AN ANALYSIS OF URBAN TRAVEL TIMES: A RANDOM PARAMETERS HAZARD-BASED APPROACH

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ABSTRACT

The traditional approach to urban travel analysis includes a detailed and complex modeling system that considers activity/trip generation (including time-of-day of trip) and destination, mode, and route choices. While the insights that one can gain from such a comprehensive approach are undeniable, a more simplistic approach that focuses on travel time alone (which by its nature will implicitly include the complex decision-making related to destination, route, activity and time-of-day choices), can also provide valuable information for policy makers into the determinants of congestion, the behavior and destination choices of travelers, and so on. However, in such an approach, the unobserved heterogeneity that is introduced by simplifying a complex decision-making process must be addressed. In this paper, the determinants of travel time-to-destination for an urban area are studied while explicitly accounting for unobserved heterogeneity using hazard-based duration models with random parameters. Using an extensive geocoded trip dataset from Athens, Greece, time-to-destination model estimation results indicate that travel time duration is significantly affected by a number of factors such as sociodemographic and trip characteristics, travel mode, frequency of trip, and time of day of the trip. In addition, the effect of many of these factors was found to vary across the population, thus underscoring the need for using a random-parameters formulation in studying urban travel times with this approach.

INTRODUCTION

Urban travel-time analysis requires the study of a complex decision process that deals with activity/trip generation, and destination, mode, and route choices, all of which can be modeled to estimate resulting travel times for specific travelers in a given urban transportation network. Over the years, to study complex traveler decisions and to develop models capable of predicting the likely travel-times (time to destination) resulting from new transportation projects, shifts in residential populations, and so on, detailed urban models have been constructed based on the traditional four-step process (trip generation, trip distribution, mode choice and traffic assignment), and extensions with activity-based models and dynamic urban network models.

As an alternative to an extensive urban transportation modeling system, a more simplistic approach to gain some insight into the factors that determine individual travel times is to model travel times directly (implicitly including the complex decision making relating to destination, route, activity and time-of-day choices). With such an approach, numerous research efforts have investigated the relationships between travel time (origin to destination) and a wide variety of influential factors such as trip purpose, traveler socio-economic characteristics, financial and demographic information for the origin and destination locations, transportation mode, frequency of trip and trip departure-time choice (*1-9*). The effect of other travel measures, such as total trip making on a given day, has also been found to affect both the travel time and the duration of the activity to which travel is being undertaken (*10-13*).

In terms of methodological approaches used to study urban travel times, a variety of approaches have been applied including simple regression, three-stage least squares (simultaneously estimating travel time and activity duration) and hazard-based duration models (*11-15*). However, in any study of individual travel times, the issue of unobserved heterogeneity (resulting from the fact, among others, that actual observed travel times result from a complex process – one in which the analyst is likely to have limited information in terms of relevant explanatory variables), is a methodological concern that must be carefully considered.

In this paper the focus is on identifying important factors that determine travel times (time-to-destination) by applying hazard-based duration models with heterogeneity in the hazard function and in the parameters of explanatory variables. Accounting for heterogeneity in these two ways is shown to provide significantly better models in terms of statistical fit and the subsequent inferences drawn.

METHOD AND APPROACH

The elapsed time traveling until travelers reach their destination is an important element for identifying travel patterns and improving mobility, accessibility, and safety of travelers. While such travel times are continuous data that can be modeled by traditional ordinary least squares, they can also be considered as duration data and viewed as the time that transpires until a trip ends. Under such an approach, hazard-based duration models can be used and these models can provide additional insights into important duration effects such as the manner in which the probability that a trip will end (soon), changes over the time the trip has lasted (*16-21*).

For travel time durations, hazard-based models will consider the conditional probability of a trip duration ending at some time t, given that it has not ended until time t and the hazard function is written as (*21*):

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \quad (1)$$

where $F(t)$ and $f(t)$ are the cumulative distribution function and the density function of travel times, respectively, and $S(t)$ is the survival function (the probability that a trip duration is greater than or equal to time t). In this case the hazard function gives the rate at trip travel times are ending at time t, given that they have lasted up to time t. If this hazard function is upward sloping over the duration of the trip ($dh(t)/dt>0$), it means that the probability that a trip will end soon increases the longer the trip lasts. If the hazard function is downward sloping over the duration of the trip ($dh(t)/dt<0$) it means that the probability that a trip will end soon decreases the longer the trip lasts. Finally, if the hazard function is constant over the duration of the trip ($dh(t)/dt=0$) it means that the probability that a trip will end soon is not dependent on how long the trip has lasted.

To account for the effect of explanatory variables in hazard models, a proportional hazards approach can be used where the explanatory variables act multiplicatively on some underlying (or baseline) hazard function such that (*21*):

$$h_n(t \mid \boldsymbol{X}) = h_0(t)\, EXP(\boldsymbol{\beta X}_n), \quad (2)$$

where, $\boldsymbol{X_n}$ is a vector of explanatory variables associated with traveler n, $\boldsymbol{\beta}$ is a vector of estimable parameters, and $h_0(t)$ is the baseline hazard that denotes the hazard when all elements of the explanatory variables vector are zero. In estimating Equation 2, a common approach is to consider various parametric forms of the underlying hazard function (non-parametric approaches are also used but their duration effects – how the hazard changes over time – can be difficult to interpret). The most widely used parametric forms include the Weibull and log-logistic models. The Weibull model allows monotonically increasing or decreasing hazard functions (implying the probability of a trip duration ending can increase or decrease the longer the trip lasts). With parameters $\lambda > 0$ and $P > 0$, the Weibull distribution has the density function,

$$f(t) = \lambda P(\lambda t)^{P-1} EXP[-(\lambda t)^{P}], \quad (3)$$

with hazard,

$$h(t) = (\lambda P)(\lambda t)^{P-1}, \quad (4)$$

As indicated in Equation 4, if the Weibull parameter P is greater than one, the hazard increases monotonically with trip duration; if P is less than one, it is monotonically decreasing with the trip duration; and, if P is equal to one, the hazard is constant over time.

The log-logistic model has been previously applied to travel time durations by Martchouk et al. (*22*) and has the advantage of allowing for a more realistic nonmonotonic hazard function. However, because more complex versions of the Weibull model will be considered to account for heterogeneity across observations, the monotonic hazard function restriction of the Weibull model is effectively relaxed. In our subsequent empirical work, the log-logistic model did not perform as well as the Weibull-model variants that were considered. Thus, the log-logistic formulation is not presented in this paper.

As previously mentioned, a critical concern in the application of hazard models to travel times is the possibility of unobserved heterogeneity. There are two ways of addressing this. First, the traditional proportional-hazards approach (see Equation 2) assumes that the baseline hazard function, $h_0(t)$, is homogenous across observations. However, the possibility that the baseline hazard may vary across observations due to unobserved heterogeneity is a very real possibility and has been found to be significant in a number of studies (*21*, *23-24*). A common approach is to introduce heterogeneity by assuming a distribution across the population, and the gamma distribution has been a popular choice for this. To see how this is done for the Weibull model (see Washington et al. (*21*) for a detailed discussion), let w represent heterogeneity, $g(w)$ be its gamma distribution over the population with mean 1 and variance θ, and $S(t|w)$ a conditional survival function (see Equation 1), the unconditional survival function is,

$$S(t) = \int_0^{\infty} S(t \mid w) g(w) dw = \left[1 + \theta(\lambda t)^P\right]^{-1/\theta}, \qquad (5)$$

resulting in the hazard function,

$$h(t) = \lambda P(\lambda t)^{P-1}[S(t)]^{\theta}, \qquad (6)$$

Note that if $\theta = 0$ the hazard reduces to Equation 4, which is the Weibull model without heterogeneity in the baseline hazard.

The second way to account for heterogeneity is to allow some (or all) of the model parameters to vary across observations. To account for heterogeneity in this random-parameters manner (unobserved factors that may vary across observations), Greene (*25*) developed a method for incorporating random parameters in hazard-based duration models (see also Anastasopoulos (*26*) for an application of this approach). This approach considers estimable parameters as,

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \varphi_i, \qquad (7)$$

where φ_i is a randomly distributed term (for example a normally distributed term with zero mean and variance equal to σ^2). The variation of $\boldsymbol{\beta}_i$ has density $q(\boldsymbol{\beta}_i|\varphi)$, where φ is a vector of parameters of the density distribution (frequently referred to as mixing distribution).

Because maximum likelihood estimation of the random parameters hazard-based duration models is computationally cumbersome (due to the required numerical integration of the duration function over the distribution of the random parameters), a simulation–based maximum likelihood method is used (see Train (*27*)). The most popular simulation approach uses Halton draws which have been shown to provide a more efficient distribution of draws for numerical integration than do purely random draws (see Bhat (*28*)).

DATA

The data used in this study were collected through an extensive travel survey done in the Greater Athens, Greece, Metropolitan area. The surveys were collected in 2005 and included geocodes for all trip origins and destinations, permitting detailed time and distance estimations for all trips performed.

The demographic information includes gender (four age categories: 0 to 19, 20 to 34, 35 to 64, and above 65 years old), age, number of the household members, and number of vehicles and motorcycles owned. The household and origin and destination areas' financial level is categorized into high (annual income greater than €50,000), medium (annual income €20,001 to €50,000), and low (annual income €6,000 to €20,000). The study area is geographically divided into five locations: Athens (the center of the city, largely corresponding to the Central Business District), Piraeus (the Port area), East Attica, West Attica (mainly industrial facilities), and suburbs.

The population density of the household area and of the origin and destination locations are coded as low (1 to 23 residents per hectare), medium (24 to 51 residents per hectare), high (52 to 153 residents per hectare), and very high (154 to 225 residents per hectare). This categorization of population density is based on the proportion of residence per hectare of each municipality taking into account the overall building environment. For example, the municipalities of Athens and Piraeus have very high population densities, which are characterized by extremely dense with multi-floor buildings. In contrast, the suburbs have lower population densities with private houses with large private gardens spread over space.

The travel modes considered are bicycle, motorcycle, passenger car, taxi, bus, metro, and on foot. The travel purpose includes trips for traveling to work, daily shopping (referring to purchases related to everyday needs and includes purchases from super markets, groceries, bakeries, etc.), long-term shopping (referring to purchases related to general non-everyday needs, such as clothes, shoes, cosmetics, books, computers, and so on), education, entertainment, and sports. Time of the day of the trip is divided into categories that correspond to daily activity cycles. Finally, the frequency of repeated trips during a week is also reported. Table 1 lists descriptive statistics for selected variables (see Perperidou (*29*) for a detailed description of these data).

MODEL ESTIMATION RESULTS

Three hazard-based duration models are considered; a Weibull model with fixed parameters, a Weibull model with gamma heterogeneity and fixed parameters, and a Weibull model with gamma heterogeneity and random parameters. Both the Weibull model with fixed parameters and the Weibull model with gamma heterogeneity and fixed parameters are estimated using standard maximum likelihood methods. The Weibull model with gamma heterogeneity and random parameters is estimated by specifying a functional form of the random parameter density (see Equation 7) and using simulation-based maximum likelihood with 500 Halton draws. While past research by Bhat (*27*), Train (*28*), Milton et al. (*30*), Anastasopoulos and Mannering (*31*-*32*), Anastasopoulos et al. (*33*-*37*) and others, have shown that 200 Halton draws is usually sufficient for accurate parameter estimation, this number of Halton draws was not sufficient to provide stable parameter estimates for our data. After extensive testing, 500 Halton draws were found to provide stable parameter estimates.

For the functional form of the random-parameters density functions, consideration was given to the normal, lognormal (which restricts the impact of the estimated parameter to be strictly positive or negative), uniform, Weibull and triangular distributions. In all cases the normal distribution proved to be the distribution that provided the best statistical fit.

Table 2 presents parameter estimates for the three models estimated. It should be noted that in this table, the signs are presented such that a negative sign of a parameter estimate decreases trip duration (increases the hazard) and a positive sign increases the trip duration (decreases the hazard). Figure 1 illustrates the estimated hazard functions.

Turning to the estimation results, note first that the Weibull model parameter P is positive (indicating a monotonically increasing function) and is significantly different from zero for all models, which implies that the longer a trip lasts the more likely it is to end soon. However, as shown in Figure 1, models with heterogeneity effectively result in hazard functions that increase to a point and decrease thereafter. This means that after a certain inflection point, the longer that the trip lasts the less likely it is to end soon. For the Weibull model with gamma heterogeneity and fixed parameters this point is about 23 minutes (meaning that after a trip has lasted 23 minutes the hazard is decreasing and the likelihood of the trip ending soon becomes smaller as the trip lasts longer) and for the Weibull model with gamma heterogeneity and random parameters this inflection point is roughly 17 minutes. Martchouk et al. (*22*) found a similar inflection point in their study of freeway travel times.

Table 2 shows that the estimated parameter signs for the Weibull model with gamma heterogeneity and fixed parameters are identical to those found for the conventional Weibull model. However, are some differences in the parameter values and corresponding *t*-statistics. All explanatory variables are statistically significant and the parameter θ, which represents heterogeneity, is statistically different from zero (*t*-statistic of 15.822). A likelihood ratio test is used to compare the two models,

$$X^2 = -2\left[LL(\hat{\boldsymbol{\beta}}_w) - LL(\hat{\boldsymbol{\beta}}_{wh}) \right], \tag{8}$$

where $LL(\hat{\boldsymbol{\beta}}_w)$ is the log-likelihood at convergence for the conventional fixed-parameters Weibull model, and $LL(\hat{\boldsymbol{\beta}}_{wh})$ is the log-likelihood at convergence for the Weibull model with gamma heterogeneity and fixed parameters. The statistic is chi-squared distributed with one degree of freedom (representing the additional parameter estimated θ), and the resulting X^2 statistic of 521 indicates that there is 99.99% confidence that heterogeneity is present in the underlying hazard function.

The estimation results of the Weibull with gamma heterogeneity and random parameters shows that six variables produced statistically significant normally-distributed random parameters and that the parameter θ, representing hazard-function heterogeneity, is again statistically different from zero (*t*-stat of 18.303). A likelihood ratio test comparing the Weibull with gamma heterogeneity and fixed parameters with the Weibull with gamma heterogeneity and random parameters shows that the random parameters model is statistically superior with over 99% confidence. Figure 2 presents a graphical representation of the actual versus the predicted trip durations for the fixed and random parameters Weibull with gamma heterogeneity models. The mean-predicted over the actual values for the two classes of models indicate that the random-parameters model provides better overall fit relative to the fixed-parameters model.

The six random-parameters were the constant term, passenger car as the transportation mode, and the distances for work, education, daily shopping, and sports trips (the latter are continuous variables pertaining to the origin-destination distances, grouped by trip purpose). Due to the relatively large parameter estimates and small standard deviations of the parameter distribution, almost all of the parameters for each observation have the same sign as the mean parameter estimate. The one notable exception is the variable representing the distance traveled for education trips (with its mean parameter estimate of 0.187 and standard deviation of 0.163) which results in a normally distributed random parameter with 87.4% of the distribution being greater than zero, and 12.6% being less). In addition, the large values of the distance by trip purpose for daily shopping and for sports (both being random parameters, as most of the distance by trip purpose parameters, meaning that their effect on travel time varies across the observations) compared to the rest of the distance by trip parameters, should also be noted. Given the numerous shopping and sport choices offered in the Greater Athens Metropolitan area, and the large radius of the study area (roughly 20 miles), this is an interesting yet expected finding (see Anastasopoulos et al. (*38*)).

With regard to the random parameters findings for trip distances, the estimates show that as trip distances increase, the vast majority of travelers are likely to have longer trip durations as one would expect (note that using the distance variable by trip purpose provided a far better statistical fit – both in terms of overall model fit, and in terms of the statistical significance of the individual parameters – as compared to using the distance irrespective of the trip purpose). However, the significance of the random parameters shows that there is considerable variability across the population which likely reflects variances in time of departure, congestion, and routes and destinations chosen, and so on.

Continuing with the estimation results for the Weibull model with gamma heterogeneity and random parameters, a number of economic and demographic characteristics are found to affect trip duration. The affluence (high financial status) of the origin and destination locations is likely to be associated with longer trip durations. Given the geography of the Greater Athens area, high financial-level locations tend to be several kilometers apart and through congested areas which makes traveling from one location to another last longer. The travel time is also found to decrease when the population density of the origin and destination are simultaneously high or low which likely reflects the characteristics of the road network between these locations in Athens. Also, when the population density of the travelers' origin is medium to low, the travel time is likely to be lower which may reflect the characteristics of the destination choices of travelers who live in such areas.

Turning to the travel-mode variables, traveling on foot is found to result in shorter travel times which may reflect the short-trip preference of this mode and the fact that foot travel is not significantly affected by congestion. A similar analogy may be made for motorcycles where travelers may prefer short distances and also move through traffic (between cars) to mitigate the effects of congestion. In contrast, traveling by any mass transit mode such as bus, train, tram, and metro usually results in longer travel time – which likely reflects the effect of destination choice and congestion. Interestingly, traveling with a taxi is likely to result in shorter trip durations that may be due to the time saved from the door to door trip that taxis may offer (no lost time for parking, or to get to the transit station). Passenger cars are also found to have a strong effect in reducing the trip duration, but the effect of this variable is found to vary across the observations, the likely result of traffic congestion, destination choices, and so on.

Finally, the time of day and frequency of the trip are also found to affect trip duration. If the trip occurs at night, between 10 pm and 6 am, it is likely to result in increased duration, which can be attributed to the distribution of destination. Given that many popular locations are either in the city center or in the suburbs (on the south or north side), it is expected that travelers may spend some extra time to reach these spots. In addition, the frequency of transit service is reduced after midnight and, as a result, travelers may have to wait for transport, or use their passenger car or a taxi to reach their destination. Further, the results indicate that non-work related trips that are repeated within the week (more than two times) result in lower trip durations, a possible reflection of travelers' familiarity with the route characteristics and their ability to find ways to reduce travel times, particularly for short distance trips.

SUMMARY AND CONCLUSIONS

To study trip durations in Athens, three hazard-based duration models were estimated: the Weibull model with fixed parameters, the Weibull model with gamma heterogeneity and fixed parameters, and the Weibull model with gamma heterogeneity and random parameters. The estimation results clearly show that the Weibull model with gamma heterogeneity and random parameters provides the best statistical fit to the data. Six random parameters were found to be statistically significant (all normally distributed): the constant term, passenger car as transport mode, distance covered for work, education, daily shopping and sports. The model estimation results show that, in addition to these random-parameter variables, a number of other factors were found to play in the determination of trip durations. These include the affluence (financial level) of trip origin and destination locations, demographic characteristics of origin and destination (population), trip purpose (travel to work, school, long term shopping, entertainment), transport mode (traveling by motorcycle, bus, train, tram and metro, taxi, or on foot), frequency of trips, time of trip, and the distance covered for entertainment – all of which were found to significantly affect trip duration although their effect is constant across the observations.

Even though the demonstrated approach is simplistic when compared to the traditional activity/trip generation-destination approach in urban travel analysis, it provides some interesting findings, by addressing the unobserved heterogeneity that is introduced by simplifying the complex decision-making process through the use of random parameters. This approach can further provide interesting insights into the effects of economic factors, geographic characteristics, demographic characteristics, trip information, travel mode, trip frequency and time of day on travel time durations in urban areas – and the information gathered from the estimation of such duration models can be used as a basis to guide important transportation policy decisions. Further implementation of this approach to other cities in Europe, the USA, or elsewhere, and exploration of spatial and temporal variabilities, is expected to shed more light to its empirical applicability as an alternative to the traditional activity-based approach.

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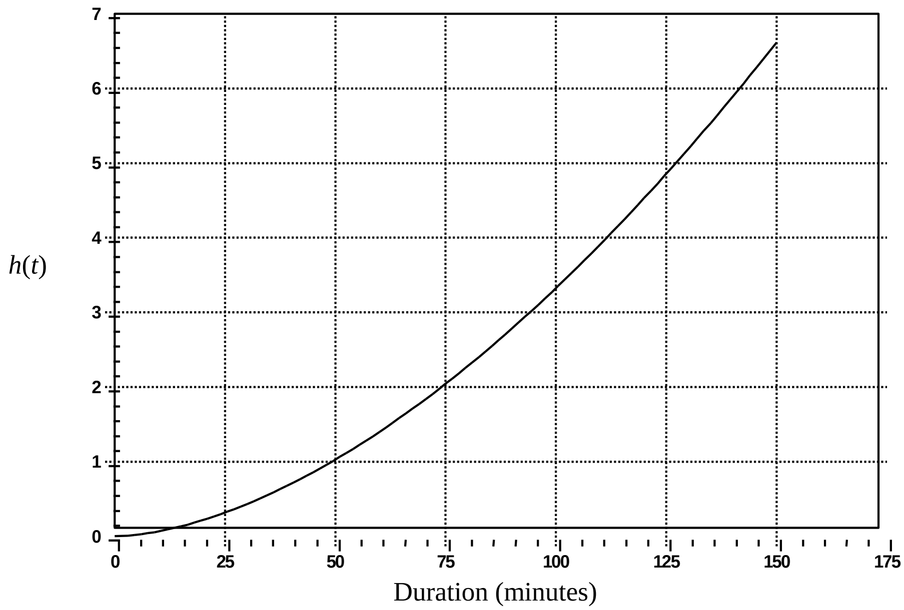
TABLE 1 Descriptive Statistics of Selected Variables

Variable	Mean or Percentage	Standard Deviation
Trip duration (in minutes)	18.069	14.383
Distance to destination (in kilometers)	2.975	3.491
Gender of traveler (1 if male, 0 otherwise)	50.1%	
Traveler's age: 19 years old or less/ 20 to 34 years old/ 35 to 64 years old/ 65 years old or more	20.7%/ 32.9%/ 34.8%/ 11.6%	
Number of vehicles in the household: 0/ 1/ 2/ 3	15.6%/ 40.2%/ 35.3%/ 8.9%	
Residence population density: low/ medium/ high/ very high	16.2%/ 10.8%/ 37.5%/ 35.5%	
Population density of origin: low/ medium/ high/ very high	16.9%/ 11.9%/ 40.5%/ 30.7%	
Population density of destination: low/ medium/ high/ very high	16.2%/ 10.8%/ 37.5%/ 35.5%	
Financial level of area for trip origin (1 if high income level of area, 0 otherwise)	0.545	
Residence population density (1 if medium-low, 0 otherwise)	0.246	
Financial level of area for trip destination (1 if high income level of area, 0 otherwise)	0.185	
Population density of origin and destination (1 if both are low, 0 otherwise)	0.128	
Population density of origin and destination (1 if both are high, 0 otherwise)	0.336	
Trip purpose (1 if traveling to work, 0 otherwise)	0.064	
Trip purpose (1 if traveling to school, 0 otherwise)	0.127	
Trip purpose (1 if traveling to long term shopping, 0 otherwise)	0.124	
Trip purpose (1 if traveling to entertainment spot, 0 otherwise)	0.332	
Transportation mode (1 if traveling on foot, 0 otherwise)	0.508	
Transportation mode (1 if motorcycle, 0 otherwise)	0.016	
Transportation mode (1 if bus, train, tram, and metro, 0 otherwise)	0.024	
Transportation mode (1 if passenger car, 0 otherwise)	0.307	
Transportation mode (1 if taxi, 0 otherwise)	0.017	
Frequency of specific trip (1 if more than 2 times a week, 0 otherwise)	0.381	
Time of trip (1 if 10 pm - 6 am, 0 otherwise)	0.146	
Distance by trip purpose (distance traveled for work, in km)	0.300	1.578
Distance by trip purpose (distance traveled for education, in km)	0.425	1.908
Distance by trip purpose (distance traveled for daily shopping, in km)	0.243	0.642
Distance by trip purpose (distance traveled for entertainment, in km)	1.334	2.842
Distance by trip purpose (distance traveled for sports, in km)	0.175	0.853

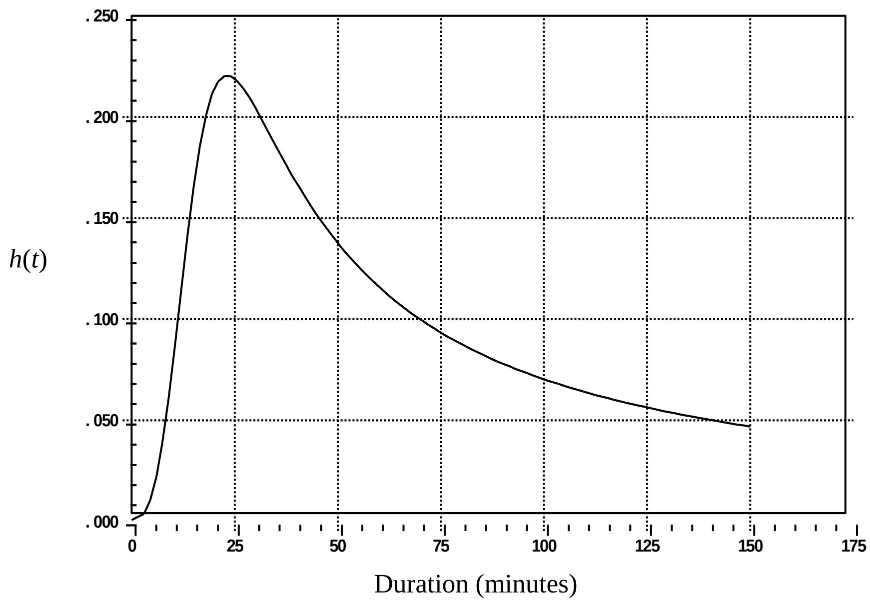
TABLE 2 Model Estimation Results

Dependent variable: trip duration in minutes	Weibull model (Fixed Parameters)		Weibull model with Gamma heterogeneity (Fixed Parameters)		Weibull model with Gamma heterogeneity (Random Parameters)	
Variable	Parameter Estimate	*t*-statistic	Parameter Estimate	*t*-statistic	Parameter Estimate	*t*-statistic
Constant	2.325	107.75	2.305	106.22	1.895	187.12
Std.Dev. of parameter distribution					*0.340*	*147.87*
Financial level of area for trip origin (1 if high income level of area, 0 otherwise)	0.022	2.09	0.034	2.70	0.044	8.69
Residence population density (1 if medium-low, 0 otherwise)	-0.072	-7.29	-0.059	-4.20	-0.044	-7.92
Financial level of area for trip destination (1 if high income level of area, 0 otherwise)	0.056	4.19	0.034	2.22	0.028	4.50
Population density of origin and destination (1 if both are low, 0 otherwise)	-0.054	-4.24	-0.090	-5.19	-0.039	-5.84
Population density of origin and destination (1 if both are high, 0 otherwise)	-0.099	-8.80	-0.092	-7.00	-0.069	-13.14
Trip purpose (1 if traveling to work, 0 otherwise)	1.050	31.84	0.981	30.66	1.313	93.86
Trip purpose (1 if traveling to school, 0 otherwise)	0.672	31.47	0.582	28.94	0.764	75.52
Trip purpose (1 if traveling to long term shopping, 0 otherwise)	1.080	56.74	0.927	44.74	1.304	138.36
Trip purpose (1 if traveling to entertainment spot, 0 otherwise)	0.837	42.90	0.740	39.36	1.096	120.31
Transportation mode (1 if traveling on foot, 0 otherwise)	-0.563	-36.12	-0.573	-33.55	-0.553	-84.61
Transportation mode (1 if motorcycle, 0 otherwise)	-0.313	-16.09	-0.557	-14.72	-0.412	-37.66
Transportation mode (1 if bus, train, tram, and metro, 0 otherwise)	0.188	6.12	0.199	5.78	0.052	4.03
Transportation mode (1 if passenger car, 0 otherwise)	-0.207	-14.16	-0.272	-15.82	-0.355	-53.03
Standard deviation of normally distributed parameter					*0.072*	*22.23*
Transportation mode (1 if taxi, 0 otherwise)	-0.271	-7.68	-0.294	-7.32	-0.297	-19.41
Frequency of specific trip (1 if more than 2 times a week, 0 otherwise)	-0.051	-4.73	-0.054	-4.71	-0.018	-3.57
Time of trip (1 if 10 pm - 6 am, 0 otherwise)	0.094	7.16	0.116	7.10	0.134	20.75
Distance by trip purpose (distance traveled for work, in kilometers)	0.068	14.11	0.068	15.51	0.085	43.11
Standard deviation of normally distributed parameter					*0.011*	*9.18*
Distance by trip purpose (distance traveled for education, in kilometers)	0.130	40.68	0.126	46.24	0.187	103.69
Standard deviation of normally distributed parameter					*0.163*	*76.28*
Distance by trip purpose (distance traveled for daily shopping, in kilometers)	0.411	45.69	0.351	44.41	0.843	109.75
Standard deviation of normally distributed parameter					*0.020*	*6.65*
Distance by trip purpose (distance traveled for entertainment, in kilometers)	0.076	30.26	0.082	35.40	0.094	91.56
Distance by trip purpose (distance traveled for sports, in kilometers)	0.403	66.62	0.322	59.28	0.761	119.93
Standard deviation of normally distributed parameter					*0.127*	*61.90*
θ			0.518	15.82	0.593	18.38
P	2.695	113.00	3.636	58.00	3.559	64.940
$LL(0)$	-9454.5		-9454.5		-9454.5	
$LL(\beta)$	-3952.8		-3692.3		-3072.6	
Number of observations	7124		7124		7124	

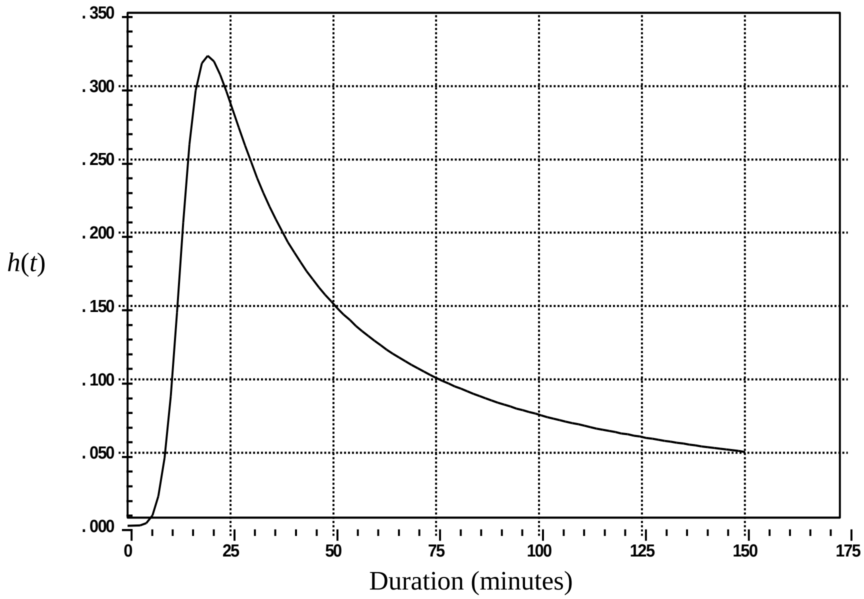
[*] Elasticity and pseudo-elasticity (for categorical variables) values are estimated at the sample mean.



a) Weibull model

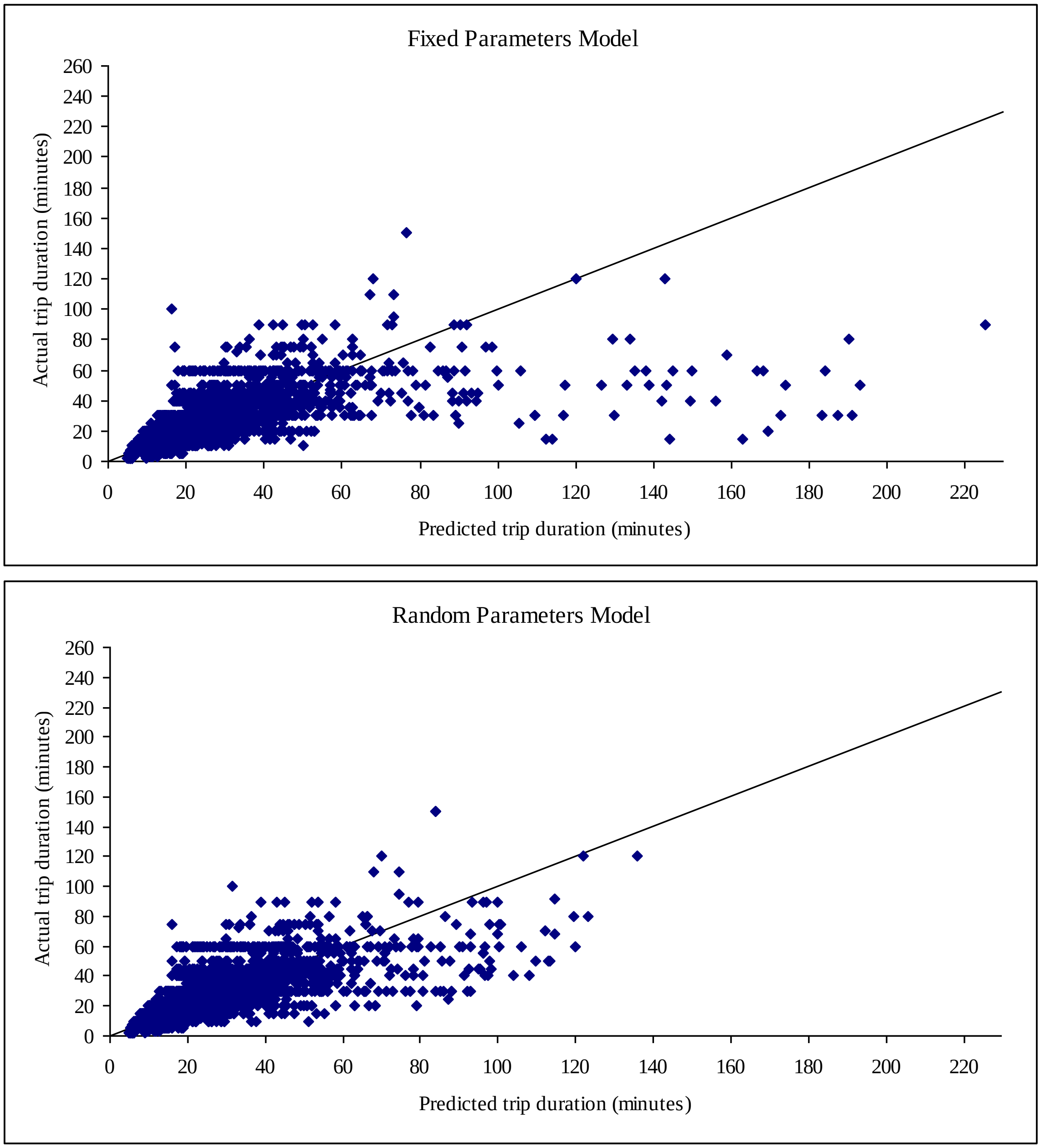


b) Fixed parameters Weibull model with gamma heterogeneity



c) Random parameters Weibull model with gamma heterogeneity

FIGURE 1 Hazard functions for the trip duration models.



*The straight lines indicate the equivalence of mean-predicted and actual values

FIGURE 2 Mean-predicted vs. actual trip duration of fixed (top) and random (bottom) parameters Weibull with Gamma heterogeneity models.