Households Long-Term Decision Making Process: Vehicle Transactions, Employment, and Residential Location Choices

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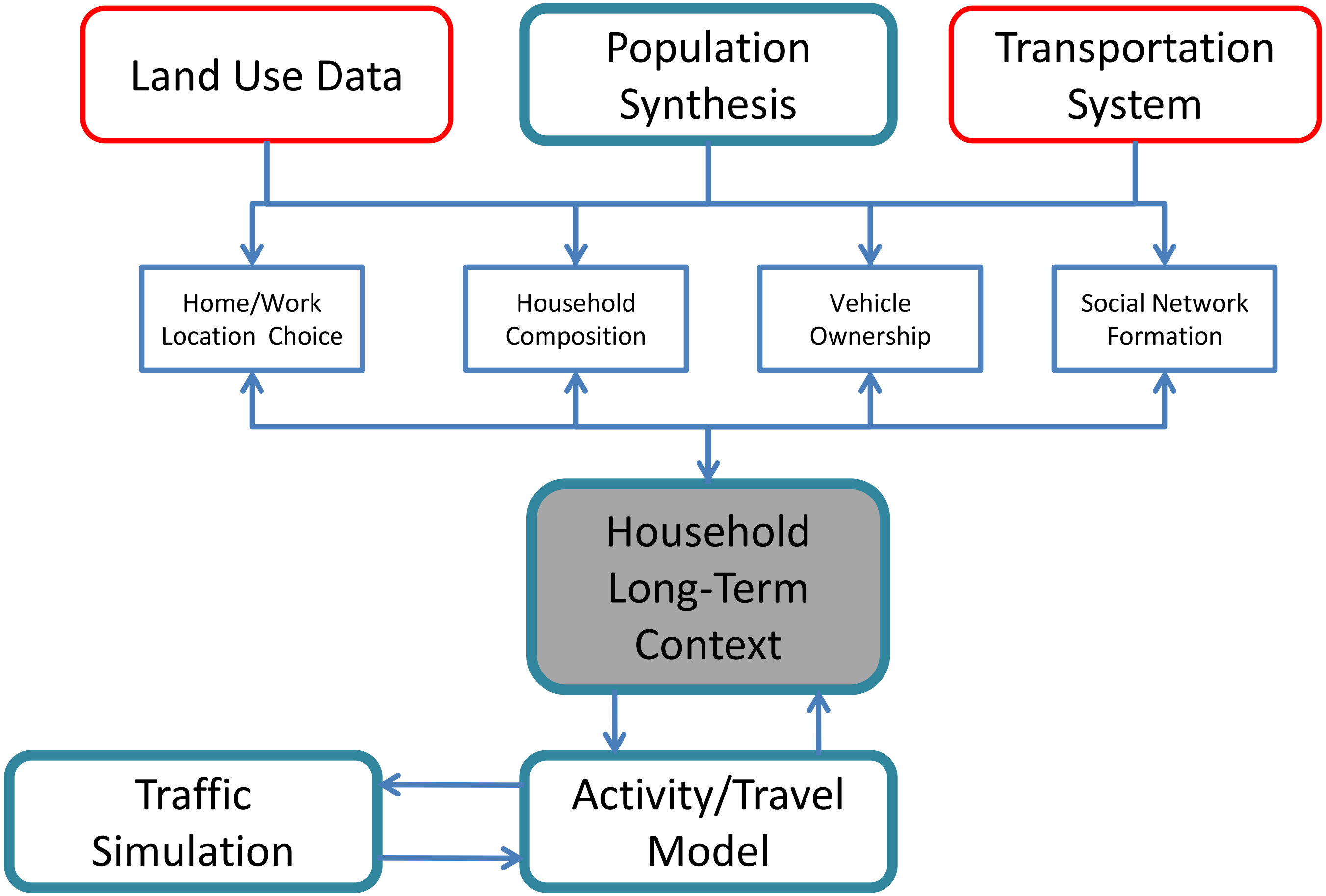
General Framework



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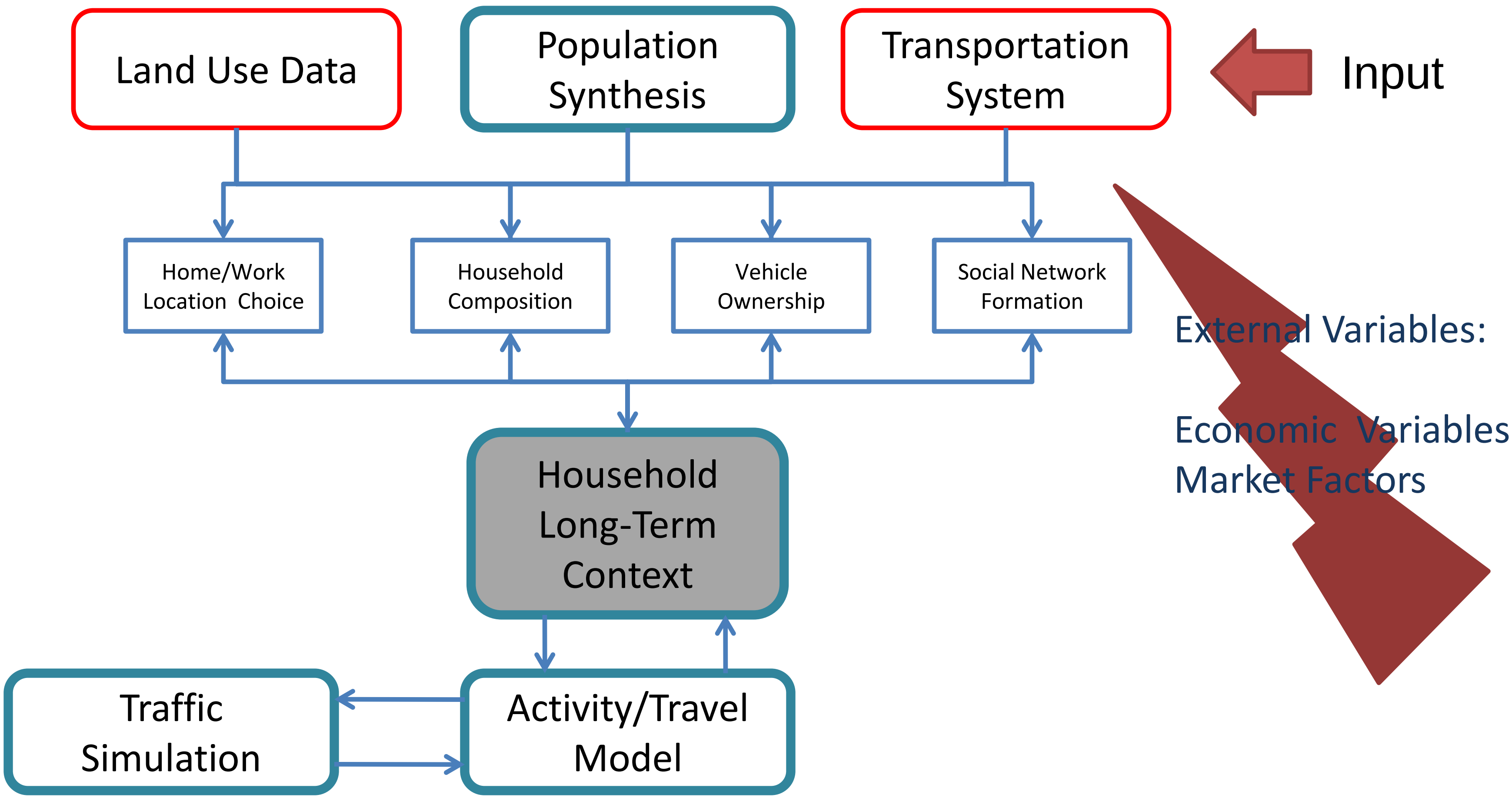

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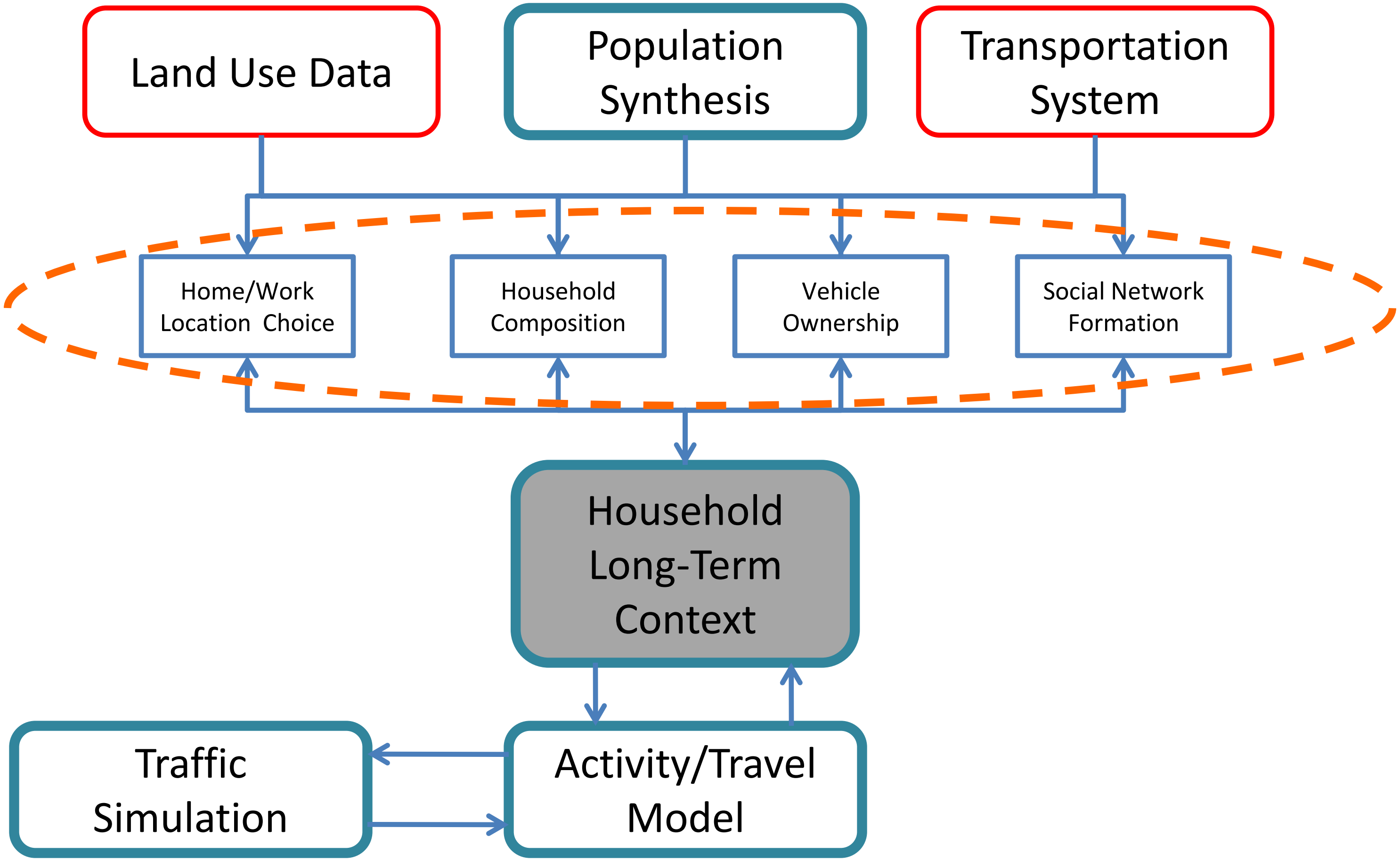

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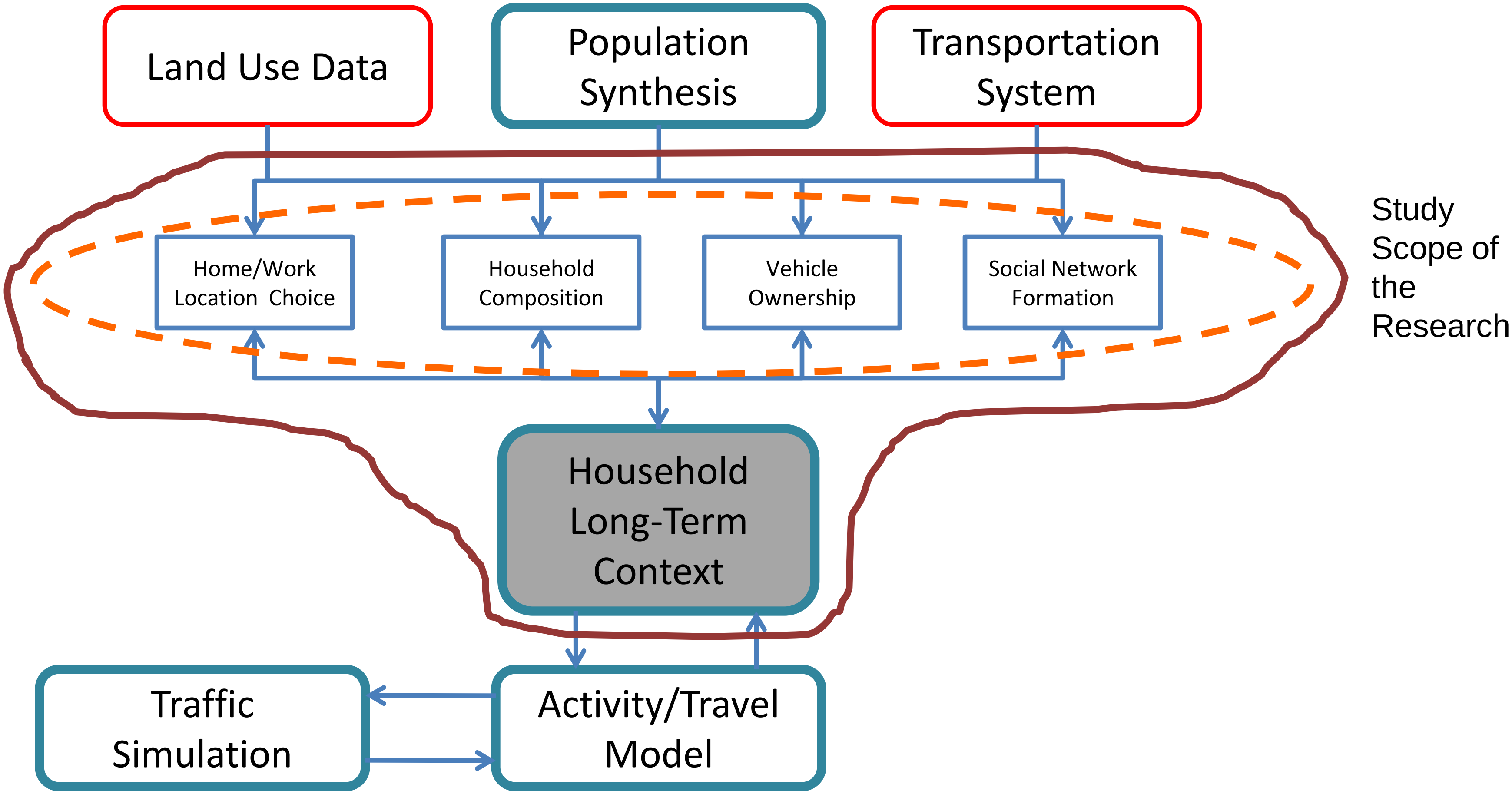

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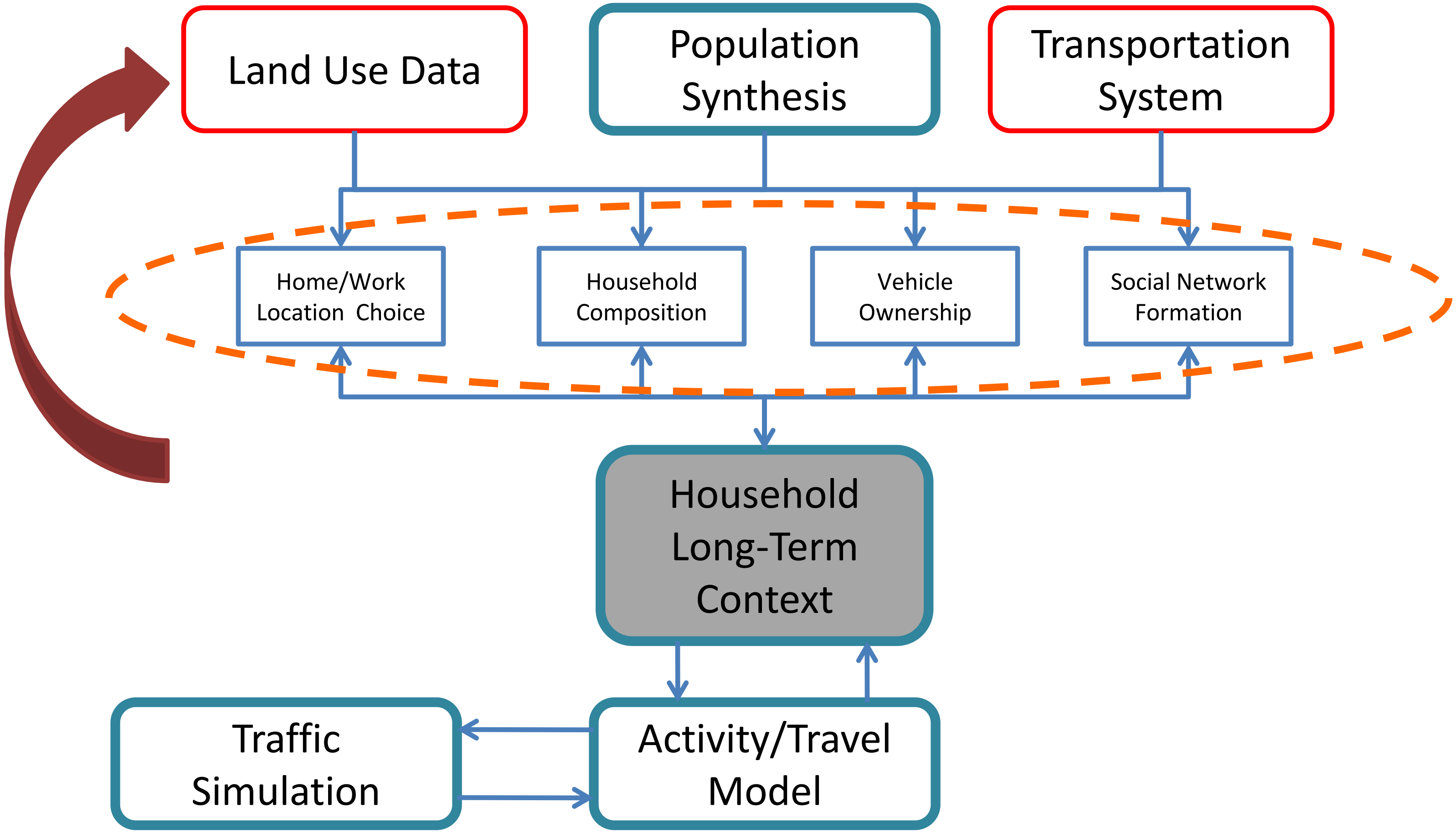

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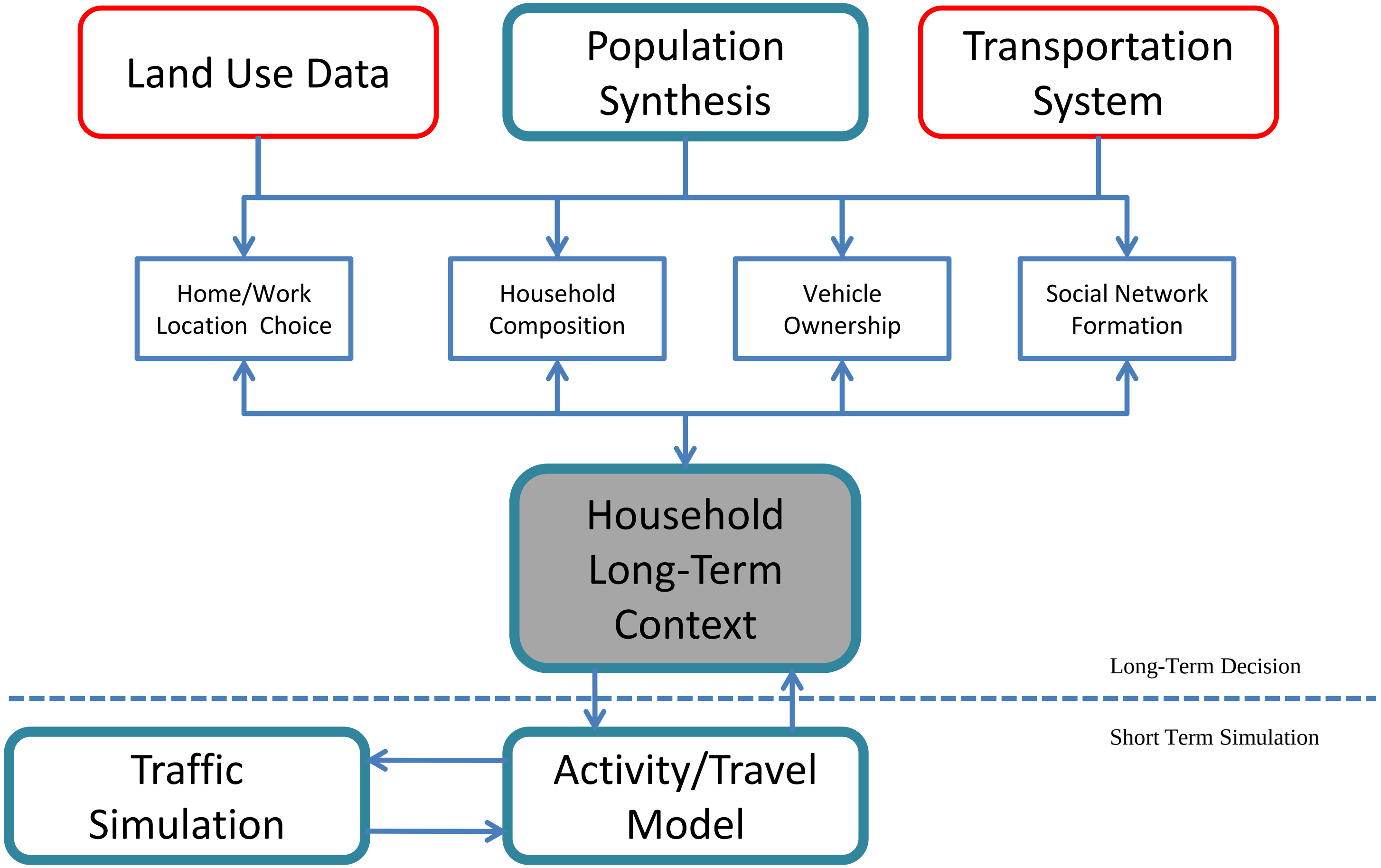
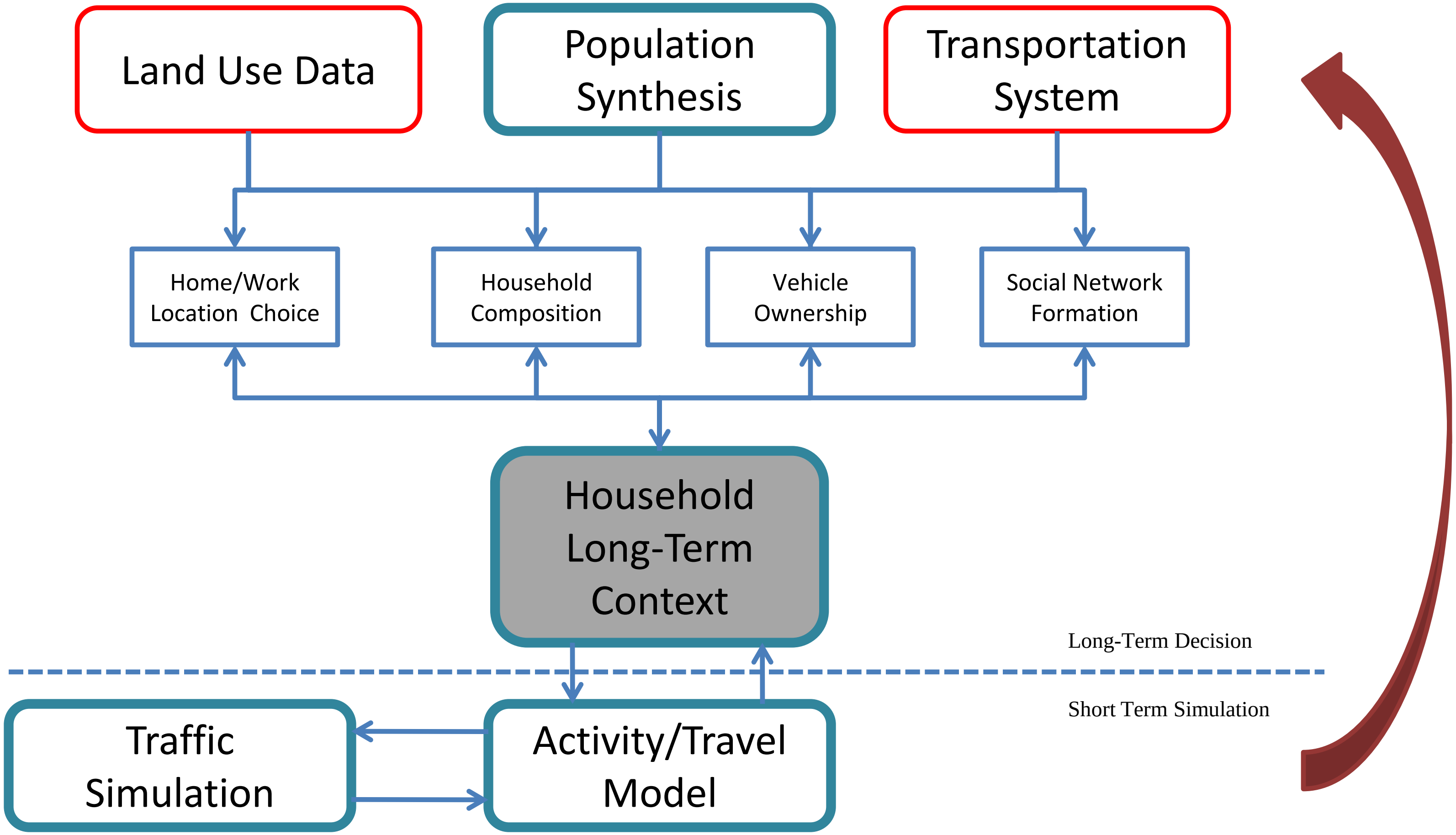


General Framework



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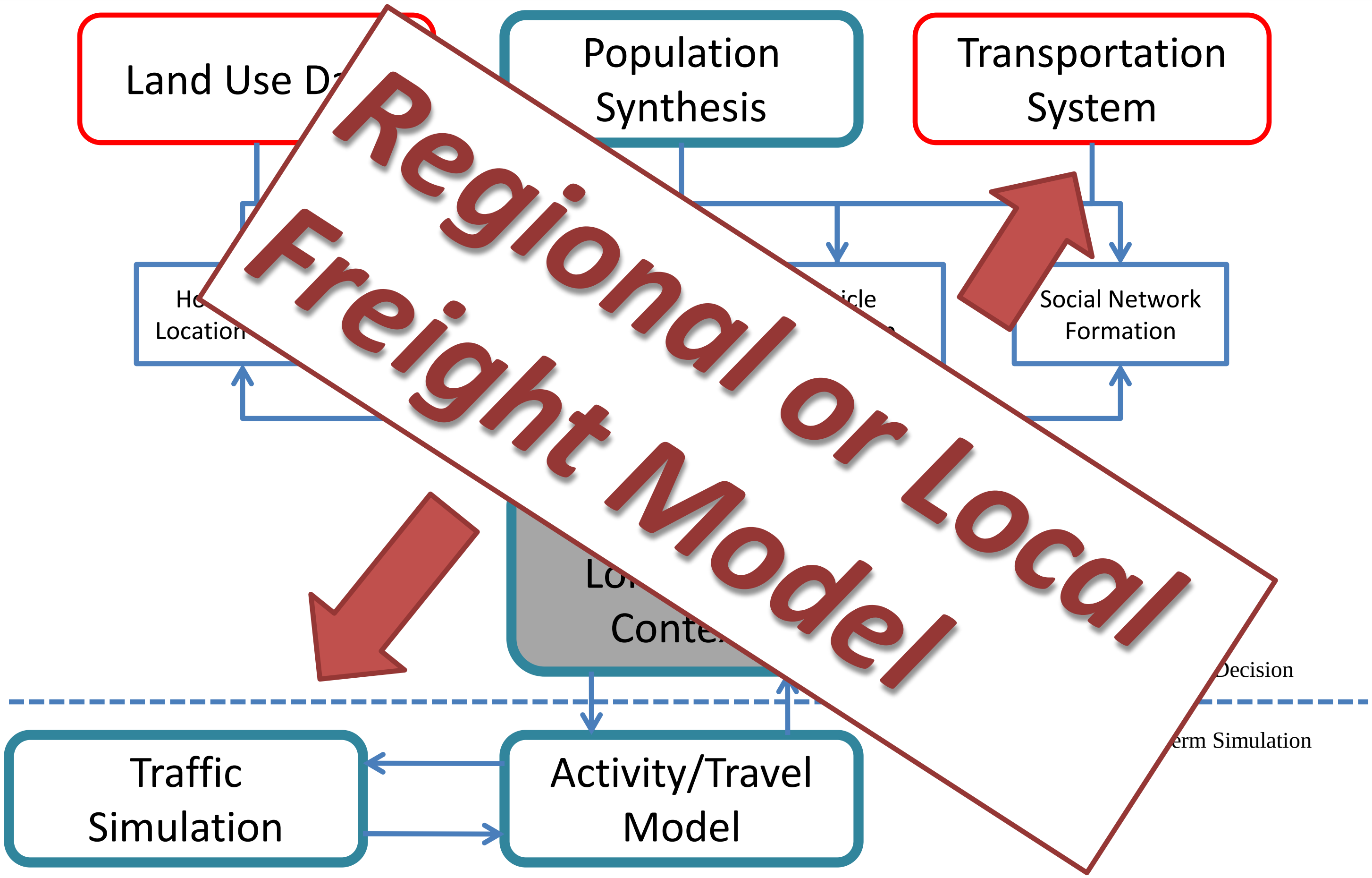


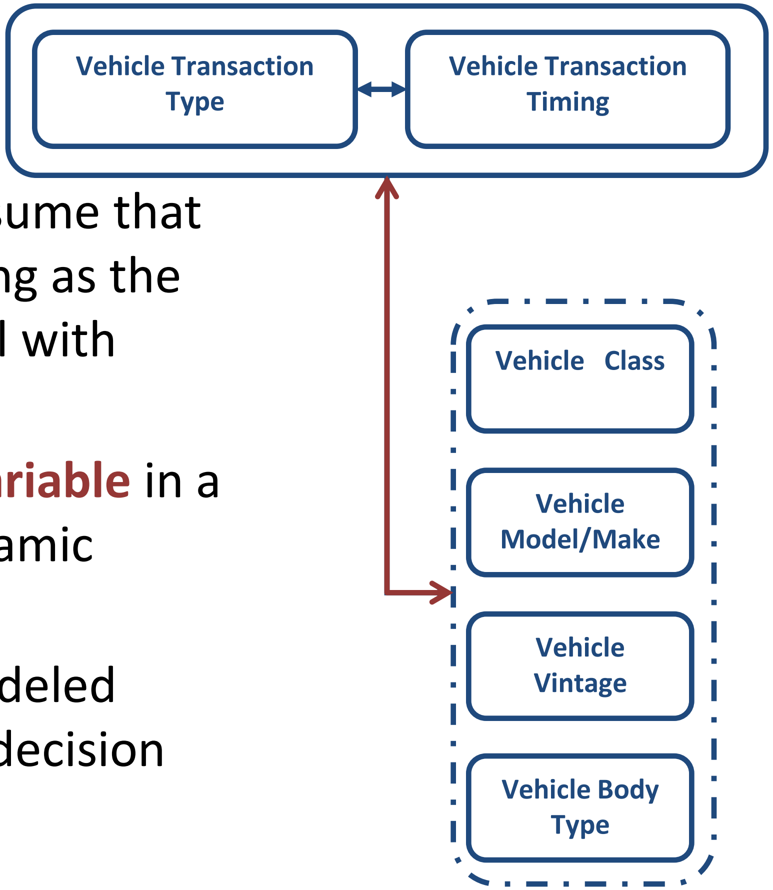
Vehicle Transaction

- Vehicle Ownership Models
  - Aggregate Vehicle Ownership Models
    - Total number of vehicles in a zone during a period of time (GDP, Fuel Price, etc)
    - Watch a population cohort over time (License holding behavior)
    - Studying demand and supply of car market
  - Disaggregate Vehicle Ownership Models
    - Static Models
    - Dynamic Models

Vehicle Transaction

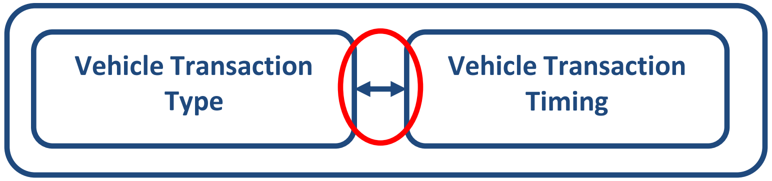
- Vehicle Ownership Models
  - Dynamic Models
    - Dynamic car-ownership models assume that no transaction will take place as long as the household maintains its utility level with respect to its vehicle fleet.
    - *Transaction timing* is the **central variable** in a vehicle transaction model or a dynamic vehicle ownership model.
    - Other vehicle attributes can be modeled conditional on vehicle transaction decision

or even jointly



Vehicle Transaction

- Vehicle Ownership Models
  - Dynamic Models
    - A Joint vehicle transaction timing and type decision model is presented here



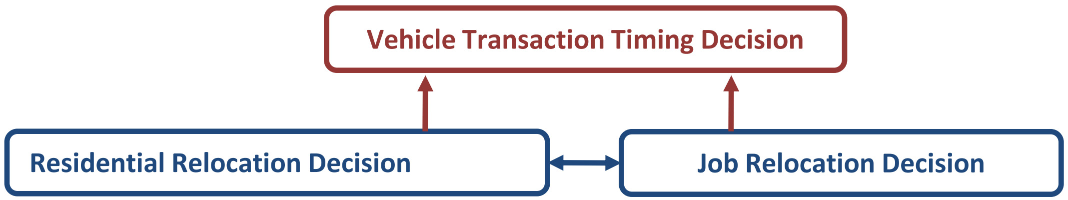
Residential Relocation

- Residential and Job Relocation Timing Decision
  - Residential and job search behaviors are commonly discussed together because of their close relationship.
  - This link between these two decisions, **commute distance**, has convinced the researchers to jointly model these two decisions
  - 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.

  So job relocation is not studied in detail in this study.

Residential Relocation

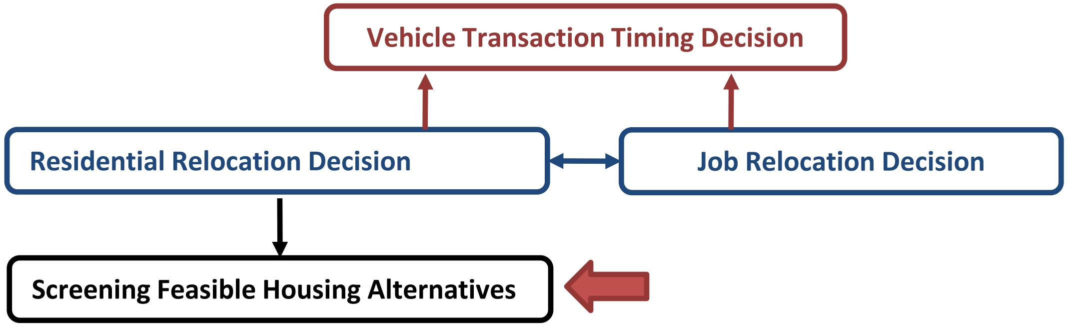
- Residential and Job Relocation Timing Decision
- Timing Decision (Jointly)



Residential Relocation

- Housing Search Model
- Conditional on residential relocation timing

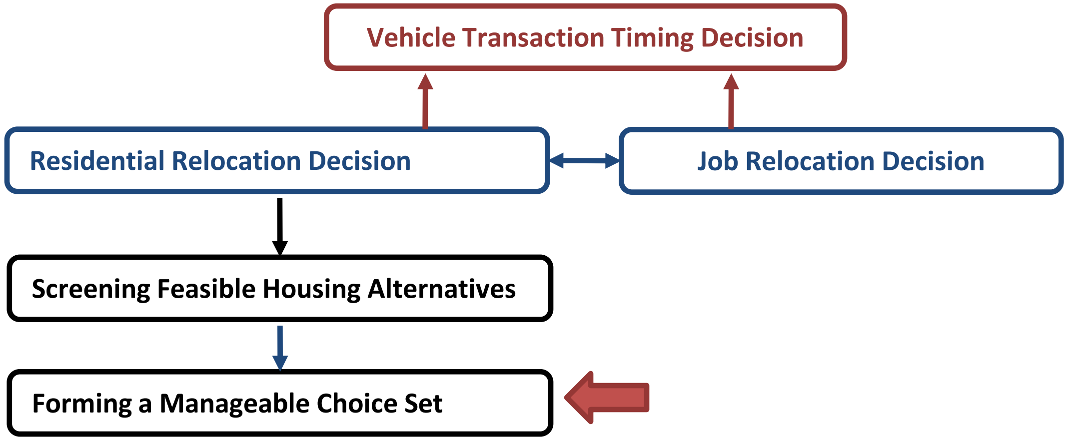
- The housing search process starts with an alternative formation and screening stage. At this level households evaluate all potential alternatives based on their lifestyle, preferences, and utilities to form a manageable choice set with a limited number of plausible alternatives.



Residential Relocation

- Housing Search Model
- Conditional on residential relocation timing

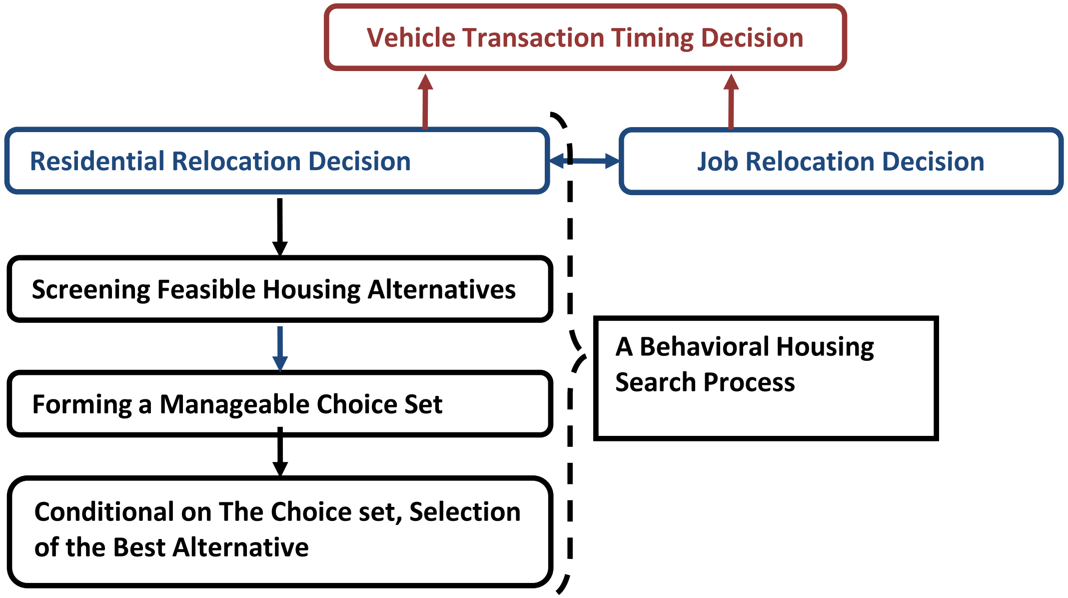
- A household specific choice set is drawn from the entire possible alternatives in the area based on the average household work distance to each alternative



Residential Relocation

- Housing Search Model
- Conditional on residential relocation timing

- Following the choice set formation step, a discrete choice model is utilized for modeling the final residential zone selection of the household.



Data

- Major Datasets

Household automobile ownership in Toronto

Panel data

900 households

9 years period from 1990 to 1998

Decision Making Unit (Individuals within a household that make vehicle ownership decisions in conjunction with each other)

Puget Sound Transportation Panel Survey

A longitudinal panel survey

10 waves from 1989 to 2002 in Seattle

The last three waves of the PSTP are used in this study to estimate the parameters of the model.

Additional Data

The built-environment characteristics were borrowed from an adjunct survey of the PSTP (Housing Search and Interdependencies among the major household decisions)
Land values and house prices are mainly obtained by county assessment departments (Housing Search)

Provided by Puget Sound Regional Council

Hazard-Based Duration Models, Methodology

- Continuous Formulation
  - The hazard function can be expressed as a function of the probability density function *f(t)* and the cumulative distribution function *F(t)*, as shown in the following equation.

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

The hazard, *h(t)*, gives the rate at which events (such as purchasing a vehicle) are occurring at time *t*, given that the event has not occurred up to time *t*.

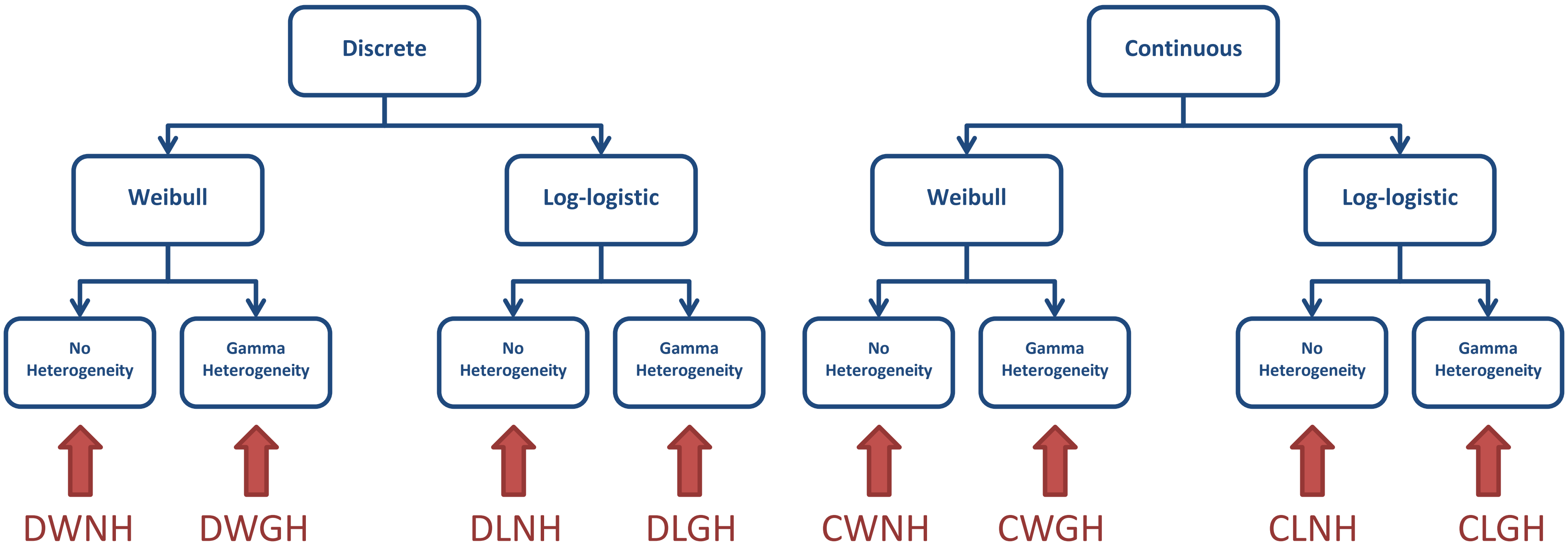
Survival Function

$$S(t) = \frac{f(t)}{h(t)}$$

Analysis on Different Parametric Hazard Models

- Model Definitions

Eight parametric hazard formulations are developed and their goodness-of-fits are compared against each other.



Analysis on Different Parametric Hazard Models

- Modeling Results
- Eight Models with alternative baseline ha heterogeneity

is a criterion for model selection among a class of parametric models with different numbers of parameters.

Model Type	Likelihood at Convergence	Number of Parameters	BIC
CWNH	-1280.84	26	1366.42
CWGH	-1280.76	28	1372.93
CLNH	-1280.84	28	1373.01
CLGH	-1284.08	31	1386.12
DWNH	-1292.17	26	1377.75
DWGH	-1290.64	28	1382.81
DLNH	-1291.97	28	1384.14
DLGH	-1291.67	31	1393.71

Lower BIC implies better fit

BIC= - $\ln(L_C)+0.5\,p\,\ln(N)$

$\ln(L_C)$ is the log-likelihood value at convergence

p is the number of parameters

N is the number of samples

The continuous model with monotonic baseline hazard outperforms other models and including unobserved heterogeneity DOES NOT improve the general goodness-of-fit of the models

Generally continuous models provide better results

Analysis on Different Parametric Hazard Models

- Modeling Results
- Eight Models with alternative baseline hazard and gamma distributions for heterogeneity

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BIC= $-\ln(L_C)+0.5\,p\,\ln(N)$

$\ln(L_C)$ is the log-likelihood value at convergence

p is the number of parameters

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Weibull models have smaller BIC values which implies that they provide better model fits.

Shape parameters of log-logistic baseline hazards were al greater than one which means they were all non-monotonic

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$\ln(L_C)$ is the log-likelihood value at convergence

p is the number of parameters

N is the number of samples

Including Unobserved heterogeneity does not necessarily improve the goodness-of-fit

Competing Hazard Model

- Introduction

Vehicle Transaction Decision

Transaction Type Decision

Tr

Trade

Acquisition

Sell

There is a *competing behavior* among these transaction types which should be included in the model to have accurate results.

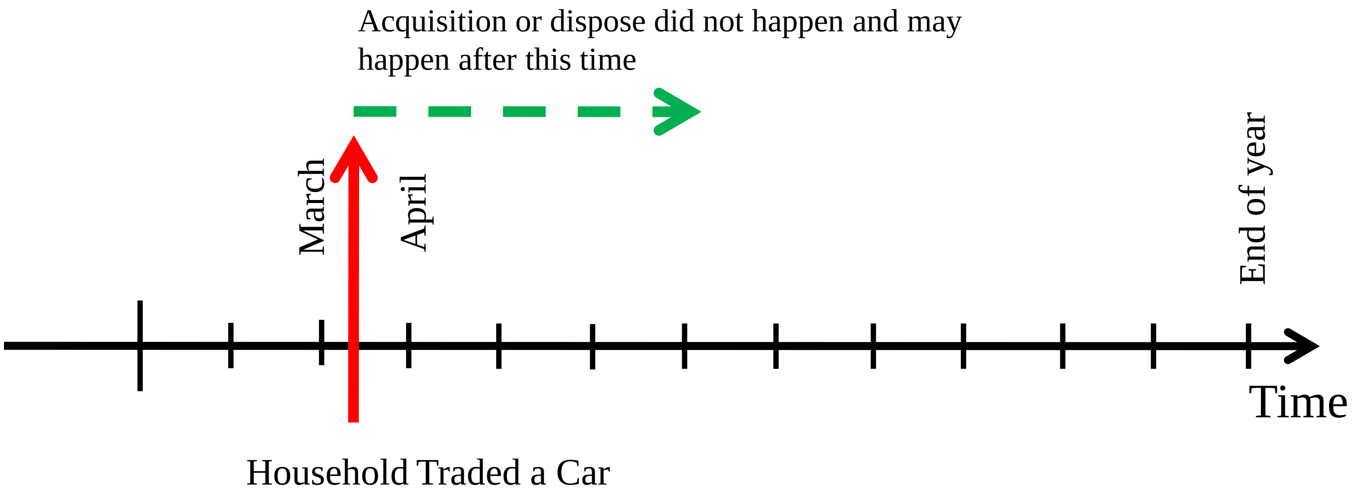
There is no true competing dynamic vehicle transaction decision model in the literature.

The existing competing models in other fields such as economics have considered only two competing events

Competing Hazard Model

- Assumptions

It is assumed that the transactions occur in discrete time intervals



Competing Hazard Model

- Methodology

Likelihood function for modeling the competing transaction type and timing for the case that trade transaction has been observed

$$P_{Tra}^{t} = P[Tra = 1, \text{ Acq} = 0 \text{ and Dis} = 0 \text{ at } (\text{t} - 1, \text{ t})] =$$

$$\underbrace{\int_{\delta_{t-1}^{Tra}-x\beta_{Tra}}^{\delta_t^{Tra}-x\beta_{Tra}}}_{\text{A trade transaction was observed}} \underbrace{\int_{\delta_t^{Acq}-x\beta_{Acq}}^{\infty}\int_{\delta_t^{Dis}-x\beta_{Dis}}^{\infty}}_{\text{Acquisition and dispose transactions were not observed}} f(\varepsilon_{Tra},\varepsilon_{Acq},\varepsilon_{Dis})\, d\varepsilon_{Dis}\, d\varepsilon_{Acq}\, d\varepsilon_{Tra}$$

δ_t^{i} is the logarithm of the integrated baseline hazard of failure type i (Trade, Acquisition and Dispose

A Copula Function is used to replace this joint function

A copula distribution approximates the multivariate joint probability density function using the marginal distributions in a closed-form function

$$f(\varepsilon_{Dis},\varepsilon_{Acq},\varepsilon_{Tra}) = \underbrace{f(\varepsilon_{Dis})\, f(\varepsilon_{Acq})\, f(\varepsilon_{Tra})}_{\text{Marginal Distributions}} \times \underbrace{c_{\theta}(F(\varepsilon_{Dis}), F(\varepsilon_{Acq}), F(\varepsilon_{Tra}))}_{\text{Copula Function (Gumbel in this case)}}$$

Competing Hazard Model

- Results and Findings
  - Explanatory Variables

Individual's attributes

Age and gender of the car owner

Attributes of the DMU

Income (log) , Housing Tenure, No. of Vehicles, Former members, New members, Workers, Adults, Youths, and Children, Education status

Attributes of the vehicle

Age, Price, MPG, Weight, New/Used

Vehicle and market interaction:

Avg depreciation cost, Avg parking cost, Avg fuel cost

Competing Hazard Model

- Results and Findings
  - General Model Comparison Results

Weibull model outperforms the log-logistic model

Model Type	Likelihood at Convergence	Number of Parameters	BIC
Gumble Copula with Weibull Baseline	-4026.71	30	4126.70
Gumble Copula with Log-logistc Baseline	-4059.96	33	4169.94
No Copula With Weibull Baseline	-4486.34	29	4582.99
No Copula with Log-logistic Baseline	-41[illegible]13	32	4294.78

with-copula models considerably dominate the *without-copula* models.
If the interdependencies among the transaction types are included in the modeling formulation, it is expected that the model better explain the household and individual's behaviors.

BIC= - $\ln(L_C)+0.5\, p \ln(N)$
$\ln(L_C)$ is the log-likelihood value at convergence
p is the number of parameters
N is the number of samples

Competing Hazard Model

- Results and Findings
  - Simulation results

The estimated model of this study was found to replicate **77%** of the trade decisions, **96%** of the acquisition decisions and **96%** of the disposal decisions correctly.

It was found that the shortage in accurately predicting trade decisions has been connected to almost the same amount of redundancy in overestimating the total number of disposal decision.

Introduction

- Major household decisions

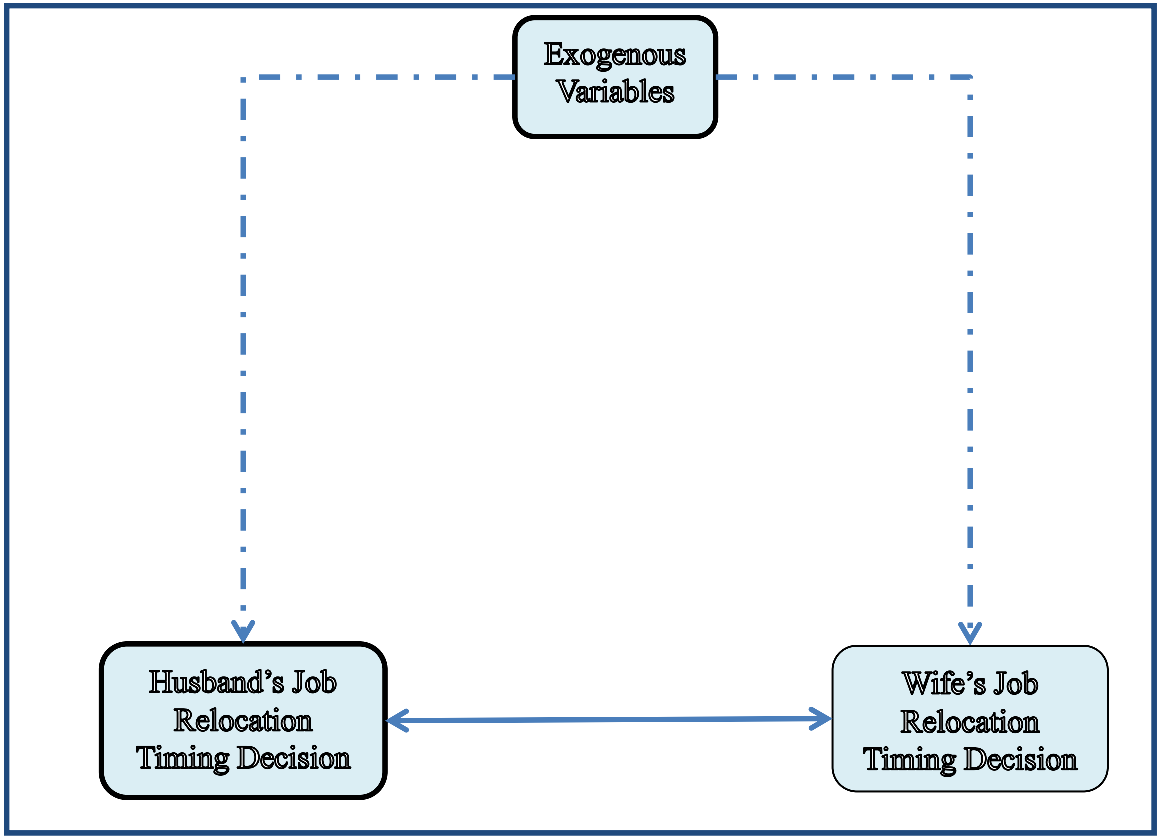
This study introduce a disaggregate dynamic model for major household decisions on durable products.

Vehicle
Residential Location
Job Location

An ideal framework encompasses these decisions along with the specific components of each one of them in a joint structure. Nonetheless, here only the timing decisions are studied.

Introduction

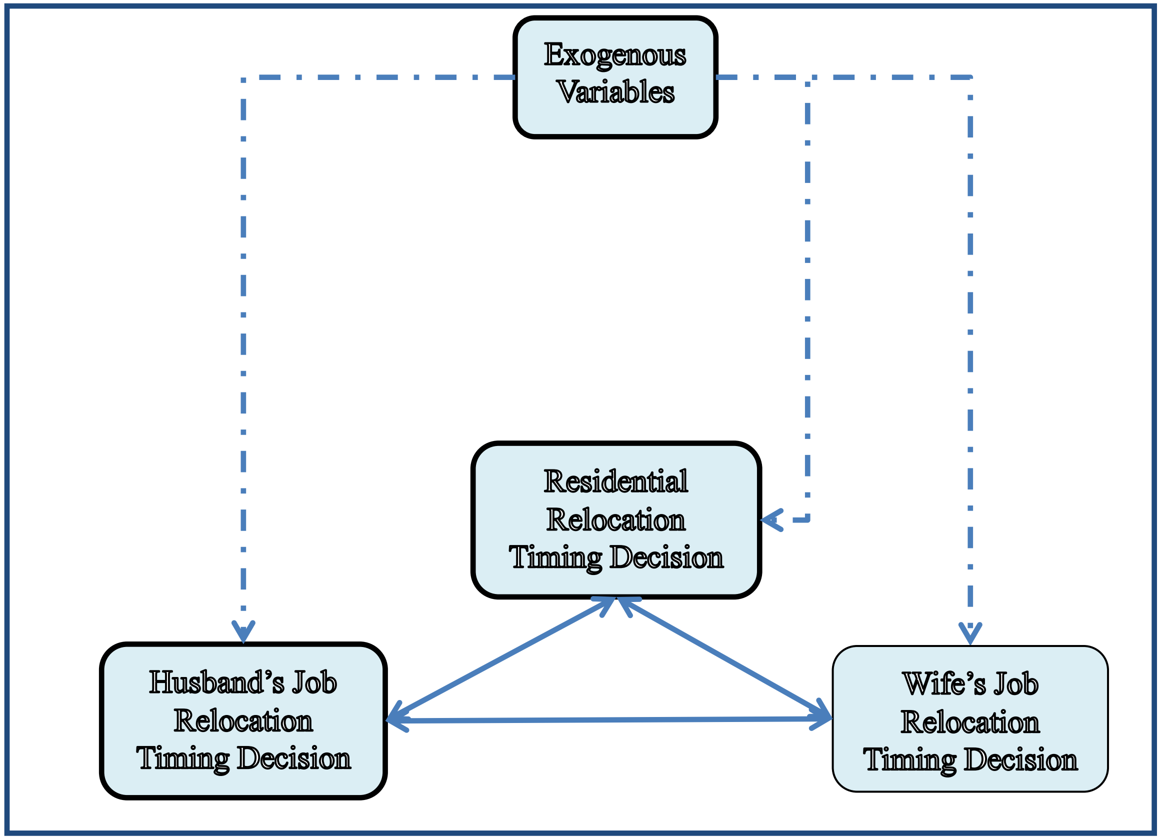
- Framework



Job relocation decision is made at the individual level but it is influenced by other members' decisions

Introduction

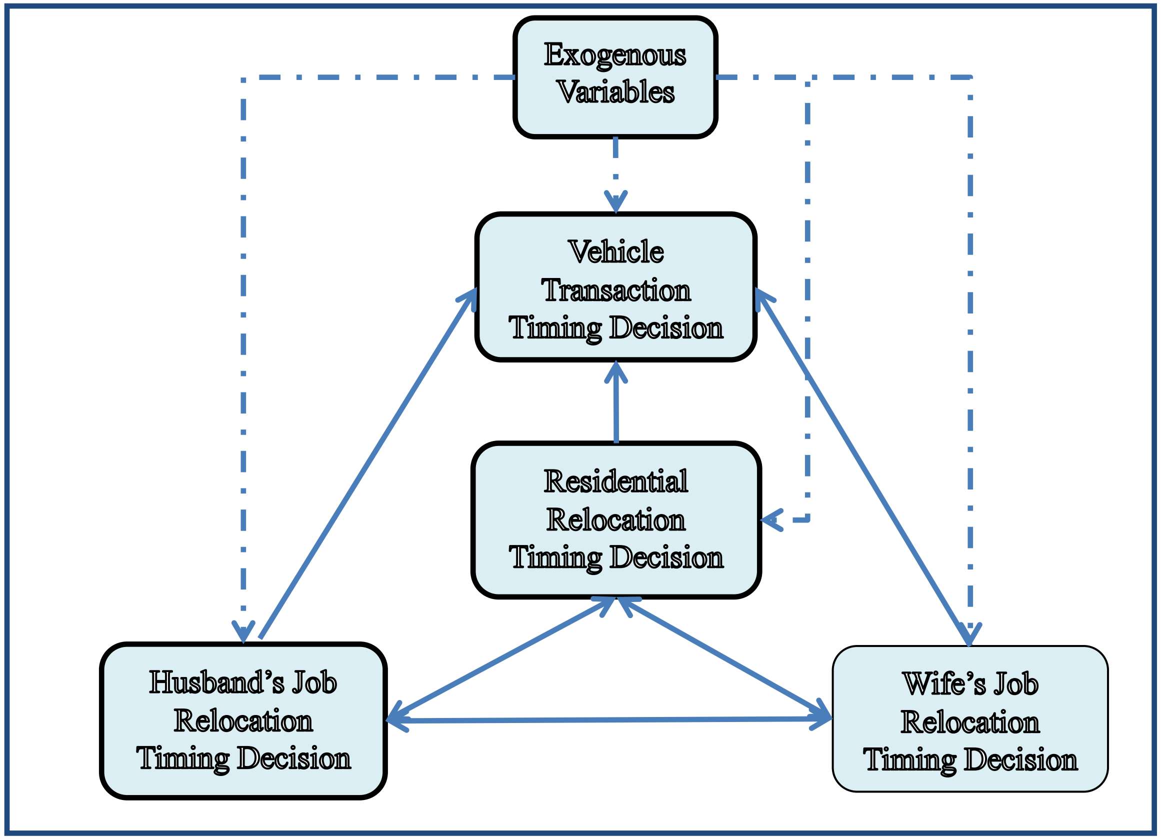
- Framework



Job relocation decisions and residential relocation decision are jointly modeled to incorporate the two-way impact between these decisions

Introduction

- Framework



Model and Results

- Explanatory variables

Individual's attributes

Age

Attributes of the household

Income (log) , Housing Tenure, No. of Vehicles, former members, New members, Workers, Adults, Youths, and Children

Economic Characteristics

Gas Price Change** and **Unemployment Rate Change

Built Environment and Land-Use

Housing Units Density, Real Estate Jobs Density, Education Jobs Density, Total Job Density and Spatial Employment Population

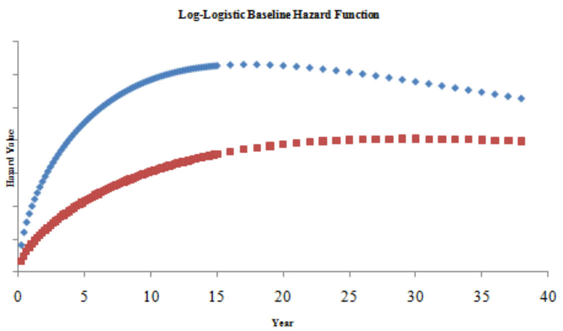
Activity Attributes ➡ *Can be borrowed from an activity-based model*

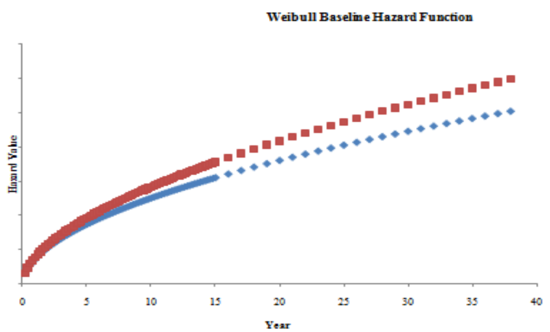
Household Travel Time, Household Activity Time, Husband Travel Time and Husband Work Distance

Model and Results

- Baseline Hazard Analysis
- Weibull and log-logistic baseline hazard function for job relocation decisions

Husband Wife





The **log-logistic** function shows a more rapidly increasing hazard rate for both the husband and wife during the first **ten years** followed by a decreasing rate for the husband and very little change for the wife after **10- to 15 years**.

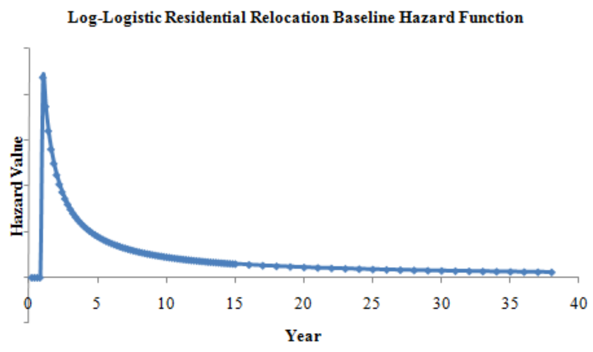
The **Weibull** model gives a steadily increasing rate in both the husband and wife hazard

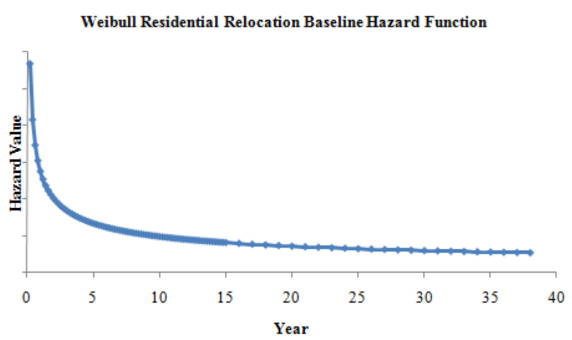
Therefore, both log-logistic and Weibull hazards give monotonically increasing patterns for the meaningful job relocation durations which is on average between three and four year in the case of the utilized data

On average 3.2 years

Model and Results

- Baseline Hazard Analysis
- Weibull and log-logistic baseline hazard function for residential relocation decisions





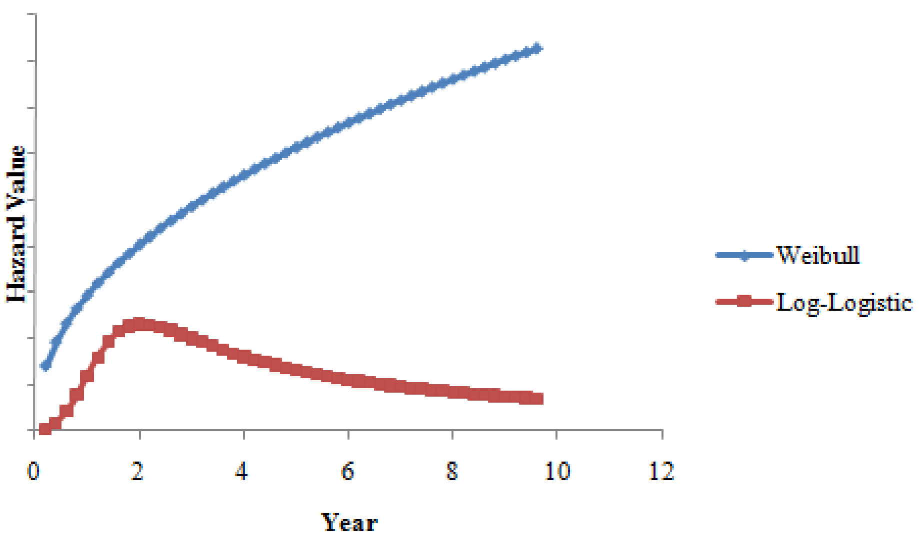
The BIC comparison between the log-logistic and Weibull baseline hazard functions prefers the log-logistic function for residential relocation decisions

But the most prominent differences are in the first year .

However, for relocation durations greater that 1 year, 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.

Model and Results

- Baseline Hazard Analysis
- Weibull and log-logistic baseline hazard function for residential relocation decisions



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 means people prefer not to make a transaction before two years and their willingness to make a transaction declines after the two year point.

Model and Results

- 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**	JRW-RRL-VTL (Best model)
7	757	7	39	-2980	-2861.50	3013.98	
8	757	8	39	-2937	-2817.43	**2973.22**	JRL-RRL-VTL (Second best model)

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*

Introduction

- Study Framework

Choice Set Formation
- A manageable set of alternatives is selected from the universal choice set

Selection Probability
- Probability of being selected in the choice is calculated which is used for sampling correction purpose.

Actual Choice Selection
- The most desired alternative in the choice set of alternatives is selected

Household members form their choice sets by screening available alternatives and filtering them based on their priorities, and preferences.

Introduction

- Study Framework

Choice Set Formation
- A manageable set of alternatives is selected from the universal choice set

Selection Probability
- Probability of being selected in the choice is calculated which is used for sampling correction purpose.

Actual Choice Selection
- The most desired alternative in the choice set of alternatives is selected

Using the selection probabilities the sampling bias is adjusted. Then by using a discrete choice model the final residential location is selected

Choice Set Formation

- Evaluation of the choice set formation models

			Predictive Ability	Set Size
Random Draws	Truly Included Final Decision (1)	Average Choice Set Size (2)	(1)/693 (%)	(2)/741 (%)
25	94	23	13.56%	3.10%
50	167	43	24.10%	5.80%
100	241	77	34.78%	10.39%
200	367	128	52.96%	17.27%
300	424	165	61.18%	22.27%
400	446	195	64.36%	26.32%
500	506	219	73.02%	29.55%
600	518	239	74.75%	32.25%
700	524	255	75.61%	34.41%

There are two important factors in evaluating a choice set generator algorithm: **the predictive ability of the algorithm** and **size of the generated choice sets**. Unfortunately, these two factors are negatively correlated.

Sample Selection Probability

- Probability Calculation

Out of the **824** Transportation Analysis Zones (TAZ) in the **Seattle Metropolitan Area**, ***741*** of them are included in the *universal choice set* available to the households from which they select their residential locations.

$$f_i(wd) = \left[\gamma \ wd^{\gamma - 1} \exp(-\theta_x X_i)\right] \times \left[e^{-wd^{\gamma} \exp(-\theta_x X_i)}\right]$$

It is assumed that depending on the individual household's attributes, decision makers have some threshold for the maximum commute distance beyond which housing alternatives will not be attractive to the household.

In such cases the household will reject any alternative with the distance surpassing the threshold defined for the household.

Probability of being selected in the choice set

Desired work distance

The work distance with the highest probability

Actual work distance

The average distance to the household employed members' work locations

Using the *desired work distance* and *actual work distance* the probability of being selected is calculated for each alternative

Actual Choice Selection

- Methodology

A discrete choice model is employed for residential location selection in which a sampling selection correction factor is included.

This sampling correction factor works like the LOGSUM variable of nested logit models and it accounts for the impact of choice set formation method into the discrete choice model

$$P_{ij} = \frac{e^{\mu V_{ij} - \ln C_{ij}}}{\sum_{l=1}^{L} e^{\mu V_{il} - \ln C_{il}}}$$

Where

$$C_{ij} = \frac{q_{ij}}{\sum_{k=1}^{K} q_{ik}}$$

&

Where μ is a scale parameter and V_{ij} is the deterministic utility, K is total number of alternatives (741) and L is the total number of alternatives in the choice subset. The C_{ij} alternative specific term corrects for sampling bias.

Roughly speaking, q_{ij} *represents exponential of subtraction between* the most *desired work distance* and the alternative residential location distance to the household employed members' work locations (*actual work distance*).

Actual Choice Selection

- Explanatory Variables

Land use and built-environment variables

Parameter	Name	Average
Log of total number of jobs*	Jobs	4.20
Log of total number of real estate, rental and leasing jobs**	Real	0.38
Log of total number of finance and insurance jobs**	Fina	0.43
Log of number of residential housing units	Unit	2.52
Log of Industrial square feet**	Indsqf	4.94
Log of manufacturing jobs-Neighbors**	Manu_N	3.04
Log of utility jobs-Neighbors**	Util_N	0.31
Log of total number of finance and insurance jobs-Neighbor**	Fina_N	2.65
Log of government square feet-Neighbors**	Govsqft_N	10.49
Log of number of children (<16)/Area***	Child	6.14
Log of number of middle age (<44 and >35)/Area***	Midage	6.20
Log of number of seniors (<75 and >64)/Area***	Senior	5.15

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

The first three variables in the table represent the **employment densities** in the area

The next two variables relate to the **residential and industrial land use** in the zones.

"Log" values are used instead of the actual value to address **the arbitrary boundary issues** that may happen in spatial locations search models

Actual Choice Selection

- Explanatory Variables

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Log of number of middle age (<44 and >35)/Area***	Midage	6.20
Log of number of seniors (<75 and >64)/Area***	Senior	5.15

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

The next four explanatory variables are included in the model to account for spatial dependency between contiguous zones.

These four variables represent the land use conditions in the zones surrounding the zone under consideration.

"Log" values are used instead of the actual value to address **the arbitrary boundary issues** that may happen in spatial locations search models

Actual Choice Selection

- Explanatory Variables

Land use and built-environment Variables

Parameter	Name	Average
Log of total number of jobs*	Jobs	4.20
Log of total number of real estate, rental and leasing jobs**	Real	0.38
Log of total number of finance and insurance jobs**	Fina	0.43
Log of number of residential housing units	Unit	2.52
Log of Industrial square feet**	Indsqf	4.94
Log of manufacturing jobs-Neighbors**	Manu_N	3.04
Log of utility jobs-Neighbors**	Util_N	0.31
Log of total number of finance and insurance jobs-Neighbor**	Fina_N	2.65
Log of government square feet-Neighbors**	Govsqft_N	10.49
Log of number of children (<16)/Area***	Child	6.14
Log of number of middle age (<44 and >35)/Area***	Midage	6.20
Log of number of seniors (<75 and >64)/Area***	Senior	5.15

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

Population density was also included in the model, as was density of children and seniors in a TAZ, which can imply whether a TAZ is family oriented or not

"Log" values are used instead of the actual value to address **the arbitrary boundary issues** that may happen in spatial locations search models

Actual Choice Selection

- Explanatory Variables

Monetary-Related Variables

Parameter	Name	Average
Absolute difference between average zonal income and HHld income (X100,000) ***	DiffInc	0.23
Poor X (Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives)***	PoorLandVal	1.44
Middle X Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives***	MiddleLandVal	7.68
Rich X Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives***	RichLandVal	2.09
Transit percentage usage X binary variable for decrease in gas price***	TransitDec	0.07

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

Households look for zones which are more similar to their socio-demographic attributes

Actual Choice Selection

- Explanatory Variables

Monetary-Related Variables

Parameter	Name	Average
Absolute difference between average zonal income and HHld income (X100,000) ***	DiffInc	0.23
Poor X (Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives)***	PoorLandVal	1.44
Middle X Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives***	MiddleLandVal	7.68
Rich X Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives***	RichLandVal	2.09
Transit percentage usage X binary variable for decrease in gas price***	TransitDec	0.07

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

The land value for each zone is not used directly in the model, **however,** it is transformed into the log of the absolute value of the difference in land value for each TAZ from the current residential location

Households with less than 25,000 annual income are called poor, household with annual income greater than 75,000 are called rich and others are called middle.

Actual Choice Selection

- Explanatory Variables

Monetary-Related Variables

Parameter	Name	Average
Absolute difference between average zonal income and HHld income (X100,000) ***	DiffInc	0.23
Poor X (Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives)***	PoorLandVal	1.44
Middle X Log of absolute difference between average zonal land value and the average land value of the zone in which HHld lives***	MiddleLandVal	7.68
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Transit percentage usage X binary variable for decrease in gas price***	TransitDec	0.07

** 450 meters by 450 meters gridcells*
*** 750 meters by 750 meters gridcells*
**** TAZ*

The percentage of transit users in a zone is interacted with a variable which indicates a decrease in the gas price (in real terms) between waves, on the thought that transit oriented areas may be less attractive in an environment of declining fuel prices

Actual Choice Selection

- Results and Findings
- Interpretation of some of the variables

Parameters	Estimation	t-value
PoorLandVal	-0.268	-7.25
Middle LandVal	-0.2923	-19.25
RichLandVal	-0.2968	-10.58
Correction Factor	0.3259	11.44
DiffInc	-0.8824	-2.2
Child	0.2621	2.61
Midage	-0.2246	-1.84
Senior	-0.1574	-2.72
TransitDec	-2.5705	-2.45
Log_Likelihood at Convergence		-2370
Likelihood Ratio		592.95

It can be interpreted from the **negative** sign of LandVal parameters that zones with greater difference from the land value of the current residential zone become **less attractive** to the household since they become either less affordable or too affordable, i.e. **not having the desired amenities, quality, etc. the household is accustomed to**.

Actual Choice Selection

- Results and Findings
- Interpretation of some of the variables

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PoorLandVal	-0.268	-7.25
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Log_Likelihood at Convergence		-2370
Likelihood Ratio		592.95

Analyzing different sample sizes showed no more than 42% difference on average between the presented results in table.

But if a random sample is drawn for each household the parameter estimations are at least 300% of what is presented in table.

Therefore, it can be concluded that the utilized correction factor can give consistent parameter estimates.

Actual Choice Selection

- Results and Findings
- Interpretation of some of the variables

Parameters	Estimation	t-value
PoorLandVal	-0.268	-7.25
Middle LandVal	-0.2923	-19.25
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Correction Factor	0.3259	11.44
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TransitDec	-2.5705	-2.45
Log_Likelihood at Convergence		-2370
Likelihood Ratio		592.95

The findings of this study also confirm the intuitive result that zones with greater differences in income relative to the households' income are less attractive.

Actual Choice Selection

- Results and Findings
- Interpretation of some of the variables

Parameters	Estimation	t-value
PoorLandVal	-0.268	-7.25
Middle LandVal	-0.2923	-19.25
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TransitDec	-2.5705	-2.45
Log_Likelihood at Convergence		-2370
Likelihood Ratio		592.95

As fuel costs become ***less*** of an issue to families, they appear to ***stop*** focusing as much on transit-oriented zones.

Summary and Conclusion

- Hazard-Based Duration Models

Contribut

1- Several specifi rd-
based models l
and analyzed.

2- A competing ha
three vehicle tr
was introduced

For example,

there is no guarantee that including *unobserved heterogeneity* improves the modeling results,

or there is *non-monotonic* baseline hazards do not necessarily outperform the *monotonicc* formulations.

Findings

If accuracy of the models is a concern, it is recommended that for each case study, different specifications of the hazard-based are tested because there is not *a general and universal rule* of the superiority of one specification over others.

Summary and Conclusion

- Hazard-Based Duration Models

Contributions

Findings

1- Several specifications of hazard-based models were discussed and analyzed.

It was found that the competing hazard model considerably outperform the non-competing model.

2- A competing hazard model for three vehicle transaction types was introduced. →

Through a simulation analysis, it was shown that the presented formulation appropriately captures the competing behavior between the transaction types.

Summary and Conclusion

- Residential Location Search

Contributions

1- The interdependencies among the major household decisions was modeled. →

2- A behavioral housing search model was introduced

Findings

It was shown 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.

Additionally, it was found that job relocation does not accelerate a household vehicle transaction decision. Furthermore, change in household residential location has a positive effect on the transaction decision.

Summary and Conclusion

- Residential Location Search

Contributions

1- The interdependencies among the major household decision was modeled.

2- A behavioral two-stage housing search model was introduced →

Findings

An interesting advantage of the choice set formation method was that, ***most of the time***; it includes the final decision of the decision maker in the choice set.

Sampling bias resulted from selecting a subset of alternatives in the discrete choice model was eliminated by including a sampling correction factor. ***It was found that the sampling correction factor efficiently results in consistent parameter estimations.***

Future Directions

- Some of the major improvements to the presented models

- Further analysis on non-parametric hazard models
  This dissertation only studied parametric hazard models

- Improving the competing hazard model with considering other types of copula functions
  This dissertation only considered Gumbel copula

- Studying the impact of other major household decisions such as school location search
  Other than residential relocation, job relocation and vehicle transaction timing decisions

- Including the error correlation among the alternatives in the housing search model

Thank you

Thank you