daily travel patterns are largely habitual and that these habitual patterns are remarkably stable in the short run," and "[t]he notion that behaviour is habitual, routine, or stereotyped implies that people exhibit a high level of repetition in their choice of modes, destinations, and activities" (Hanson and Huff, 1988, p. 368).

Seeking such typical patterns, however, is not a trivial task. To begin with, data sets suitable for such an expedition are extremely rare and far apart. Moreover, locating typical patterns by itself does not reveal very much about the variability in daily travel. In fact, the finding that "over the five week observation period, each person exhibited more than one typical daily pattern" (Hanson & Huff, 1988, p. 369) suggests the need for a more elaborate analytical structure. Huff and Hanson propose "to differentiate among three very different sources of variation in an individual's travel behaviour from one day to the next: systematic or predictable variation; ephemeral or non-recurring aspects of travel; and long term, structural change" (Huff & Hanson, 1990, p. 230).

Consider weekly grocery shopping, for example. If it is done on a fixed day of the week, it would generate a "systematic or predictable variation." Visiting an appliance store to acquire a large freezer, on the other hand, would contribute to "ephemeral or non-recurring aspects of travel," while possessing the large-capacity freezer as a result would probably induce a "long term, structural change" in grocery shopping behavior. This differentiation, however, tells little about the magnitude and patterns of variability in daily travel behavior. Some reflections on travel behavior itself seem to be in order.

As the approaches by Chapin (1978) and Hägerstrand (1970) exemplify, an individual's behavior can be characterized from two perspectives: that the individual's behavior is driven by needs and desires, and that behavior is governed by a set of constraints. Then, variability in needs, desires and constraints must be associated with day-to-day variability in travel behavior as well. It is not difficult at all to see that needs and desires for certain types of activities vary from day to day. For example, a need for grocery shopping does not arise when there is an adequate level of food stock at hand. In fact theoretical models of shopping trip frequency have been developed as inventory control models where the cost of travel, purchase price, and inventory cost are balanced (e.g., Bacon, 1971; Narula et al., 1983; Thill, 1985, 1986). Likewise, a typical individual would not have the desire to go to the movie theater everyday. Observed "waiting times," or elapsed times, between two successive engagements in activities of a given type would reveal the characteristics of the accumulation

of needs and desires over time. Duration models have been applied to investigate the distributive nature of waiting times (e.g., Kim and Park, 1997; Schönfelder and Axhausen, 2001; Bhat et al., 2004).

To see how constraints influence travel behavior, consider social commitments such as a commitment to be employed for paid work. A commitment to work typically implies that one must report at the workplace by a certain time each workday, and stay there to work for a certain number of hours. Quite often the commitment produces very stable, or repetitive, constraints and therefore repetitive behavioral patterns. Other types of social commitments may produce quite random constraints, e.g., meeting a client to show product samples or making a business trip to a remote city. There are also random events that modify the constraints, e.g., a commuter's car broke down the day before and he must pick it up from the garage on the way back from work.

Constraints such as a worker having to report at work by a certain time of day are major elements that constitute Hägerstrand's time-space prism. The prism, which is illustrated in Figure 1, indicates the area in the time-space coordinates that a worker can occupy. In the figure, x_W is the location of the workplace, and x_H is the location of the worker's home. He cannot leave home before τ_o , and he must be at the workplace by time τ_t . The parallelogram shown in the figure, two of whose vertices are located at (x_H, τ_o) and (x_W, τ_t) , is Hägerstrand's prism. The slope of its sides represents the speed with which the worker can travel (v). Given the constraints that he cannot leave home before τ_o and must report at work by τ_t , his movement in time and space is restricted to be within the prism, as shown by the example trajectories in the figure. The bottom vertex located at (x_H, τ_o) , from which the prism begins, shall be called "origin vertex" and the one located at (x_W, τ_t) , where the prism ends, shall be called "terminal vertex." As these vertices move, the prism changes its position and size, and the extent of the worker's potential action space also changes. This is illustrated in Figure 2.

Researchers in the area of activity-based analysis of travel behavior¹ have adopted the concept of prism to examine the properties of travel behavior (Burns, 1979; Jacobson, 1979; Kitamura et al., 1981; Landau et al., 1981; Damm, 1982), and to simulate activity and travel in time and space (Lenntorp, 1978; Axhausen, 1989, 1990; Kitamura et al., 1997, 2000a; Arentze et al., 2001). These studies in general demonstrate the importance and usefulness of the notion of prisms and the constraints in space and time that they represent.

Researchers' attention, however, has never been directed to the fact that an individual's prism could change its vertex locations from day to day and his behavior would vary accordingly. The most dramatic example would be the daily behavior of a worker who works different shifts from day to day. Although most people live within more stable timeframes, they nonetheless vary over time, at least occasionally. For example, a worker may have a breakfast meeting with a client scheduled at a downtown restaurant (in this case, both the time and space coordinates of the terminal vertex of this worker's morning prism will be different). Or, a parent may have to stay home till 7:45 AM when his daughter will be picked up for a field trip (in this case the time coordinate of the origin vertex will be different).

This study is concerned with how routine a routine really can be. To explore this question, the study examines the day-to-day variability of the time coordinate of a prism vertex, i.e., how

¹ For reviews of the activity-based analysis of travel behavior, see, e.g., Jones et al. (1983), Damm (1983), Kitamura (1988b), Jones et al. (1990), Axhausen and Gärling (1992), and Ettema and Timmermans (1997).

the location along the time axis of a prism vertex varies from day to day. This variability of a prism vertex implies how the timeframe which governs an individual's daily schedule varies from day to day. When the timeframe varies, it is likely that the individual's behavior also varies. When the timeframe is stable, on the other hand, a routine can be maintained. The analysis presented in this paper attempts to determine how much of the variation in travel behavior is due to the variation in the timeframe.

Underlying the study is the recognition that, if one wishes to know the nature of day-to-day variability in travel behavior, then, he must know the variability of a prism vertex location. Yet, to the best knowledge of the authors, no results, either theoretical or empirical, have been accumulated about the day-to-day variability of prism constraints. It is thus unknown how much of the variability in daily travel behavior is due to the variability of prism constraints. This is, presumably to a large extent, due to the fact that prism constraints are quite often unobservable.

Recently, application of stochastic frontier models has been proposed as a means to estimate the location of an unobserved prism vertex (Kitamura et al., 2000b; Pendyala et al., 2002; Yamamoto et al., 2004). This study builds on these earlier studies and attempts to evaluate both longitudinal and cross-sectional variations in the location of a prism vertex using 42-day diary data collected in Germany. It examines the worker's morning prism before work, and the departure time of the first trip in the prism, which is mostly a supposedly routine commute trip. The study investigates: (i) how the time coordinate of the origin vertex varies from worker to worker, and also from day to day for a given worker, (ii) how much of the variations can be explained systematically by observed variables, how much are due to unaccounted differences across workers, and how much are purely random, and (iii) how the vertex location of a prism is related to the starting time of the first trip in the prism. These issues are addressed in this study using statistical models of the prism vertex location and trip starting time.

Although this study is motivated primarily by the desire to gain knowledge about the variation characteristics of prism constraints, its results have certain practical implications. For example, by knowing the relationships between prism constraints and the attributes of the worker, it is possible to determine who tends to be subjected to tighter, or looser, constraints. One would anticipate that those individuals with looser constraints have larger degrees of flexibility in trip making, and are therefore more amenable to policy measures that call for behavioral change. These individuals would then be the primary target of the measures.

This paper is organized as follows. The analytical approaches, especially the application of stochastic frontier models and the decomposition of variations, are discussed in the next section. In the following sections, the data set used is briefly described, and the results of model estimation are presented for both stochastic frontier models of the prism vertex location and linear regression models of the departure time of the first trip in the prism. The variations in prism vertex location and departure time are then decomposed into systematic and random variations. These are each further decomposed into within-person and between-person variations. This is followed by a concluding section that offers a summary of study results and their implications.

Analytical Approach

Consider, as before, a worker who must report at work by τ in the morning. Suppose this worker is located at his home before leaving for work. Then his behavior before work is

constrained by a prism whose origin vertex is located at (x_H, τ_o) and terminal vertex at (x_W, τ_t) . The time coordinate of the origin vertex, τ_o , is unobserved and unknown. The stochastic frontier model is applied in this study to estimate τ_o .

Let t_o be the beginning time of the first trip and t_t be the ending time of the last trip in the prism. Then, at the origin vertex, $\tau_o \leq t_o$, and at the terminal vertex, $t_t \leq \tau_t$. From these inequalities,

$$t_o = \tau_o + u_o, \quad t_t = \tau_t - u_t \quad (1)$$

where u_o and u_t are non-negative random variables. The stochastic frontier model can be applied to estimate unobserved τ_o or τ_t based on the above relations.

Let

$$Y_i = \beta' X_i + \varepsilon_i = \beta' X_i + v_i + u_i \quad (2)$$

where i denotes the individual, Y_i is the observed dependent variable (in this case an observed trip beginning time), β a vector of coefficients, X_i a vector of explanatory variables, v_i and u_i random error terms, $-\infty < v_i < \infty$, $u_i \geq 0$, and $\text{Cov}(u_i, v_i) = 0$, namely, u_i and v_i are uncorrelated. Comparing Eqs. (1) and (2) indicates that $\beta' X_i + v_i$ can be viewed as the time coordinate of the origin vertex of a prism with the random element, v_i . This formulation ensures that the observed trip starting time, Y_i , will not be before $\beta' X_i + v_i$ because u_i is non-negative. A model for the terminal vertex can be formulated similarly as $Y_i = \beta' X_i + v_i - u_i$. In the econometric literature on stochastic frontier models, a normal distribution is often applied to v_i , and a truncated (half) normal distribution to u_i . For details on the distributional forms and model estimation, see Aigner et al. (1977) and Waldman (1982).

As described in the next section, the data set used in this study comprises repeated observations of daily travel from each survey respondent. Let T be the total number of days for which observations are available from the respondent (for simplicity of exposition, it is assumed that observations are available for T days from every respondent), and Y_{it} be the starting time of the first trip in the prism on day t . Thus the data used in this study comprise $(Y_{i1}, Y_{i2}, \dots, Y_{iT})$ and $(X_{i1}, X_{i2}, \dots, X_{iT})$ for individual i . Because these repeated observations are available, it is possible for this study to determine the variability of the prism vertex location and departure time for each individual. They also facilitate the estimation of unobserved heterogeneity as discussed below.

Suppose there are unobserved factors influencing the prism vertex location, that take on different values across individuals, but remain the same over time for a given individual, and let the effects of these factors collectively represented by an individual-specific error component, α_i . This term represents unobserved heterogeneity, i.e., differences across individuals that cannot be attributed to variables that are in the model, but remain stable over time for each individual. Let this error component be normally distributed with a mean 0 and variance σ_α^2 , i.e., $\alpha_i \sim N(0, \sigma_\alpha^2)$, and be introduced into the model of Eq. (2) as

$$Y_{it} = \beta' X_{it} + \varepsilon_{it} = \beta' X_{it} + \alpha_i + v_{it} + u_{it}, \quad t = 1, 2, \dots, T \quad (3)$$

where $u_{it} \geq 0$ as before, and $v_{it} \sim N(0, \sigma_v^2)$. Also, suppose u_{it} is from a half-normal distribution with parameter σ_u for all individuals and at all observation time points. The probability density function of u_{it} is given as

$$g_{u_{it}}(x) = \frac{2}{\sqrt{2\pi}\sigma_u} \exp\left(-\frac{x^2}{2\sigma_u^2}\right), \quad x \geq 0. \quad (4)$$

The error components are all assumed to be uncorrelated (i.e., $\text{Cov}(v_{it}, v_{i't'}) = \text{Cov}(u_{it}, u_{i't'}) = \text{Cov}(v_{it}, u_{i't'}) = \text{Cov}(\alpha_i, u_{i't'}) = \text{Cov}(\alpha_i, v_{i't'}) = 0$ for $\forall i, i', \forall t, t'$, except the case where $i = i'$ and $t = t'$).²

This model is adopted in this study with the intent of accounting for unobserved heterogeneity in the time coordinate of the prism vertex. It should be noted, however, that this error component may be interpreted to represent heterogeneity in the deviation between the prism vertex location and the trip starting time, rather than heterogeneity in vertex location. In other words, α_i may be taken to indicate how the vertex location varies from individual to individual even when the vector of explanatory variables, X_i , takes on the same value (in this case $\beta' X_{it} + \alpha_i$ is interpreted to represent the expected location of prism vertex for individual i), or, it may be taken to indicate how the mean difference between the prism vertex location and trip starting time varies across individuals (in this case, $\alpha_i + u_{it}$ is taken as the deviation between the vertex and trip starting time). Unfortunately it is not possible to determine which is a more plausible interpretation based on statistical analysis of the data at hand.

Using this model, longitudinal, or day-to-day, variations in vertex location are decomposed into: systematic variations due to day-to-day changes in factors that influence the vertex location, and purely random variations. Likewise cross-sectional variations across individuals are decomposed into: systematic variations due to differences in contributing factors (observed heterogeneity) and random variations unaccounted for by observed factors (unobserved heterogeneity). In the analyses presented below, the variability of the departure time of the first trip of the prism is also examined using the same data set and is compared with the variability of the vertex location. Through this comparison, inferences are made on how tightly a prism vertex constrains the departure time.

The systematic variation of the prism vertex location is decomposed as follows. Let the predicted time coordinate of the prism vertex on day t for individual i be $\hat{V}_{it} = \hat{\beta}' X_{it}$, where $\hat{\beta}$ is the estimated coefficient vector, and let $\bar{\hat{V}}_i = \frac{1}{T} \sum_{t=1}^T \hat{V}_{it}$, and $\bar{\bar{V}} = \frac{1}{N} \sum_{i=1}^N \bar{\hat{V}}_i$. Then, the total systematic variation in vertex location, $\sum_i \sum_t (\hat{V}_{it} - \bar{\bar{V}})^2$, can be decomposed as

$$\sum_i \sum_t (\hat{V}_{it} - \bar{\bar{V}})^2 = \sum_i \sum_t (\hat{V}_{it} - \bar{\hat{V}}_i)^2 + \sum_i T (\bar{\hat{V}}_i - \bar{\bar{V}})^2. \quad (5)$$

² Although the individual error components are assumed to be uncorrelated, the sum of the error components is serially correlated because of the inclusion of the individual-specific term.

where the first term on the right-hand side is the sum of within-person variations, and the second term is the between-person variations.³

The total random variation in vertex location can be represented as

$$NT(\sigma_{\alpha}^2 + \sigma_v^2). \quad (6)$$

The variance of the individual-specific error term, σ_{α}^2 , multiplied by NT , represents the variation due to unobserved heterogeneity. $NT\sigma_v^2$, on the other hand, is the variation due to purely random elements, or, white noise. Note that the variance of the error term, u_{it} , is not involved here because the analysis is not concerned with the difference between the prism vertex location and the departure time of the first trip in the prism.

The total variation in prism vertex location is not observable in this case because a prism vertex itself is not observable. Since it is the sum of the systematic and random variations, however, it can be estimated as

$$\sum_i \sum_t (\hat{V}_{it} - \bar{V})^2 + NT(\sigma_{\alpha}^2 + \sigma_v^2). \quad (7)$$

The relationships presented in this section are applied in this study to probe into the nature of the variability across individuals or from day to day of the prism vertex location or departure time.

The Data and Models

The Mobidrive data set is used in the statistical analysis of this study. The Mobidrive project, funded by the German Ministry of Research and Education, involved a six-week travel diary survey conducted in Karlsruhe and Halle, German cities of about 300,000 inhabitants, in the fall of 1999. A total of 317 persons over 6 years of age from 139 households participated in the survey. Altogether, the respondents reported 45,532 trips on 11,737 person-days. The sample used in the analysis of this study comprises 116 workers in the data set. For details of the Mobidrive project and the resultant data set, see Axhausen et al. (2002) and Zimmerman et al. (2001).

As noted earlier, the analysis of this study focuses on the time coordinate of the origin vertex of a worker's morning prism on a weekday (Monday through Friday), and the departure time of the first trip in the prism. Stochastic frontier models are developed for the prism vertex, and linear regression models for the departure time. Individual-specific error components are introduced into both types of models.

The dependent variable of the models, the departure time of the first trip in the prism, is expressed in minutes, with midnight being 0; thus 6:00 AM is represented as 360 and 9:30 AM as 570. Repeated measurements of daily travel are available for an average of 28.0 weekdays from each respondent of the survey, and all available measurements are used for model estimation. An individual-specific random error component is introduced into stochastic frontier models as in Eq. (3).

³ See, e.g., Scheffé (1959).

The set of explanatory variables in the models (see Table 1) contains variables that may appear endogenous at first. The duration of the commute trip (*commute time*) depends on the mode used and the departure time of the trip. The dummy variable indicating whether the first trip in the prism is a commute trip (*first trip is commute trip*) of course depends on the individual's travel decision. These two variables thus represent consequences of the individual's travel decision and the travel decision is governed by prism constraints. They are endogenous in this sense.

These variables are included in the models as explanatory variables based on the following considerations. It is expected that a worker will either plan ahead for the first trip of the day, or adopt a well programmed routine, because the worker's first trip on a weekday is closely tied to how the day is started, which is most presumably planned or programmed beforehand. Attributes of the commute trip will undoubtedly be brought into the planning exercise. If an established routine is adopted, commute trip attributes are also taken into consideration in the sense that the routine has been formed while taking them into account. Consequently, the earliest possible time a worker is willing to leave home will depend on whether he is commuting to work on the day, and also on how long it takes to commute. These two variables can thus be considered as explanatory variables. Yet, it is nonetheless the case that these variables reflect consequences of travel decisions which are governed by prism constraints. Regarding these variables as exogenous is a rather strong assumption, and the authors are unable to provide either empirical evidence substantiating this assumption or previous arguments in the literature supporting or objecting it. This must be kept in mind when interpreting the empirical results of this study.

This leads to the next question of what exactly it is that the stochastic frontier models depict. It would be evident from Eqs. (1) and (2) that $\beta' X_i + v_i$ (or $\beta' X_{it} + \alpha_i + v_{it}$ in Eq. (3)) represents the earliest possible time of departure, and as such it constitutes a prism vertex. Yet, it is not clear whether this point represents a "constraint" that is fixed by external forces. It has been noted earlier (Kitamura et al., 2000b) that observed travel behavior is governed by subjective beliefs and perceptions about the constraints supposedly at work. Then, there may be no prism vertex at work in the sense of Hägerstrand. In fact it is rather unconvincing to argue that the origin vertex of a morning prism is fixed completely by external forces as a constraint in the strict sense of the word. For example, one could drive out of home at 3:00 AM if one wishes and makes arrangements for his sleep beforehand. In fact one does so when he has to take the first flight in the morning for a business trip, or when he is going out for fishing on a Saturday. Yet, he would view it infeasible to leave home at 3:00 AM on a normal workday. A view is adopted in this study that the origin vertex of the morning prism is a threshold that is set by the individual, rather than being an externally established constraint. In other words, it is conjectured that the prism vertex constitutes a "soft" constraint. It is not entirely imposed by external forces, but is at least partially self-imposed by the individual while considering the plan for the day. From this view, the prism vertex location is partially a product of the individual's planning effort.⁴

⁴ In the discussions of this study, the origin vertex of the morning prism and the beginning time of the first trip of the day are conceptually distinguished. An alternative view would be to treat the beginning time of the first trip as the origin vertex of the morning prism, which is obviously not adopted in this study. Likewise, it may be argued that the work starting time cannot be automatically assumed as the terminal vertex of a morning prism because the work starting time has nowadays become quite flexible for many workers and does not constrain workers' behaviors as it once did. This is not addressed in this study; reexamining roles played by a work starting (or ending) time remains as a future task.

Estimation Results

Estimated stochastic frontier models are presented in Table 1 along with least-squares models of the departure time (the models presented in this paper are all estimated using LIMDEP Version 7.0 or 8.0, by Econometric Software, Inc.). The first two models in the table (V1 and V2) are stochastic frontier models of the origin vertex of a worker's morning prism. The coefficient estimates of *first trip is commute trip*⁵ indicate that the vertex location is moved earlier by about 75 min when the first trip is a commute trip. The table also indicates that male workers tend to have vertices that are located about 20 min earlier than those of their female counterparts. Married workers and those with children also tend to have vertices located earlier. On the other hand, higher-income workers, those living in central city or in Karlsruhe tend to have vertices located later in time.

With a t-statistic of 2.92, parameter σ_α , which represents the standard deviation of the individual-specific error component, α_i , is highly significant (Model V2), offering evidence for the presence of unobserved heterogeneity in prism vertex location.⁶ Namely, the vertex location varies from worker to worker as the value of α_i varies, in ways that cannot be explained by the variables in the data set. Recall that the value of this error component does not vary over time for a given worker. The coefficient estimates of the explanatory variables are quite stable between the two models, except for those of *family with child(ren)* and *living in CBD*, but Model V2 with the error component has larger estimated t-statistics for most of the explanatory variables.

Although estimation results are not presented in this paper, models with four dummy variables representing days of the week were also estimated. The coefficient estimates of the day-of-the-week dummy variables turned out to be insignificant, both individually and collectively as a group, and for both models with and without the individual-specific error component (χ^2 of 3.22 with 4 degrees of freedom for the model without the error component, and 0.86 for the model with the error component). As far as the time coordinate of the origin vertex of a worker's weekday morning prism is concerned, there is no statistically significant systematic variation by day of the week.

As a result, the models of the origin vertex contain only two explanatory variables that may vary from day to day: *commute time* and *first trip is commute trip*. Consequently, the models contain only these two explanatory variables that systematically account for day-to-day variations in vertex location. This scarcity of explanatory variables is presumably because it has not been customary in the travel behavior analysis field to measure variables that may be associated with day-to-day variability in travel in travel surveys. For example, a parent may have to chauffeur his child to a piano lesson on a certain day of the week, generating a systematic variation, but such information is not included in most travel survey data, including the one used in this study. The reader should keep in mind that some of the variations are reported as random variations in this study because factors that may explain them are not observed, and they may in fact be systematic variations.⁷ As a future extension,

⁵ The first trip of the day was a commute trip for approximately 80% of the time in the data.

⁶ The likelihood-ratio statistic for σ_α obtained from the difference in $L(\beta)$ between Models V1 and V2 ($-2(-20087+19943) = 288$, $df = 1$) is much more significant than the t-statistic associated with it. This may be due to the correlations among the estimates of σ_α , σ_α and σ_α which would tend to make the t-statistic for each estimate smaller.

⁷ On the other hand, it is conceivable that *commute time*, which represents the travel time as perceived and

it is desired that variables associated with day-to-day variability, such as those representing social commitments or intra-household task allocation, be sought and measured.

Table 1 also shows estimation results for three versions of least-squares models of the departure time, one without any error component (Model *D1*), one with an individual-specific component (*D2*), and one with individual- and time-specific components (*D3*), formulated as

$$Y_{it} = \theta' X_{it} + \varepsilon_{it}, \quad (8a)$$

$$Y_{it} = \theta' X_{it} + \zeta_i + \nu_{it}, \text{ and} \quad (8b)$$

$$Y_{it} = \theta' X_{it} + \zeta_i + \varpi_t + \zeta_{it} \quad (8c)$$

respectively, where Y_{it} is the departure time by individual i on day t , X_{it} is a vector of explanatory variables as before, θ is a vector of coefficients, ζ_i is an individual-specific error component, ϖ_t is a time-specific error component, and ε_{it} , ν_{it} and ζ_{it} are purely random error terms. All error components are assumed to be normally distributed and mutually independent.

These least-squares models are formulated with the same set of explanatory variables as the stochastic frontier models of the prism vertex location. Comparing the coefficient estimates of the two sets of models indicates that the coefficients of *commute time* and *first trip is commute trip* are larger in their absolute values in the least-squares models of the departure time. It appears the attributes of commute trips are more directly related to the departure time than to the vertex location.

The model with the time-specific error component (*D3*) does not show any noticeable improvement in the model's fit, nor is its inclusion well supported theoretically. As was the case for the prism vertex location, variations associated with the day of the week are statistically insignificant. Based on these results, no time-specific component is considered in the subsequent modeling effort.

Another set of models of the departure time is developed without restricting the explanatory variables to the ones in the models of the prism vertex. Results are presented in Table 2. Both models with and without an individual-specific component are estimated. The last two models (*D6* and *D7*) include the expected location of the prism vertex (\hat{V}) obtained from the stochastic frontier model with α_i (Model *V2*), to infer the effect of the prism vertex location on the departure time. The new explanatory variables introduced here are: *size of party*, *main mode = car/motorcycle*, *main mode = bicycle/walk*, and *number of activities per day*. Excluded from the models are *household size*, *household income* and *parent*.

The most significant variable is again *first trip is commute trip*, which has coefficient estimates of -110 to -120 in the models without the expected vertex location; workers leave home earlier by about 2 hours when the first thing they do is to commute. One might anticipate that a worker would leave home earlier if he pursues some non-work activity first. The estimation results here indicate that is not the case.

The coefficient estimates of *number of activities per day* indicate that workers with more

reported by the respondent, is likely to be more stable than the actual commute time. If this is in fact the case, then *commute time* as an explanatory variable under-represents systematic day-to-day variation.

out-of-home visits to make tend to leave earlier, by approximately 10 minutes per visit. *Size of party*, which represents the number of co-travelers of the first trip (including the worker himself), has significant positive coefficient estimates; a worker who is making the first trip of the day with co-travelers tend to leave home later. Likewise the coefficients of *main mode = car/motorcycle* and *main mode = bicycle/walk* indicate that workers using these individualized travel modes tend to leave home later. Since *commute time* is in the models with negative coefficient estimates, it is unlikely that these results are artifacts of the association between commute duration and commute travel mode. It may be the case that these workers who use individualized travel modes or those who are traveling in parties tend to leave later to avoid traffic congestion.

Because the stochastic frontier models of the prism vertex location and the least-squares models of the departure time share several explanatory variables, inclusion of the expected vertex location (\hat{V}) reduces the coefficient estimates of these common variables, most noticeably *first trip is commute trip*. Yet, these variables have the same respective effects on departure time in the models with \hat{V} as in the models without \hat{V} .

The coefficient of *expected vertex location* is estimated at 0.689 in the model without an error component (D6), and at 0.650 in the model with one (D7). Taking the estimate from the model with the error component, it may be inferred that, *ceteris paribus*, a worker's departure time would on average be 39 minutes earlier (or later) when the vertex is moved earlier (later) by 1 hour.

The coefficient estimates of Models D5, V2 and D7 are presented together in columns (a), (b) and (c) in Table 3, along with the estimated total effects of each explanatory variable on the departure time in column (d). The total effect of an explanatory variable is computed as the sum of its direct effect as represented by the coefficient of Model D7, and the indirect effect through \hat{V} , which is computed as 0.650 times its coefficient in Model V2. The total effects in column (d) thus computed may be compared with the coefficient estimates in column (a), which are obtained without involving the notion of prism vertex.

Overall, the coefficient estimates in column (a) are consistent with the estimated total effects presented in column (d). This result suggests that the stochastic frontier model of the prism vertex location and the least-squares model of the departure time with estimated vertex location \hat{V} have successfully decomposed each variable's effect on departure time into the effect on the prism vertex location and that on the departure time given a vertex location. The only noticeable discrepancy is found for the total effect of marital status (-38.8), which is much larger in its absolute value than the coefficient estimate of the model of departure time (-26.9). This is presumably due to the inclusion of *parent*, which is undoubtedly correlated with *married*, in the model of the vertex location. Considering the fact that the stochastic frontier model has an entirely different error structure than the least-squares model, the consistency shown here is quite noteworthy.

Comparing the coefficient estimates of columns (b) and (c), then, it is possible to infer the relative magnitudes of the direct effect and the indirect effect (through prism vertex location) on the departure time for each explanatory variable. Most obviously, *household size*, *household income* and *parent* are included only in the stochastic frontier model of prism vertex location, having only indirect effects on the departure time in this model specification. On the other hand, *size of party*, *main mode = car/motorcycle*, *main mode = bicycle/walk*,

and *number of activities per day* have only direct effects. The coefficient of *living in Karlsruhe* in column (b) is much larger than that in column (c); its indirect effect is much larger than its direct effect. *Married* and *living in CBD* show the same tendency. Conversely, *Family with child(ren)* has a larger direct effect than the indirect effect.

The results offer indications that stationary explanatory variables whose values do not change in the short-term (*household size, household income, parent, living in Karlsruhe*) tend to influence departure time indirectly through its influence on the vertex location. Transient variables (*size of party, main mode = bicycle/walk, main mode = bicycle/walk, number of activities per day*), on the other hand, tend to influence departure time more directly. Notable are effects of *commute time* and *first trip is commute trip*, whose coefficient values do not vary very much between the two models, indicating that they respectively influence the vertex location and the departure time by about the same amount, and the indirect effect is about 65% of the direct effect.

Decomposing the Variation

The variations of the prism vertex location and departure time are decomposed into systematic variations and random variations, which are each further decomposed into within-person variations and between-person variations. The results are summarized in Table 4. The sums of squares of the frontier model with the individual-specific error component (Model V2 of Table 1) are evaluated as shown in the table. Note that, since the term, u_{it} , of this model is for the deviation between the time coordinate of the prism vertex and the departure time of the first trip, its variance is not included as part of the error sum of squares for vertex location.

Quite noticeable in Table 4 is the difference in total variance between the two models; the total variance of the departure time (72,842,499) is more than 7 times larger than that of the prism vertex location (10,115,356). The variance of the prism vertex location is estimated at 3110.5, while that of the departure time is 22399. The departure time of the first trip of a worker on a weekday varies from day to day and from worker to worker much more substantially than does the origin vertex of the morning prism.

Of the estimated total sum of squares of the frontier model, 47.9% is the regression sum of squares (SSR), and 52.1% is the error sum of squares (SSE). Of the regression sum of squares, approximately one-third (34.5%) is attributed to within-person (day-to-day) variations and about two-thirds to between-person variations (the relative magnitudes of the variance components are illustrated in Figure 3). The prism vertex location does vary systematically from day to day depending on the commute duration and on whether the first trip in the prism is a commute trip, which in turn depend on various factors that influence the worker's daily itinerary. Of the error sum of squares, only 0.7% is attributable to the individual-specific error component, or, unobserved heterogeneity. Although the estimation result has indicated the significance of σ_a , the variance of the error component is small relative to that of v_{it} which represents white noise.

Accounting for only 16.5% of the total sum of squares, the fraction of the regression sum of squares is much smaller in the linear regression model of the departure time. This sum is almost evenly split between within-person variations and between-person variations. Namely, systematic day-to-day variations and systematic between-person variations equal each other approximately for the departure time. Turning to the error sum of squares, the individual-specific error component accounts for over one-quarter, and white noise less than

three-quarters, of the error sum of squares. Unlike the case for the prism vertex location, unobserved heterogeneity is prominent in the model of the departure time.

Summarizing the findings of this section,

- The total sum of squares of the departure time is more than 7 times larger than that of the prism vertex location. The departure time of the first trip in a prism is much more variable than the prism vertex location.
- Variation of the prism vertex location is more systematic than that of the departure time. For the prism vertex location, almost one-half of the total variations is systematic. The corresponding value for the departure time is only 16.5%.
- Of the systematic variations of the prism vertex location, 34.5% are within-person, or day-to-day, and the remaining 65.5% are between-person, yielding a within-person to between-person ratio of about 1 to 2. The systematic variations of the departure time are almost exactly evenly split between the two; within-person variations account for 50.1% and between-person 49.9%. Compared with the departure time, the prism vertex has a much larger fraction of systematic variations, but a smaller fraction of the systematic variations is within-person, or day-to-day.
- The individual-specific error component accounts for a larger fraction of the total variations for the departure time than for the prism vertex location (21.6% vs. 0.4%). Unobserved heterogeneity is more dominant with the departure time than with the prism vertex location.

The departure time is more variable than the prism vertex location, and is influenced more by random factors. Conversely, the prism vertex location varies more systematically as the explanatory variables change their values, both from day to day and between individuals, but more so between individuals. Unlike the case for the prism vertex, unobserved heterogeneity is prominent with the departure time. Namely, some individuals tend to leave earlier, and some later, than the model predicts, suggesting the presence of unobserved contributing factors whose effects do not vary over time.

Conclusion

An individual's daily travel is constrained by time-space prisms as much as it is driven by the needs and desires of the individual and his household. The variability of a prism vertex location implies how the timeframe of the individual's daily schedule varies from day to day; it determines how routine a routine really can be. With the intent of revealing the variability of a prism vertex location, six-week travel diary records contained in the Mobidrive data set have been examined in this study.

Taking the case of the morning prism of commuters and the first trip within the prism, the statistical analyses of this study have examined longitudinal and cross-sectional variations of prism vertex locations and departure times. The analyses applied stochastic frontier models to locate the unobserved time coordinate of a prism vertex, and linear regression models to estimate the departure time of the first trip in the prism. An individual-specific error component is introduced into both types of models to account for unobserved heterogeneity, i.e., differences across individuals that do not change over time and are not explained by the explanatory variables in the model.

By applying the two types of models, the study has successfully shown how each contributing variable influences the location of a prism vertex and the departure time of the

first trip. Furthermore, it has been shown that the effect of a variable on the departure time can be divided into direct and indirect effects. The indirect effect of a variable is the one it exerts on the departure time through its effect on the location of the prism vertex. The study results have shown that a unit change in a prism vertex location influences the departure time by 0.65 unit. For example, if a vertex is moved earlier by 10 minutes, the departure time of the first trip in the prism will tend to move earlier by 6.5 minutes. It has also been shown that stationary factors tend to influence the vertex location more than the departure time, and transient factors tend to influence the departure time more than the vertex location.

The statistical analyses have revealed that the departure time has much larger variations than the prism vertex location, and a larger fraction of the variations is due to random factors. The prism vertex location, on the other hand, varies more systematically with the explanatory variable values, both from day to day and across individuals. Unobserved heterogeneity is prominent with the departure time, but not with the prism vertex. In other words, Most of the random variations in the vertex location are white noise. For the departure time of the first trip in the prism, on the other hand, systematic variations are much smaller, unobserved heterogeneity is much larger, and white noise accounts for over 60% of the total variations.

The results imply that the origin vertices of workers' morning prisms are located with a much smaller variance and are more systematically varying than the departure times of the first trips in the prisms. Larger degrees of variability and unobserved heterogeneity are associated with the departure times of trips made under prism constraints. Suggested by this is the presence of large degrees of flexibility associated with trip making. It appears as if there is room for behavioral modification with respect to the departure time of a morning trip.

By showing that the time coordinate of a prism vertex does vary from day to day as well as from individual to individual, and by comparatively analyzing the variations in the vertex location and the departure time, this study has shed a new light on the variability in daily travel behavior. The empirical findings of this study add to the body of knowledge on multi-day travel behavior. At the same time, they will find practical applications in transportation planning, e.g., in the simulation of individuals' travel behavior under prism constraints, or in the assessment of possibilities for behavioral modification in response to policy measures. The study, however, is subject to several limitations as discussed earlier in this paper, including the limited range of explanatory variables that account for within-person, or day-to-day, variations. Addressing these limitations remains as future tasks.

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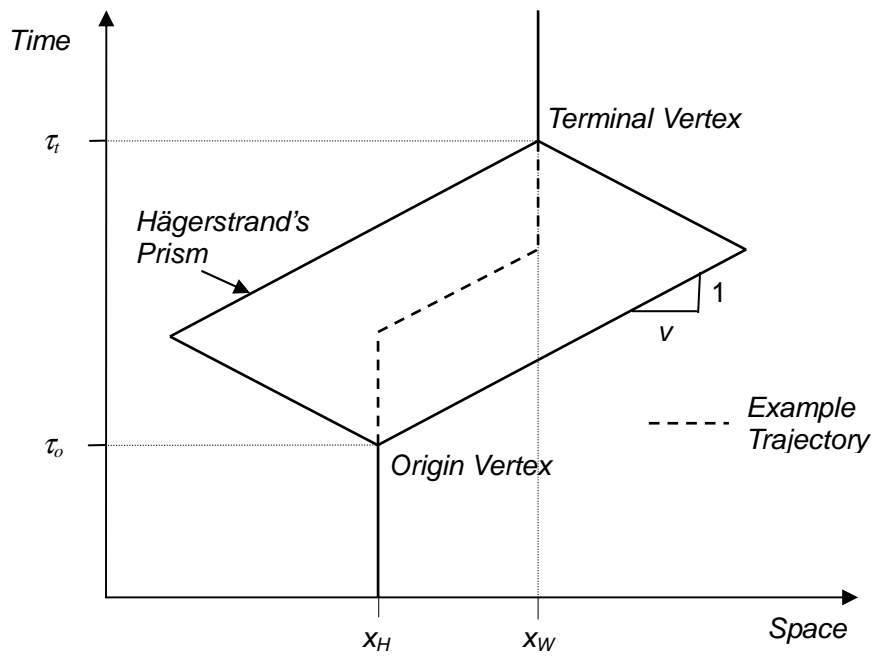
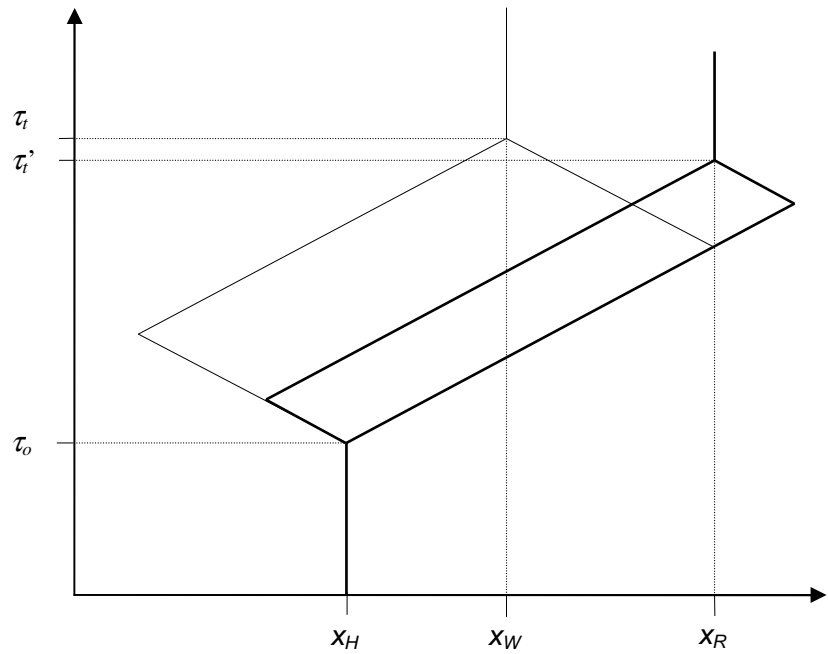
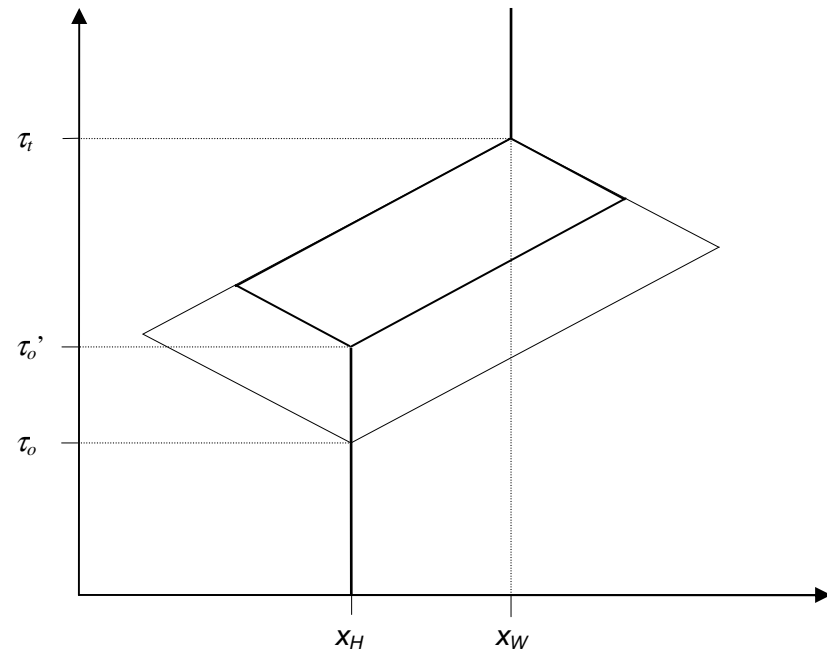


Figure 1. A Worker's Morning Prism and Its Vertices



A breakfast meeting at a restaurant located at X_R begins at τ_t' .



A child is to be picked up at τ_0' for a field trip.

Figure 2. Example Day-to-day Variations in a Worker's Morning Prism

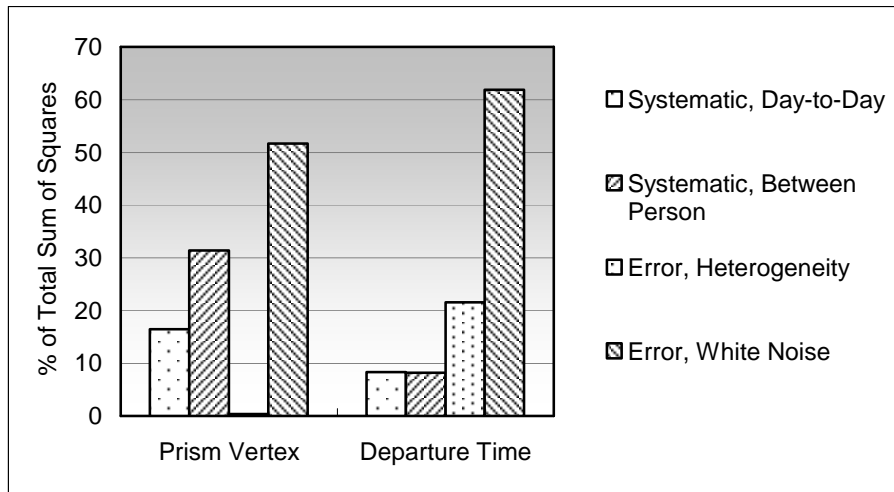


Figure 3. Relative Magnitudes of the Variance Components of Prism Vertex Location and Departure Time

Table 1. Stochastic Frontier Models of Prism Vertex Location and Least-squares Models of Departure Time

	Stochastic Frontier Models of Prism Vertex Location				Least-squares Models of Departure Time of First Trip in Prism					
	(V1)		(V2)		(D1)		(D2)		(D3)	
	$Y_{it} = \beta' X_{it} + v_{it} + u_{it}$		$Y_{it} = \beta' X_{it} + \alpha_i + v_{it} + u_{it}$		$Y_{it} = \theta' X_{it} + \varepsilon_{it}$		$Y_{it} = \theta' X_{it} + \zeta_i + v_{it}$		$Y_{it} = \theta' X_{it} + \zeta_i + \bar{\omega}_i + \zeta_{it}$	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Constant	396	48.17	392	93.59	610	59.75	606	23.57	605	23.51
Commute time (min.)	-0.31	-2.58	-0.24	-4.01	-0.54	-4.60	-0.32	-2.53	-0.32	-2.51
First trip is commute trip [D]	-75.6	-17.28	-75.9	-32.57	-124.3	-20.05	-120.1	-17.83	-119.7	-17.78
Household size	-5.26	-1.68	-5.61	-3.52	-5.65	-1.60	-3.79	-0.38	-3.59	-0.36
Household income (in 1,000DM)	6.53	4.79	5.94	8.42	3.66	2.54	2.46	0.61	2.42	0.60
Male [D]	-22.0	-5.05	-19.6	-8.69	-22.6	-4.32	-22.2	-1.49	-22.2	-1.50
Parent [D]	29.8	4.53	31.6	9.30	22.9	3.00	20.6	0.95	20.5	0.95
Married [D]	-29.2	-5.52	-28.1	-10.37	-36.0	-5.87	-36.7	-2.12	-37.1	-2.14
Family with child(ren) [D]	-28.5	-4.65	-19.5	-6.00	-41.4	-6.24	-43.6	-2.28	-43.6	-2.28
Living in CBD [D]	19.3	3.21	27.5	7.06	31.6	3.65	40.4	1.69	41.2	1.72
Living in Karlsruhe [D]	34.3	7.87	33.4	14.59	18.7	3.55	17.2	1.15	17.1	1.14
σ_α			3.45	2.92						
σ_u	188		192							
σ_v	50.5		40.1							
$\sigma_\varepsilon, \sigma_v, \sigma_\zeta$					136.2		120.2		120.0	
σ_ζ							70.3		70.4	
$\sigma_{\bar{\omega}}$									12.12	
L(0)					-20860					
L(C)	-20326		-20326							
L(β)	-20087		-19943		-20602					
R^2					0.146		0.145		0.145	
Adjusted R^2					0.144					

Number of sample individuals = 116, number of cases = 3,253

[D]: 0-1 dummy variable

The least-squares models of departure time are estimated with multi-stage procedures and the R^2 's or variance estimates are not comparable across the models.

Table 2. Revised Least-squares Models of Departure Time with and without Expected Vertex Location

	Without Expected Vertex Location				With Expected Vertex Location (\hat{V})			
	(D4)		(D5)		(D6)		(D7)	
	$Y_{it} = \theta' X_{it} + \varepsilon_{it}$		$Y_{it} = \theta' X_{it} + \zeta_i + v_{it}$		$Y_{it} = \theta' X_{it} + \gamma \hat{V} + \varepsilon_{it}$		$Y_{it} = \theta' X_{it} + \gamma \hat{V} + \zeta_i + v_{it}$	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Constant	581.	47.65	561.	28.03	302.	4.62	297.	1.69
Commute time (min.)	-0.69	-5.77	-0.43	-3.31	-0.57	-4.68	-0.28	-1.72
First trip is commute trip [D]	-118.9	-18.73	-110.8	-16.08	-67.5	-5.05	-61.6	-1.84
Male [D]	-22.6	-4.29	-27.6	-1.95	-11.7	-2.01	-17.0	-1.08
Married [D]	-25.5	-4.95	-26.9	-1.91	-18.4	-3.43	-20.5	-1.40
Family with child(ren) [D]	-36.8	-5.73	-33.6	-1.89	-27.9	-4.14	-26.0	-1.41
Living in CBD [D]	33.4	4.02	38.1	1.72	14.3	1.53	20.9	0.84
Living in Karlsruhe [D]	25.7	5.22	24.4	1.80	2.00	0.27	1.66	0.08
Size of party	46.0	8.72	38.1	7.36	46.0	8.74	38.1	7.38
Main mode = car/motorcycle	12.3	1.90	39.5	4.19	15.7	2.41	40.3	4.27
Main mode = bicycle/walk	-0.25	-0.03	25.4	2.56	5.25	0.70	26.7	2.69
Number of activities per day	-9.74	-7.92	-9.10	-7.31	-9.90	-8.07	-9.11	-7.32
Expected vertex location (\hat{V})					0.689	4.36	0.650	1.51
$\sigma_\varepsilon, \sigma_v$	133.3		117.7		133.0		117.7	
σ_ζ			69.5				69.2	
L(0)	-20860				-20860			
L(β)	-20533				-20523			
R^2	0.183		0.176		0.187		0.181	
Adjusted R^2	0.180				0.184			

Number of sample individuals = 116, number of cases = 3,253

[D]: 0-1 dummy variable

The models are estimated with multi-stage procedures and the R^2 's or variance estimates are not comparable across the models.

Table 3. Direct Effects (a), Net Effects (b) and Total Effects (d) of Variables on Departure Time

	(a) Least-squares Model of Departure Time		(b) Stochastic Frontier Model of Prism Vertex Location		(c) Least-squares Model of Departure Time with \hat{V}		(d) Total Effect on Departure Time
	$Y_{it} = \theta' X_{it} + \zeta_i + v_{it}$		$Y_{it} = \beta' X_{it} + \alpha_i + v_{it} + u_{it}$		$Y_{it} = \theta' X_{it} + \gamma \hat{V} + \zeta_i + v_{it}$		
	Coef.	<i>t</i>	Coef.	<i>t</i>	Coef.	<i>t</i>	
Constant	561.	28.03	392	93.59	297.	1.69	551.8
Commute time (min.)	-0.43	-3.31	-0.24	-4.01	-0.28	-1.72	-0.44
First trip is commute trip [D]	-110.8	-16.08	-75.9	-32.57	-61.6	-1.84	-110.9
Household size			-5.61	-3.52			-3.65
Household income (in 1,000DM)			5.94	8.42			3.86
Male [D]	-27.6	-1.95	-19.6	-8.69	-17.0	-1.08	-29.7
Parent [D]			31.6	9.30			20.5
Married [D]	-26.9	-1.91	-28.1	-10.37	-20.5	-1.40	-38.8
Family with child(ren) [D]	-33.6	-1.89	-19.5	-6.00	-26.0	-1.41	-38.7
Living in CBD [D]	38.1	1.72	27.5	7.06	20.9	0.84	38.8
Living in Karlsruhe [D]	24.4	1.80	33.4	14.59	1.66	0.08	23.4
Size of party	38.1	7.36			38.1	7.38	38.1
Main mode = car/motorcycle	39.5	4.19			40.3	4.27	40.3
Main mode = bicycle/walk	25.4	2.56			26.7	2.69	26.7
Number of activities per day	-9.10	-7.31			-9.11	-7.32	-9.11
Expected vertex location (\hat{V})					0.650	1.51	

(a) Model D5 of Table 2, (b) Model V2 of Table 1, (c) Model D7 of Table 2.

The total effect in column (d) of each variable is computed as the coefficient in column (b) times 0.650 plus the coefficient in column (c).

Table 4. Analysis of Variance of Prism Vertex Location and Departure Time

		Frontier Model of Vertex Location			Regression Model of Departure Time		
			SS	%		SS	%
SSR	Within-person	$\sum_i \sum_t (\hat{V}_{it} - \bar{\hat{V}}_i)^2$	1670917	34.5 16.5	$\sum_i \sum_t (\hat{Y}_{it} - \bar{\hat{Y}}_i)^2$	6021498	50.1 8.3
	Between-person	$\sum_i T(\bar{\hat{V}}_i - \bar{\bar{V}})^2$	3174864	65.5 31.4	$\sum_i T(\bar{\hat{Y}}_i - \bar{\bar{Y}})^2$	6009419	49.9 8.2
	Subtotal		4845781	100.0 47.9		12030917	100.0 16.5
SSE	Error Component	$NT\sigma_\alpha^2$	38719	0.7 0.4	$NT\sigma_\zeta^2$	15725002	25.9 21.6
	White Noise	$NT\sigma_v^2$	5230857	99.3 51.7	$NT\sigma_v^2$	45086580	74.1 61.9
	Subtotal		5269575	100.0 52.1		60811582	100.0 83.5
Total			10115356	100.0		72842499	100.0

SSR = regression sum of squares, SSE = error sum of squares
 $NT = 3,253$

The sums of squares are evaluated for the stochastic frontier model with the individual-specific error component (Model V2 in Table 1), and the linear regression model with the error component without expected vertex location (Model D5 in Table 2). The R^2 statistic shown in Table 2 does not agree with the square sums in this table because the latter are based on recalculated predicted values of departure times.