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Modeling interdependencies between vehicle transaction, residential relocation and job change

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Abstract This paper introduces a vehicle transaction timing model which is conditional on household residential and job relocation timings. Further, the household residential location and members' job relocation timing decisions are jointly estimated. Some researchers have modeled the household vehicle ownership decision jointly with other household decisions like vehicle type choice or VMT; however, these models were basically static and changes in household taste over time has been ignored in nearly all of these models. The proposed model is a dynamic joint model in which the effects of land-use, economy and disaggregate travel activity attributes on the major household decisions; residential location and members' job relocation timing decisions for wife and husband of the household, are estimated. Each of these models is estimated using both the Weibull and log-logistic baseline hazard functions to assess the usefulness of a non-monotonic rather than monotonic baseline hazard function. The last three waves of the Puget Sound Panel Survey data and land-use, transportation, and built environment variables from the Seattle Metropolitan Area are used in this study as these waves include useful explanatory variables like household tenure that were not included in the previous waves.

Keywords Job relocation · Residential relocation · Vehicle transaction · Hazard-based model · Weibull baseline hazard · Log-logistic baseline hazard

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Introduction

There are complex interdependencies among major household decisions such as work location, residential location and vehicle transaction choices (in this study, buy and sell). Intuitively, it is clear that these decisions are interrelated; accordingly they should be jointly modeled while taking account of exogenous factors that differentially influence each of these decisions. For instance, we expect mortgage rates to influence residential relocation timing, unemployment rates to affect job relocation decisions and gas price fluctuations to affect vehicle transaction decisions.

An ideal modeling framework encompasses the above-mentioned major decisions along with the specific components of each one of them in a joint, comprehensive and dynamic structure. The model components or sub-models can be different for each decision. Similarly, the modeling structure can differ for different individuals meaning that residential location can be of more interest in someone's opinion while job contiguity may have higher priority for another person. The residential relocation decision may include, becoming active in the market, screening the potential alternatives based on household dynamics and attributes, and choice process for selecting the new residential location. On the other hand, the vehicle transaction decision may include choices such as transaction timing, transaction type and vehicle vintage, model and type selection. Typically, the first step of such a dynamic hierarchical choice model is the process of estimating the timing of the household decisions. For example in the case of the vehicle transaction decision, one can argue that the household vehicle fleet size at a given time can be estimated as a function of the current total number of vehicles in the household fleet plus all the vehicles that will be purchased, minus those vehicles that will be sold or retired. Therefore, understanding the timing of the transaction decision is an important element for predicting the number of vehicles in the household fleet. It seems that the transaction time is usually ignored in household vehicle ownership models. Accordingly, this study introduces a joint model to predict the timing of residential and job relocations which subsequently affect the household vehicle transaction decision. Residential relocation and vehicle transaction decisions are modeled at the household level while job relocation decisions are modeled at the individual level.

Traditionally, event timing in many fields such as transportation, economics, psychology, medical and political science have been modeled using hazard-based duration models pioneered by Cox (1959, 1972) and Cox and Oakes 1984). The Weibull hazard function, which is monotonically increasing/decreasing, has been most commonly used in these studies. The current study also utilizes a hazard-based duration formulation. However, in this case, we consider both the Weibull (monotonic) and log-logistic (non-monotonic) baseline hazard functions.[1] The comparison between these two functions provides useful insights into the behavior under study. Application of Weibull baseline hazard function in duration models, especially for modeling residential relocation timing, has a long history (Henley 1998). Nonetheless, a monotonic hazard function has not found to be necessarily the best distribution for modeling relocation timing decision (Davies 1984; Clark and Withers 1999). As a result, a key contribution of this paper is to discuss alternative baseline hazard functions other than the monotonic forms. As another innovative element, a unified system of equations for four major and long-term household decisions is presented in this paper. This system of equations is constructed by employing survival models. This

[1] The log-logistic function can be either monotonic or non-monotonic depending on its distribution parameters.

construction can be considered as a unique contribution to the literature of duration and hazard models (see Van Ommeren et al. 1997 and 1999).

The Puget Sound Transportation Panel Survey (PSTPS) dataset is used along with land-use, network skims, and built environment attributes from the Seattle Metropolitan Area. The PSTPS is a panel survey that covers 10 waves starting from 1989 until 2002 covering Seattle and its surrounding areas. This panel data provides household and individual socio-demographic time varying attributes which enables us to develop more accurate models. As previously stated, this study employs the last three waves of the panel data due to the unavailability of some variables in earlier waves. The most important variable collected only in the last three waves is residential duration which is the most important variable in the residential relocation timing decision model. Tenure and household life style changes are also available only in the last three waves. It is also worth mentioning that the dataset only includes the individuals who live in the Seattle area and not those who move into the region.

The impact of built environment variables on the household choice of durable goods, such as a car, is included as well as their impact on occupation choice. Further, macro-economic variables like unemployment rate changes and gas price fluctuation are included in the models. The modeling framework of this study is also linked to a disaggregate activity-based travel demand model with household and individual travel time and activity duration as included as feedback variables.

The rest of the paper is organized as follows. First, a review of key literature on vehicle ownership and household residential and job relocation behavior is discussed. Next, the model derivation and the mathematical formulation of the system of equations including the selection of explanatory variables are described. Third, the datasets used in this study are described and their key variables are discussed; this discussion specifically identifies limitations of the data set with respect to the behaviors modeled. Fourth, model estimation results are presented and interpreted. Finally, conclusions and future research directions are outlined.

Literature review and background

This section covers five major parts, including previous vehicle ownership models, joint vehicle ownership studies, dynamic vehicle ownership models, hazard-based formulation background and its application in vehicle ownership and residential and job relocation models. Some of the earliest reviews about vehicle ownership models were undertaken by Bates et al. (1981), Allanson (1982) and Button et al. (1982). The early models were mainly aggregate and provided aggregate estimates of the number of vehicle per person in each zone or the supply of cars in the car market, for example (Dargay and Gately 1999 and Manski 1983). Generally, car ownership growth was the main topic in these early studies and income was considered to be the main driving force behind car ownership growth. Although, most of the early vehicle ownership models were aggregate, a few static or (pseudo)-dynamic disaggregate vehicle ownership models have been developed since the mid-80s that applied discrete choice methods to analyze household car type choices (Hensher et al. 1992).

More recently, behavioural vehicle ownership models have been modeled at the disaggregate (e.g., household) level. Disaggregate vehicle ownership models can be categorized into two general groups, static and dynamic models (de Jong et al. 2004). Bhat and Pulugurta (1998), Whelan (2001)and (2007), and Rich (2001), developed static disaggregate vehicle ownership models. Improvements to the computational power in recent years have attracted many researchers to develop more advanced dynamic disaggregate vehicle ownership models. Dynamic car-ownership models assume that a transaction takes place when the household's expected vehicle fleet utility level due to a transaction exceeds its current vehicle fleet utility level. Differences in expected and current utility levels may result from changes in the attributes of owned vehicles, changes in the vehicles available in the market place and changes in household taste. Together, these changes justify the adoption of dynamic over static or comparative static models (Mannering and Winston 1985). Bunch et al. (1996) developed a dynamic car ownership model for California, utilizing duration models for three transaction types: dispose of, replace or acquire a new vehicle. The Dutch Dynamic Vehicle Transaction Model (DVTM) is another hierarchical modeling framework that utilized similar approach for the Netherlands. A hazard duration modeling framework was used in the DVTM and vehicle type choice, annual car use, and style of driving were considered as sub-models of the DVTM. A series of papers by De Jong (1991) and (1996) and de Jong and Pommer (1996) presented these models. Another example of dynamic vehicle ownership models is the work by Mohammadian and Miller in Toronto, Canada (Mohammadian and Miller 2003).

Household vehicle ownership is occasionally modeled jointly with other household characteristics like annual VMT. Although, the majority of these jointly developed models are static, they still introduce a robust modeling approach. Golob and Brownstone (2005) modeled the impacts of residential density, vehicle usage and energy consumption at the household level. Bhat and Sen (2006b) studied household vehicle holding type and usage using a multiple discrete–continuous extreme value model. They also modeled the impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use (Bhat and Sen 2006a). Vehicle choice and usage is also modeled using a discrete–continuous model by Fang (2008) who jointly modeled vehicle choice and usage, including residential density as an explanatory variable.

The other household decisions of interest in this study are discussed together because of their close relationship. Different components of job and residential relocation decisions have been the topic of research in fields such as economics, policy studies and environmental design. There is a close dependency between job and residential location search behavior through their impact on individual, household or aggregate commute distance. This link and commute distance, has convinced the researchers to jointly model these two decisions (Kim 1992). The spatial employment search is a systematic process; that is, workers choose jobs, in part, to reduce their commute time based on the human capital model of migration (Greenwood, 1975). Many econometric frameworks have been tried to jointly model the search process of these decisions. For instance, Waddell (1996) modeled the interaction of workplace, residential mobility, tenure, and location choices in a Nested Logit framework. Wayne (1987) modeled home and job distance from the city center in a simultaneous regression. However, other studies in the literature have considered residential and job location decisions of the household separately (Clark et al. 2003 and Kim 1992). For example, Sermons and Koppelman (1998) modeled residential location as a function of male and female work location.

Residential and job relocation decisions can be modeled either statically or dynamically. One commonly used option for dynamically modeling job and residential relocation decisions includes the hazard risk-based models. Van Ommeren et al. (1999) utilized search theory along with duration formulation and jointly modeled the relationship between residential and job relocation. Alternatively, static models utilize cross section data in such models which do not include transaction timing (Van Ommeren et al. 1997). Like the vehicle ownership case, the static job search models can be more commonly observed in the literature because of their lesser data requirements (Alonso 1964 and Simpson 1980).

Job search behavior is generally more complex than residential search behavior because more external agents such as the employer‘s behavior, skill acquisition and existing job opportunities affect employment location opportunities. Therefore, the job supply and demand attributes should be included in a comprehensive job type, location and timing decision model. Nonetheless, commute distance still plays a significant role in the job search models. For instance, Rouwendal (1999) studied spatial job search behavior based on the labor market and workers behavior taking into account wage rates, commuting distances and working hours as relevant job characteristics.

Residential location search is also well studied in environmental and urban design, economics and other fields. Renting or purchasing a new residence, relocation timing and price and type of the new residence are some of the subcategories of a comprehensive housing search model. Relocation timing, the first step of such a model, has received very little attention. Unlike relocation timing, housing price has been an attractive research topic for which hedonic price models are usually used (Kim 1992). Wheaton (1990) discussed household housing search behavior based on vacancy and price using a market matching model.

As noted earlier, the effect of elapsed time in any change behavior can be represented by using a hazard model. The proportional hazard model that was originally introduced by Cox (1972) considered the failure time to be a random variable which may have a parametric, semi-parametric or non-parametric form. Following Cox’s introduction of the hazard framework, Lancaster (1979) applied a proportional hazard model to an unemployment duration dataset. He used three different forms for the likelihood function including the product of density and survival functions. Proportional hazard models have frequently been studied in econometrics and mathematics and many modifications have been applied to their concept (Elbers and Ridder 1982; and Heckman and Singer 1984).

In the transportation field, Hensher and Mannering (1994) pioneered the application of hazard models to transportation problems. Their article illustrates the basic concepts of hazard models along with the probable fields in which hazard models might be applied and utilized.

Bhat (1995b) also studied hazard models and applied them to transportation related problems. He studied both parametric and non-parametric hazard models for shopping activity behavior over a discrete failure time scale. He later introduced a hazard model with the concept of utility function and utilized it in an application of activity-behavior analysis during the evening work-to-home commute (Bhat 1995a).

While major decisions are typically made at the household level, incorporating each individuals’ (household members’) influences on the household decisions has been a topic of great interest. McElroy and Horney (1981) demonstrated the importance of the husband and wife’s impact on major mobility decisions like house and car ownership. Similarly, Sermons and Koppelman (2001) showed the relative importance of husband and wife’s commute travel on residential location. This study refines that concept by modeling the job relocation timing decision of husband and wife, if they are employed, jointly with household residential relocation timing decision.

Methodology and formulation

Continuous formulation

The proportional hazard model formulation consists of a baseline hazard and covariates. Unlike other studies (e.g., Yamamoto et al. 1997) in which only the Weibull distribution was employed for the baseline hazard, the log-logistic function is also examined in this study. It is worth noting that log-logistic distribution can present a non-monotonic hazard function while the Weibull distribution cannot. The parametric proportional hazard can be formulated as:

$$h_i(t) = \lim_{\Delta t \to o} \frac{\Pr(t + \Delta t \geq T_i \geq t | T_i \geq t)}{\Delta t} = h_{i0}(t) \times \exp(-\beta x_i) \quad (1)$$

where $h_i(t)$ is the probability of failure for individual i given that it has survived until time T and the hazard probability is formulated as a function of covariates (x_i) that can influence the outcome. Moreover, $h_{i0}(t)$ is considered as the baseline hazard. β is the vector of parameters to be estimated. One may rewrite Eq. 1 using Weibull or log-logistic baseline hazard functions:

Weibull baseline hazard:

$$h_i(t) = \gamma t^{\gamma - 1} \exp(-\beta_x X_i) \quad (2)$$

Log-logistic baseline hazard:

$$h_i(t) = \frac{\frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1}}{1 + \left(\frac{t}{\alpha}\right)^{\beta}} \exp(-\beta_x X_i) \quad (3)$$

where γ is the shape parameter of the Weibull distribution, α and β are scale and shape parameters of log-logistic distribution, X denotes explanatory variables, and β_x is the vector of parameters.

The survival function which is defined as the probability of surviving an event until it fails at time T, is formulated as:

$$S(t) = \exp\left[-\int_0^t h(u)du\right] \quad (4)$$

Discrete formulation

Other than the commonly used continuous hazard formulation, failures can be assumed to occur in discrete time intervals. The continuous formulation is more compatible with what happens on reality for failure data while the discrete formulation is more compatible with the data collection process. For example in the longitudinal data used in this study, transaction failure times are reported in a year scale and there is no information about the exact month or the day of the transaction. So, the discrete formulation could be an intuitive candidate for modeling the transaction data utilized in this study. Nonetheless, it is recommended that both of these formulation types are examined to see which one provides better model fits. Under the discrete assumption for event occurrences the previous equations cannot be used anymore and a new set of equations should be utilized.

Equations 5 and 6 show the discrete hazard functions with Weibull and log-logistic baseline hazards, respectively.

$$prob(l^k < T_i \leq u^k) = e^{-(l^k)^{\gamma} e^{-\beta x_i}} - e^{-(u^k)^{\gamma} e^{-\beta x_i}} \tag{5}$$

where u^k and l^k are respectively the upper and lower bounds of the kth failure interval.

$$prob\left(l^k < T_i \leq u^k\right) = e^{\log\left(\frac{1}{1+\left(\frac{l^k}{\alpha}\right)^{\beta}}\right) e^{-\beta x_i}} - e^{\log\left(\frac{1}{1+\left(\frac{u^k}{\alpha}\right)^{\beta}}\right) e^{-\beta x_i}} \tag{6}$$

Since further discussion on the methodology of this study is completely dependent on a selection between continuous and discrete formulations, a brief and simple analysis on the model fit of these two formulations using the data of this study is initially provided and discussed.

Comparison between discrete and continuous formulations

In order to evaluate which one of the mentioned hazard model types provide better fit when they are separately applied to the data of this study, a simple analysis is initially presented and discussed. Then, based on the results of this discussion the inter-dependent formulation of this study will be discussed.

Table 1 shows the likelihood values for four hazard formulations of Eqs. 1 to 4 for four timing decisions, husband job relocation, wife job relocation, household vehicle transaction and household residential location. These models are developed for the same covariates to make the likelihood values comparable.

As it can be seen in Table 1, the continuous formulation, for both log-logistic and Weibull baseline hazard functions, performs better than the discrete formulation. Furthermore, the models with log-logistic baseline hazard function also show better general model fit. Nonetheless, it should be kept in mind that the log-logistic baseline hazard function has two parameters while the Weibull hazard function has only one parameter. A comprehensive analysis on the superiority of log-logistic baseline hazard function over Weibull baseline hazard function and vice versa will be presented latter.

This section attempted to show the advantage of employing the continuous hazard formulation for the utilized data of this research. Based upon this conclusion, the joint

Table 1 Combinations of discrete and continuous hazard formulations

	Husband job	Wife job	Vehicle	Residential
Weibull				
Continuous				
LogLL value	−779.03	−853.04	−471.53	−156.76
Discrete				
LogLL value	−802.91	−880.92	−490.14	−163.35
Log-logistic				
Continuous				
LogLL value	−671.44	−720.26	−442.88	−125.94
Discrete				
LogLL value	−766.03	−835.28	−446.68	−144.65

formulation of this study is developed by using the continuous hazard formulation. This joint formulation for household major decisions is explicated in the next section.

Joint formulation

The simple form of the hazard function shown in Eq. 1 is the starting point of the joint hazard formulations used this study. The process starts by coupling the simple hazard functions for the husband's and wife's job relocation timing decisions; each of which consists of two major parts as in Eq. 1; the baseline hazard part and the exponential covariate part. The exponential covariate part can include time varying covariates as well as endogenous variables from other timing decisions both at the household and individual levels. The incorporated endogenous variables in the husband's job relocation hazard function can be the wife's job relocation timing and the household residential change. In the base case, models with no endogenous variable (the *nev* superscript) are estimated in which only exogenous covariates are included. These are described as exogenous variable models where no endogenous variable is included among their explanatory variables. In other models (without the *nev* superscript) both exogenous and endogenous variables are considered. These models may include the wife's job relocation hazard function in the husband's job and residential relocation timing hazard functions and similarly for husband's job relocation hazard function. The mathematical formulations of the husband's and wife's job relocation timing hazard are presented in Eqs. 7 and 8.

$$\begin{cases} h_{Wife}(t_{Wife}, x_{WIfe}, h_{Hus}^{nev}, h_{Rs}^{nev}) = h_0^{WIfe}\, e^{-\left(\beta_{Wife}x_{Wife} + \beta_{RsWife}h_{Rs}^{nev} + \beta_{HusWife}h_{Hus}^{nev}\right)} \\ h_{Rs}^{nev}(t_{Rs}, x_{Rs}) = h_0^{Rs}\, e^{\beta_{Rs}x_{Rs}} \\ h_{Hus}^{nev}(t_{Hus}, x_{Hus}) = h_0^{Hus} e^{\beta_{Hus}x_{Hus}} \end{cases} \tag{7}$$

$$\begin{cases} h_{Hus}(t_{Hus}, x_{Hus}, h_{Wife}^{nev}, h_{Rs}^{nev}) = h_0^{Hus}\, e^{-\left(\beta_{Hus}x_{Hus} + \beta_{RsHus}h_{Rs}^{nev} + \beta_{WifeHus}h_{Wife}^{nev}\right)} \\ h_{Rs}^{nev}(t_{Rs}, x_{Rs}) = h_0^{Rs}\, e^{\beta_{Rs}x_{Rs}} \\ h_{Wife}^{nev}(t_{Wife}, x_{Wife}) = h_0^{Wife} e^{\beta_{Wife}x_{WIfe}} \end{cases} \tag{8}$$

where (depending on log-logistic or Weibull distribution assumption):

$$\begin{cases} h_0^{Hus} = h_0^{Hus}(t_{Hus}) = \dfrac{\frac{\beta_{Hus}^0}{\alpha_{Hus}}\left(\frac{t_{Hus}}{\alpha_{Hus}}\right)^{\beta_{Hus}^0 - 1}}{1 + \left(\frac{t_{Hus}}{\alpha_{Hus}}\right)^{\beta_{Hus}^0}} \quad \text{or} \quad = \gamma_{Hus} t_{Hus}^{\gamma_{Hus} - 1} \\ h_0^{Rs} = h_0^{Rs}(t_{Rs}) = \dfrac{\frac{\beta_{Rs}^0}{\alpha_{Rs}}\left(\frac{t_{Rs}}{\alpha_{Rs}}\right)^{\beta_{Rs}^0 - 1}}{1 + \left(\frac{t_{Rs}}{\alpha_{Rs}}\right)^{\beta_{Rs}^0}} \quad \text{or} \quad = \gamma_{Rs} t_{Rs}^{\gamma_{Rs} - 1} \\ h_0^{Wife} = h_0^{Wife}(t_{Wife}) = \dfrac{\frac{\beta_{Wife}^0}{\alpha_{Wife}}\left(\frac{t_{Wife}}{\alpha_{Wife}}\right)^{\beta_{Wife}^0 - 1}}{1 + \left(\frac{t_{Wife}}{\alpha_{Wife}}\right)^{\beta_{Wife}^0}} \quad \text{or} \quad = \gamma_{Wife} t_{Wife}^{\gamma_{Wife} - 1} \end{cases}$$

and where h_{Wife} and h_{Hus} stand for the hazard of husband and wife occupation relocation timing, h_{Rs} stands for the hazard of household residential relocation timing, h_{Wife}^{nev} and h_{Hus}^{nev} stand for the shortened hazard of husband and wife occupation relocation timing, and h_{Rs}^{nev} stands for the shortened hazard of residential relocation timing in which only time varying covariates are included, β_{Hus}, β_{Wife} and β_{Hus} are time varying covariate coefficient vectors, $\beta_{HusWife}$, $\beta_{WifeHus}$, β_{RsHus} and β_{RsWife} are the coefficients of the shortened hazards and β^0_{Rs}, β^0_{Hus}, β^0_{Wife}, α_{Rs}, α_{Hus}, α_{Wife}, γ_{Rs},γ_{Hus} and γ_{Wife} are baseline hazard scale and shape parameters.

Similarly, household residential relocation timing hazard function can be formulated shown in Eq. 9

$$\begin{cases} h_{Rs}(t_{Rs}, x_{Rs}, h^{nev}_{Wife}, h^{nev}_{Hus}) = h^{Rs}_0\, e^{-\left(\beta_{Rs}x_{Rs} + \beta_{HusRs}h^{nev}_{Hus} + \beta_{WifeRs}h^{nev}_{Wife}\right)} \\ h^{nev}_{Hus}(t_{Hus}, x_{Hus}) = h^{Hus}_0\, e^{\beta_{Hus}x_{Hus}} \\ h^{nev}_{Wife}(t_{Wife}, x_{Wife}) = h^{Wife}_0\, e^{\beta_{Wife}x_{WIfe}} \end{cases} \tag{9}$$

where β_{WifeRs} and β_{HusRs} represent the effect of wife and husband job relocation hazard on the household residential relocation timing hazard. Other definitions are similar to what were presented for the previous two equations.

Finally, Eq. 10 presents the household vehicle transaction timing hazard function that is formulated using the previously mentioned hazards for wife and husband job relocation and household residential relocation.

$$h_{Veh}(t_{Veh}, x_{Veh}, h_{Wife}, h_{Hus}, h_{Rs}) = h^{Veh}_0\, e^{-(\beta_{Veh}x_{Veh} + \beta_{HusVeh}h_{Hus} + \beta_{WifeVeh}h_{Wife} + \beta_{RsVeh}h_{Rs})} \tag{10}$$

where (depending on Weibull or log-logistic assumption):

$$h^{Veh}_0 = h^{Veh}_0(t_{Veh}) = \frac{\frac{\beta^0_{Veh}}{\alpha_{Veh}}\left(\frac{t_{Veh}}{\alpha_{Veh}}\right)^{\beta^0_{Veh}-1}}{1 + \left(\frac{t_{Veh}}{\alpha_{Veh}}\right)^{\beta^0_{Veh}}} \quad \text{or} \quad = \gamma_{Veh} t_{Veh}^{\gamma_{Veh}-1}$$

and where h_{Veh} stands for the hazard of household vehicle transaction timing, x_{Veh} is the time varying covariate coefficient vector, β_{HusVeh}, $\beta_{WifeVeh}$ and β_{RsVeh} represent the influence of residential and job relocation timing on household vehicle transaction timing and β^0_{Veh}, α_{Veh}, γ_{Veh} are baseline hazard scale and shape parameters. The rest of the definitions are as described earlier.

So far the hazard functions for job and household relocation and vehicle transaction timing decisions and the relationship among them have been formulated and discussed. These hazard functions are linked and should be estimated simultaneously. The likelihood function of these hazards is

$$L = \prod_{i=1}^{N} \prod_{j=\text{Res,Wife,Hus,Veh}} h_{ij}(t)^{y_{ij}} \times S_{ij}(t) \tag{11}$$

where N is the number of observations,y_{ij} is equal to one if the household makes a transaction or relocate depending on the value of j and zero otherwise and $S_{ij}(t)$stands for the survival function which is formulated using Eq. 4.

Left and right censorship

Left truncating and right censoring should be taken into account to avoid estimation bias in hazard-based models. Right censorship is handled in this study through considering survival in the likelihood function. Accordingly, once the survey is terminated, the value of surviving until the end of the survey is considered in the formulation instead of the probability of the outcome failure. For treating the left censoring problem, researchers have recommended a few solutions including filtering the truncated observations or even ignoring the left censorship effects Guo (1993). The Puget Sound longitudinal panel survey provides an opportunity for handling the left truncating problem in a simple way. Initially, it should be noted that there is no left censorship for the residential mobility duration in PSTP, because the length of time the household has resided at the current residence was asked in the survey. The PSTP covers 13 years of data starting from 1989 ending at 2002 and there are 10 waves in this panel survey. In this study, the last three waves (1999, 2000 and 2002) of the PSTP which are the waves with the most useful variables and the preceding waves are used to measure both the time varying covariates as well as the failure time variable. Employing this simple tracking method reduces the left censoring effect so that it can be ignored. Therefore, residential duration has not been censored and the job duration and the vehicle ownership duration are tracked back for 10 years before the starting time of the first utilized wave. It is important to recognize that average duration of vehicle acquisition and disposal in PSTP data is 3.5 years and average job duration is 3.2 years. Therefore, tracking households for several years significantly cuts down the chance of left censorship. More specifically, in PSTP dataset less than 10 percent of job relocations and less than 6 percent of the vehicle transaction times are left censored.

Baseline hazard analysis

An important element of this study is to evaluate the effectiveness of adopting a non-monotonic log-logistic hazard function in place of the commonly used, monotonic Weibull baseline hazard function, which is most widely used for modeling failure rates. Yamamoto et al. (1999) found that in a study of vehicle holding duration the Weibull distribution provides better likelihood estimate than (the negative exponential, gamma, log-logistic, and log-normal distributions). However, our analysis shows that better models can be developed by using the non-monotonic log-logistic ($\beta > 1$) baseline hazard function in some contexts. A joint 3-way interdependent household timing decisions model with constants only is estimated by maximizing the likelihood function in Eq. 10. Table 2 shows the different combinations of Weibull and log-logistic baseline hazard functions used for each of the models and Table 3 reports the estimated log-likelihood values and statistical analysis between them.

Analysis of the estimation results in Table 3 provides the information needed to evaluate whether use of the Weibull or log-logistic hazard function should be used in the baseline (no covariates) models. The effect of using the Weibull vs the log-logistic baseline function is assessed in four sets of two models for each of the four model components (job relocation of wife and husband are changed together and are called job relocation mutually). The comparison for the Job Relocation Timing Model is obtained by comparing the BIC for model pairs 1–3, 2–4, 5–7 and 6–8; each model pair is identical with respect to the other two model components. We evaluate the comparison in each of the four pairs using the Bayesian Information Criterion which includes both the log-likelihood and the number of model parameter as

$$BIC = -\ln(L_c) + 0.5p\ln(N) \tag{12}$$

Table 2 Combinations of Weibull and log-logistic baseline hazard functions used

ID	Abbreviation	Decision	Weibull	Log-logistic
1	JRW-RRW-VTW	Job Relocation Timing Baseline Hazard	X	
		Residential Relocation Timing Baseline Hazard	X	
		Vehicle Transaction Timing Baseline Hazard	X	
2	JRW-RRL-VTW	Job Relocation Timing Baseline Hazard	X	
		Residential Relocation Timing Baseline Hazard		X
		Vehicle Transaction Timing Baseline Hazard	X	
3	JRL-RRW-VTW	Job Relocation Timing Baseline Hazard		X
		Residential Relocation Timing Baseline Hazard	X	
		Vehicle Transaction Timing Baseline Hazard	X	
4	JRL-RRL-VTW	Job Relocation Timing Baseline Hazard		X
		Residential Relocation Timing Baseline Hazard		X
		Vehicle Transaction Timing Baseline Hazard	X	
5	JRW-RRW-VTL	Job Relocation Timing Baseline Hazard	X	
		Residential Relocation Timing Baseline Hazard	X	
		Vehicle Transaction Timing Baseline Hazard		X
6	JRW-RRL-VTL	Job Relocation Timing Baseline Hazard	X	
		Residential Relocation Timing Baseline Hazard		X
		Vehicle Transaction Timing Baseline Hazard		X
7	JRL-RRW-VTL	Job Relocation Timing Baseline Hazard		X
		Residential Relocation Timing Baseline Hazard	X	
		Vehicle Transaction Timing Baseline Hazard		X
8	JRL-RRL-VTL	Job Relocation Timing Baseline Hazard		X
		Residential Relocation Timing Baseline Hazard		X
		Vehicle Transaction Timing Baseline Hazard		X

Table 3 Statistical analysis for difference scenarios

Scenario id	NumObs	NumHzPar	NumExpPar	LLConst	LLVal	BIC
1	757	4	39	−3074	−2887.84	3030.37
2	757	5	39	−3031	−2843.91	2989.76
3	757	6	39	−3069	−2887.60	3036.76
4	757	7	39	−3025	−2843.91	2996.39
5	757	5	39	−2985	−2861.86	3007.71
6	757	6	39	−2942	−2817.33	**2966.49**
7	757	7	39	−2980	−2861.50	3013.98
8	757	8	39	−2937	−2817.43	**2973.22**

NumObs number of observations, *NumHzPar* number of hazard function parameters, *NumExpPar* number of parameters for explanatory variables, *LLVal* likelihood at convergence, *LLConst* likelihood with only constant

where ln (L_c) is the log-likelihood value, p is the number of parameters and N is the sample size. The model with lowest BIC in each pair is preferred. In this case, the differences in the BIC within each pair of model are very small; the BIC is smaller for the log logistic

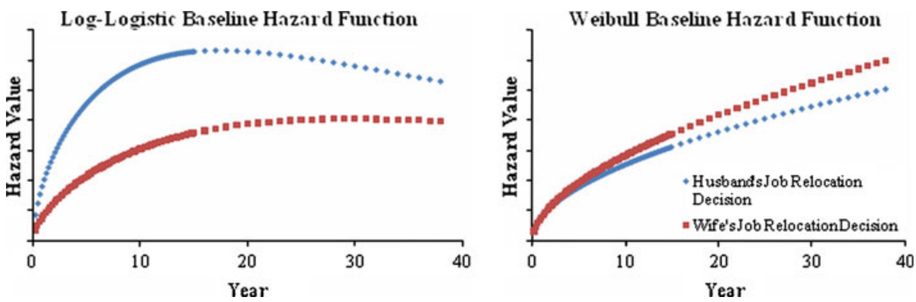

Fig. 1 Weibull and log-logistic baseline hazard function for job relocation decisions

hazard function than the Weibull hazard function for two pairs, approximately equal for one pair and larger for one pair.[2] Based on this information, we can conclude that the choice of a baseline hazard function is not statistically important.

Similarly, pairs 1–2, 3–4, 5–6 and 7–8 can be used to compare the baseline hazard functions for the Residential Relocation Timing Model and model pairs 1–5, 2–6, 3–7 and 4–8 for the Vehicle Transaction Timing model. In both cases, the BIC for the log-logistic baseline hazard function is substantially lower than for the Weibull baseline hazard function and we conclude that the log-logistic function should be used for both of these model components.

By comparing the BIC values for all eight models, we see that the lowest value is for Model 6 with the Weibull hazard function for the Job Relocation Timing model component and the log-logistic hazard function is preferred for the Household Relocation and Vehicle Transaction Timing models. These findings are consistent with the preceding results.

Finally, to better validate the best selected models (i.e., 6 and 8), these two models are compared against the other two models (2 and 4) with the second best likelihood values at convergence using the likelihood ratio test. For example, the likelihood ratio for comparing models 6 and 4 is equal to 52.96 with one degree of freedom which is statistically significant at the 0.001 level. This finding is in line with the BIC analysis presented in Table 3 suggesting that models 6 and 8 are statistically more desirable than the other 6 models.

The effect of using the log-logistic (non-monotonic) hazard function rather than the Weibull hazard function in each of these three cases is illustrated in Figs. 1, 2 and 3. Figure 1 shows the estimated baseline hazards for wife and husband job relocation decisions. The log-logistic function which can be monotonic or non-monotonic shows a more rapidly increasing hazard rate for both the husband and wife during the first 10 years followed by a decreasing rate for the husband and very little change for the wife after 10- to 15 years., The Weibull model gives a steadily increasing rate in both the husband and wife hazard Therefore, both log-logistic and Weibull hazards give monotonically increasing patterns for the meaningful job relocation durations which is on average between three and 4 year in the case of the utilized data.

The BIC comparison between the log-logistic and Weibull baseline hazard functions prefers the log-logistic function for residential relocation decisions (Table 4) but the most prominent differences are in the first year (where no data are available). However, for

[2] The difference in the BIC between each pair of models may differ as there is likely to be some interaction among parameters and specification in a complex model structure.

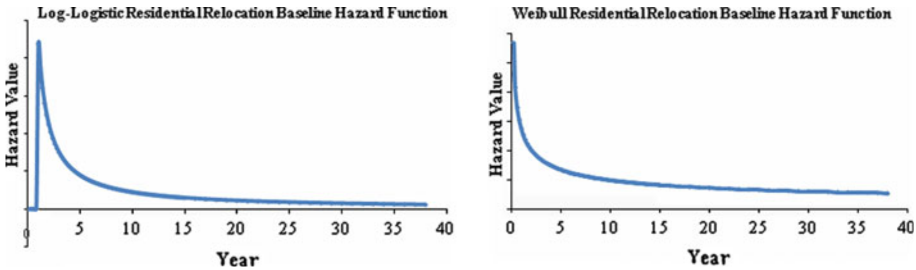

Fig. 2 Weibull and log-logistic baseline hazard function for residential relocation decisions

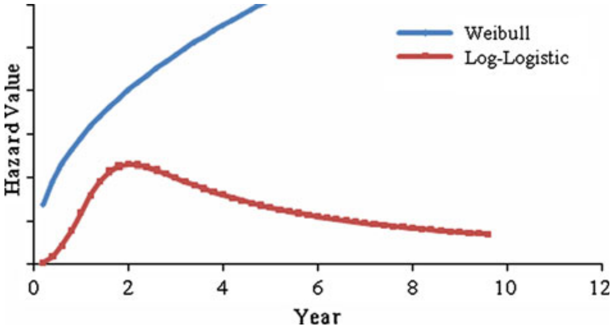

Fig. 3 Vehicle transaction decision baseline hazard functions

Table 4 Best fitted distribution to the dependent variables

Distribution	Residential relocation		Husband job relocation		Wife job relocation		Vehicle transaction	
	K–S Statistic	Rank	K–S Statistic	Rank	K–S Statistic	Rank	K–S Statistic	Rank
Beta	0.56611	11	0.45967	11	0.33927	11	0.29184	11
Chi-squared	0.19875	4	0.19875	6	0.19875	3	0.19875	4
Exponential	0.2651	7	0.23343	7	0.24575	9	0.28313	9
Gamma	0.25471	6	0.17824	2	0.18759	2	0.21191	6
Gen. extreme value	0.19139	3	0.18508	3	0.20161	4	0.18818	3
Laplace	0.3466	10	0.29214	10	0.27364	10	0.28517	10
Log-logistic	**0.16252***	**1**	0.18882	4	0.202	5	**0.16952***	**1**
Logistic	0.32973	9	0.25606	9	0.24255	8	0.27759	8
Lognormal	0.17891	2	0.19745	5	0.20988	6	0.17565	2
Normal	0.32552	8	0.24417	8	0.23324	7	0.2775	7
Weibull	0.22426	5	**0.17355***	**1**	**0.18698***	**1**	0.20293	5

*The smaller the KS statistic is for a distribution, the closer that distribution is to the data, $\alpha < 0.001$

relocation durations greater that 1 year (Fig. 2), the log-logistic hazard drops more rapidly than the Weibull hazard which suggests that household decision makers becoming increasingly resistant to change residential location over time.

Finally, it was shown that employing a log-logistic hazard function can significantly improve the general likelihood value at convergence. As shown in Fig. 3, log-logistic baseline hazard provides a non-monotonic baseline hazard while the Weibull baseline hazard is monotonically increasing. The log-logistic baseline hazard increases up to 2 years and then decreases which suggests people prefer not to make a transaction before 2 years and their willingness to make a transaction declines after the 2 year point. The modeling results of this paper indicate that the non-monotonic form of log-logistic function provides a better fit to the vehicle transaction timing decision. Assuming a non-monotonic form, expectedly an increasing pattern, for the hazard function means that as time elapses the household's tendency toward making a transaction increases. However this is not always correct. It can be correct to a specific point during which household looks for higher quality of life and may changes its fleet to gain more utility. After that turning point, household reaches to a stable point willing to maintain its lifestyle and not changing the number of vehicles in the fleet. It should be still considered that other long-term decisions, such as relocation decisions, can accelerate or decelerate this behavior, as the models of this study also suggest.

Before ending the baseline hazard analysis section, a statistical analysis on the distribution of the survival times is presented. An extensive curve fitting exercise was undertaken for this purpose. It was found that the job relocation decision survival time follows a Weibull distribution while log-logistic distribution provides the best fit to the residential relocation timing and vehicle transaction timing values. Table 4 shows the results of the distribution test on the four variables based on Kolmogorov–Smirnov statistics (Chakravarti et al. 1967 and Eadie et al. 1971).

The results that are presented in the above table clearly emphasize on the fact that Weibull and log-logistic distributions are the best parametric candidates for the baseline hazard function of the utilized data.

Data and variables

The Puget Sound Transportation Study (PSTS) is the first general-purpose travel panel survey in an urban area of the United States (Murakami and Watterson 1992). It consists of a longitudinal panel survey which includes ten waves, from 1989 to 2002, collected in the Seattle Metropolitan Area and its surrounding counties. The data for each wave is organized into three data files including trip information, household and individual attributes while vehicle attributes are only presented for one of the waves in an extra file. The last three waves of the PSTP are used in this study to estimate the parameters of the model. The last three waves of PSTS were chosen for this study because residential duration, which is one of the most important variables in the residential relocation timing decision, is available only in these three waves. Definitions and categories of household life styles also were changed in the last three waves. In addition to the PSTP data, land-use, built environment, and transportation network data variables for the Seattle Metropolitan Area and its surrounding counties are borrowed from studies by Mohammadian and Zhang (2007) and Silva and Goulias (2007).

Table 5 shows a summary of the total number of job relocations, residential relocations and vehicle transactions observed in the data. As it can be seen in this table, the impact of these decisions on each other is prompt and observed during the same year. While the lagged impact of these decisions on each other seems to be trivial. Furthermore, it can be concluded from Table 5 that although residential relocation is a rare event, the endogeneity

Table 5 Summary of the counts for relocation durations and transaction durations

Total number of observations	615
Total residential moves	73
Total job moves	406
Total vehicle transactions	182
Total residential moves followed by a job move after 1 year	5
Total job moves followed by a residential move after 1 year	10
Total vehicle transactions and husband job relocations in the same year	105
Total vehicle transactions and wife job relocations in the same year	93
Total husband and wife job relocations in the same year	188
Total wife job and household residential relocations in the same year	34
Total husband job and household residential relocations in the same year	35
Total vehicle transaction and household residential relocations in the same year	17

between it and household members' job relocation decision is very tight. This is confirmed with the support of modeling results of this study as well.

While the size of available records for some cases in PSTP dataset is relatively small, it should be noted that the uniqueness of the PSTS and availability of other complementary datasets have enabled the development of a complex modeling structure as one of early attempts for considering the inter-dependencies among these decisions. Nonetheless, this study disseminates the need for having a richer panel data in which long-term household decisions are observed in further detail and with higher accuracy.

A wide range of independent variables is utilized in this study to account for as many of the relevant factors as possible. These variables include the built environment characteristics of the TAZ in which the household resides and the TAZ in which the husband/wife works. They also include the travel activity attributes of household members. These travel attributes provide the important links between the developed joint model of this study and an activity-based travel demand model with a dynamic traffic assignment module. Another set of variables influencing the household decisions are macroeconomic attributes of the region in which the household lives. Finally, household socio-demographic attributes and household members' personal characteristics are also included among the set of independent variables.

There are four built environment variables in the pool of independent variables:

1. Average number of jobs in a grid cell of 150 m by 150 m in the TAZ in which the person works,
2. Total number of workers in the TAZ in which the person works,
3. Average number of particular job types in a grid cell of 750 m by 750 m in the TAZ in which household lives, and
4. Average number of residential housing units in a grid cell of 750 m by 750 m in the TAZ in which household lives.

It should be noted that various job categories like managerial, professional, administrative, health care, real estate and educational service were tested, however only real estate and educational jobs were found to be significant in the models. Moreover, average commercial and industrial square feet, count of arterial intersection and morning and evening transit availability in the grid cells of 150 m by 150 m were tested and found not to be significant in the models.

Unemployment rate changes and gas price changes for Seattle area in 1999, 2000 and 2002 were found to be significant in the models. On the other hand, annual consumer credit, vacancy rate, consumer loans owned and mortgage indices were examined and found not to be significant in the models.

Household and individual socio-demographic attributes are the last group of independent variables utilized in this study. Age, number of children, number of vehicles, work distance and many other variables were found to be significant and are included in the model in Table 6.

Husband's average travel time, household average travel time and household average activity duration are the significant activity attributes variables in the final model. Other activity variables like wife's average travel time and activity duration, and husband and wife total number of trips were insignificant. This is consistent with the findings of Sermons and Koppelman (2001) that husband's commute travel time is far more important than wife's commute travel time in residential location choice. Since these variables may result in endogeneity issues when a location change has occurred in the current year, therefore, they should be utilized in the model before movement estimation.

Models and the results

The likelihood functions presented in the methodology and formulation section are coded in SAS 9.1 environment and non-linear procedure (NLP) of SAS is applied to maximize the likelihood function. Unknown parameters are estimated using the second-derivative methods of Trust Region Optimization (TRUREG) algorithm of NLP.

The estimation results for the four component models: husband work relocation timing, wife work relocation timing, residential relocation timing and vehicle transaction timing are provided in four models. The models differ in terms of both the baseline hazard functions and the explanatory variables. The JRW-RRL-VTL model for which the detailed results are presented uses the Weibull baseline hazard function for job relocation decisions (both wife and husband) and the log-logistic baseline hazard function for residential relocation and vehicle transaction decisions. In each case, the selection of the baseline hazard function is based on statistically significant differences in estimation results. The detailed estimation results of the joint models are reported in Table 7. A brief discussion of possible explanations and interpretations of the model estimation results is provided in the next four sections. It should be noted that the effect of the covariates in hazard model is facilitated by incorporating a negative sign for all the parameters. Thus, a negative value implies an increase in hazard.

Husband job relocation model

The model coefficients for the husband job relocation sub-model are discussed first. The first four parameters in the household job relocation model have negative signs which imply that husbands are more likely to change jobs, if they live in households with a higher number of employed members; if there are more vehicles in the household (both possibly because they feel more secure financially); if household members have longer trip distances, or if they work in TAZs with more jobs available. Household members average travel time can be significantly affected if husband changes his work location because this change directly affect the household average travel time and it can indirectly have an impact on the mode choice, route selection and even destination choice of other household

Table 6 Variables used in the models

Variable	Definition	Mean	Std. Dev.
Individual's attributes			
Age of wife		39.89	20.03
Age of husband		39.60	20.45
Attributes of the household			
Tenure	1, if the household rents a home; 0 otherwise	0.14	0.35
Number of adults	Number of household adults who are older than 18 years old	1.86	0.69
Former members	Number of household members who left the household since last wave	0.18	0.45
New members	Number of household members who joined the household since last wave	0.16	0.42
Number of children	Number of members with age between 1 and 5 years old	0.10	0.37
Income (log)	Natural LOG of the income of the household		
Employed	Number of household members employed	1.78	0.65
Fleet size	Number of vehicles held by household, before possible transaction	2.14	1.09
SOV	Household travel mode is single occupied vehicle	0.61	0.49
Built environment variables			
Real job	Average number of real estate, rental and leasing jobs in a gridcell of 750 m by 750 m in the TAZ in which household lives	0.39	1.38
Units	Average number of residential housing units in a gridcell of 750 m by 750 m in the TAZ in which household lives	14.83	21.43
Wifeworkers	Number of workers in the TAZ in which wife works	2004.67	1200.35
Wifeeduw	Average number of educational service jobs in a gridcell of 750 m by 750 m in the TAZ in which wife works	1.36	4.73
Husbandjobw	Average number of jobs in a gridcell of 150 m by 150 m in the TAZ in which husband works	1725.93	4729.16
Activity attributes			
AveTTHHld	Log of average household travel time	21.14	12.36
AveATHHld	Log of average household activity time	267.22	118.97
HusbandAveTTInd	Log of average husband travel time	17.76	15.58
Husband Wkdist	Husband work distant, if moved the previous locations	9.79	9.63
Economic characteristics			
GasPChg	Gas price change since last wave ($)	0.12	0.23
URChg	Unemployment rate change from last wave (%)	1.21	1.10

members. Relating to the fourth variable with a negative value, it can be said that working in zones with more jobs lets the husband to keep his job option open and not close his job search process. In other words, the finding of this study admits the common sense that existence of fewer jobs around a person makes him thinking of holding to his job.

Husbands are less likely to change jobs if there is an increase in Unemployment Rate since the last wave (greater difficulty finding a new job). Finally, the wife's job relocation, represented by the predicted hazard, can decrease the chance of husband job relocation

Table 7 Parameter estimation for four joint models with different baseline hazard functions

Variable	JWRLVL	
	Parameter	*t*-value
Husband job relocation		
Const	4.71	7.52
Sigma/alpha	1.50	24.18
Beta	–	–
Employed	−0.48	−3.25
Fleet size	−0.09	−1.19
AveTTHHld	−0.56	−2.94
Husbandjobw	−0.35	−2.69
Husbandwkdist	0.03	1.43
URChg	3.72	4.44
Wife hazard on husband	2.05	3.46
Residential hazard on husband	−9.14	−1.71
Wife job relocation		
Const	3.69	5.88
Sigma/alpha	1.57	30.31
Beta	–	–
Employed	−0.28	−2.49
Wife age	0.01	1.26
SOV	−0.18	−1.85
AveTTHHld	−0.44	−2.99
Wifeeduw	−0.01	−1.21
Wifeworkers	1.32	2.31
Husband hazard on wife	1.39	2.64
Residential hazard on wife	−10.68	−2.67
Residential relocation		
Const	9.61	4.64
Sigma/alpha	0.96	289.37
Beta	89.77	7.64
Tenure	−0.54	−2.61
New members	0.39	1.18
Husband age	0.04	2.17
AveAThhld	−0.47	−1.29
Husband AveTTInd	−0.56	−2.53
Real job	−0.09	−2.15
Husband hazard on residential	2.08	1.32
Wife hazard on residential	1.97	1.67
Vehicle transaction		
Const	0.61	4.07
Sigma/alpha	1.58	4.40
Beta	3.35	6.11
Number of children	0.30	1.40
Fleet size	−0.71	−9.30

Table 7 continued

Variable	JWRLVL	
	Parameter	*t*-value
Number of adults	0.21	1.39
Former members	−0.83	−6.19
Units	20.93	3.60
AveTTHHld	0.06	3.94
AveATHHld	0.11	7.11
GasPChg	−0.99	−2.20
Husband hazard on vehicle	0.10	0.23
Wife hazard on vehicle	1.14	1.48
Residential hazard on vehicle	−9.54	−1.58

while household residential relocation can increase the chance of husband job relocation. This can be explained by the fact that a wife's job relocation may prevent husband from immediate job change which may result in job loss or decrease of income for a period of time. On the other hand, husband seems to be more likely to change his job location if household residence has already been changed probably to reduce his commute distance.

Wife job relocation model

In the case of wife job relocation model, there are again four variables which accelerate wife job relocation if they increase and they have negative values in wife job relocation model. These negative variables are studied first starting with number of employed members in the household. Similar to the husband job relocation mode, this variable found to accelerate the relocation decision, possibly because of the financial security that more employed members provide to a wife and let her think more freely about changing her job. Therefore, more employed members in the household can provide the financial flexibility to the wife so that she may more freely think about job relocation. Average household travel time is another variable that the wife job relocation model has in common with the husband job relocation model and it can be interpreted the same way it was explained before. Wives who live in household, whose main mode of transportation is lonely driving automobile, are also more flexible in changing their job location than those who carpool or take transit, possibly because they have access to more job opportunities. The fourth variable with a negative value in the wife job relocation model is total number of education al job in the zone in which wife works. Educational service jobs are not generally location dependent. For example teachers may change their job location if they are needed as substitutes in other schools. Therefore, wives working in TAZs with more educational service jobs might work in educational related jobs and these jobs are more mobile job categories.

There are two variables in this sub-model which have positive values, wives age and number of workers in the TAZ in which wife works. So, as the wives get older they become more reluctant to change their job location. Unlike total number of educational service jobs, total number of workers in a TAZ, which can show employment stability while it also can imply a competitive employment situation, postpones job relocation decision of a household wife. Husband's job relocation, represented by the predicted hazard function, impedes wife to change her job location while household residential relocation, again represented by a predicted hazard function, can encourage her to find a job closer to the new residence.

Residential relocation model

The third sub-model listed in Table 7 presents household residential relocation timing parameters. Starting from the first covariate in the residential relocation model, it was found that renter households change their residential location which is completely in line with what was expected for them. If a new member joints the household, this event holds the household back of moving to a new location. Intuitively, it was found that seniors are less likely to change their home location and they prefer to stay in their current residence. The negative sign of household average activity time imply that households with longer duration activities are less likely to change their residential location. Pro-intuitively, households that have husbands with longer commute distance are more likely to change their residential location to reduce the annual travel time and distance which directly reduces the household annual cost. Finally, households residing in TAZs with greater number of real estate, leasing and rental jobs are expected to change their residence easier, possibly because they can more easily trade their residence.

The two endogenous variables employed in the residential relocation model found to be statistically significant. Husband and wife job relocations hazard values both reduce the chance of household residential relocation if they have already occurred. This can be readily explained by knowing that job relocation itself might have occurred to reduce commute distance, therefore it does not cause residential relocation again. Therefore, it can be concluded from these findings that job and residential relocation causality is a two way relationship where job relocation impedes residential relocation while residential relocation can trigger job relocation for both wife and husband.

Vehicle transaction model

The last joint sub-model which is the primary objective of this study is the vehicle transaction timing model. As it was shown in Table 7, larger number of children and number of adults limit the household expenditure flexibility of making a transaction while households with larger vehicle fleet size are more likely to make vehicle transactions because possibility of trading and disposing increases as the household fleet of vehicles enlarges. If household loses a member, it thinks about making a transaction to adjust the household vehicle needs. Intuitively, living in dense urban areas can reduce the chance of vehicle transaction because cost of owning and maintaining a vehicle in dense urban areas are significant.

Two travel attribute variables were found to be statistically significant in the household decision on vehicle transaction timing including household average travel time and household average activity time. Having longer travel time or activity duration can reduce the desire of household for making a vehicle transaction while these variables found to accelerate job and residential relocation decision. With increasing concerns about gas price, gas price changes over the time have been included among the pool of explanatory variables tested in this study. It was found that increase in gas price increases the probability of vehicle transaction and interestingly, the magnitude of one unit increase is greater than a case that a household member leaves the household.

Based on the sign of the predicted hazard values it can be concluded that job relocation is less likely to trigger a household vehicle transaction decision. Nonetheless, the influence of wife job relocation is by far greater than the husband's decision. Additionally, change in household residential location has a positive effect on the transaction decision. In other words, if a residential location change has occurred, a vehicle transaction can be also expected.

Conclusion and future work

A joint dynamic model is developed in this study in which vehicle transaction timing is a function of endogenous job and residential relocation timing. Job relocation timing decision is modeled for both husband and wife at the individual level. These two sub-models are also simultaneously dependent to the residential relocating timing decision at the household level. All three sub-models influence the household vehicle transaction timing decision.

Utilizing a panel data and incorporating a hazard-based system of equations, one of the major contributions of this study is to introduce a dynamic framework for modeling timing of three critical household decisions. In order to improve the goodness-of-fit of the model, two different baseline hazard functions were examined. These include a Weibull hazard function which can be only monotonically increasing or decreasing and a log-logistic hazard function which can have a non-monotonic hazard pattern for specific beta values. It was found that the non-monotonic log-logistic function can considerably improve the overall model fit when used for residential relocation and vehicle transaction timing decisions but there is no significant difference between these two hazard functions in the case of job relocation timing decision; the Weibull distribution was selected because of its slight superiority over log-logistic baseline hazard function.

Furthermore, the impact of other exogenous variables including transportation, land-use and economic variables were also examined. The use of household and individual travel activity attributes such as travel time and activity duration showed that larger travel time and activity duration can increase the chance of job and residential relocation while it can reduce the probability of vehicle transaction. These types of variables can be employed to link the developed model with a disaggregate activity-based model. Two other exogenous variables, gas price change and unemployment rate that change over time were utilized in this study to incorporate the impact of supply side of marker of these long-term decisions. It was found that that a gas price increase can accelerate the vehicle transaction decision while larger unemployment rate can also influence the husband‘s decision on job relocation. The disaggregate decisions of individuals and households can be aggregated up to a broader resolution (e.g., county, or city level) as a measure for urban land use forecasting. This can help to study and evaluated the impacts of disaggregate behaviors on urban form while the influence of general policies on household decisions can be also investigated.

Further research is underway to capture heterogeneity effects in the proposed model. The authors are aware about the importance of considering the correlation among unobserved heterogeneity the proposed formulation. However, since the formulation becomes significantly complicated by considering the unobserved heterogeneity in the presented joint formulation, therefore, the authors left this task for future research to sufficiently discuss it in a separate study as soon as it is finalized. Linking the current system of equations to a housing search and vehicle type/vintage choice models will also remain as future advances. Finally, it is desired to also include the impact of school location decision among the other long term household decisions. However, this task was left a future task when such information (e.g., school quality data) is available.

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