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16. Abstract

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Microsimulation of Household and Firm Behaviors:

Anticipation of Greenhouse Gas Emissions for Austin, Texas

By

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Research Report SWUTC/09/167272-1

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May 2009

ABSTRACT

Anthropogenic greenhouse gas (GHG) emissions can be attributed to household and firm travel and building decisions. This study demonstrates the development and application of a microsimulation model for household and firm evolution and location choices overtime, along with evolution of the light duty vehicle fleet, residential building stock and travel decisions of persons and businesses in Austin, Texas over a 25-year period (from 2005 to 2030). Year 2005 zonal-level population and address-level employment data for the Austin, Texas region, coupled with various other aggregate data sets, are used to simulate the evolution of individual households and firms over time and space. Simulation results suggest a nearly 130% increase in vehicle-miles traveled (VMT), as population increases. and nearly the same increase in GHG emissions under the business-as-usual scenario. Total GHG emissions from household energy consumption are predicted to increase nearly 86% over the 25-year forecast period in the base scenario, and around 70% in other scenarios. In contrast, average energy demand per firm is predicted to increase by 57% over the 25-year forecast period, mainly due to a transition to larger firm sizes.

EXECUTIVE SUMMARY

Global climate change is an issue that has received much attention in the past few years. Energy demands associated with travel, space conditioning and powering household devices are leading contributors of greenhouse gas (GHG) emissions. An understanding of household and firm behavior over time is key to anticipating future energy consumption patterns and related greenhouse gas emissions. Vehicle purchase and home-type decisions are central to such calculations. This study develops a basic framework for modeling household and firm attributes over time along with land development and location choices, vehicle holding, vehicle use and energy consumption models. Data from the Residential Energy Consumption Survey (RECS) and Commercial Building Energy Survey (CBECS) permit estimation of near- and long-term household and firm energy demands and GHG emissions.

Household and firm simulation models are run at one-year time steps, in order to forecast Austin's future under five scenarios: a Business as Usual or BAU scenario, UGB (restricting location alternatives of households and firms to more developed zones, within an urban growth boundary), PRICING (introducing a gas tax and fixed toll on all roads), EXPCAP (expansion of highway capacity) and SH130 (introducing a new highway, to the east of the highly congested I-35 corridor). Households and population are forecasted to grow by 109 percent and 70 percent, respectively, over the 25-year forecast period, while the total number of jobs is estimated to rise 110 percent. By the year 2030, all five scenarios are predicted to exhibit greater spatial concentration of firms and households than presently exists in the Austin region. Firms tend to locate in central zones across all five scenarios, with no evidence of significant location pattern differences. This may be due to the cross-sectional nature of the data sets used to calibrate the location choice models, which presently favor a job-rich central city. Explicit expressions of constraints (on job densities, for example) by zone may prove helpful in future implementations of this work.

Three-county Austin-area household and commercial vehicle travel survey data provided parameters for trip generation and distribution models. In order to appreciate changes in emissions due to changing vehicle ownership patterns, a multi-class assignment procedure was used for traffic assignment. Simulation results suggest a nearly 130% increase in vehicle-miles traveled (VMT) and nearly the same increase in GHG emissions under the business-as-usual scenario. Regional VMT predictions in the UGB and PRICING scenarios are lower than those in the base scenario. Average household electricity consumption predicted to fall by 11% over time in the base scenario, and nearly 20% in other scenarios, driven by a shift to multi-family housing units..

Lack of control totals on population and employment forecasts can lead to certain issues. For example, jobs cannot outnumber workers to any great extent, and vehicles should not outnumber persons. The flexible model specified allows such behaviors over the long-term, suggesting that parameter adjustments and checks and balances throughout model application can become critical in avoiding unreasonable estimates. Of course, caps and balance-restrictions on added households and firms can avoid such predictions.

While microsimulation of urban systems is data and computing intensive, it provides a rich and adaptable tool for estimating energy and travel demands while evaluating various policies. It allows transportation planners to explore potential responses of individuals and businesses to changes in the urban environment and predict the long-term implications of policy decisions. This study seeks to provide robust forecasts of future greenhouse gas emissions via integrated models of transport and land use, opening doors for improved policy analysis and recommendations.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

DISCLAIMER

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CHAPTER 1: INTRODUCTION

Energy security and climate change are top issues in today's world, requiring immediate attention. The majority of anthropogenic greenhouse gas (GHG) emissions come from transport of persons and goods, plus building energy demands. The U.S. Energy Information Administration (EIA 2006) estimates that the nation's transportation, residential and commercial sectors contribute at 28%, 17% and 18% of total U.S. emissions, respectively. U.S. GHG emissions rose 13% between 1990 and 2003, while those from the transportation sector rose 24% (Brown et al. 2005). The latter can be largely attributed to increasing vehicle ownership levels and trip distances, as well as greater trade flows both domestically and internationally (Polzin 2006).

In addition to personal transportation, households use electricity, natural gas and other sources of energy for space conditioning and powering household devices. A look at American Housing Survey data (AHS 2005) reveals that single-family home sizes have risen by more than 50% over the past few decades. Accompanied by household size reductions (from 3.11 person per household in 1970 to 2.59 in 2000 [Polzin 2006]), this has led to higher GHG emissions from the residential sector. Hence, a proper understanding of household demographic dynamics, travel behavior and land use patterns is a critical component in devising urban transportation and land use policies. Better management of land use and transportation patterns to reduce VMT and GHG emissions could yield significant co-benefits of reduced pollution, congestion, protected green space and improvements in human health (Bomberg and Kockelman, 2007).

Overall the transportation sector is responsible for 28% of all US GHG emissions. Practitioners around the world are debating effective ways to control the rise in GHG emissions from personal transport for a sustainable future. Rising gasoline prices, emerging engine technologies, and changes in fuel-economy policy are anticipated to result in a variety of behavioral changes. These include adjustments in driving habits, such as greater use of trip chaining and public transport in the short term. In the long term, such changes are likely to impact a wider sphere of decisions, including household vehicle holdings (number, make and model), vehicle purchase

and retirement timing decisions and household and employment location choices. Policymakers and travel demand modelers are wondering what the long-term and the short term effects are and what these changes are.

The model specified here is used to anticipate the evolution of households and firms in Austin, Texas over a 25-year period (from 2005 to 2030). A microsimulation approach is used to track 10% of households (which are then scaled up to 100%) and 100% of firms over time and space. The simulation ties evolutionary models of households and firms with models of travel behavior to provide robust forecasts of land use, transport, vehicle ownership, energy use, and GHG emissions patterns. The models of life-cycle transitions for households and firms, location choice have been estimated using a variety of available data sets and lack of quality data is a serious issue for modeling. However, this study's primary objective is to develop and demonstrate the application of an integrated modeling framework for land use, and travel demand and carbon emission forecasts in a microsimulation environment and simply the ability to code and run such models using standard software and hardware is a valuable exercise.

CHAPTER 2: LITERATURE REVIEW

There is a growing awareness that the way of life practiced in the most affluent countries of the world is driven by increasing energy needs and is not sustainable (Salomon et al. 2002). The causes of growing energy consumption and pollution by transport have a distinct spatial and urban dimension (Moeckel et al. 2002). Increasing income levels and continuing low transport costs lead urban workers to choose housing locations in suburban locations in order to enjoy larger homes and lower land prices. This results in higher demand for travel and energy. Predicting future travel demand and energy consumption patterns is the first step in planning development and controlling future emissions. Policymakers, planners, engineers, scientists, and practitioners seek effective ways to anticipate and control the increasing trend in GHG emissions for a sustainable future. Understanding life-cycle transitions in the demographic profile of households and firms and changes in trip making habits are keys for accurate forecasting. Technological advances today provide the computational capacity to trace each agent separately, and predict households and firms future spatial and temporal characteristics using "microsimulation". The next section outlines the key advantages of this method and some of the earlier work done.

Microsimulation was first used in social science applications in the 1960s (see, e.g., Orcutt 1957), yet very few applications in spatial context exist, covering a wide range of phenomena such as urban development, transport behavior, demographic and household dynamics and housing choice (Moeckel et al. 2002). These models seek to reproduce human behavior at the individual level. Single events of distinct agents (e.g., households and firms) are the basic building block of microsimulation. Wegener et al. (1986) identified three kinds of processes in microsimulation:

- *Choices* represent a selection among alternatives (e.g., a household's vehicle purchases).
- *Transitions* represent a change from one state to another state (e.g., birth of child, ageing, death and marriage).

– *Policies* are taken by public authorities to alter the processes of traffic generation and urban development (e.g., urban growth boundaries and fuel taxes).

Microsimulation offers a convenient platform for anticipating these transitions at a disaggregate level. Many processes cannot be reliably modeled at the aggregate level, and advances in computation are allowing a disaggregate approach. Many researchers have focused on behavior of the agents involved, especially households and, to a lesser extent, firms, along with their land use and transport interactions (e.g., Miller et al. 1998, Timmermans 2003, Waddell et al. 2003, and Salvini et al. 2005). However, the literature lacks studies of household and firm behavior in an integrated and dynamic framework. More and more aspects of travel behavior also are being applied in a microsimulation framework (Miller et al., 2004). Examples include residential location choice (Otter et al. 2001), household and firm demographics (Khan et al. 2002, and Maoh et al. 2005) and auto ownership (Berkovec, 1985).

Microsimulation's primary advantage stems from our desire to analyze the impacts of policies at the individual level. Microsimulation models can incorporate individual and micro processes based on behavior theory. The heterogeneity of observed information can be fully represented in the model and maintained during simulation. The output can then be aggregated to levels suitable for addressing research and more applied questions. However, such advantages should be viewed in the context of added complexity and increased data and computational requirements (Goulias and Kitamura 1992). More and more aspects of travel behavior, involving both temporal and spatial dimensions, are being applied in a microsimulation framework (Miller et al. 2004). The absence of special panel surveys required to model life-cycle transitions has resulted in very few models tracking household evolution in great detail. Of course, the ability to correctly forecast the future spatial distribution of population is core to appreciating the interaction of land use and transport systems. Most location choice models (of existing and relocating households) rely on multinomial logit models (see, e.g., Bhat and Guo 2004 and Bina et al. 2006), and a greater variety of vehicle purchase models have been estimated (see, e.g., Zhao and Kockelman 2000, Mohammadian and Miller 2003 and Mannering et al. 2002).

Several land use development models are in practice today. The most common include Putman's (1983) gravity-based Integrated Transport Land Use Planning Model (ITLUP), Miller et al.'s (2001) Integrated Land Use, Transport and Environment (ILUTE) model, Timmermans' (2000) A Learning-Based Transportation Oriented Simulations System (ALBATROSS) model, Waddell's (2005) UrbanSim and Hunt's (2007) Production Exchange Consumption Allocation System (PECAS) model . Conventional, static equilibrium models are unable to capture the dynamics of urban system evolution, which are thought to be better explained using a dynamic disequilibrium approach (Miller et al., 2004). An agent-based modeling approach provides an effective way of modeling complex dynamic systems at a disaggregate level. Absence of quality panel data sets for households and firms is the main barrier for such work. A variety of existing models are discussed in more detail below.

2.1.1 UrbanSim

UrbanSim emphasizes relatively small grid cells while tracking the grid cell locations of individual households and jobs. In UrbanSim, a 150m x 150m grid cell is 5.56 acres, while the average Austin TAZ is 1691 acres – or 300 times larger. While many models either ignore constraints on land use and built-space availability, UrbanSim emphasizes these key facets of urban form (Waddell et al. 2003). It also uses a dynamic disequilibrium approach to forecast land use patterns, in contrast to many past models, which tended to rely on cross-sectional equilibrium approaches (Waddell et al. 2003). Hence, travel utilities typically remain constant between several successive runs of the travel demand model. Aggregate forecasts of economic activity and demographics also are exogenous to UrbanSim. It uses random utility maximization (RUM) theory to estimate employment and household relocate ion models wherein individual jobs and households are used as units of analysis.

2.1.2 ILUTE

ILUTE seeks to forecast a region's evolution over time by simulating individuals, households and firms. It employs a range of modeling methods including logit models, rule-based (computational process) models, and their combination (Miller et al., 2004). ILUTE identifies

location choices of households and firms, which evolve within the model, as critical components of an integrated urban model. If forecasted spatial pattern is incorrect, subsequent travel demand forecasts would be misleading too. ILUTE includes microsimulation of demand– supply interactions in the residential and commercial real estate markets. ILUTE uses a discrete time approach to evolve urban systems which are constantly adapting to changing environment (Miller and Salvini, 2001). Modeling decision processes often involves large number of alternatives as choice set. Random sampling and/or rule-based search processes are used to reduce the choice set before implementing random-utility models to predict choice behavior.

2.1.3 PECAS

PECAS stands for "Production Exchange Consumption Allocation System". It focuses on the exchange of goods, services, labor and space between the actors in the economy who produce such things and those who consume such things. PECAS has two modules, a spatial economic model and a land development model. They are typically run in sequence year-by-year to develop a path-dependent forecast of how future conditions are influenced by current and future policies (Hunt and Abraham 2007).

2.2 Greenhouse Gas Emissions Estimation

Greenhouse gas emissions are increasingly becoming part of the U.S. and political agenda. The U.S. Energy Information Administration (EIA 2006) estimates that the nation's transportation and residential sectors contribute at 28% and 17% of total U.S. emissions, respectively. U.S. GHG emissions rose 13% between 1990 and 2003, while those from the transportation sector rose 24% (Brown et al. 2005), which can be largely attributed to increasing vehicle ownership levels and trip distances, as well as greater trade (Polzin 2006). Personal transport is responsible for 12% of the world's anthropogenic CO2 emissions and 19% of U.S. emissions (Wadud et al. 2007, EPA 2006). Many countries around the world, along with the State of California, believe that a reduction of 80% in emissions by 2050 is necessary for a sustainable climate future. Carbon taxation and trading, with caps or taxes on upstream sources, are methods suggested for emissions reduction.

Major sources of emissions from households are gasoline combustion by vehicles and electricity/natural gas usage for space conditioning. Passenger car contribute about 35% of the transportation sector's total GHG emissions, while light duty trucks account for 27% and heavy duty trucks another 19% (EIA 2006). Over the 2007-2050 period, EPA (2007) estimates that one-half of the increase in emissions from the transportation sector will come from passenger vehicles, 20 percent will come from heavy-duty trucks, 10 percent from aviation changes, and nearly 20 percent from other, non-road modes. Vehicle fuel is the main source of GHG emissions, and can be closely estimate via gasoline sales. However, to estimate future fuel demands (and thus GHG emissions), one must anticipate vehicle holdings and usage patterns. Vehicle ownership models are described in more detail in the next section.

In addition to transportation, households use electricity, natural gas and other sources of energy regularly for space conditioning and powering household devices. Emissions from buildings continue to grow at over 2% every year (EIA 2005). Energy demands per capita have fallen over 25% in the last 25 years in the U.S., but population increases have more than offset any potential emissions savings. A look at American Housing Survey data (AHS 2005) reveals that single-family home sizes have risen by over 50% over the past few decades. Accompanied by household size reductions (from 3.11 in 1970 to 2.59 in 2000 [Polzin 2006]), this has been a key reason for higher GHG emissions from the residential sector. Space heating and cooling together account for about 26% of residential electricity use (EIA 2001). Other heavy uses are refrigeration, water heating, and lighting. Home size influenced heating and cooling demands are the key determinants of future household energy demands.

Recently, household energy demand has been analyzed to anticipate the effect of alternate pricing schemes and consumers' response to energy taxes. Brannlund et al. (2004) and Berkhouta et al. (2004) estimated energy demand using Gorman's (1959) two-stage budgeting model. In both studies, households are assumed to allocate their total budget between energy and non-energy consumption categories in the first stage. In the second stage, they decide how much

of their energy expenditures to allocate across different energy carriers (electricity and gas are the two most considered). Reiss and White (2005) developed a three-tier methodology for assessing different pricing schemes for electricity using Residential Energy Consumption Survey (RECS, 1999) data. Their model focuses on the heterogeneity in households' demand elasticities, their relation to appliance holdings and other household characteristics, and how these elasticities inform household consumption responses to complex (nonlinear) price schedule changes. As a first step, they developed a regression model of energy demand as a function of energy prices, income and appliance ownership. In this study, we use basic linear regression models of household and firm energy consumption.

2.3 Vehicle Ownership Models

To estimate greenhouse gas emissions from transport, it is necessary to understand how vehicle ownership is evolving along with changing demographic profiles of households. Various dimensions of household vehicle ownership – including the number and type (make/model) of vehicles owned, miles traveled using each vehicle, and age and fuel type of each vehicle have been modeled by others, mainly using discrete choice specifications. The review here is by no means comprehensive, but aims to highlight some of the key models in this area. One of the first disaggregate studies is by Lave and Train (1979), who used a multinomial logit model for vehicle type choice. Their model controlled for several household attributes, vehicle characteristics, gasoline prices, taxes on larger vehicles. They found that higher income households prefer more expensive cars and younger individuals prefer higher performance cars. Berkovec (1985) developed a simulation model to combine a disaggregate model of vehicle choice with an econometric model for forecasts of automobile sales, fleet attributes and retirement. Manski and Sherman (1976) developed separate multinomial logit models for the number of vehicles owned and vehicle type for households owing one or two vehicles. Choo and Mokatarian (2004) modeled the "most used" vehicle in a household's fleet. They found that travel attitudes, personality, lifestyle, and mobility factors are useful predictors of vehicle types owned and of the most used vehicle within a household. Others have looked at two or more dimensions using joint models and nested logit models. For example, Mohammadian and Miller

(2003a) studied the purchase and retirement of vehicles (by type) via a nested logit structure. Mannering and Winston (1985) employed a dynamic utilization framework using panel data from either side of the 1979 oil shock. They modeled number, type and use of vehicles via discrete choice and linear regression techniques. Other studies in this category include joint choice of vehicle ownership levels and vehicle body types (Hensher and Plastrier, 1985) and the number of vehicles owned and their usage (Golob and Wissen, 1989).

One of the major issues in modeling vehicle choice using discrete choice models is the formulation of choice sets. The rising number of makes and models available in the market makes it almost impossible to estimate a model that includes all alternatives of them, since most statistical software limits the number of alternatives that can be included. Two different procedures have been adopted to address this problem. The first is to use a random sampling procedure for the choice set, as suggested by McFadden. In this approach, a computationally feasible number of alternatives (25 to 30, for example) are taken from the entire pool of available makes and models. The second approach is to consider simply general categories of vehicles type as the choice set. This could be the body type (such as sedan, coupe, pickup truck, sports utility vehicle, van, etc. – as done in Train (1979), Kitamura et al., (2000), and Choo and Mokatarian, (2004)), fuel type (Hensher and Greene 2001), acquisition type Mannering et al. (2002) and/or vehicle vintage (Mohammadian and Miller, 2003b). With large or random choice sets, analysts typically cannot include many or any person- or household-specific attributes in the set of explanatory factors (except, e.g., when interacted with another, generic variable – like household income times fuel economy divided by the price of gas). The models developed in this work emphasize vehicle types as alternatives, and thus more easily permit the inclusion of non-generic attributes (like household income and size, interacted with alternative-specific constants).

2.4 Summary

This study seeks to forecast greenhouse gas emissions from transport and housing and future travel demand patterns under different policy scenarios via a microsimulation model. Microsimulation modules include models of demographic development, household formation,

firm lifecycles, housing and vehicle choices. One key advantage of microsimulation lies in the detailed outputs, which can be manipulated (and aggregated) in a number of ways.

In the absence of quality panel data, this study uses several aggregate and disaggregate data sets for these models. Various assumptions about household and firm demographics have been made in the process. The various data sets used in this study and the model's simulation framework are discussed in the following chapters.

CHAPTER 3: DATA DESCRIPTION AND MODEL FORMULATION

This study aims to estimate greenhouse gas emissions for 2030 from a microsimulation framework (Figure 3.1). Microsimulation models seek to replicate the evolution of individual agents like households and firms and thus are generally data intensive. The availability of large-scale panel data is essential for development of these models.

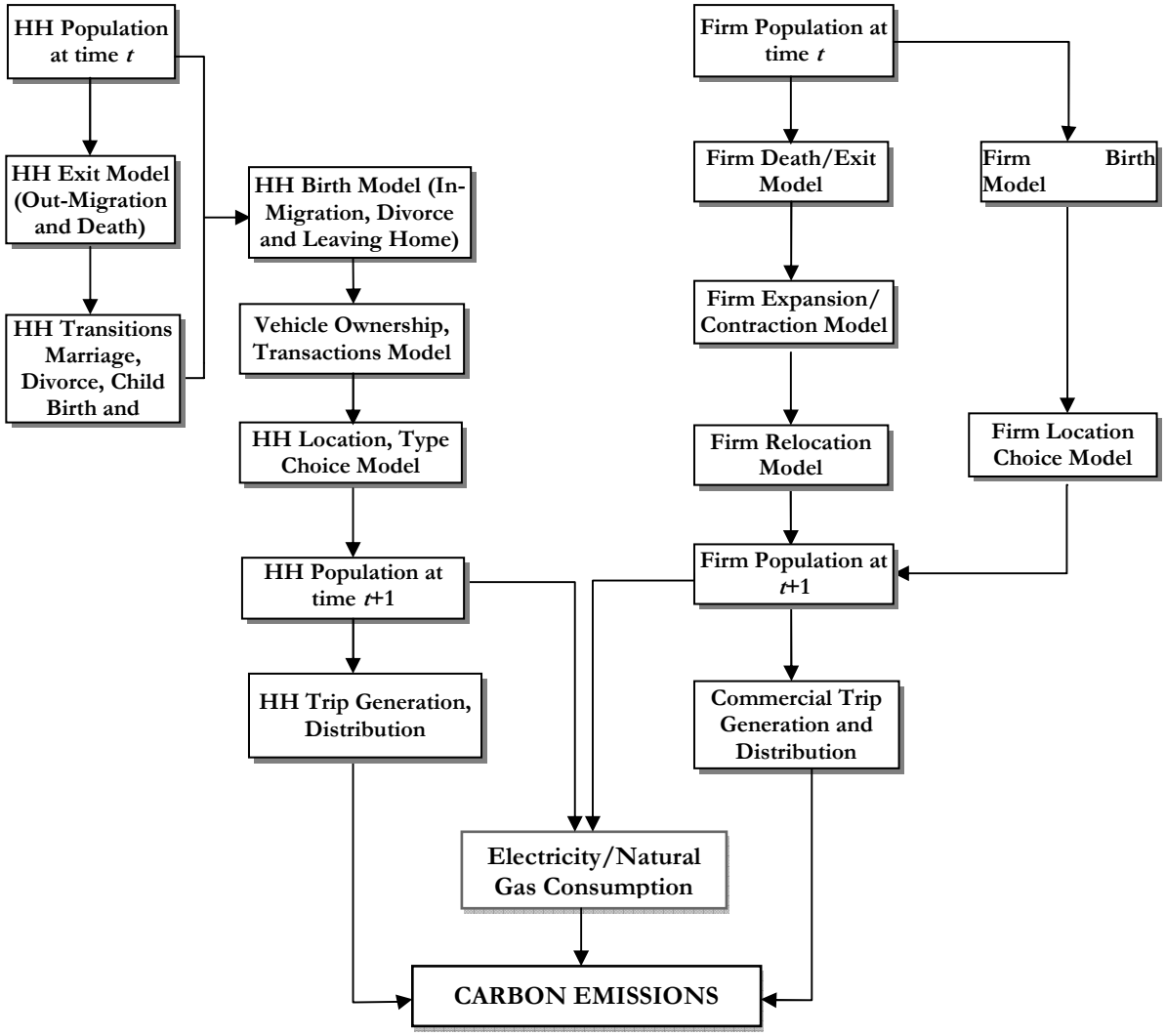


Figure 3.1: Overall Simulation Framework

In the absence of such panel data, cross sectional datasets from Census, travel surveys, GIS archived data on land use have been used in this study, to model discrete events and stages in the urban evolutionary process. This chapter first introduces household, firm, vehicle data sets and the models that have been estimated using them. In the subsequent sections, models for travel demand, energy estimation and land development are presented.

3.1 Household and Firm Data Sets

McWethy (2006) synthesized Austin households data for year 2005 (base year) population using the 5-percent Public Use Microdata Sample (PUMS) of the 2000 Census of population for three Texas counties (Travis, Williamson and Hays). Public Use Microdata Sample Areas (PUMAs) are geographical areas containing at least 100,000 individuals. PUMS data contains approximately 5,000 individuals from each PUMA. The block-group level data had to be aggregated into Traffic Analysis Zones (TAZ's) in order to be consistent with other data sets used in this study. In the synthetic population, seven person types were defined for analysis purposes:

- Pre-school children (ages 0 through 5),
- Pre-driving school-age children (ages 6 through 16),
- Driving school-age children (ages 17 and 18),
- Non-working adults,
- Student adults (full-time students only),
- Part-time working adults (1-39 work hours per week), and
- Full-time working adults (40+ hours of work per week).

The model system simulates future households using sub-models for birth (of children and of households), death of individuals (and other forms of household dissolution), migration, and young adults leaving home. More details about the household evolution process can be found in Kumar (2008).

Data on TAZ-level land use shares (aggregate) and demographic data was obtained for the year 1997 from the Capital Area Metropolitan Planning Organization (CAMPO). This data set also provides year 2007 estimates of all demographic attributes. 1997 and 2007 data were used to impute TAZ-level estimates for the year 2005 (base year). These data sets rely on population - equivalent density (PED) measure to classify TAZ's as rural, suburban, urban, and CBD. The definition of PED and classification criteria for TAZ's is as follows: PED = [Zone Pop + (Regional Pop/Regional Emp) x Zone Emp)]/Zone Acres. The zone is classified as a CBD if PED $\geq$ 15, Urban if 8 $\leq$ PED < 15, Suburban if 1 $\leq$ PED < 8 and Rural if PED < 1, where Pop and Emp stand for population and employment in the zone, respectively.

Point location data for all firms in the three-county Austin region was provided by the Texas Workforce Commission and geo-coded by CAMPO. In 2005 Hays, Travis and Williamson counties contained 32,063 firms employing 655,722 full- and part-time workers.

The study region consists of 1,074 TAZ's, and zone-level statistics for the year 2005 were imputed by Kumar (2008) from the CAMPO's 1997 and 2007 data sets. 57% of the firms belong to the service sector and account for 44% of the jobs, while educational establishments account for only 2% of the firms but 11% of the jobs. Fig 3.2 shows the spatial distribution of these firms. Future firms are forecasted using models of firm birth, death, and growth and location choice. A Markovian process was assumed to anticipate firm growth and contraction (across firm-size categories), along with logit and Poisson model specifications for firm location choice. Details about firm evolution models can be found in Kumar and Kockelman (2008).

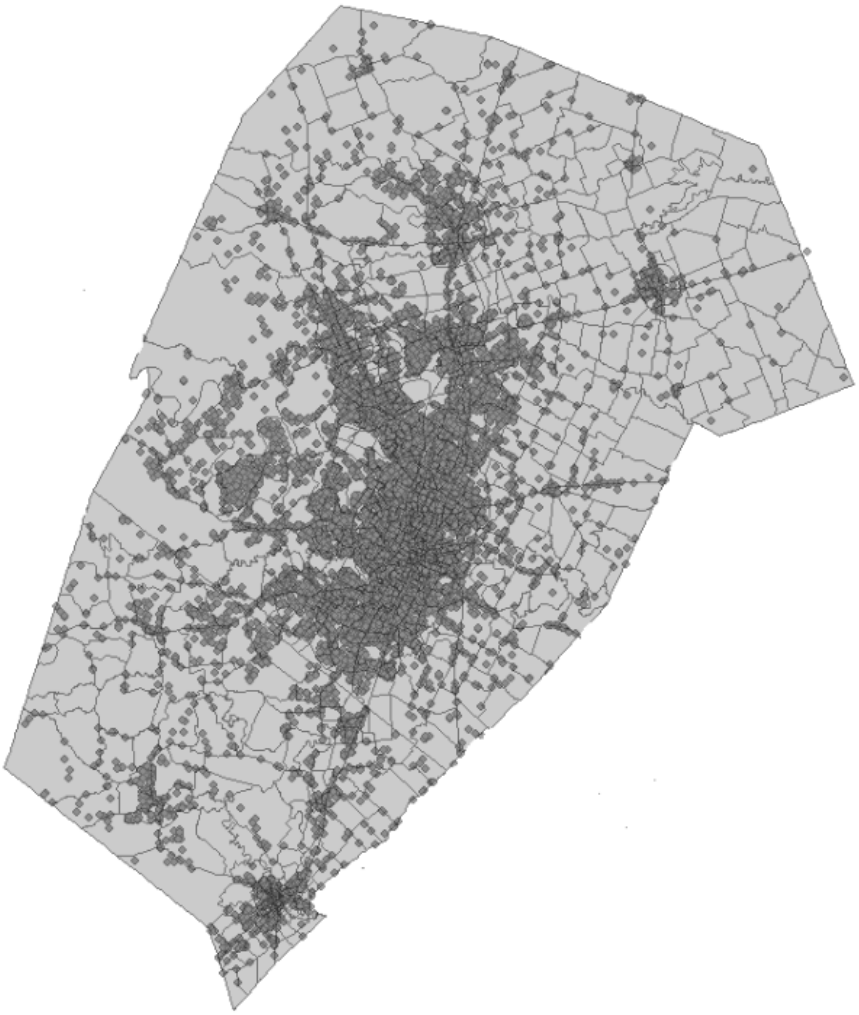


Figure 3.2: Point Location of Firms across the Austin Region

3.2 Vehicle Ownership and Purchase/Loss Models

3.2.1 Data Description

Vehicle type and number owned in a household are modeled using 2006 Austin Travel Survey data. Year 2007 purchase prices and engine size (in liters), were obtained for each make/model from *Ward's Automotive Yearbook* (2007). After excluding zero-vehicle households and records with missing information, the final sample set included 2346 vehicles across 1342 households. Vehicles have been classified into nine broad classes: (1) luxury cars, (2) large cars, (3) midsize cars, (4) subcompact cars (5) compact cars, (6) pickup trucks, (7) sports utility vehicles (SUVs), (8) cross-over utility vehicles (CUVs), and (9) vans (minivans and cargo vans).

To model vehicle buying and selling decisions (transactions) data from the Toronto Area Car Ownership Study (TACOS) was used. TACOS is a retrospective survey conducted by the University of Toronto (Roorda et. al. 2000) and contains information on household vehicle transactions over nine years (from 1990 to 1998). Miller et. al, (2003) used a mixed logit model to analyze vehicle transactions in the TACOS data at the level of "decision making unit[1]". Models of vehicle transactions reported here, however, are at the household level.

Table 3.1 provides a summary of household attributes from the ATS and TACOS data along with Census 2000 estimates for Austin region. The average household income is slightly higher than the Census estimated income ($47,212). Household size, employment and number of children are approximately same as the Census estimates.

Table 3.1: Summary of Household Characteristics

S No	Attribute	ATS	TACOS	Census
1	No. of people in household	2.78	2.74	2.40
2	No. of employees in household	1.18	1.28	1.33
3	Pre-school going children (Ages 0-5)	0.29	0.23	0.20
4	Pre-driving children (Ages 6-16)	0.45	0.43	0.36
5	No. of vehicles in household	1.91	1.28	2.06
6	Household income ($)	$53,667	$52,649	$47,212

The average number of vehicles per household in the ATS dataset is 1.91, which is slightly lower than the national average of 2.06 (NHTS 2001). Figure 3.3 gives the distribution of vehicle ownership levels in the sample. Nearly 50% of the households have two vehicles, and 19% have more than two. Almost 3% of Austin households do not own a vehicle. Figure 3.4 provides vehicle-type frequencies in the 2006 ATS data set. 26% of all ATS vehicles are trucks, which is significantly higher than the national share of 18% (NHTS 2001).

[1] Miller et al. (2003) defined the decision making unit as any set of persons within a household that make vehicle ownership decisions cooperatively.

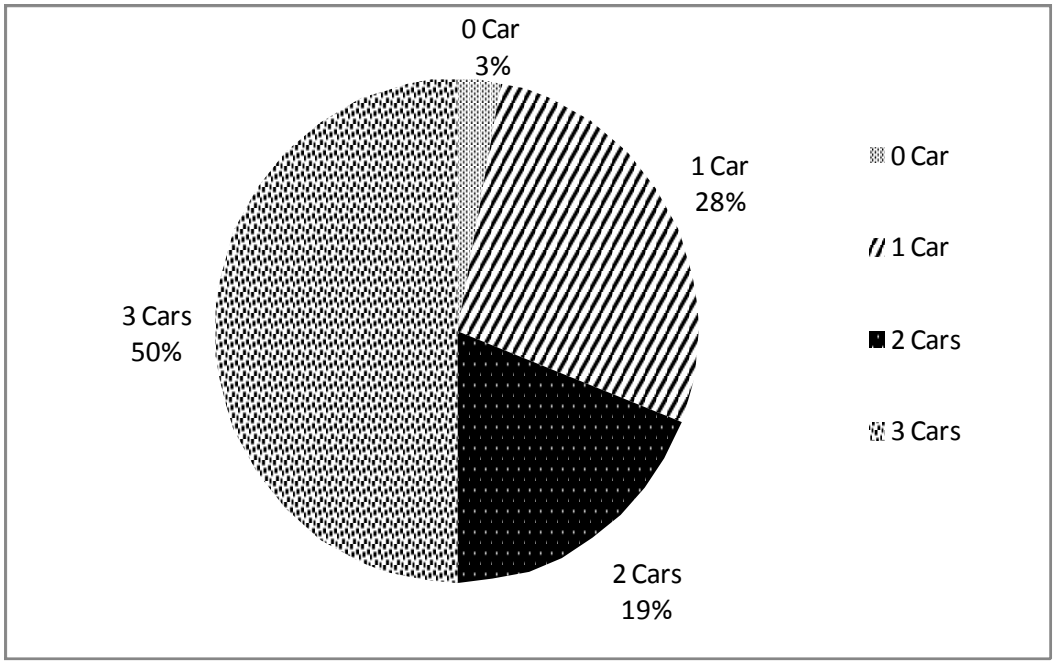


Figure 3.3: Vehicle Ownership Levels in Austin Households (2006)

Passenger cars (luxury, large, midsize, small) constitute about 44% of Austin's household fleet, whereas other light duty trucks (i.e., vans, sports utility vehicle (SUVs), and cross utility vehicle (CUVs) constitute the remainder. Among one-vehicle households, pickups constituted only 17% (Figure 3.4) of such vehicles, similar to the cases of SUVs and vans. Thus, households are more likely to own a light-duty truck as a second vehicle. Among two-vehicle households with at least one pickup, the second vehicle was most likely to be some type of SUV (accounting for 26% of such households) and, next, a midsize car (15% of such households). The share of small cars is nearly 20% in this segment of households (higher than the overall share of 14%).

Table 3.2 presents average characteristics for the different vehicle classes, from *Ward's Automotive Yearbook (2007).* As one may expect, pickups have the lowest fuel economy (combined city/highway fuel economy) and the largest area, and luxury cars are the most expensive. Small cars enjoy a relatively high fuel economy but lower engine displacement and horsepower. SUVs tend to cost quite a bit more than passenger cars (with the exception of luxury cars), exhibit lower fuel economy, and have larger footprints. GHG score is an indicator of

expected lifecycle emissions from the vehicle considering all steps in the use of a fuel, from production and refining to distribution and final use; excluding vehicle manufacture.

Table 3.1: Summary of Vehicle Characteristics

SNo	Class	Fuel economy (mpg)	Price ($)	Area (sq ft)	GHG score	Weight (lbs)	Engdis. (lit/cu in)
1	CUVs	18.08	26,932	92.04	5.63	8440	3.015
2	Large cars	17.57	30,734	105.11	5.51	8415	4.075
3	Luxury cars	18.61	48,004	94.01	5.50	8130	3.655
4	Midsize cars	19.00	25,614	95.65	6.00	7515	3.500
5	Pickups	14.67	26,825	115.13	3.83	10430	4.430
6	Compact cars	20.65	29,576	84.12	6.31	7012	2.240
7	Subcompact cars	26.60	16,726	82.94	7.70	5807	1.930
8	SUVs	15.10	35,221	104.65	4.04	10166	4.710
9	Vans	15.18	27,411	110.55	4.64	9989	4.115

As noted above, the TACOS data set provides vehicle purchase and retirement data over 9 years (from 1990 to 1998), resulting in 4096 household-years worth of information. 79% of these observations were 'do-nothing' decisions (household did not buy or sell a vehicle in that year), 11% of such data points lost[2] *and* gained at least one vehicle in a given year, and 8% simply added a vehicle, while the remaining 2% of data points lost or gave up a vehicle.

3.2.2 Model for Number of Vehicles in a Household

For modeling vehicle ownership level, a negative binomial regression model, a Poisson model and an ordered probit model were investigated. The overdispersion parameter of negative binomial model was found to be statistically insignificant, while the Poisson model had counter intuitive signs for the coefficients, with a low likelihood ratio index. Hence an ordered probit model was used in this study. Table 3.3 gives the results of the vehicle-ownership count model, where the response variable is the number of vehicles held by a household (for estimating

[2] Lost refers to losing a vehicle refers to either crash or theft of vehicle

vehicles owned in base year). Four levels of vehicle ownership were modeled here: 0, 1, 2, 3+. vehicles (per household).

Household size and number of workers have a positive effect on ownership levels, as expected. The number of pre-driving age children was estimated to have a negative effect, relative to an additional adult, which is again intuitive. In addition to household income, median neighborhood income was found to have a positive and statistically significant effect, which suggests some kind of location and status effect. Other land use variables that were found to be statistically significant are zone type (rural vs. non-rural) and distance to the region's CBD, both with positive effect. This may be due to the higher number of transit facilities available in more central and less rural locations.

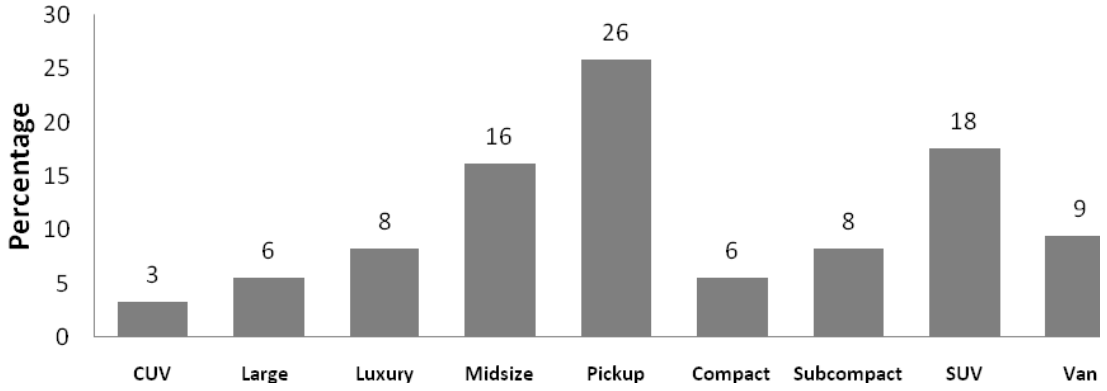


Figure 3.4: Vehicle Class Shares in ATS 2006

Table 3.3: Ordered Probit Model for Number of Vehicles in Household

Variable	Coef.	t-statistic
No. of people in household	0.952	13.2
No. of employees in household	0.278	5.75
Pre-school going children (Ages 0-5)	-1.07	-11.3
Pre-driving children (Ages 6-16)	-0.897	-10.2
Driving age children (Ages 16-18)	-0.523	-3.61
Rural zone	0.152	1.48
Household income (x 10^{-5})	0.727	7.33
Middle household income in zone(x 10^{-6})	0.805	4.38
Distance to CBD (miles)	9.12E-03	2.15
Log Likelihood at convergence	-1130.25	
R-squared	0.2522	

3.2.3 Model for Class of Vehicle

A multinomial logit model was estimated for vehicle types owned. As discussed in Section 2.3, there are more than 600 makes and models of vehicles available in the market. This makes it almost impossible to estimate a model that includes all of them as alternatives, since most statistical software limits the number of alternatives that can be included. The models developed in this work emphasize vehicle types as alternatives, and thus more easily permit the inclusion of non-generic attributes (like household income and size, interacted with alternative-specific constants).

The pickup truck class was used as the base alternative in this model. All alternate specific constants were estimated to be negative and statistically significant – except for those on vans and midsize cars. In other words, vans and midsize cars appear to offer the same utility as pickups – ceteris paribus. Table 3.4 presents the results from multinomial logit model.

Table 3.4: Multinomial Logit Model for Vehicle Class

Variable	Coef.	t-statistic
Alternate Specific Constants		
Cross-utility vehicle	-1.594	-8.22
Large car	-2.371	-5.67
Luxury car	-0.588	-2.96
Midsize car	-7.45E-02	-0.41
Compact car	-1.169	-4.89
Subcompact car	-1.088	-4.89
Sports utility vehicle	0.379	2.08
Van	-0.218	-1.15
Price Variables		
Fuel price / Household income * 10^4	-0.602	-2.46
Price of vehicle / Household income	-0.104	-1.78
Demographic Variables		
Household Size * (Compact, subcompact, midsize cars)	-0.220	-5.72
Household Size * (Large, luxury cars)	-0.173	-4.70
No. of workers in household * Midsize car	0.121	1.99
High Income(>$75000) * Luxury car	0.290	1.70
Age of house head * Large car	2.48E-02	3.88
No. of female members in household * Subcompact car	0.306	3.83
No. of pre-school children * Van	-0.462	-3.07
Land Use Variables		
Rural region indicator * Pickup	0.177	1.58
Suburban region indicator * Large car	0.200	1.39
Household density in zone * (Subcompact, compact cars) * 10^{-3}	8.32E-03	1.71
Household density in zone * SUV *10^{-3}	-0.103	-1.53
Retail firms within 5 miles * SUV *10^{-4}	-0.125	-2.06
Retail firms within 5 miles * Van *10^{-4}	-9.25E-02	-1.53
Apartment indicator * (Subcompact, compact cars)	0.259	1.35
Apartment indicator * Pickup	-0.479	-3.05
Vehicle use		
No. of trips by household * Compact	-2.26E-02	-1.75
No. of trips by household * Subcompact	-4.49E-02	-2.74
Log Likelihood at convergence	-4649.22	
R-squared	0.098	

The ratio of vehicle price to household income has a negative coefficient, as expected (and consistent with previous findings). However, the ratio of fuel cost (in dollars per mile) to household incomes was estimated to be more significant statistically, than the vehicle price. Various household demographics also were found to have statistically significant effects here. Larger households exhibit a preference for vans and utility vehicles, no doubt due to the larger seating and luggage capacities of these vehicles. Female drivers (number of female drivers in the household) apparently have a preference for smaller cars, which may be due to ease of driving and maneuverability, as compared to other vehicle types. The number of workers in a household has statistically significant effect on the utility of mid-size vehicles, relative to other types, which is surprising. One possible reason for this may be because workers commute daily, thus prefer comfortable vehicles (midsize vehicles tend to have larger leg room, head room) for daily commutes. The age of a household's head also was found to have a positive effect on the systematic utility of large cars.

As evident in Table 3.4's values, neighborhood land use patterns also were found to have some effect on vehicle choices, and this study modeled the residential location choices of individual households, over the 25-year period. A few interesting results emerge here: First, a neighborhood's household density reduces the utility of SUV ownership while increasing the utility of small cars. This may be due to tighter parking conditions, narrower streets, shorter driving distances, more environmentally conscious households, and any number of other features. Those living in rural areas are more likely to acquire pickup trucks, whereas those in suburban zones appear to be most attracted to large cars ceteris paribus. High local retail firms' density was estimated to have a negative effect on the utility of SUVs and vans. The last two variables in Table 3.4's land use category are for apartment dwellers, who were found to be more likely to own small cars and less likely to own pickups, as expected (due to the relatively commercial or urban nature of most apartment locations).

3.2.4 Model for Vehicle Purchase/Loss Decisions

As household and vehicle characteristics change over time, the composition of a household's vehicle fleet also changes. To capture these dynamics over a period of years, a multinomial logit model was estimated using the decision of the household with respect to vehicle fleet as the dependent variable. The choices available are buy a vehicle (acquire), sell a vehicle (dispose), sell a vehicle and buy a new vehicle (trade) or "do nothing". Table 3.5 presents model estimates.

When acquired, new vehicles are selected based on an MNL model for ownership patterns, as described earlier. The "do-nothing option" (neither buying nor sell/releasing a vehicle in a given year) is taken as the base or reference alternative in this model. All the other alternate-specific constants are estimated to be negative in sign (indicating that they are preferred less than the do-nothing option). The addition of pre-school children, drivers and workers tends to trigger acquisition decisions, which is intuitive.

Table 3.5: Multinomial Logit Model Estimates for Vehicle Transactions by a Household in a Given Year

Variable	Coef.	t-statistic
Acquire 1 vehicle	-3.46	-10.26
Dispose 1 vehicle	-4.77	-9.12
Trade (Acquire and Dispose 1 vehicle)	-3.58	-11.1
Acquired * No. of preschool children	0.294	1.87
Acquired * No. of retired people	0.367	1.65
Acquired * No. of drivers	0.286	2.1
Acquired * No. of full-time employees	0.322	1.89
Acquired * Max. age of vehicle in household	-0.066	-1.81
Disposed * Max. age of vehicle in household	0.129	3.16
Trade * No. of persons in household	0.437	1.74
Trade * New drivers in household	-0.565	-1.75
Trade * Household income($) *($10^{-5}$)	1.14	2.56
Trade * Max. age of vehicle in household	0.151	6.73
No. of observations	4096	
R-squared	0.53	

3.3 Travel Demand Models

Data from the 1996-97 Austin Travel Survey (ATS) was used to estimate parameters for the various travel demand models, developed by Lemp (2007). The model uses standard approaches: regression models for trip generation; joint multinomial logit models for destination, mode, and time-of-day (TOD) choice; constant vehicle-occupancy assumptions; and static deterministic user equilibrium traffic assignment routines.

Household trips increase with household size, vehicles, and income largely. Separate models for home based and non-home based, work and non-work trips were developed. For mode and TOD choice, joint multinomial logit models were estimated for each of the four trip types- home-based work (HBW), home-based non-work (HBNW), non-home-based work (NHBW), and non-home-based non-work (NHBNW). Here the mode alternatives include drive alone (single occupancy) auto, shared ride (occupancy greater than 1) auto, transit, and walk/bike. The TOD alternatives

include 4 time-of-day periods: AM peak (6 am – 9 am), midday/evening (9 am – 3 pm and 7 pm – 9 pm), PM peak (3 pm – 7 pm), and overnight (9 pm – 6 am). Table 3.6 shows the result of joint mode-destination choice model.

External-internal and external-external trips were exogenous to the simulation model and added to the Origin-Destination matrix for traffic assignment. External-internal trips and external-external trips were assumed to increase by a constant factor (2% every year).

Table 3.6: Multinomial Logit Model for Joint Destination and Mode Choice (Source: Lemp 2007)

Variable	HBW		HBNW		NHBW		NHBNW	
	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic	Coef.	t-statistic
Generalized cost	-0.028	-7.90	-0.047	-20.9	-0.013	-4.66	-0.0193	-7.01
Shared ride (SR) ASC	-1.444	-12.7	1.615	22.1	-1.391	-6.90	0.4548	3.18
Transit (TR) ASC	-1.487	-5.42	0.930	4.79	-3.384	-4.74	-1.0179	-3.08
Walk / Bike (WB) ASC	-1.505	-5.14	0.784	6.08	-3.447	-4.79	-1.461	-4.08
Midday (MID) ASC	-0.724	-12.9	1.026	17.5	2.026	20.0	2.049	17.1
Off Peak (OP) ASC	-1.819	-22.3	-0.488	-6.20	-2.276	-8.38	-1.197	-5.21
PM peak (PM) ASC	-0.207	-4.42	0.741	12.0	1.263	11.7	1.267	9.88
SR / MID ASC	0.137	0.90	-0.890	-11.46	0.235	1.11	-0.373	-2.46
SR / ON ASC	0.065	0.28	-0.720	-6.92	-	-	1.025	3.92
SR / PM ASC	0.591	4.67	-0.326	-4.32	-0.072	-0.31	0.1341	0.84
TR / MD ASC	1.840	5.25	0.481	2.18	-0.391	-0.49	-1.236	-3.03
TR / ON ASC	1.236	2.17	-0.754	-1.40	N/A	N/A	0.5676	0.90
TR / PM ASC	0.495	1.46	-0.105	-0.48	-1.205	-1.20	-1.268	-2.85
WB / MID ASC	0.239	0.67	-0.466	-3.36	1.505	2.08	0.073	0.19
WB / OP ASC	-7.441	-0.33	-0.644	-2.96	N/A	N/A	1.200	2.29
WB / PM ASC	-0.132	-0.39	-0.568	-3.80	1.031	1.37	-0.062	-0.16
Auto surplus (specific to SR)	-1.297	-11.8	-1.472	-21.9	-	-	-	-
Auto surplus (specific to TR)	-2.231	-7.74	-2.286	-12.8	-	-	-	-
Auto surplus (specific to WB)	-1.053	-3.58	-1.467	-13.1	-	-	-	-
Auto surplus (specific to peak [AM or PM] & SR)	-	-	-0.312	-4.78	-	-	-	-
No. of observations	3,126		7,286		1,864		2,762	
Log Likelihood at convergence	-5,488.1		-15,445.8		-2,938.7		-5,311.3	
R-Squared	0.027		0.038		0.0060		0.011	

As households evolve and purchase or let go of vehicles, the composition of vehicle fleets change, thus impacting fuel consumption and emissions. Since it is computationally intensive to track the number of trips and the distance traveled by each vehicle in each household, and assign these to the network with different operating costs based on various distinct fuel economies, households were classified into five categories (<20 mph, 20-22 mph, 22-24 mph, 24-26 mph and >26 mph) based on the average fuel economy of all vehicles owned by the household. The

trips by each category of household were loaded separately onto the network (alongside commercial/truck trips) using multi-class assignment. The multi-modal multi-class assignment model in TransCAD is a generalized cost assignment that lets one assign trips by individual modes or user classes to the network simultaneously. Each mode or class can have different congestion impacts, different volume-delay function parameters, and different values of time. The output consists of volume flows by mode and/or class for each link, from which the total VMT traveled by each class can be computed. Greenhouse gas emissions are finally computed using the VMT outputs for each class using their respective fuel economies. This allows for certain changes in the vehicle fleet to be accounted for when calculating emissions. (For example, if rural and suburban households are more likely to gas guzzlers and make longer trips, this effect will be provided directly via TransCAD's outputs.)

Logsums from a commercial trip distribution (Kumar, 2008) model serve as zonal accessibility indices for firm location choice. These accessibilities were computed as follows:

$$Access_i = \sum_j \frac{A_j}{e^{(\gamma_1 . time_{ij} + \gamma_2 . dist_{ij})}}$$

where A_j is the attraction (population and employment), $time_{ij}$ is the peak period travel time from zone i to zone j, and γ_1 and γ_2 and are parameters from logit models of commercial trip destination choice. Population (A_j = population in zone j) and employment (A_j = employment in zone j) accessibilities are estimated separately and used in the location choice model.

For household location choice, logsum accessibility indices (given by equations listed below) were computed using the travel demand model outputs. These values provide the link between the land use and travel demand model components (see, e.g., Ben-Akiva and Lerman, 1985):

$$L_{ij} = \ln\left(\sum_{m \in C} \exp(U_{nijmt})\right)$$

$$U_{nijmt} = \beta_{1nmt} + \beta_{GC,n}\left(\frac{Cost_{nijmt}}{VOTT_n} + TT_{nijmt}\right)$$

where i and j are the index origin and destination zones, respectively; n indicates trip type (e.g., HBNW); m indicates mode; t denotes TOD; β_{1nmt} is the alternative specific constant from the joint mode-TOD choice model; β_{GC} is the coefficient of generalized trip costs; TT is travel time; $VOTT$ is the assumed value of travel time ($9 per person-hour for work trips and $4.5 per person-hour for non-work trips); and $COST$ indicates trip cost (assumed to be $0.20 per vehicle-mile).

3.4 Energy Consumption Estimation

3.4.1 Residential Energy Consumption

Household energy demand was estimated using data from the 2001 Residential Energy Consumption Survey (RECS), conducted by the Energy Information Administration (EIA). The RECS is a national survey of nearly 5000 households that collects energy related data for occupied primary housing units once in 4 years. While electricity is consumed by all the households, natural gas is used only in 60% of the U.S. households. The proportion of households consuming other fuels – (e.g., kerosene and fuel oil) is less than 2% and hence consumption of those fuels is not been considered in this study.

The data set contains information on the household demographics, dwelling unit attributes, weather characteristics (heating degree days [HDD] and cooling degree days [CDD]) from 4822 households. Average annual household consumption (national) of electricity and natural gas are expected to be 10,569 kWh and 436 ccf, respectively. Based on estimates from the National Center for Climatic Data (NCDC 2006), HDD and CDD values for the region are 1674 and 2974; these values are assumed constant throughout the simulation period.

Table 3.7: Descriptive Statistics for RECS (2001) Data

Variable	Minimum	Maximum	Mean	Std. Dev.
Annual kWh of electricity consumed	0.00	65,942	10,569	7,383
Annual ccf ('00) of natural gas consumed	0.00	4,882	436	506
$/kWh (electricity)	0.00	0.40	0.10	0.03
$/ccf (natural gas)	0.04	7.21	1.01	0.33
No. of people in household	1	15	2.631	1.476
Pre-school going children (Ages 0-5)	0	2	0.038	0.200
No. of adults over 65 years of age	0	6	0.342	0.641
Household income ($)	$2,500	$100,000	$43,177	$27,947
Cooling degree days (base 65 F)	0	5,161	1,326	981
Heating degree days (base 65 F)	0	10,045	4,224	2,022
Age of home (years)	0	61.52	37.08	18.74
Square footage (interior space)	0	15,136	1712	1223

Table 3.7 provides summary statistics for the RECS data set. Unit cost of electricity and natural gas has been calculated from the expenditure amount provided, and is assumed to be constant for all households in Austin at $0.07/kWh for the entire simulation period.

Table 3.8: Residential Energy Consumption Model Results (OLS)

Variable	Natural Gas (ccf/year)		Electricity (kWh/year)	
	Coef.	t-statistic	Coef.	t-statistic
Constant	161.4	3.06	14433	23.64
$ /ccf (natural gas) or $/kWh (electricity)	-8666	-10.68	-78788	-24.63
Cooling degree days (base 65)	-0.027	-2.451	0.255	1.687
Heating degree days (base 65)	0.043	5.649	-0.019	-0.208
Northeast indicator	-82.96	-2.539	751.5	1.48
Midwest indicator			-1342	-2.919
West indicator	-134.6	-4.619	-2703	-11.26
CBD indicator			-2935	-12.62
Urban region indicator			-2036	-7.661
Suburban region indicator			-2417	-9.325
Multi-family > 5 units unit indicator	-297.4	-14.86	-832.9	-3.533
Multi-family 2-4 units indicator	-55.08	-2.394	-626.4	-2.22
No. of people in household	46.67	10.32	1514	19.25
Pre-school going children (Ages 0-5)	-42.46	-1.366	-1900	-4.779
No. of adults over 65 years of age	46.69	4.372	-712.2	-5.78
Household income ($)	9.6E-04	3.74	0.037	11.95
Age of housing unit	4.149	11.8	-19.46	-4.411
Total sq ft (excluding basement and garage areas)	0.048	2.989	-1.136	-4.522
Total heated sq ft * Northeast	0.104	5.383	-0.747	-3.124
Total heated sq ft * West	0.049	3.023		
Total sq ft * HDD	1.40E-05	3.612	1.47E-04	4.245
Total sq ft * CDD			8.84E-04	15.02
No of observations	2922		4821	
R-squared	0.48		0.52	

Ordinary least squares regression was used to estimate annual electricity and natural gas consumption by households. As shown in Table 3.8, age and type of housing unit, along with several household demographics, serve as explanatory variables for both forms of energy demand. CO_2 equivalents for these forms of energy in Texas are 1.46 lbs CO2 per kWh (EIA

2002) and 117.8 lbs CO2 per Btu for natural gas (EIA 2005). These conversion factors are helpful for estimating Austinites' carbon footprint, now and into the future.

3.4.2 Commercial Building Energy Consumption

Details of energy consumption by commercial buildings are provided by the EIA in its Commercial Buildings Energy Consumption Survey (CBECS). This is a national level sample survey of commercial buildings and their energy suppliers conducted every four years.

Table 3.9: Descriptive Statistics for CBECS (2003) Data

Variable	Minimum	Maximum	Mean	Std. Dev.
Annual kWh of electricity consumed	36	194,434,138	2,046,075	6,142,762
Annual ccf of natural gas consumed	0	6,359,230	58,805	226,590
Price of electricity $/kWh	0.126	74	0.949	1.459
Price of natural gas $/ccf	0.018	3.047	0.093	0.059
Heating degree days (base 65 F)	0	11,059	4489.45	2260.12
Cooling degree days (base 65 F)	20	5,904	1350.74	1025.10
Age of building (years)	0	232	33.87	29.66
kWh per worker	41.6	5,784,242	24,116	108,889
ccf per worker	0	38,110.67	883.24	1,997.58
ccf per sq ft	0	12.19	0.57	0.81
kWh per sq ft	0.01	352.17	17.14	19.98

To anticipate the energy demand of firms, once again ordinary least squares models were estimated based on CBECS (2003) data. Table 3.9 provides the descriptive statistics for commercial buildings.

Table 3.10: Commercial Building Energy Consumption Model Results (OLS)

Variable	kWh/year/worker		ccf/year/worker	
	Coef.	t-statistic	Coef.	t-statistic
Constant	604.9	0.29	29.44	0.70
Price in $/kWh or $/ccf	-35,099	-3.42	-42.64	-4.13
Cooling degree days	1.02	1.22		
Heating degree days			0.0906	12.30
Age of the building (years)	-130.4	-4.73		
Sq ft / worker	15.7	116.1	0.149	26.86
Sq ft / worker * Indicator for retail firms	-3.33	-4.42	-8.9E-03	-0.60
Sq ft / worker * Indicator for education firms	-7.72	-5.26	0.0141	0.59
Sq ft / worker * Indicator for service firms	-9.44	-11.61	0.0603	3.43
No. of observations	4470		3024	
R- squared	0.75		0.25	

The average age of commercial structures is slightly less than that of residential buildings. The majority of commercial buildings are in the smallest size categories: More than half (53%) are 5,000 square feet or less and nearly three-quarters (73%) are 10,000 square feet or smaller, which leads to high variation in the amount of energy demand across buildings. To somewhat counter this effect, average energy demand per worker rather than the total energy demand was used as the response variable when estimating commercial energy demand models (Table 3.9). Results from these models are reported in Table 3.10. Retail firms have lower electricity and natural gas demand, as compared to basic firms, whereas service and educational firms have lower natural gas demands but higher electricity demand.

3.5 Land Development Models

Land development models, locate new residential and commercial development in the region. For the base year, the number of housing units is obtained from Census block data and aggregated to TAZ level. Household location decisions closely relate to other choices of housing type, distance to work and automobile ownership decisions. Models were developed for new

housing units built (for each of three types of housing units), household location choice (across TAZ's), and residence type choice (single-family or multi-family). In each model year, it is assumed that development happens first and then households/firms select the locations and building units depending on the availability of built space. In the real world, consumers and suppliers interact more directly with prices adjusting to clear and regional markets. In this study, however, land prices are not considered in location choice models and residence type choice, which is a huge limitation. The shares of the three types of housing units for the base year is based on Census 2000 block and block group data, aggregated to the zonal level. This section explains the data sets, assumptions used and models estimated for different stages in the development process.

3.5.1 Residence Type Choice Models

Multinomial logit models predict the type of housing unit a household chooses to live in. Three residence types are specified: single-family unit (detached or attached), multi-family unit (2-4 units) and larger multi-family (with at least 5 units). The residential type choice model is used to predict the base year housing units as well as allocate future year households (newly formed households and households moving into the region. Data from the 2001 branch of RECS data set was used for this model. Table 3.11 shows the model results.

Table 3.11: Multinomial Logit Model for Residence Type Choice

	Multi-Family 2-4 units		Multi-Family More than 5 units	
Variable	**Coef.**	**t-statistic**	**Coef.**	**t-statistic**
Constant	-0.760	-4.42	-0.564	-3.61
Urban region indicator	0.969	7.73	1.455	12.54
Suburban region indicator	0.436	2.45	0.706	4.43
No. of people in household	-0.159	-3.89	-0.272	-7.22
No. of employees in household	-0.404	-4.11	-0.698	-5.92
Household income ($'000)	-0.0251	-9.72	-0.0224	-10.32
No. of vehicles	-0.118	-1.94	-0.164	-3.03
No. of observations	4491			
R-squared	0.41			

The constants are negative, which means that single family units (the base category) are preferred to multi-family units, ceteris paribus. Households in city and suburban regions are more likely to live in multi-family units than households in rural neighborhoods. The model also shows that higher Household income households have less preference for multi-family housing units, which is generally intuitive.

3.5.2 Development of New Housing Units

Development of new homes is influenced by various factors, including demand for housing in a neighborhood, cost of land, access to employment opportunities, soil conditions, and so forth. GIS land use data for 2003 and 2005 is available for all parcels inside the 240 traffic analysis zones that lie within City of Austin or its 2-mile extraterritorial jurisdiction halo. This data was aggregated to obtain the single-family and multi–family housing units in each zone for both years (2003 and 2005). Several zones showed no new residential development between the two years, so Tobit models were used to allow for these many zero values. Tables 3.12 and 3.13 show the results of the estimated models.

Table 3.12: Tobit Model Results for New Single-Family Units Developed in a Zone

Variable	Coef.	t-statistic
Constant	-891.7	-8.26
Undeveloped area in the zone (sq ft)	2.17E-06	2.90
Rural region indicator	732.6	7.52
Suburban region indicator	424.1	5.61
Square root of population in the zone	21.51	1.84
Sigma	335.5	
No. of observations	240	
No. of censored observations (at zero)	42	
R-squared	0.061	

Table 3.13: Tobit Model Results for New Multi-Family Units Developed in a Zone

	Multi-Family Unit (2-4 units)		Multi-Family Unit greater than 5 units	
Variable	**Coef.**	**t-statistic**	**Coef.**	**t-statistic**
Constant	29.98	2.84	-304.1	-2.24
Undeveloped area (sq ft)	1.44E-07	1.98	6.95E-06	7.98
Distance to CBD (miles)	-3.134	-4.73	-7.53	-2.27
Household density	1.64E-03	1.71	-0.312	-1.55
Population density	2.78E-03	1.65	-0.118	-1.62
Sigma	32.35		402.3	
No. of observations	240		240	
No. of censored observations (at zero)	113		121	
R-squared	0.085		0.072	

As expected, new homes are more likely to develop in zones with more undeveloped area. Single family units are more likely to be built in rural and suburban regions, while multi-family units favor zones closer to CBD. Newly developed housing units were assigned area based on the area of existing housing units, of similar home type in the zone. To simulate these unit sizes, a floor-area ratio (FAR) of 0.25 was used for single-family units and 0.75 for multi-family units. The newly generated single-family and multifamily units defined by home size, were allocated to individual households based on a location choice model and residence type choice model (3.5.1). The location choice model (at the zone level) is based on estimates developed by Kumar and

Kockelman (2008). When the number of households choosing a zone exceeds the number of available housing units, households are assigned their preferred housing type (single-family/multi-family) randomly, and the rest are assigned the next most preferred zone, where vacant housing units exist.

3.5.3 New Firms

Firms also are located based on Kumar and Kockelman's (2008) location choice model, and area is assigned based on the average area per worker used in the zone, as per Table 3.12's estimates. The built-space required by a firm varies by industry. Travis County Appraisal District (TCAD) provides information on the area and age of commercial structures which are taxed in Travis County zones. The average square footage and age of structures in each zone is regressed on zonal attributes including distance to the CBD and zone type indicator variables, with results shown in Table 3.14. As expected, buildings in CBD regions are older and offer relatively low values of square footage per worker.

Table 3.14: Ordinary Least Squares Models of Square Footage and Age of Commercial Buildings in a Zone

	Area per Worker (sq ft)		**Age of Building (year)**	
Variable	**Coef.**	**t-statistic**	**Coef.**	**t-statistic**
Constant	52.90	4.94	37.79	10.34
CBD indicator	-47.02	-3.08	9.18	1.62
Urban region indicator	-36.75	-4.17	-	-
Suburban region indicator	-21.33	-3.01	-1.59	-1.57
Distance to CBD (miles)	2.23	1.83	-1.16	-5.15
Distance to CBD^2 (miles^2)	-0.081	-1.94	-	-
No. of observations	480		480	
R-squared	0.12		0.13	

On average, built space associated with workers increases as one moves away from the CBD, while building age falls. Space requirements are expected to vary across the four firm categories, since basic firms generally require more area per employee than any other firm type. In this study, however, the same value of square footage per worker is used. This is a limitation of the

current model and presents scope for improvement. Parameters obtained are then used to predict required statistics on building size and age across all zones for the base year.

3.6 Summary

This chapter highlighted the microsimulation framework used to track each household and firm in Austin region. A discussion of different models developed for vehicle ownership, location choice, supply of built space, energy demand estimation was provided including information on strengths and weaknesses. The next chapter describes the results of the model application in the Austin region.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter provides a summary of the model applications and the scenarios investigated in this study. The Austin metropolitan region consists of 1,074 traffic analysis zones (TAZs) spread over three counties: Travis, Williamson and Hays. For the model base year of 2005, there are approximately 450,000 households in the region and over one million people. In model application, the households and firms are evolved by application of the sub-modules discussed in Chapter 3, using Monte Carlo methods. Traffic assignment procedures are performed on the Austin's coded network for 1997 by Capital Area Metropolitan Planning Organization (CAMPO), which consists of over 10,000 links.

Microsimulation of household and firm evolution, including location choices, vehicle ownership and energy, was carried out using MATLAB® (MathWorks 2007a). The results of this simulation are discussed here.

4.2 Scenario Development

Five scenarios were used to forecast changes in land use patterns and household and firm energy demands. The region is shown in Figure 4.1 and the five different scenarios are as follows:

a. Business as usual (BAU)

b. Imposition of an urban growth boundary (UGB)

c. Gas tax and road tolls (PRICING)

d. Expanded (doubled) capacity of Austin's primary freeway (EXPCAP)

e. Introduction of a new highway (SH130).

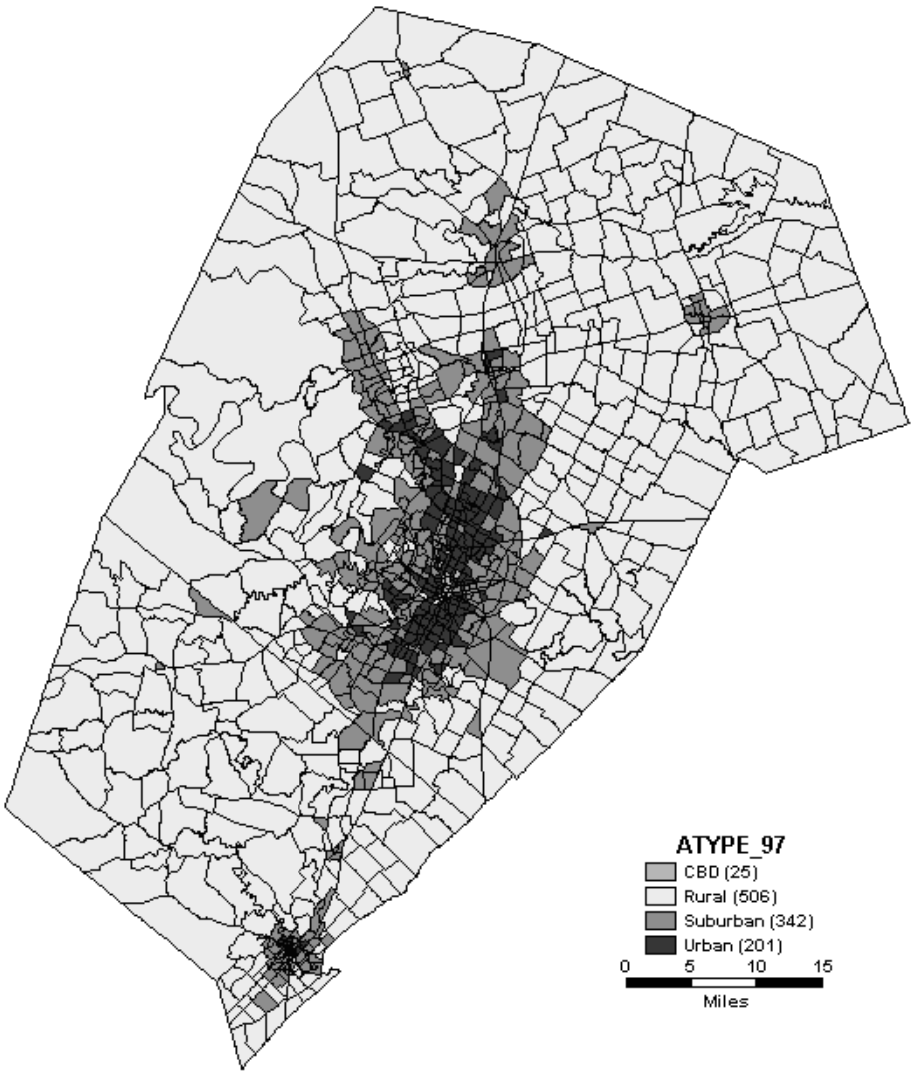


Figure 4.1: The Austin Region (Travis, Williamson and Hays Counties)

In the base scenario, no changes are made to the transportation network of the region or its land use characteristics. This scenario serves as a base for comparing results from all other scenarios. In the UGB scenario, the location alternatives of all new households and firms are restricted to the 617 (out of 1,074) TAZs that enjoyed at least two job equivalents per acre in 2005 or were contiguous with such zones. In the third scenario (PRICING), gas prices are set to $6 per gallon (rather than the base level of $3/gallon) and a fixed toll of 10 cents per mile is imposed on all roads. The last two scenarios investigate changes in the location patterns and energy demands due to expansion of Austin's highway. In the expanded capacity scenario (EXPCAP), capacity

along the regions' most congested transportation corridor – I-35(nearly 80 miles) is doubled. In the last scenario, a new highway, SH 130, is introduced into the network and its effect is studied. SH-130 is a 49-mile highway, extending from Interstate 35 (I-35) north of Georgetown southward to U.S. 183, southeast of Austin. It passes though Williamson and Travis counties and bypasses Austin's congested core (www.sh130.com), along with famously congested sections of I-35.

Figure 4.2 shows the overall simulation framework. Households and firms are added and removed at one-year time intervals. Firm population and household population are assumed to evolve independently (but growth rates are pre-specified thus ensuring balance), and the commercial and household trips are combined and loaded on the transportation network. Travel demand modeling was performed every 5 years, so travel times could be updated for the household and firm location modules. Detailed estimates of household and firm attributes and location patterns, travel demand model results and greenhouse gas estimates are provided in the next section.

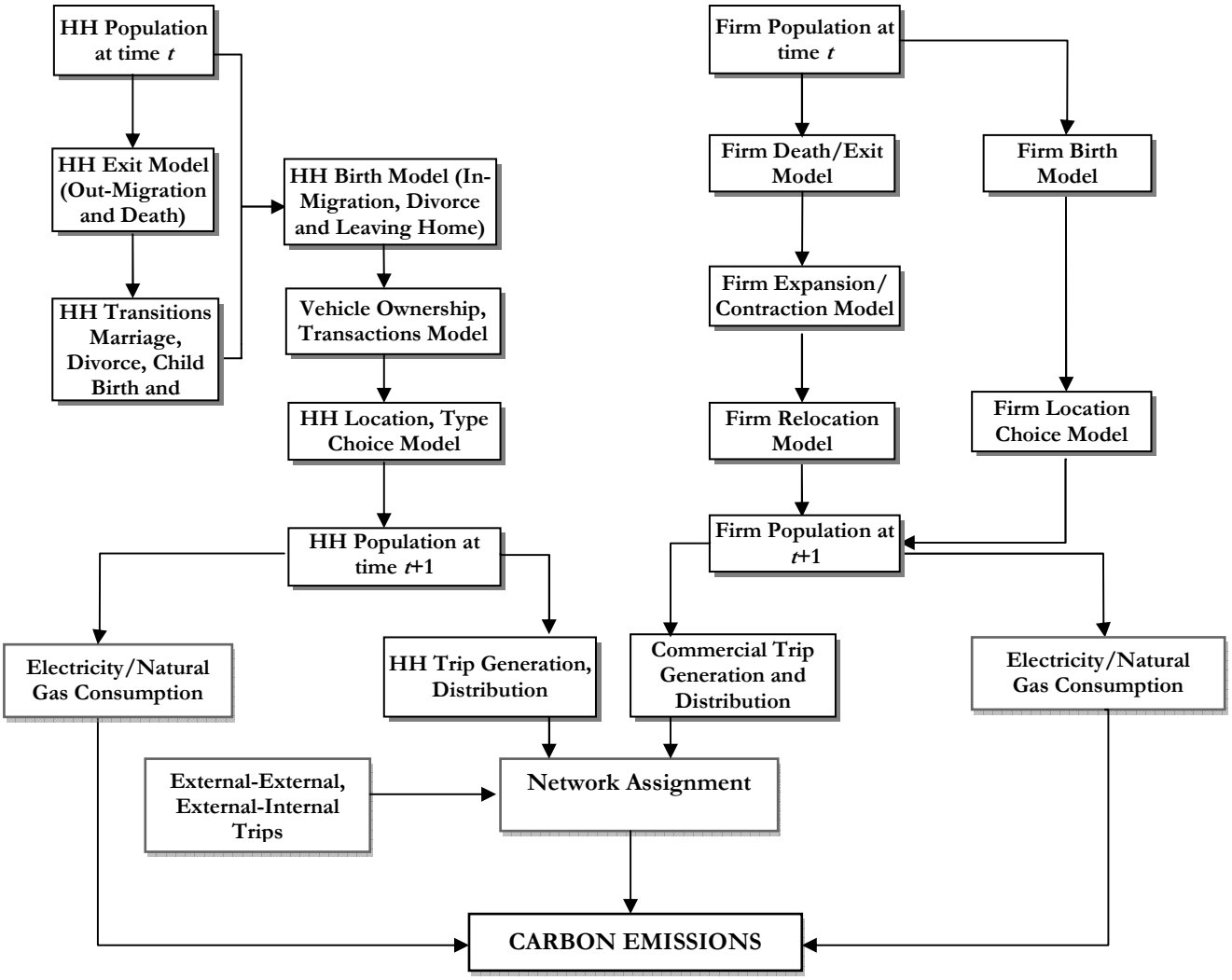


Figure 4.2: Overall Simulation Framework

4.2 Households and Firms

4.2.1 Households

To speed calculations, only a 10-percent sample of households was simulated, in terms of demographic evolution and location choices. All simulated households and individual members were scaled up by a factor of 10 for purposes of mapping land use patterns, generating trips,

loading the network and computing energy demands. Table 4.1 shows population attributes for the simulation period 2005 through 2030 in 5 year increments.

Table 4.1: Forecasts of Population Attributes over Time

	Year 2005		**Year 2010**		**Year 2015**	
No. of households	451,003		561,190		626,800	
No. of persons	1,148,177		1,402,970		1,529,520	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Household size	2.55	1.47	2.5	1.4	2.48	1.3
Vehicles	1.94	0.95	2.06	0.96	2.09	1.03
Household income	$59,496	$51,542	$58,996	$52,799	$57,257	$54,243
Fraction of households with…						
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Pre-school age children	0.15	0.36	0.18	0.39	0.17	0.37
Pre-driving children	0.23	0.42	0.22	0.41	0.2	0.4
Driving age children	0.06	0.24	0.05	0.22	0.05	0.22
Non-working adults	0.2	0.4	0.19	0.39	0.18	0.39
Student adults	0.15	0.35	0.15	0.35	0.14	0.35
Part-time working adults	0.34	0.47	0.32	0.47	0.3	0.46
Full-time working adults	0.68	0.47	0.66	0.47	0.65	0.48
	Year 2020		**Year 2025**		**Year 2030**	
No. of households	717,110		865,440		944,600	
No. of persons	1,568,930		1,706,722		2,085,710	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Household size	2.43	1.23	2.41	1.35	2.37	1.41
Vehicles	2.12	1.08	2.13	1.12	2.15	1.18
Household income	$57,337	$53,159	$58,341	$50,876	$58,067	$52,341
Fraction of households with…						
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Pre-school age children	0.15	0.36	0.15	0.35	0.15	0.35
Pre-driving children	0.18	0.38	0.16	0.36	0.15	0.36
Driving age children	0.05	0.21	0.04	0.2	0.04	0.19
Non-working adults	0.18	0.38	0.17	0.37	0.16	0.37
Student adults	0.14	0.35	0.14	0.35	0.14	0.35
Part-time working adults	0.28	0.45	0.26	0.44	0.24	0.43
Full-time working adults	0.64	0.48	0.62	0.49	0.61	0.49

The number of households and persons are simulated to grow by 109% and 70%, respectively, over the 25-year period. Average household size is expected to fall by 7% by 2030, while real

income per household is expected to remain largely unchanged and average vehicle ownership levels (per household) increases by just 10%. The fractions of households with part-time and full-time workers are forecasted to fall over time, which may be entirely due to lower future household sizes.

4.2.2 Firms

Firms were assumed to grow at 2% every year. Predictions suggest greater concentration in central regions than presently exits, as firms are expected to favor urban and CBD zones. During the simulation period, firms are expected to grow at 32% (Table 4.3) with a steady increase in number of firms in all sectors. In terms of absolute numbers, increase in the number of service firms is the highest.

Table 4.2: Firm Composition by Category

	2005		2015		2030	
Firm Type	**Count**	**%**	**Count**	**%**	**Count**	**%**
Basic	7,219	18.92	7,298	17.10	7,462	14.88
Retail	6,884	18.04	7,461	17.45	8,352	16.66
Education	802	2.10	1,014	2.36	1,479	2.95
Service	23,256	60.94	27,031	63.10	32,846	65.51

Firm transitions from one size category to another are modeled using Markovian transition matrices, estimated by Kumar (2008). These matrices were estimated using cross sectional data from Statistics of U.S. Businesses (SUSB) and favor shifts toward larger firm-size categories, which results in a high increase in job numbers, as compared to the increase in firm counts. Table 4.4 shows the distribution of firms by size category for years 2005, 2015 and 2030. The share of firms with more than 500 workers increases from under 3% to slightly over 6%. A steady increase in the fraction of firms in the 20+ worker category is observed. In the end, this leads to a 110% increase in the region's total job count over the 25-year simulation period.

Table 4.3: Firm Counts and Shares by Size, from 2005 to 2030

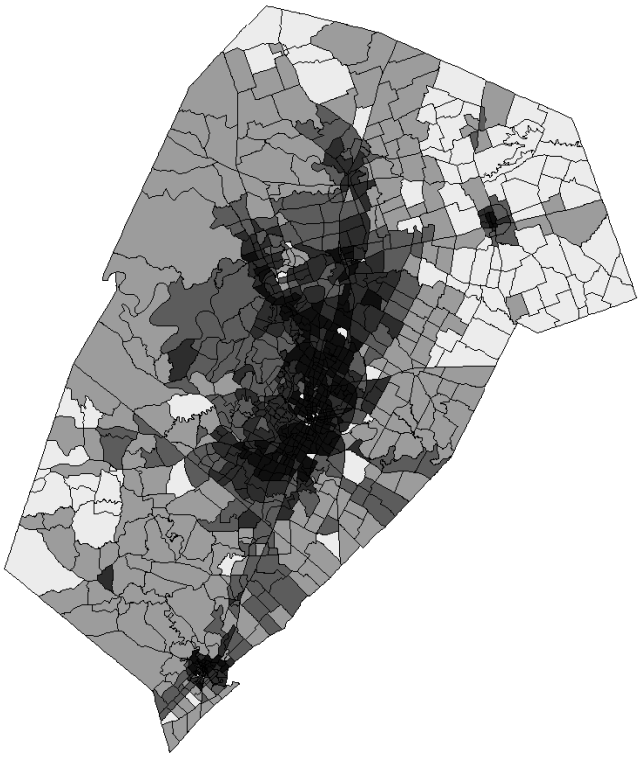
	2005		2015		2030	
No. of Firms	**38,161**		**42,802**		**50,139**	
Size of Firm	**Count**	**%**	**Count**	**%**	**Count**	**%**
1-4	15,059	39.46%	15,410	36.07%	16,471	32.85%
5-9	8,984	23.54%	9,617	22.50%	10,462	20.87%
10-19	5,504	14.42%	6,332	14.79%	7,317	14.59%
20-99	5,228	13.70%	6,486	15.13%	8,294	16.54%
100-499	2,369	6.21%	3,203	7.45%	4,574	9.12 %
500+	1,017	2.67%	1,754	4.07%	3,021	6.03 %

4.2.3 Location Patterns

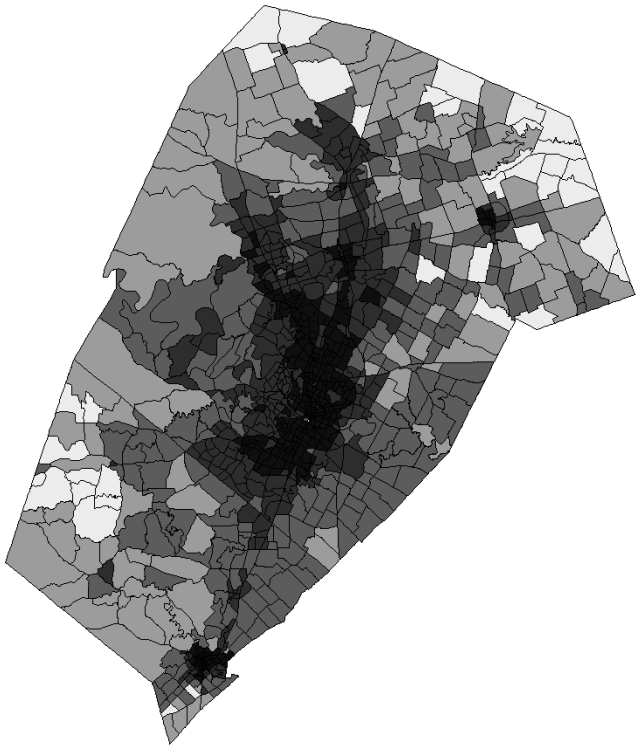
Households exhibit strikingly different location patterns under the five scenarios. Figures 4.3 through 4.6 illustrate these patterns for the base year (2005) and the forecast years 2015 and 2030. As expected, the models predict much greater household density in the centrally located zones when a growth boundary policy is implemented (UGB) as compared to the BAU case. In the extended capacity scenario (EXPCAP), households clearly shift towards zones alongside I-35.

Housing unit type choices are closely related to household location choices. As undeveloped land available in the central region continues to decline, households tend to locate into multifamily housing units. In 2030, nearly 55% of households are simulated to reside in multi-family housing units, as compared to 37% in 2005. Table 4.4 gives the proportion of housing units in 2005, 2015 and 2030. In the UGB scenario, the shift to multifamily housing units is greater (60% by 2030) because of the restriction imposed on choice alternatives. A similar increase in multi-family units is seen in the last two scenarios, as policies of I-35 expansion and SH-130's addition raise central area accessibility values, attracting households back to Austin's center, while densifying development alongside its major highway corridors.

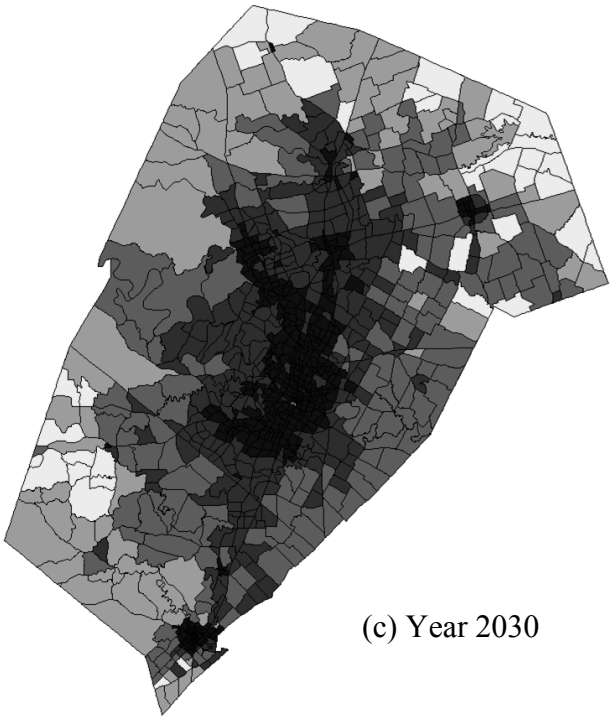
In general, firms tend to locate in central zones, with no evidence of significant location-pattern differences across scenarios. However, for the EXPCAP and Figures 4.7 and 4.8 shows the spatial distribution of firm and job densities values for years 2005, 2015 and 2030 in the BAU case. Distribution of firms and job density by category is shown in Figures 4.9 and 4.10.



(a) Year 2005 (Base)



(b) Year 2015



(c) Year 2030

Household density – households/square

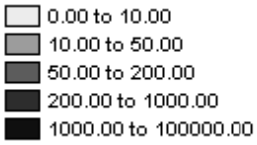
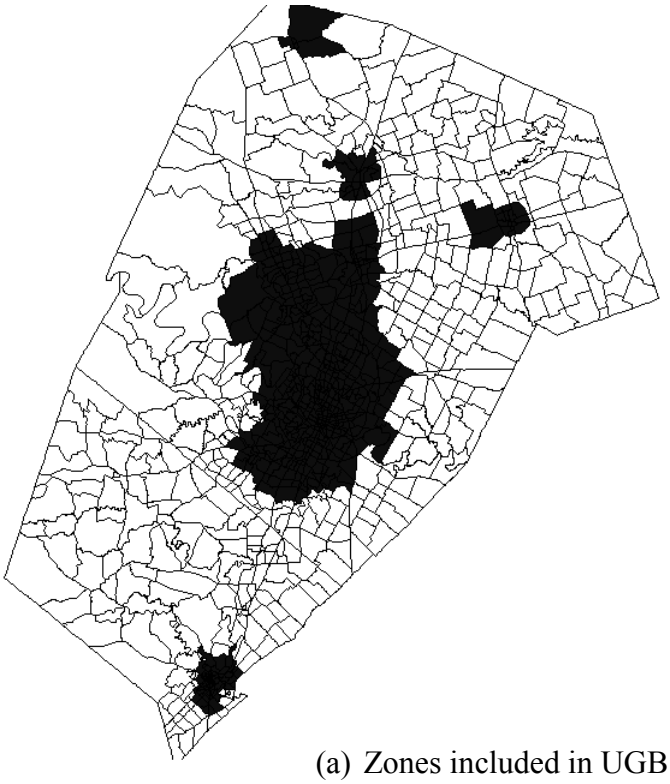
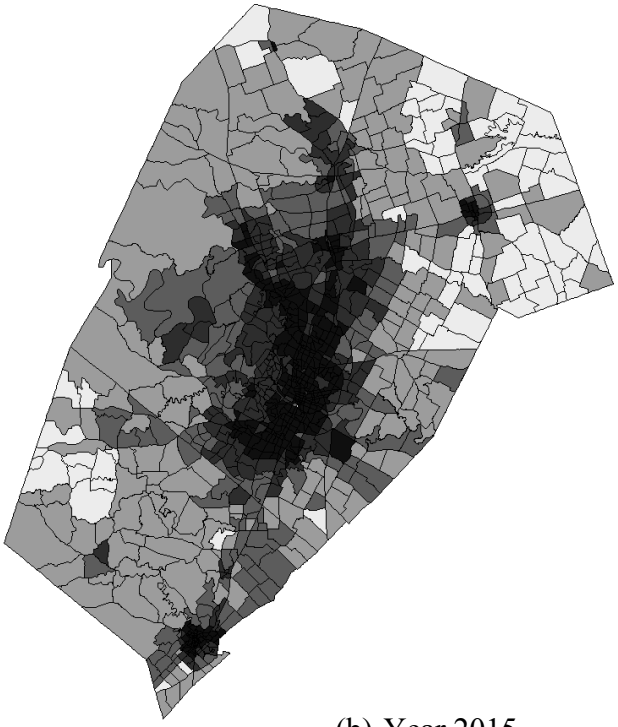


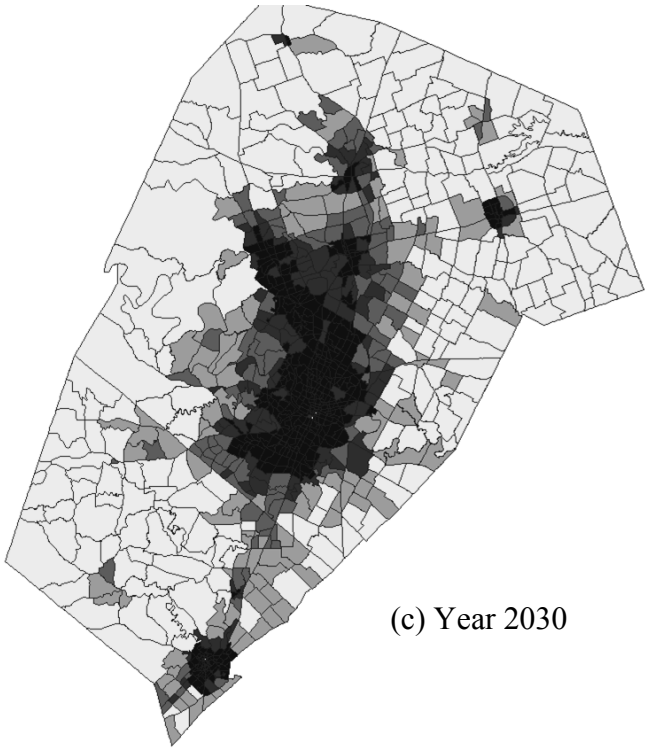
Figure 4.3: Household Density – Households/Square Mile in BAU scenario (a) Year 2005 (Base) (b) Year 2015 (c) Year 2030



(a) Zones included in UGB



(b) Year 2015



(c) Year 2030

Household density – households/square

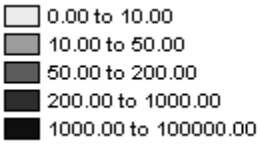


Figure 4.4: Household Density – Households per Square Mile in UGB scenario: (a) Zones included in UGB, (b) Year 2015, (c) Year 2030.

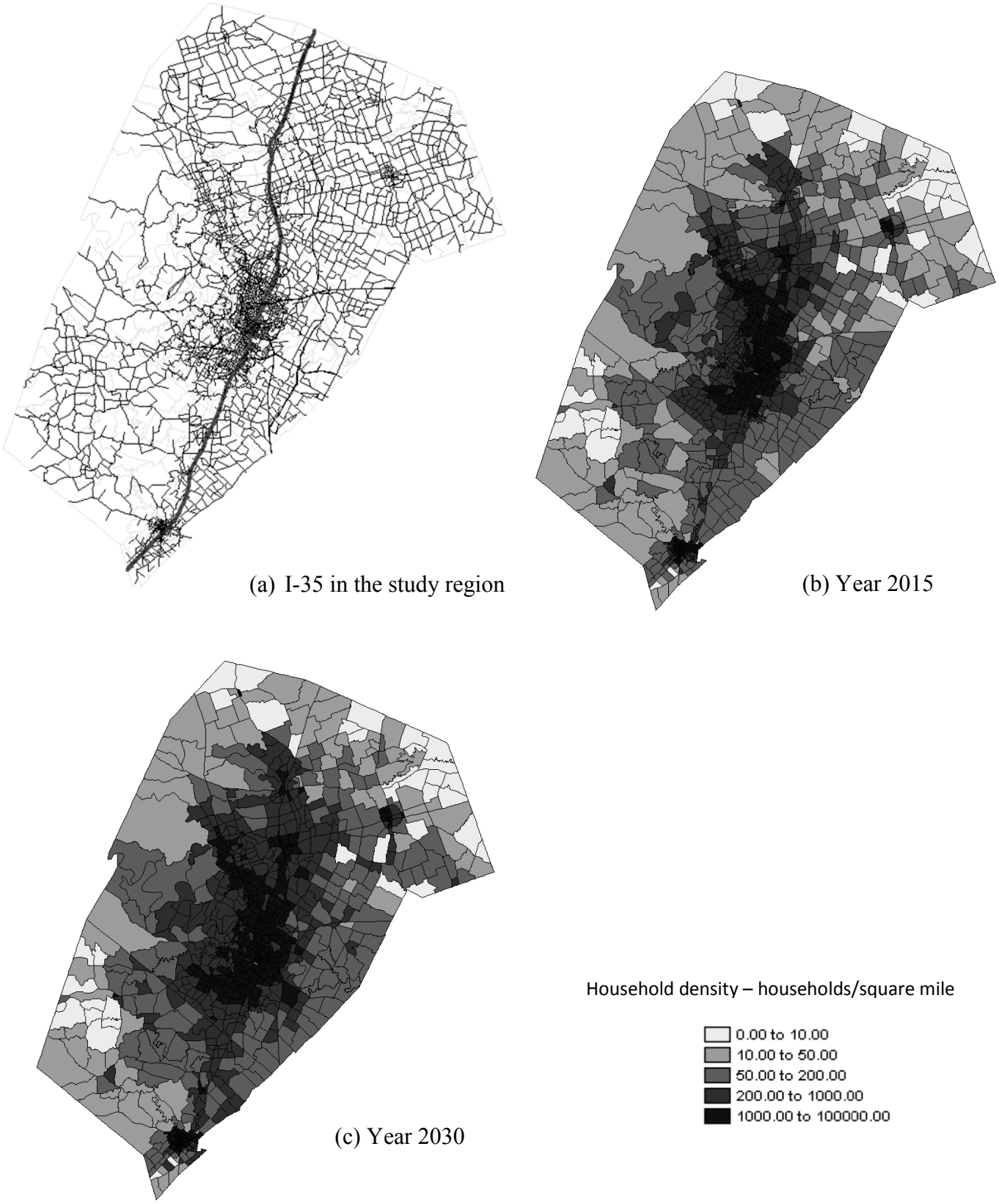
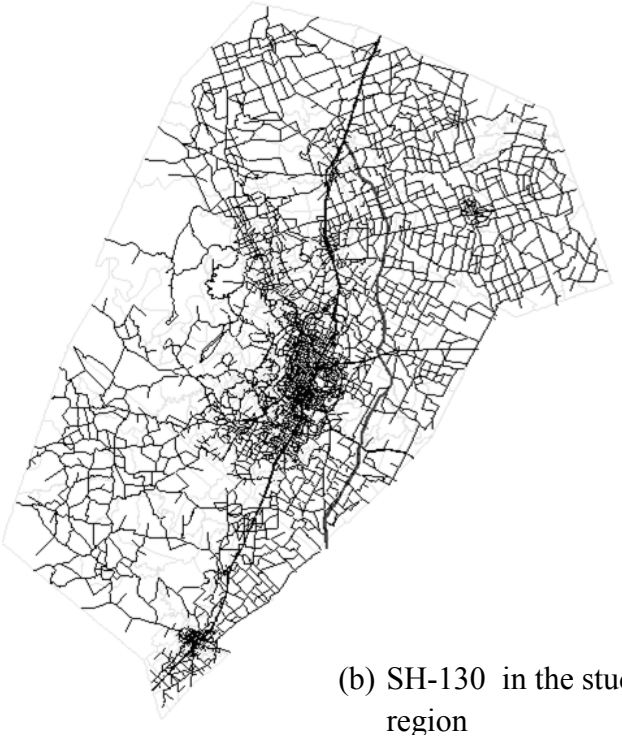
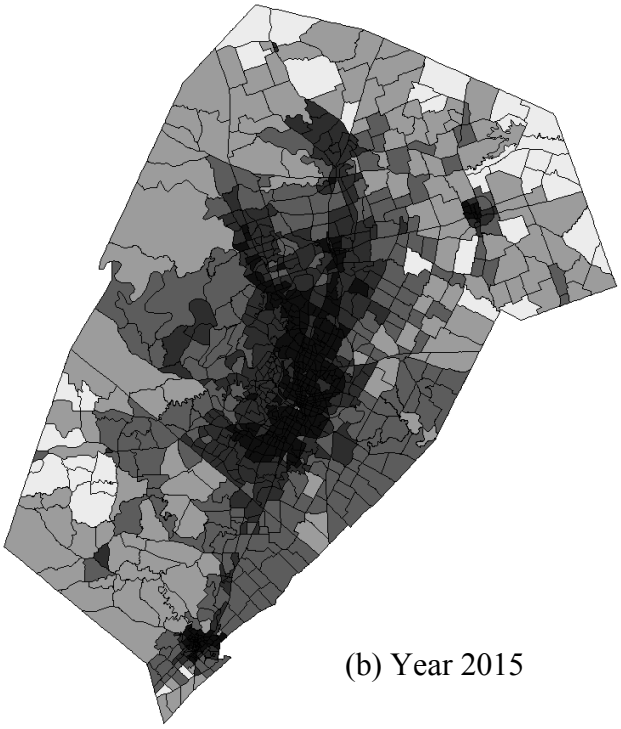


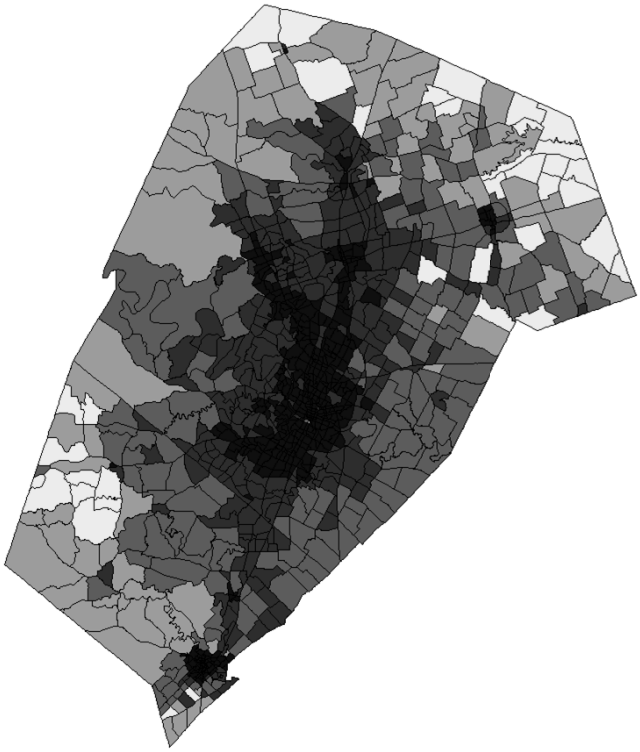
Figure 4.6: Household Density – Households per Square Mile in EXPCAP Scenario (a) I-35 Location in Network, (b) Year 2015, (c) Year 2030.



(b) SH-130 in the study region



(b) Year 2015



Household density – households/square

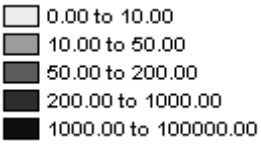


Figure 4.6: Household Density – Households per Square Mile in SH 130 Scenario (a) SH 130 Location in Network, (b) Year 2015, (c) Year 2030.

Table 4.4: Housing Units by Type in 2005, 2015 and 2030

	BAU		UGB		PRICING		EXPCAP		SH 130	
2005	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Single family units	282,590	62.54	282,590	62.54	282,590	62.54	282,590	62.54	282,590	62.54
Multi-family 2–4 units	47,730	10.56	47,730	10.56	47,730	10.56	47,730	10.56	47,730	10.56
Multi-family more than 5 units	121,480	26.88	121,480	26.88	121,480	26.88	121,480	26.88	121,480	26.88
2015										
Single family units	398,572	59.47	379,723	56.67	384,917	54.46	398,056	55.38	399,503	55.58
Multi-family 2–4 units	84,113	11.81	71,263	10.37	82,734	12.38	83807	11.66	81,632	11.36
Multi-family more than 5 units	236,115	28.72	267,814	32.96	251,149	33.17	236,937	32.96	237,665	33.06
2030										
Single family units	426,761	45.18	384,839	40.74	402,827	42.65	429,222	45.44	413,177	43.74
Multi-family 2–4 units	107,517	11.38	105,683	11.19	109,597	11.60	106,910	11.32	105,683	11.19
Multi-family more than 5 units	410,321	43.44	454,078	48.07	432,176	45.75	408,468	43.24	425,740	45.07

Figure 4.7: Firm Density (per Square Mile) by Location in BAU Scenario:(a) Year 2005, (b) Year 2015, (c) Year 2030.

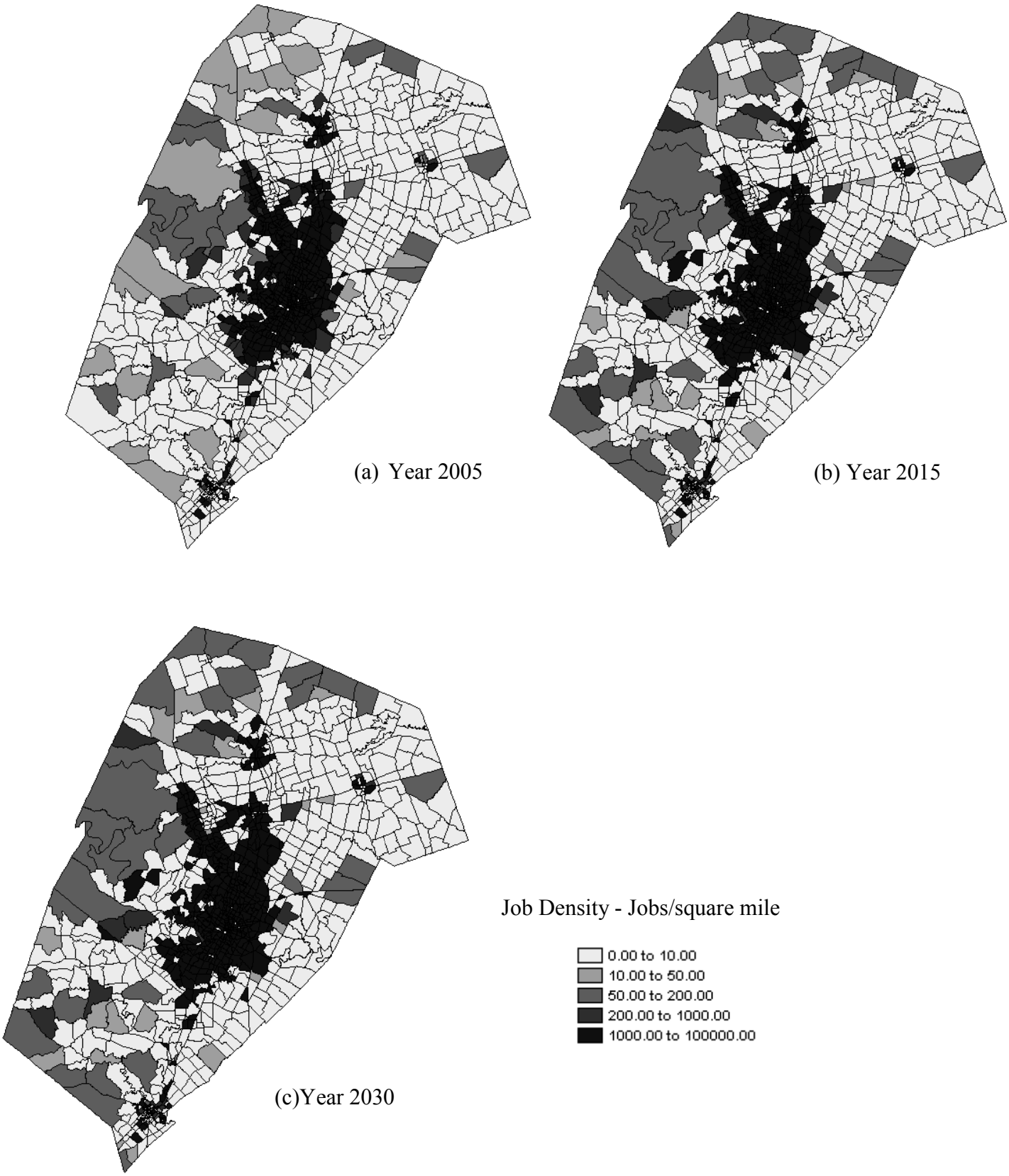


Figure 4.8: Job Density (per Square Mile) by Location in BAU Scenario :(a) Year 2005, (b) Year 2015, (c) Year 2030.

Figure 4.9: Firms (per Square Mile) by Category (2030) in BAU Scenario:

(a) Basic, (b) Educational , (c) Retail, (d) Service.

Figure 4.10: Jobs (per Square Mile) by Category in 2030 in BAU Scenario:

(a) Basic, (b) Educational , (c) Retail, (d) Service.

4.3 Travel Demand Models

The travel demand and traffic assignment modules were run once every 5 years; hence, travel times remain largely constant between subsets of successive years in the overall simulation. Since population and employment distributions change every year, of course, accessibility indices and densities were updated, impacting firm and household and firm location choices. This section describes results of the travel demand model, as well as various assumptions that underlie the model. Household and commercial trip generation and distribution models were run during each simulation period; but external-internal and external-external trips were exogenous to the simulation (which is a model limitation and provides scope for improvement) and added to the OD matrix for traffic assignment. External-internal trips and external-external trips were assumed to increase by a constant factor (2% every year).

The key variables used for household trip generation are household size, annual income and number of vehicles in the household. Vehicle ownership decisions were predicted using models detailed in Section 3.3. The numbers of vehicles in different classes in year 2030 are listed in Table 4.5. Average vehicle ownership is highest in the BAU scenario, and lowest in the pricing scenario, as expected. Households are located in rural zones in BAU scenario which increases the need to own vehicles. The effect of a gas tax (in the pricing scenario) is somewhat apparent in the number and composition of year 2030 vehicles, as the model predicts slight reductions in the shares of large cars and pickups, thus allowing for a higher percentage of compact and subcompact cars (due to higher fuel efficiency than large cars) as well as SUVs (SUVs are more fuel efficient than their closest substitute pickups & vans). The composition of vehicle fleet is nearly identical in EXPCAP and SH130 scenarios, with a reduction in the share of pickups and an increase in share of passenger cars, relative to the BAU scenario.

In order to appreciate the changes in emissions due to changing vehicle ownership patterns, traffic assignment was done using a multi-class assignment in TransCAD (Caliper Corporation, 2002). As an example, this approach allows for less central households to adapt their travel patterns to their often higher per-mile travel costs, which are a result of their tendency to purchase less fuel

efficient vehicles – such as SUVs and pickup trucks. In order to reflect such distinctions, households were classified into five average fuel economy categories (less than 20 mpg, 20 to 22 mpg, 22 to 24 mpg, 24 to 26 mpg, and over 26 mpg) based on the average of vehicles in each synthetic households. Trips generated in each zone were distributed among the five categories, as per local household fuel-economy shares. In the PRICING scenario, gasoline price effects are observed in both the vehicle ownership and desination/mode choice model probabilities, as vehicle purchasers seek to avoid more costly vehicles (everything else constant) and households with less fuel efficient vehicles experience higher driving costs (per mile traveled). Commercial and External trips were loaded as separate classes, along with the above five classes. For greenhouse gas emissions estimation, a fleet-wide average fuel economy of 20 mpg was used for external trips and 8 mpg for all (internal) commercial trips.

Figure 4.11 shows VMT for each of the seven classes across the five scenarios. Consistent with vehicle ownership shares, the BAU scenario has the largest fraction of VMT in the lowest fuel economy class (thanks to its relatively high pickup truck share). Table 4.6 shows total scenario VMT along with the time of day splits. The base case had 4 million trips generating over 40 million VMT. VMTs generated under the scenarios are reported in Table 4.5. In the business as usual case, VMT are expected to increase 130% by 2030. Implementation of UGB restricts the rise to 98 percent, where as the pricing scenario restricts to 120%. The highest increase is in the case of last scenario – SH 130 (150 %). Compared to the business-as-usual scenario this translates to nearly 10% higher VMT. Expansion of I-35 also increases the VMT considerably, leading to 6% increase as compared to the base by 2030. The split of VMT among the different times of day is fairly constant between all the scenarios except the pricing scenario, where more trips are observed in the off-peak time period.

VMT weighted V/C ratios and average speeds are reported in Table 4.7. V/C ratios and average speeds are higher in the UGB scenario as compared to the BAU scenario which is expected, due to densification of central zones. In the EXPCAP and SH130 scenarios, V/C ratios drop and average speeds increase, as expected, due increased access along the region's major freeways.

Table 4.5: Vehicle Fleet Composition in 2030 by Scenario

Variable	BAU		UGB		PRICING		EXPCAP		SH130	
	Count	%	Count	%	Count	%	Count	%	Count	%
Avg. number of vehicles per household	2.26		2.08		1.95		2.05		2.02	
CUVs	43,634	2.05	45,839	2.34	42,423	2.31	37,069	1.92	38,576	1.91
Large cars	148,141	6.96	137,518	7.02	129,841	7.07	135,148	7.05	136,334	6.75
Luxury cars	278,191	13.07	252,900	12.91	236,910	12.9	249,252	12.91	249,768	12.37
Midsize cars	363,968	17.1	345,950	17.66	319,185	17.38	336,326	17.42	339,573	16.82
Pickups	406,963	19.12	345,166	17.62	309,636	16.86	358,529	18.57	356,295	17.65
Subcompact cars	73,858	3.47	74,244	3.79	68,135	3.71	69,698	3.61	66,662	3.30
Compact cars	102,379	4.81	101,082	5.16	93,846	5.11	94,797	4.91	95,936	4.75
SUVs	365,458	17.17	349,867	17.86	322,491	17.56	341,153	17.67	337,139	16.70
Vans	343,960	16.16	306,575	15.65	292,005	15.9	308,717	15.99	398,444	19.74

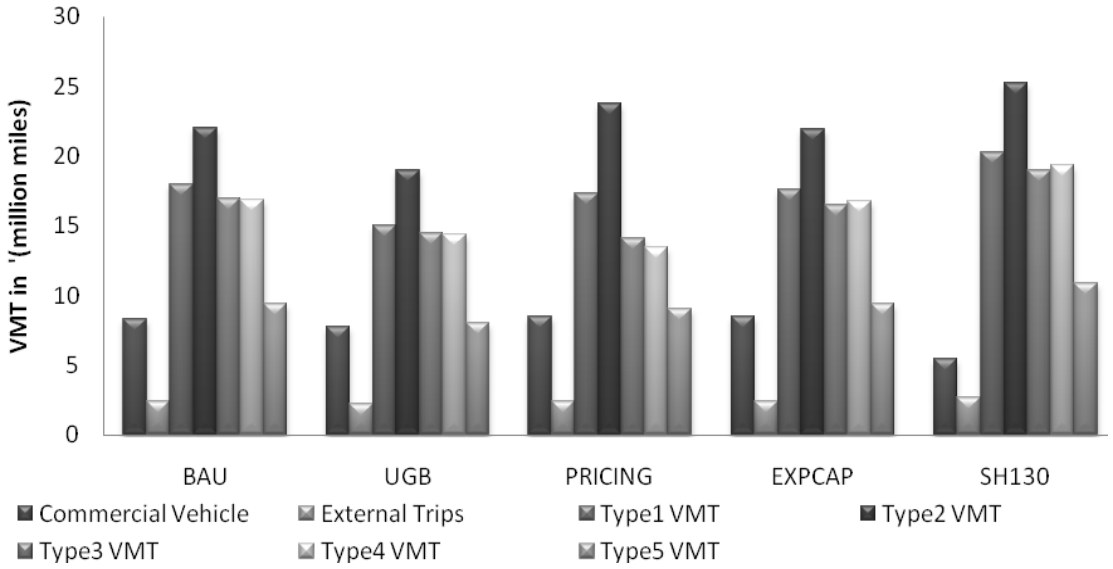


Figure 4.11: Vehicle Miles Traveled by Roadway Class in 2030 across Scenarios

Table 4.6: Vehicle Miles Travelled in 2030 by Time of Day

	BAU	UGB	PRICING	EXPCAP	SH 130
2005					
Total			**40,901,209**		
AM			8,648,682		
MID			15,371,508		
PM			12,824,063		
OP			4,056,955		
2030					
Total	93,889,070	80,906,949	89,611,023	99,657,273	102,925,936
AM	15,871,613	13,371,047	15,362,128	16,113,182	16,895,278
MID	40,156,662	35,161,275	36,512,793	43,494,848	44,738,667
PM	27,370,536	23,768,263	26,028,821	29,372,683	30,367,483
OP	10,490,258	8,606,363	11,707,281	10,676,559	10,924,507
% Change from BAU		(13.83)	(4.56)	6.14	9.63

Note: The time-of-day slots are AM peak (6 am – 9 am), midday/evening (9 am – 3 pm and 7 pm – 9 pm), PM peak (3 pm – 7 pm), and overnight (9 pm – 6 am)

Table 4.7: Year 2030 VMT Weighted V/C Ratios and Average Speeds across Scenarios

		BAU	UGB	PRICING	EXPCAP	SH130
	Daily	0.62	0.66	0.63	0.60	0.60
Flow weighted Average V/C Ratio	AM	0.66	0.70	0.69	0.62	0.62
	MID	0.58	0.63	0.59	0.58	0.58
	PM	0.65	0.68	0.63	0.64	0.64
	OP	0.58	0.65	0.62	0.56	0.56
	Daily	45.20	43.52	44.59	46.93	47.70
Flow Weighted Average Speed	AM	34.60	32.88	36.40	35.52	35.51
	MID	47.27	42.74	46.17	47.51	48.98
	PM	42.27	39.74	43.17	44.51	45.98
	OP	56.64	58.72	52.63	60.18	60.33

4.4 Energy Estimates

4.4.1 Emissions from Vehicle Fuel Consumption by 2030

To translate VMT changes into an equivalent GHG emissions, standard values of conversion provided by EPA (2005) are used. A gallon of gasoline is assumed to produce 8.8 kilograms (or 19.4 pounds) of CO_2. EPA's computer model for estimating emissions for highway vehicles, MOBILE 6, estimates fleet wide fuel economy as 20.3 mpg, which is used for external trips. However, since this study uses a multi-class assignment model based on fuel economy of vehicles, emissions can be estimated using the average fuel economy of each class as well. Estimates using average fuel economy are lower (by nearly 5%) than the estimates computed using separate fuel economy values. The estimates provided here are for vehicle emissions only, and do not include lifecycle emissions such as emissions associated with the production and distribution of fuel. Table 4.8 provides these results. Laws passed recently (CLEAN Energy Act of 2007) require the nation's fleet of new vehicles to average 35 miles per gallon by the year 2020. Plug-in hybrid electric vehicles are expected to be released soon into market. These vehicles require battery re-charging after moderate use are expected to save owners 50% or more in fuel costs. Such policies and technologies are essential to reduce carbon emissions from the transportation sector.

Table 4.8: Greenhouse Gas Emissions from Transportation in 2030

	BAU	UGB	PRICING	EXPCAP	SH130
VMT (million per weekday)	94	81	90	100	103
% change as compared to BAU		-13.83	- 4.56	6.14	9.63
Carbon emissions (million lbs of CO2 per year)	95	83	91	101	98
% change as compared to BAU		-13.07	- 4.51	6.30	3.48

4.4.1 Household Energy Demand

Household energy demand was estimated applying the regression model results from Residential Energy Consumption Survey (RECS) data (Table 3.7) for each household. Based on National Center for Climatic Data (NCDC 2006) estimates, the number of Heating Degree Days (HDD) and Cooling Degree Days (CDD) values for the Austin region (relative to a base temperature of 65 degrees Fahrenheit) are 1674 and 2974. These values are assumed constant throughout the simulation period (though climate changes could increase both values, by making weather patterns more extreme. Energy consumption is forecasted to increase at a much lower rate than VMT (Table 4.6).

Table 4.9: Home Energy Demand for Year 2005 through Year 2030

	2005	2015	% change	2030	% change
No. of households	451,180	561,190	24.43	94466	109.08
UGB Scenario					
Total annual electricity demand (MWh)	6,866,971	7,798,622	13.57	11,656,095	69.74
Annual average electricity demand per household (kWh)	15,226	13,897	(8.73)	12,340	(18.96)
Total annual carbon emissions from electricity (million lbs of CO2)	10,025	11,386	8.06	17,018	69.74
Total annual natural gas demand ('000 ccf)	115,403	140,859	22.06	231,455	100.56
Annual average natural gas demand per household (ccf)	256	251	(1.87)	245	(4.20)
Total annual carbon emissions from natural gas (million lbs of CO_2)	1,384	1,690	22.10	2,434	75.90
Total annual carbon emissions from electricity and natural gas (million lbs of CO_2)	11,410	13,076	14.65	19,795	73.43
BAU Scenario					
Total annual electricity demand (MWh)	6,866,971	8,213,279	19.61	12,772,262	86.00
Annual average electricity demand per household (kWh)	15,226	14,635	(3.88)	13,521	(11.20)
Carbon emissions (million lbs of CO2)	10,026	11,991	11.43	18,648	86.00
Annual natural gas demand ('000 ccf)	115,403	142,542	23.52	238,984	107.09
Average ccf of natural gas demand per household (ccf)	256	254	(0.70)	253	(1.09)
Total annual carbon emissions (million lbs of CO_2)	1,384	1,711	24.98	2,868	107.09
Total annual carbon emissions from electricity and natural gas (million lbs of CO_2)	11,410	13,702	20.01	21,515	88.56

Overall electricity consumption is estimated to increase by 86 percent by 2030 in the BAU scenario, and just 70 percent in the UGB scenario, mainly due to the presence of more multi-family units in the UGB case, as discussed in Section 4.2. The average electricity demand is predicted to fall over time, by 11% in the BAU scenario and nearly 19% in the UGB scenario. Average natural gas demand, however, is predicted to remain very steady, from 2005 to 2030, leading to an increase of over 108 percent in overall energy demand (and associated GHG emissions). Overall, the greenhouse gas emissions from

residential sector are expected to increase 88% in BAU scenario and 73% in UGB scenario. Table 4.9 summarizes these results.

4.4.2 Firm Energy Demand

Energy demand from firms continues to rise during the simulation period. Commercial building energy demands for electricity and natural gas were estimated by applying regression model results from analysis of the 2003 Commercial Buildings Energy Consumption Survey (CBECS) data (Table 3.10) for each firm. The sizing of new buildings (in terms of square footage per employee) is assumed to grow at a constant rate of 2% every year. Average annual demand for electricity per firm is forecasted to increase by as much as 106% (in the BAU scenario), while natural gas demand per firm is predicted to increase 60%, driven mainly by the increase in firm size. Table 4.10 presents these results.

Table 4.10: Energy Demand Forecast for Firms: Year 2005 through Year 2030

Variable	2005	2015	2030
No. of firms	38,161	43,085	50,284
Annual electricity demand (MWh)	26,555,858	36,514,538	54,819,617
Annual average electricity demand (kWh)	695,890	847,500	1,090,200
Carbon emissions from electricity (million lbs of CO_2)	38,772	53,311	80,037
Annual natural gas demand	317,121,403	523,816,242	670,708,849
Annual average natural gas demand (ccf)	8,310	11,529	13,338
Carbon emissions from natural gas (million lbs of CO_2)	3,805	6,286	8,049
Annual total carbon emissions (electricity and natural gas) (million lbs of CO2)	42,577	59,597	88,086

4.5 Discussion

This chapter described the estimation of household and firm evolution, vehicle ownership, land use patterns, and related greenhouse gas emissions by 2030 under five distinctive scenarios. Of course, every simulation is different (due to the program's implicit use of different seeds for every sub-simulation), and it is important to get a sense of the simulation's own variability. Across the scenarios,

the total number of households and firms vary by less than 3% (for households) and 6% (for firms). Greater variation is seen in the case of firm counts due to their smaller overall values and the discrete nature of firm existence and location choice. Accessibility indices and count-weighted indices are reported in Table 4.11, while per capita carbon emissions are reported in Table 4.12. The region's count-weighted household density is predicted to increase by nearly 105% under the 25-yearBAU scenario, and almost triple under the UGB scenario, which seems to be dramatic to be realistic. The region's count-weighted job density value, however, increases at a lower rate (40%) than household density, with the increase remaining fairly constant across scenarios.

Table 4.11: Year 2030 Household and Job Densities

	BAU	UGB	PRICING	EXPCAP	SH130
Accessibility indices	962,045	750,365	929,141	937,912	938,026
Count weighted household density	3,608	5,460	3,072	3,525	3,565
Count weighted jobs density	14,810	15,093	14,288	16,893	14,460

* Accessibility index is calculated as $\sum_i Pop_i/(dCBD) + \sum_i Jobs_i/(dCBD)$, where Pop_i is the population is zone I, $jobs_i$ is the jobs in zone i and dCBD is the distance of zone i to CBD.

Table 4.12: Year 2030 Per Capita Carbon Emissions

	BAU	UGB	PRICING	EXPCAP	SH130
Transportation energy demand					
Daily VMT (million)	94	81	90	100	103
Daily carbon emissions (million lbs of CO2)	95	83	91	101	98
Annual carbon emissions per capita (tons)	5.51	4.82	5.28	5.86	5.69
Annual average VMT per capita	10,293	8,993	9,859	10,943	10,618
Residential energy demand					
Electricity emissions (million lbs of CO2)	18,648	17,018	18,569	18,578	18,974
Natural gas emissions (million lbs of CO2)	2,868	2,777	2,840	2,857	2,833
Annual carbon emissions per capita (tons)	4.16	3.83	4.14	4.15	4.22
Total annual carbon emissons per capita (tons)	9.68	8.65	9.42	10.01	9.91

In the BAU scenario, the model is integrated with a travel-demand model and estimates are provided without any other policy changes. This is the base scenario against which all other policy scenario results are evaluated. Per capita emissions from residential and transportation sectors sum to 9.68 tons per person per year. This is lower than the nation-wide average value of 23.4 tons in 2005 (WRI 2009), mainly because industrial and commercial energy contributions are not included here. Per capita emissions often are estimated to be the highest in southern U.S. locations (like Austin), due to higher

summer temperatures (requiring more electricity demand) and relatively low density land development practices (resulting in larger home sizes and longer travel distances.

In the UGB scenario, as mentioned earlier, development is constrained to zones with two or less job equivalents per acre, as shown in Figure 4.4(a). This resulted in higher central zone densities along with a shift to multifamily housing units (60% of households by 2030, versus 55% in the BAU, and 63% in year 2005). This also resulted in a slightly higher share of subcompact and compact cars, and a lower rate of related energy demands and greenhouse gas emissions. Overall, this scenario's per capita emissions stand at 8.65 tons per year in 2020, which is 11% lower than the BAU scenario's per captia emissions. As expected, the UGB scenario yields higher job and household densities than all other scenarios, due to the consolidating tendencies associated with such a boundary. Quite unexpectedly, however, the simple accessibility indices computed for the CBD are lowestunder this scenario.

In the PRICING scenario, gas prices are set to $6 per gallon (rather than the $3/gallon base price) and a toll of 10 cents per mile was imposed on all roads at all times. No striking changes in location patterns are observed (relative to the BAU scenario), but average vehicle ownership per household and overall VMT are predicted to be lower than those in the BAU scenario. The shares of compact and subcompact cars are also higher in this scenario, relative to the BAU scenario. Together, the tolls and taxes resulting in 4% lower per capita GHG emissions from the transportation sector under this scenario.

In the expanded capacity scenario (EXPCAP), capacity along the region's busiest and most congested freeway corridor, I-35, was doubled. I-35 runs north-south across the region and is a key transportation corridor. Doubling capacity of I-35 increases the accessibility of the neighboring zones and reduces travel times. This attracts households to zones that are closer to I-35. The share of pickups and minivans increases in this scenario, and overall VMT is higher than UGB, PRICING and BAU scenarios, but less than that of the SH130 scenario, which is expected.

The purpose of introducing SH130 is to improve mobility and relieve congestion along I-35 and other major transportation facilities within the Austin-San Antonio corridor. The location of the highway in the three-county region is highlighted in Figure 4.6(a). Similar to the EXPCAP scenario, households and firms tend to locate closer to the highway because of reduced travel times. VMT-related emissions

are highest in this scenario, as compared to BAU scenario. However, such solutions require significant infrastructure investments.

4.6 Summary

The application of the microsimulation model in Austin region provides few unexpected results with respect to future energy and travel demand. The household evolution model is built on a set of rules based on many assumptions about birth, marriage and household formation behavior. Markov transition matrices lead to a high number of large firms which results in jobs outnumbering workers slightly. Travel demand model results show an increase in VMT when capacities are increased. This might be because of lack of control on the number of people moving into central zones and use of base year estimates of location choice models. Firms have a somewhat unbelievably high preference for central zones when selecting new locations in all the scenarios, mainly due to the lack of a built-space development model for firms (and thus no constraint on new built space, even in the highly developed neighborhoods) and the use of cross-sectional data sets for location choices. Even though average greenhouse gas emissions per household are estimated to fall, the region's overall energy consumption rises (by nearly 88% in the home energy consumption and 108% in the transportation sector in the BAU scenario), which is considerably higher than the proposed US greenhouse emissions targets (which seek 19% *below* 2005 levels by 2020 and 71% *below* 2005 levels by 2050, according to the 2007 Lieberman-Warner Climate Security Act) . The average energy demand of firms, however, increases mainly due to the increase in the share of large firms. The following chapter provides conclusions as well as ideas for future research directions.

CHAPTER 5: CONCLUSIONS AND OPPORTUNITIES FOR FUTURE WORK

This study developed a microsimulation framework for estimating future land use conditions, traffic patterns and greenhouse gas (GHG) emissions based on a natural evolution of households and firms in the Austin area. Most importantly, it demonstrates that a microsimulation model of firms and households is feasible using largely existing datasets and standard desktop computing. The study provides all details for estimating future household and commercial energy consumption patterns via straightforward land development, location choice and travel behavior models, along with estimates for five distinct scenarios' results over a 25-year horizon in Austin, Texas.

Households and firms are key agents of urban growth, and systems-based modeling techniques help anticipate their long-term location and home-type choices, vehicle purchase decisions, and travel patterns, thereby facilitating analysis of a range of meaningful policies. This study develops and demonstrates a microsimulation framework for tracking all these behaviors in an attempt to predict the majority of regional GHG emissions, and thus inform climate change policy. Simulations suggest that Austin's overall energy demands continue to rise at an alarming rate, even though per-household energy consumption patterns are likely to fall (owing to a shift towards multi-family units and more congested networks). The models predict greater spatial concentration and density of households and firms than presently exist in the Austin region for both firms and households in all five scenarios, with the urban growth boundary (UGB) scenario resulting in the highest densities and central zone accessibility indices. Households and population are forecasted to grow by 109 percent and 70 percent, respectively, over the 25-year period, while jobs are estimated to rise 110 percent.

The number of (personal) vehicles jumps 143 percent over the 25-year while average vehicle ownership (per household) is simulated to increase just 19 percent in the BAU. Simulated vehicle ownership falls by 13% (as compared to the BAU scenario) when gas prices double (from $3 to $6 per gallon). Real household income is simulated to increase 4.3%, in all five scenarios, by 2030, while VMT is predicted to increase by 135% in the BAU scenario, and 100% (to 81 million) and 125% (to 90 miles) in the UGB and PRICING scenarios, respectively In general, the UGB policy appears to be more effective than the toll and gas price increase scenarios, in terms of curbing GHG emissions via both transportation and residential sectors. Interestingly, the firms' contributions to region-wide GHG emissions are relatively stable, across all five scenarios, owing to the high preference for central zones.

Though the region is predicted to densify (by about 105% in count weighted terms), home sizes fall (by about 14%), the vehicle fleet becomes more fuel efficient (by about 3%), and VMT per person increases (by roughly 9%) over the 25-year forecast period, GHG emissions from transportation and residential sectors are predicted to rise, presenting a tremendous energy security and environmental challenge. Proposed emission targets (19% below U.S. 2005 levels by 2020, and 71% by 2050 according to the 2007 Lieberman-Warner Climate Security Act) cannot be reached unless policy changes are encouraged. Carbon taxes and carbon caps are likely policies, but remain controversial and must be designed carefully (Nordhaus, 2002).

Even though microsimulation of a mid-size and growing urban region like Austin is data and computing-intensive, the urban systems model developed here provides a flexible tool for analyzing the impacts of various policy decisions along with demographic, environmental, transportation and other system changes. Most of the results are quite reasonable, and should prove useful to policy debates. This work demonstrates that such tools are within our reach, and thoughtful model design, data acquisition and parameter estimation are likely keys to their success. The following section provides some suggestions for model enhancements.

5.1 Model Limitations and Enhancements

This work pulls together a variety of detailed models and assumptions for anticipating the population, firm, land use, energy and emission patterns of a region's future. In the absence of panel data, imperfect data give rise to many simplifying and sometimes heroic assumptions. Obviously, a model can only be as good as the data that underlies it. There is always room for improvement, and the present modeling endeavor is no exception. In theory, microsimulation models require detailed panel data on households, firms, vehicles, energy consumption patterns, but few such data sets exist. Models of various transitions in the life of households and firms require panel data set, and changing travel demand and energy consumption requires information on price elasticity and future energy supply characteristics in future. Fuel economy is expected to rise by 20% in this model and power generation practices (in tons of GHG emissions per BTU) are assumed to be constant over time. Emerging power generation and vehicle technologies and efficient appliances will probably reduce future emissions to a much lower level than estimated here.

All models estimated as part of the simulation system present scope for improvement. Many simplifying assumptions, such as random sampling, Markovian transition processes, and the random allocation of locations and home sizes were used. Assumptions of asymmetric triangular distributions for income updating, use of vehicle transaction parameters based on dated data from Toronto, and always retiring a household's oldest vehicle first are too simplistic and require more research. No Austin network updates changes were introduced here (except for the major expansions explicitly given as scenarios), so the 1997 network is mostly maintained through 2030. On the firm simulation side, research is required for more robust transition rules (for firm size evolution). Also, firm relocation model and birth and death models ideally should be estimated using reliable panel data.

5.2 Computation Time

The model's computational demands also present a major challenge in this work, as in any other region level microsimulation. Tracking 45,180 households (a 10 percent sample) and more than 100,000 individuals over a span of 25 years, with detailed time-of-day and mode choice models is tedious, taking more than 3 days to run on a standard desktop machine (2GB RAM and 2.66GHz). In addition, the 1074-zone, 11,087-link travel demand model required between 6 and 12 hours for each run (every 5 years of simulation). A microsimulation model of this type requires estimating more than 200 parameters and tracking hundreds of attributes associated with each individual, household, firm and TAZ. Due to time constraints, only one run of the complete simulation was undertaken for five different scenarios. Ideally, more simulations would be run, to exploit and appreciate the variability inherent in each run's outputs, though added runs are obviously time-consuming.

5.3 Household and Firm Evolution Model

The framework developed here, relies on cross-sectional data to estimate models of location choice, birth, death and divorce, which is a major limitation. Though the model seeks to anticipate built space development in the region, it does not consider the simultaneous competition of households and firms for land space. It does not develop commercial buildings and assign them to one or more firms. Absence of a microsimulation model to track these attributes and a lack of market feedback mechanism is a clear limitation of this work. Assumption of a Markov process for firm sizes estimated from just two years of data is a potential shortcoming, which apparently resulted in higher numbers of large firms. The model's random selection of households and firms for death and birth decisions also could be enhanced, as data sets become available. Furthermore, no control totals are specified here:

population forecasting is entirely based on evolving processes – births, deaths, and out-migration and relocation models. This kind of flexibility can create clear issues (e.g.., year-2030 jobs out numbering available workers and higher-than-reasonable auto ownership levels), as observed in these Austin simulations.

The vehicle ownership models do not recognize the joint nature of vehicle holdings in a household; instead, they anticipate the class category of each new vehicle independent of a household's pre-existing vehicles. More advanced models are required to relax this assumption. In addition, models of vehicle purchase and loss decisions were estimated using dated data from Toronto households, so current and future Austinites' behaviors will differ somewhat. The framework also does not anticipate technology changes, fuel economy improvements and vehicle prices which will impact GHG emissions. Advances in energy production technologies (for example, a shift to renewable sources) which will also reduce carbon emissions more than recognized in this study.

The simulations assume a constant rate of firm birth and growth, and meaningful models for these processes will enhance the behavioral foundation of the larger model. The firms' ocation choice models can also be enhanced, with or without the use of panel data simply by allowing for more firm-specific behaviors. Of course, assuming that a fixed proportion of firms and households relocates every year is a significant simplification, and better models of relocation will be useful in understanding a region's changing land-use patterns. The migration module for households also assumes a net in-migration rate, implying that any household in the study area never leaves. In reality, the household profile of in-migrants can be quite different from that of out-migrants.

In the current study, household location choices are independent of the household's workers' job locations. In reality, many workers co-locate with their existing jobs in order to reduce commute costs. Tracking workplace locations for each household will also facilitate progress toward activity-based approaches for travel demand modeling as a microscopic level. An activity-based approach should also enable the analyst to model time of day and mode shifts at higher resolution,while refining the model's VMT and greenhouse gas estimates. Of course, such models will also increase computational burdens.

Finally, it should be mentioned that traffic assignment is undertaken only once every 5 model years, so that travel times remain unchanged in between, though location patterns, households and firms

continue to evolve in those periods. Such assumptions provide further scope for model improvement, as modelers attempt to better mimic the dynamics of land use and transport systems.

In summary, this study offers a basic framework for integrated microscopic simulation models of land use and travel demand for energy and emissions estimates. It also demonstrates how a wide variety of data sets and behavioral models can be used for estimating future greenhouse gas emissions based on household and firm demographics, vehicle ownership and use decisions, and building choices. Such tools may prove priceless for the challenging investment and policy decisions that confront our communities, at the local, regional and planetary levels.

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APPENDIX A: MATLAB® Code

The MATLAB microsimulation code shown here includes everything except for data input and logsum calculations, which were carried out every 5 years. The traffic assignment was done in TransCAD using separate GISDK code.

```
year=1;
for time=1:5

%%%%%%%%%%%% updating income part 2%%%%%%%%%%%%%%%%%%
   hhx=hh;
   personx=person;
   time
   [a,b]=size(person);
   [c,d]=size(hh);
   [m,n]=size(tazhhhu);
   hhhux=hhhu;

    [a,b]=size(person);
    [c,d]=size(hh);

   incomeup=rand(c,1);
   for i=1:c
     if incomeup(i)<=0.05
          hh(i,4)=hh(i,4)*.9;
      elseif incomeup(i)>0.05 && incomeup(i)<=0.1
          hh(i,4)=hh(i,4)*0.91;
      elseif incomeup(i)>0.1 && incomeup(i)<=0.15
          hh(i,4)=hh(i,4)*0.92;
      elseif incomeup(i)>0.15 && incomeup(i)<=0.2
          hh(i,4)=hh(i,4)*0.93;
      elseif incomeup(i)>0.2 && incomeup(i)<=0.25
          hh(i,4)=hh(i,4)*0.94;
      elseif incomeup(i)>0.25 && incomeup(i)<=0.3
          hh(i,4)=hh(i,4)*0.95;
      elseif incomeup(i)>0.3 && incomeup(i)<=0.35
          hh(i,4)=hh(i,4)*0.96;
      elseif incomeup(i)>0.35 && incomeup(i)<=0.4
          hh(i,4)=hh(i,4)*0.97;
      elseif incomeup(i)>0.4 && incomeup(i)<=0.45
          hh(i,4)=hh(i,4)*0.98;energ
      elseif incomeup(i)>0.45 && incomeup(i)<=0.5
          hh(i,4)=hh(i,4)*0.99;
      elseif incomeup(i)>0.5 && incomeup(i)<=0.55
          hh(i,4)=hh(i,4)*1.00;
      elseif incomeup(i)>0.55 && incomeup(i)<=0.6
          hh(i,4)=hh(i,4)*1.01;
      elseif incomeup(i)>0.6 && incomeup(i)<=0.65
          hh(i,4)=hh(i,4)*1.02;
      elseif incomeup(i)>0.65 && incomeup(i)<=0.7
          hh(i,4)=hh(i,4)*1.03;
      elseif incomeup(i)>0.7 && incomeup(i)<=0.75
          hh(i,4)=hh(i,4)*1.04;
      elseif incomeup(i)>0.75 && incomeup(i)<=0.8
          hh(i,4)=hh(i,4)*1.05;
      elseif incomeup(i)>0.8 && incomeup(i)<=0.85
          hh(i,4)=hh(i,4)*1.06;
      elseif incomeup(i)>0.85 && incomeup(i)<=0.9
          hh(i,4)=hh(i,4)*1.07;
      elseif incomeup(i)>0.9 && incomeup(i)<=0.95
          hh(i,4)=hh(i,4)*1.08;
```

```
    elseif incomeup(i)>0.95
        hh(i,4)=hh(i,4)*1.09;
    end
end

for i=1:c
    j=i;
    count=0;
    while j<a
        if hh(i,1)==person(j,1)
            person(j,9)=hh(i,4);
            count=count+1;
        elseif count>0
            j=a;
        end
    j=j+1;
    end
end

%End of updating income data without addition or subtraction of new workers

%Specifying income of the newadults-npart and nfull

incomepart=0;
incomefull=0;
countpart=0;
countfull=0;
for i=1:a
    if person(i,4)==1
        if person(i,35)>=18 && person(i,35)<25
            if person(i,41)==1

incomepart=incomepart+person(i,9);
                countpart=countpart+1;
            elseif person(i,42)==1

incomefull=incomefull+person(i,9);
                countfull=countfull+1;
            end
        end
    end
end
meanincpart=incomepart/countpart;
meanincfull=incomefull/countfull;

%End of specifying income of new adults-npart and nfull

%Updating person file
person(:,35)=person(:,35)+1;
if person(:,35)==5
    person(:,10)=person(:,10)-1;
    person(:,11)=person(:,11)+1;
    person(:,36)=0;
    person(:,37)=1;
elseif person(:,35)==16
    person(:,11)=person(:,11)-1;
    person(:,12)=person(:,12)+1;
    person(:,37)=0;
    person(:,38)=1;
end
npschtot=sum(hh(:,15));
npdritot=sum(hh(:,16));
ndritot=sum(hh(:,17));
nnwrktot=sum(hh(:,18));
nstudtot=sum(hh(:,19));
nparttot=sum(hh(:,20));
nfulltot=sum(hh(:,21));

nadulttot=nnwrktot+nstudtot+nparttot+nfulltot;
[a,b]=size(person);
for i=1:a
    newadult=rand;
    if person(i,35)==18
        person(i,12)=person(i,12)-1;
        person(i,38)=0;
        if newadult<=(nnwrktot/nadulttot)
            person(i,13)=person(i,13)+1;
            person(i,39)=1;
        elseif newadult>(nnwrktot/nadulttot) && newadult<=((nnwrktot+nstudtot)/nadulttot)
            person(i,14)=person(i,14)+1;
            person(i,40)=1;
```

```
        elseif
newadult>((nnwrktot+nstudtot)/nadulttot)
&&
newadult<=((nnwrktot+nstudtot+nparttot)/n
adulttot)
            person(i,15)=person(i,15)+1;
            person(i,41)=1;
        elseif
newadult>((nnwrktot+nstudtot+nparttot)/na
dulttot)
            person(i,16)=person(i,16)+1;
            person(i,42)=1;
        end
    end
  end

  for i=1:7
    if person(:,35+i)>0
      person(:,43)=i;
    end
  end

  for i=10:16
    if person(:,i)>0
      person(:,i+7)=1;
    end
  end

%End of updating person file

%HH file updating
  [c,d]=size(hh);
  for i=1:c
    j=i;
    count=0;
    while j<a
      if hh(i,1)==person(j,1)
        if sum(person(j,10:12))>0
          hh(i,5)=1;
        end
        hh(i,8:14)=person(j,17:23);
        hh(i,15:21)=person(j,10:16);
        j=j+1;
        count=count+1;
      elseif count>0
        j=a;
      end
      j=j+1;
    end
  end
%End of updating hh file
death=time


%%%%%%%%%%%%%%%%%%end      of
income updating%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%death
module%%%%%%%%%%%%%%%%%%%%
  [a,b]=size(person);
  random=rand(a,1);
  for i=1:a
    for j=1:100
      if person(i,35)==deathprob(j,1)
        %male=person(34)
        if person(i,34)==1
          if person(i,4)==1
            if random(i)<=deathprob(j,2)
              random(i)=-999;
            end
          else
            if random(i)<=deathprob(j,2)
              random(i)=999;
            end
          end
        else
          if person(i,4)==1
            if random(i)<=deathprob(j,3)
              random(i)=-999;
            end
          else
            if random(i)<=deathprob(j,3)
              random(i)=999;
            end
          end
        end
      end
    end
```

```
   end

%person(36,37,38,39,40,41,42)=presch,pred
ri,driving,nonwk,stud,part,full
   for i=1:a
      x=person(i,4);
      if random(i)==999
         if i<=24 %24 is max hhsize
            for k=1:i+x
               if person(i,1)==person(k,1)
                  %updating hhsize
                  person(k,4)=person(k,4)-1;
                  %end of updating hhsize

                  %updating income
                  if person(i,42)==1
                     person(k,9)=person(k,9)-
(person(k,9)/(person(k,16)+(person(k,15)*0.
5))*0.75);
                  end
                  if person(i,41)==1
                     person(k,9)=person(k,9)-
(person(k,9)/(person(k,15)+(2*person(k,16))
)*0.75);
                  end
                  %end of income update

                  %updating
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull
                  for j=36:42
                     if person(i,j)==1
                        person(k,j-
26)=person(k,j-26)-1;%npresch etc.
                        if person(k,j-
26)>0%ppresch etc.
                           person(k,j-19)=1;
                        else
                           person(k,j-19)=0;
                        end
                     end
                  end
                  %end of
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull update
               end
            end
         elseif i<=a-24
            for k=i-x:i+x
               if person(i,1)==person(k,1)
                  %updating hhsize
                  person(k,4)=person(k,4)-1;
                  %end of updating hhsize

                  %updating income
                  if person(i,42)==1
                     if
(person(k,16)+(person(k,15)*0.5))*0.75>0

person(k,9)=person(k,9)-
(person(k,9)/(person(k,16)+(person(k,15)*0.
5))*0.75);
                     else

person(k,9)=person(k,9);
                     end
                  end
                  if person(i,41)==1
                     if
(person(k,15)+(2*person(k,16)))*0.75>0

person(k,9)=person(k,9)-
(person(k,9)/(person(k,15)+(2*person(k,16))
)*0.75);
                     else

person(k,9)=person(k,9);
                     end
                  end
                  %end of income update

                  %updating
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull
                  for j=36:42
                     if person(i,j)==1
```

```
                    person(k,j-
26)=person(k,j-26)-1;%npresch etc.
                    if          person(k,j-
26)>0%ppresch etc.
                        person(k,j-19)=1;
                    else
                        person(k,j-19)=0;
                    end
                end
            end
            %end                    of
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull update
        end
    end
elseif i>a-24
    for k=i-x:a
        if person(i,1)==person(k,1)
            %updating hhsize
            person(k,4)=person(k,4)-1;
            %end of updating hhsize

            %updating income
            if person(i,42)==1
                if
(person(k,16)+(person(k,15)*0.5))*0.75>0

person(k,9)=person(k,9)-
(person(k,9)/(person(k,16)+(person(k,15)*0.
5))*0.75);
                else

person(k,9)=person(k,9);
                end
            end
            if person(i,41)==1
                if
(person(k,15)+(2*person(k,16)))*0.75>0

person(k,9)=person(k,9)-
(person(k,9)/(person(k,15)+(2*person(k,16))
)*0.75);
                else
person(k,9)=person(k,9);
                end
            end
            %end of income update

            %updating
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull
            for j=36:42
                if person(i,j)==1
                    person(k,j-
26)=person(k,j-26)-1;%npresch etc.
                    if          person(k,j-
26)>0%ppresch etc.
                        person(k,j-19)=1;
                    else
                        person(k,j-19)=0;
                    end
                end
            end
            %end                    of
n/ppresch,n/ppredri,n/pdriv,n/ponwk,n/pstud
,n/ppart,n/pfull update
        end
    end
  end
end

%Deleting dying people
i=1;
count=0;
while i<=a
    if random(i)==-999 || random(i)==999
        person(i-count,:)=[];
        count=count+1;
    else
        person(i-count,:)=person(i-count,:);
    end
    i=i+1;
end
%End of deleting dying people
clear random;
```

```
%Household file updating at the end of death module
   [a,b]=size(person);
   [c,d]=size(hh);
   hhdeathflag=zeros(c,1);
   for i=1:c
    j=1;
      count=1;
      while j<a
         if hh(i,1)==person(j,1)
            hh(i,3)=person(j,4);%hhsize
            hh(i,4)=person(j,9);%income
            if person(j,17)==1 || person(j,18)==1 || person(j,19)==1 %preskids
               hh(i,5)=1;
            else
               hh(i,5)=0;
            end
            for k=17:23 %ppresch etc.
               if person(j,k)==1
                  hh(i,k-9)=1;
               else
                  hh(i,k-9)=0;
               end
            end
            for k=10:16
               hh(i,k+5)=person(j,k);
%npresch etc.
            end
            j=a;
         else
            j=j+1;
            count=count+1;
         end
      end
      if count==a;
         hhdeathflag(i)=999;
      end
   end
[y,z]=size(hhhu);
[c,d]=size(hh);
   %Deleting dying households
   i=1;
   count=0;
   while i<=c
      if hhdeathflag(i)==999
         if hh(i-count,40)==1
            tazhhhu(hh(i-count,2),57)= tazhhhu(hh(i-count,2),57)+1;
            hhhu(y+count+1,1)=hh(i-count,2);
            hhhu(y+count+1,2)=1;
            hhhu(y+count+1,3)=0;
            hhhu(y+count+1,4)=0;
            hhhu(y+count+1,7)=1;
            hhhu(y+count+1,6)=hh(i-count,43);
            hhhu(y+count+1,5)=hh(i-count,59);
         elseif hh(i-count,41)==1
            tazhhhu(hh(i-count,2),58)= tazhhhu(hh(i-count,2),58)+1;
            hhhu(y+count+1,1)=hh(i-count,2);
            hhhu(y+count+1,2)=0;
            hhhu(y+count+1,3)=1;
            hhhu(y+count+1,4)=0;
            hhhu(y+count+1,7)=2;
            hhhu(y+count+1,6)=hh(i-count,43);
            hhhu(y+count+1,5)=hh(i-count,59);
         elseif hh(i-count,42)==1
            tazhhhu(hh(i-count,2),59)= tazhhhu(hh(i-count,2),59)+1;
            hhhu(y+count+1,1)=hh(i-count,2);
            hhhu(y+count+1,2)=0;
            hhhu(y+count+1,3)=0;
            hhhu(y+count+1,4)=1;
            hhhu(y+count+1,7)=3;
            hhhu(y+count+1,6)=hh(i-count,43);
            hhhu(y+count+1,5)=hh(i-count,59);
         end

         hh(i-count,:)=[];
         count=count+1;
      else
```

```
        hh(i-count,:)=hh(i-count,:);
      end
      i=i+1;
   end
   %End of deleting dying households
%End of household file updating after death
module
clear hhdeathfalg;
check=xlswrite('check.xls',1);
birth=year

%%%%%%%%%%%%%%%%%%end of
death module
%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%birth
module
%%%%%%%%%%%%%%%%%%%%%%

%BIRTH MODULE
%Individual file updating
   person_birth=person;
   [a,b]=size(person_birth);
   birth=zeros(a,8);
   i=1;
   while i<a
      if person_birth(i,34)==1
         i=i+1;
      else
         if person_birth(i,35)>=18
            birth(i,1)=person_birth(i,1);%hhid
            birth(i,2)=person_birth(i,35);%age
of mother

birth(i,3)=sum(person_birth(i,10:12));%no.
of children
            if i<25%age of youngest child
               x=100;
               hhsize=person(:,4);
               for j=1:i+hhsize(i)
                  if
birth(i,1)==person_birth(j,1)
                     if birth(i,3)>0

birth(i,4)=min(x,person_birth(j,35));
                     else
                        birth(i,4)=0;
                     end
                     x=birth(i,4);
                  end
               end
            elseif i>=25 && i<a-24
               x=100;
               for j=i-hhsize(i):i+hhsize(i)
                  if
birth(i,1)==person_birth(j,1)
                     if birth(i,3)>0

birth(i,4)=min(x,person_birth(j,35));
                     else
                        birth(i,4)=0;
                     end
                     x=birth(i,4);
                  end
               end
            elseif i>=a-24
               x=100;
               for j=i-hhsize(i):a
                  if
birth(i,1)==person_birth(j,1)
                     if birth(i,3)>0

birth(i,4)=min(x,person_birth(j,35));
                     else
                        birth(i,4)=0;
                     end
                     x=birth(i,4);
                  end
               end
            end
            if      person_birth(i,22)==1      ||
person_birth(i,23)==1%employment status
               birth(i,5)=1;
            else
               birth(i,5)=0;
            end

            %Birth model
```

```
            birth(i,6)=exp(0.591-
0.1098*birth(i,2)+1.893*birth(i,3)-
1.618*birth(i,4)+0.666*birth(i,5));
            birth(i,7)=birth(i,6)/(1+birth(i,6));
            %End of birth model

         end
         i=i+1;
      end
   end
%End of individual file updating

%Births and characteristics attributing
   for i=1:a
      if birth(i,1)>0
         if birth(i,7)>rand
            birth(i,8)=999;
         end
      end
      i=i+1;
   end
   count=1;
   i=1;
   while i<a
      if birth(i,8)==999
         person_birth(a+count,1)=birth(i,1);

person_birth(a+count,2:3)=person_birth(i,2:
3);

person_birth(a+count,4)=person_birth(i,4)+
1;

person_birth(a+count,5:9)=person_birth(i,5:
9);

person_birth(a+count,10)=person_birth(i,10
)+1;

person_birth(a+count,11:16)=person_birth(i,
11:16);
         person_birth(a+count,17)=1;

person_birth(a+count,18:29)=person_birth(i,
18:29);

person_birth(a+count,30)=person_birth(a+c
ount,4);

person_birth(a+count,31)=person_birth(a+c
ount,1)*100+person_birth(a+count,30);

person_birth(a+count,32)=person_birth(i,32
);

person_birth(a+count,33)=person_birth(a+c
ount,32)*100+person_birth(a+count,30);
         male=rand;
         if male<=0.5
            person_birth(a+count,34)=1;
         else
            person_birth(a+count,34)=0;
         end
         person_birth(a+count,35)=1;

person_birth(a+count,36:42)=person_birth(i,
36:42);
         person_birth(a+count,43)=1;
         count=count+1;
      end
      i=i+1;
   end
%End of births and characteristics
attributing

%Adding new borns to the original person
file
   [y,z]=size(person);
   [u,v]=size(person_birth);
   born=u-a;
   for i=1:born
      person(y+i,:)=person_birth(a+i,:);
   end
%End of adding new borns to the original
person file
```

```
%HH file updating
   [a,b]=size(person);
   [c,d]=size(hh);
   for i=(a-born+1):a
      for j=1:c
         if person(i,1)==hh(j,1)
            hh(j,3)=hh(j,3)+1;
            hh(j,5)=1;
            hh(j,8)=1;
            hh(j,15)=hh(j,15)+1;
         end
      end
   end
%End of HH file updating

%%%%%%%%%%%%%%%%end of   birth
module%%%%%%%%%%%%%%%%%%%%
clear person_birth,birth;

%%%%%%%%%%%%%%%%%%%%%%
migration
module%%%%%%%%%%%%%%%%
[a,b]=size(person);
[c,d]=size(hh);
   migrate=(1.127/100);
   migr=rand(c,1);
   for i=1:1074
      houseval(i,3)=rand;
   end
   count=0;
   for i=1:c
      if migr(i)<=migrate
         hh(c+count+1,:)=hh(i,:);
         count=count+1;
      end
   end
   match=0;
   %Updating individuals file
   newper=0;
   for i=1:count
      hhmatch=0;
      for j=1:a
         if hh(c+i,1)==person(j,1)
person(a+newper+hhmatch+1,:)=person(j,:);
            hhmatch=hhmatch+1;
         end
      end
      newper=newper+hhmatch;
   end
%End of updating individuals file
id=hh(:,1);
%Updating unique identifiers for households
and individuals
   for i=c+1:c+count
      id(i,1)=max(id(1:i-1,1))+1;
       hh(i,58)=1;
   end
   for j=a+1:a+newper
      for i=c+1:c+count
      if person(j,1)==hh(i,1)
         person(j,1)=id(i,1);
      end
      end
   end

   hh(:,1)=id(:,1);
%End of updating unique identifiers for
households and individuals

%Updating sen and hhperno
   person(:,30)=1;
   for i=1:a+newper
      j=i+1;
      countn=1;
      while j<a+newper
         if person(i,1)==person(j,1)
            countn=countn+1;
            person(j,30)=countn;
            j=j+1;
         else
            j=a+newper;
         end
      end
   end

person(:,31)=person(i,1)*100+person(:,30);
```

```
%End of updating sen and hhperno

%%%%%%%%%%%%%%%%%%migration
%%%%%%%%%%%%%%%%%%%%%%%%
%

%%%%%%%%%%%%%%%%%%divorce
module%%%%%%%%%%%%%%%%%%
divorce=time
 [a,b]=size(person);
   [c,d]=size(hh);
   hhdummy=zeros(c,3);
% identifying people working, non working
adult households in households
% with size greater than 1.
   for i=1:c
      if hh(i,3)>1
         if sum(hh(i,18:21))>1
            hhdummy(i,1)=1;
         end
      end
   end

   person(:,b+1)=0;
   hh(:,d+1)=0;
% taking persons in the above identified
households and putting a dumy
% there and creating new dummy in hh
matrix with people eligible for
% divorce
   for i=1:c
      if hhdummy(i,1)==1
         j=i;
         while j<a
            if hh(i,1)<person(j,1)
               j=j+1;
            else if hh(i,1)==person(j,1)
                  if   person(j,35)>=18   &&
person(j+1,35)>=18
                     person(j:j+1,b+1)=1;
                     hh(i,d+1)=1;

hhdummy(i,2)=person(j,35);
                  end
                  j=a;
                  else if hh(i,1)>person(j,1)
                  j=a;
                     end
                  end
               end
            end
         end
      end

   count=0;
   for i=1:c
      if hh(i,d+1)==1
         util=exp(-1.437-0.281*hh(i,3)-
0.028*hhdummy(i,2));
         hhdummy(i,3)=util/(1+util);
         if rand<=hhdummy(i,3)
            hhdummy(i,1)=999;
         end
         if hhdummy(i,1)==999
            count=count+1;
            hh(c+count,1)=hh(c+count-
1,1)+1;
            hh(c+count,3)=1;
            hh(i,3)=hh(i,3)-1;
            hh(i,4)=hh(i,4)/2;
            hh(c+count,4)=hh(i,4);
            hh(c+count,5)=0;
            hhdummy(c+count,1)=0;
            if hh(i,3)>2
               j=i;
               while j<a
                  if hh(i,1)==person(j,1)
                     for k=j+2:j+hh(i,3)
                        if rand<=0.5

person(k,1)=hh(c+count,1);

hh(c+count,3)=hh(c+count,3)+1;
                           hh(i,3)=hh(i,3)-1;
                        end
                     end
                     j=a;
                  else
```

```
                j=j+1;
              end
            end
          end
        end
      end
    end
%End of divorce module

    hh(:,d+1)=[];
    person(:,b+1)=[];

    for i=c+1:c+count
     hh(i,58)=1;  %  indicator  for  new
household formed
    end

     % apply location choice model here for
divorced households
    for i=c+1:c+count
     hh(i,58)=1;  %  indicator  for  new
household formed
    end
% end of location choice model for divorced
households

%Updating person and household files after
divorce
    for i=1:c+count
      if hhdummy(i,1)==999 || i>c
        hh(i,5)=0;
        hh(i,8:21)=0;
        count1=0;
        for j=1:a
          if hh(i,1)==person(j,1)
            person(j,2)=hh(i,2);
            person(j,24:27)=hh(i,25:28);
            count1=count1+1;
            if        person(j,43)==1        ||
person(j,43)==2 || person(j,43)==3
              hh(i,5)=1;
            end
            for m=1:7
              if person(j,43)==m
                hh(j,7+m)=1;
                hh(j,14+m)=hh(j,14+m)+1;
              end
            end
            if hh(i,6)==1
              if rand<=0.5
                hh(i,6)=1;
                hh(c+count1,6)=0;
                hh(c+count1,7)=1;
              else
                hh(i,6)=0;
                hh(i,7)=1;
                hh(c+count1,6)=1;

hh(c+count1,48:55)=hh(i,48:55);
                hh(i,48:55)=0;
              end
            elseif hh(i,6)==2
              hh(i,6)=1;
              hh(c+count1,6)=hh(i,6);
              hh(i,7)=0;
              hh(c+count1,48)=hh(i,49);
              hh(i,49)=0;
              hh(c+count1,51)=hh(i,52);
              hh(i,52)=0;

              hh(i,56)=max(hh(i,52:55));
              if hh(i,56)==hh(i,52)
                hh(i,57)=1;
              elseif hh(i,56)==hh(i,53)
                hh(i,55)=2;
              elseif hh(i,56)==hh(i,54)
                hh(i,57)=3;
              elseif hh(i,56)==hh(i,55)
                hh(i,57)=4;
              end


hh(c+count1,56)=max(hh(c+count1,52:55));
              if
hh(c+count1,56)==hh(c+count1,52)
                hh(c+count1,57)=1;
              elseif
hh(c+count1,56)==hh(c+count1,53)
```

```
                hh(c+count1,57)=2;
            elseif
hh(c+count1,56)==hh(c+count1,54)
                hh(c+count1,57)=3;
            elseif
hh(c+count1,56)==hh(c+count1,55)
                hh(c+count1,57)=4;
            end

        elseif hh(i,6)==3
            if rand<=0.5 % firs house
gets 2 vehicles second gets three vehicles

                hh(i,6)=round(hh(i,6)/2);

hh(c+count1,6)=floor(hh(i,6)/2);
                hh(c+count1,48)=hh(i,50);
                hh(i,50)=0;
                hh(c+count,52)=hh(i,54);
                hh(i,53)=0;

            hh(i,56)=max(hh(i,52:55));
            if hh(i,56)==hh(i,52)
                hh(i,57)=1;
            elseif hh(i,56)==hh(i,53)
                hh(i,57)=2;
            elseif hh(i,56)==hh(i,54)
                hh(i,57)=3;
            elseif hh(i,56)==hh(i,55)
                hh(i,57)=4;
            end

hh(c+count1,56)=max(hh(c+count1,52:55));
            if
hh(c+count1,56)==hh(c+count1,52)
                hh(c+count1,57)=1;
            elseif
hh(c+count1,56)==hh(c+count1,53)
                hh(c+count1,57)=2;
            elseif
hh(c+count1,56)==hh(c+count1,54)
                hh(c+count1,57)=3;
            elseif
hh(c+count1,56)==hh(c+count1,55)
                hh(c+count1,57)=4;
            end

            else

hh(c+count1,6)=round(hh(i,6)/2);
                hh(i,6)=floor(hh(i,6)/2);

hh(c+count,48:49)=hh(i,49:50);
                hh(i,49:50)=0;

hh(c+count,52:53)=hh(i,53:54);
                hh(i,53:54)=0;

            hh(i,56)=max(hh(i,52:55));
            if hh(i,56)==hh(i,52)
                hh(i,57)=1;
            elseif hh(i,56)==hh(i,53)
                hh(i,57)=2;
            elseif hh(i,56)==hh(i,54)
                hh(i,57)=3;
            elseif hh(i,56)==hh(i,55)
                hh(i,57)=4;
            end

hh(c+count1,56)=max(hh(c+count1,52:55));
            if
hh(c+count1,56)==hh(c+count1,52)
                hh(c+count1,57)=1;
            elseif
hh(c+count1,56)==hh(c+count1,53)
                hh(c+count1,57)=2;
            elseif
hh(c+count1,56)==hh(c+count1,54)
                hh(c+count1,57)=3;
            elseif
hh(c+count1,56)==hh(c+count1,55)
                hh(c+count1,57)=4;
            end
            end
```

```
            elseif hh(i,6)==4

                hh(c+count1,6)=(hh(i,6)/2);
                  hh(i,6)=(hh(i,6)/2);

hh(c+count,48:49)=hh(i,50:51);
                  hh(i,49:50)=0;

hh(c+count,52:53)=hh(i,54:55);
                  hh(i,54:55)=0;


                hh(i,56)=max(hh(i,52:55));
                if hh(i,56)==hh(i,52)
                  hh(i,57)=1;
                elseif hh(i,56)==hh(i,53)
                  hh(i,57)=2;
                elseif hh(i,56)==hh(i,54)
                  hh(i,57)=3;
                elseif hh(i,56)==hh(i,55)
                  hh(i,57)=4;
                end


hh(c+count1,56)=max(hh(c+count1,52:55));
                if
hh(c+count1,56)==hh(c+count1,52)
                  hh(c+count1,57)=1;
                elseif
hh(c+count1,56)==hh(c+count1,53)
                  hh(c+count1,57)=2;
                elseif
hh(c+count1,56)==hh(c+count1,54)
                  hh(c+count1,57)=3;
                elseif
hh(c+count1,56)==hh(c+count1,55)
                  hh(c+count1,57)=4;
                end

            elseif hh(i,6)==0
                hh(i,6)=0;
                hh(c+count1,6)=0;
                hh(c+count1,48:57)=0;
                hh(i,7)=1;
                hh(c+count1,7)=1;
              end
              person(j,4)=hh(i,3);
              person(j,6)=hh(i,6);
              if person(j,6)>person(j,4)
                person(j,7)=person(j,6)-
person(j,4);
              else
              person(j,7)=0;
              end
              if person(j,6)<person(j,4)
                person(j,8)=person(j,6)-
person(j,4);
              else
                person(j,8)=0;
              end
              person(j,9)=hh(i,4);
              person(j,10:16)=hh(i,15:21);
              person(j,17:23)=hh(i,8:14);
            end
          end
        end
    end
%End of updating person and household
files after divorce

    [a,b]=size(person);
    [c,d]=size(hh);

    sortrows(hh,1);
    sortrows(person,[1,-35]);

%Updating sen and hhperno
    i=1;
    while i<a
      j=i+1;
      count=1;
      while j<a
        if person(i,1)==person(j,1)
          count=count+1;
          person(i,30)=1;
          person(j,30)=count;
          j=j+1;
        else
```

```
            j=a;
         end
      end
      i=i+count;
   end

person(:,31)=person(:,1)*100+person(:,30);

person(:,33)=person(:,32)*100+person(:,30);
%End of updating sen and hhperno
%%%%%%%%%%%%%%%end of
divorce%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%marriage
module%%%%%%%%%%%%%%

   perdummy=zeros(a,6);
   for i=1:a
      if person(i,4)==1 && person(i,43)>=4
         if person(i,34)==1
            perdummy(i,1)=1;
         else
            perdummy(i,2)=1;
         end
         perdummy(i,3)=person(i,35);
      elseif person(i,4)>1 &&
person(i,43)>=4
         if i<=24
            for j=1:i+person(i,4)
               if person(i,1)==person(j,1) &&
i~=j
                  if person(i,35)>=18 &&
abs(person(i,34)-person(j,34))==1
                     flag=-999;
                  end
               end
            end
         elseif i>24 && i<a-24
            for j=i-person(i,4):i+person(i,4)
               if person(i,1)==person(j,1) &&
i~=j
                  if person(i,35)>=18 &&
abs(person(i,34)-person(j,34))==1
                     flag=-999;
                  end
               end
            end
         elseif i>=a-24
            for j=i-person(i,4):a
               if person(i,1)==person(j,1) &&
i~=j
                  if person(i,35)>=18 &&
abs(person(i,34)-person(j,34))==1
                     flag=-999;
                  end
               end
            end
         end
         if flag~=-999
            if person(i,34)==1
               perdummy(i,1)=2;
            else
               perdummy(i,2)=2;
            end
         end
         perdummy(i,3)=person(i,35);
      end
   end
   for i=1:a
      if sum(perdummy(i,1:2))>0
         util=exp(-1.869+0.129*person(i,4)-
0.032*perdummy(i,3)+0.025*sum(person(i,
41:42)));
         perdummy(i,4)=util/(1+util);
         x=rand;
         if x <=perdummy(i,4)
            perdummy(i,4)=999;
         end
      end
   end

%Identifying couples for marraige
   count=0;
   for i=1:a
      if perdummy(i,5)==0
         if perdummy(i,4)==999
            if perdummy(i,1)>0
               j=1;
               while j<a
```

```
                if perdummy(i,4)==0
                   if perdummy(j,4)==999
                      if perdummy(j,2)>0
                         if abs(perdummy(j,3)-
perdummy(i,3))<=3%age difference 3 years
                            count=count+1;

perdummy(i,5)==count;

perdummy(j,5)==count;

perdummy(i,6)=person(i,1);

perdummy(j,6)=person(j,1);
                            j=a;
                         end
                      end
                   end
                end
                j=j+1;
             end
             if count==0
                j=1;
                while j<a
                   if perdummy(i,4)==0
                      if perdummy(j,4)==999
                         if perdummy(j,2)>0
                            if
abs(perdummy(j,3)-
perdummy(i,3))<=5%age difference 5 years
                               count=count+1;

perdummy(i,5)==count;

perdummy(j,5)==count;

perdummy(i,6)=person(i,1);

perdummy(j,6)=person(j,1);
                               j=a;
                            end
                         end
                      end
                   end
                   j=j+1;
                end
             end
             if count==0
                j=1;
                while j<a
                   if perdummy(i,4)==0
                      if perdummy(j,4)==999
                         if perdummy(j,2)>0
                            if
abs(perdummy(j,3)-
perdummy(i,3))<=10%age    difference    10
years
                               count=count+1;

perdummy(i,5)==count;

perdummy(j,5)==count;

perdummy(i,6)=person(i,1);

perdummy(j,6)=person(j,1);

person(j,28:29)=person(i,28:29);
                               j=a;
                            end
                         end
                      end
                   end
                   j=j+1;
                end
             end
          end
       end
    end
%end of identifying couples for marraiges

%making new households out of marraige
%updating household file
% long time loop didnt look into wats going
on here
if count >0
   for i=1:a
```

```
j=1;
while j<a
   if perdummy(i,6)==perdummy(j,6)
      k=1;
      while k<c
         if person(i,1)==hh(k,1)
            m=k;
            k=c;
         else
            k=k+1;
         end
      end
      l=1;
      while l<c
         if person(j,1)==hh(l,1)
            n=l;
            l=c;
         else
            l=l+1;
         end
      end
      k=m;
      l=n;

      hh(k,3:4)=hh(k,3:4)+hh(l,3:4);
      if hh(k,5)==0 && hh(l,5)==0
         hh(k,5)=0;
      else
         hh(k,5)=1;
      end

      car1=hh(k,6);
      car2=hh(l,6);
      hh(k,6)=car1+car2;
      hh(k,48+car1:51)=hh(l,48:51-
car1);
      hh(k,52+car1:55)=hh(l,52:55-
car1);

       hh(k,56)=max(hh(k,52:55));
            if hh(k,56)==hh(k,52)
               hh(k,57)=1;
            elseif hh(k,56)==hh(k,53)
               hh(k,57)=2;
            elseif hh(k,56)==hh(k,54)
               hh(k,57)=3;
            elseif hh(k,56)==hh(k,55)
               hh(k,57)=4;
            end

      hh(k,6)=hh(k,6)+hh(l,6);
      if hh(k,7)==1 && hh(l,7)==1;
         hh(k,7)==1;
      else
         hh(k,7)=0;
      end

      if      sum(hh(k,8:14))==0      &&
sum(hh(l,8:14))==0
         hh(k,8:14)=0;
      else
         hh(k,8:14)=1;
      end

hh(k,15:21)=hh(k,15:21)+hh(l,15:21);
      hh(l,1)=-999;
      j=a;
   else
      j=j+1;
   end
end
end
i=1;
while i<c
   if hh(i,1)==-999
      if hh(i,40)==1
         tazhhhu(hh(i,2),57)=
tazhhhu(hh(i,2),57)+1;
      elseif hh(i,41)==1
         tazhhhu(hh(i,2),58)=
tazhhhu(hh(i,2),58)+1;
      elseif hh(i,42)==1
         tazhhhu(hh(i,2),59)=
tazhhhu(hh(i,2),59)+1;
      end
       hh(i,:)=[];
   else
      i=i+1;
```

```
        end
    end

%End of updating household file

%Updating person file
    for i=1:a
        tempcount=0;
        j=1;
        while j<c
            if perdummy(i,6)==hh(j,1)
                tempcount=tempcount+1;
                person(i,2)=hh(j,2);
                person(i,4)=hh(j,3);
                person(i,6)=hh(j,6);
                if person(i,6)>person(i,4)
                    person(i,7)=person(i,6)-
person(i,4);
                else
                    person(i,7)=0;
                end
                if person(i,6)<person(i,4)
                    person(i,8)=person(i,6)-
person(i,4);
                else
                    person(i,8)=0;
                end
                person(i,9)=hh(j,4);
                person(i,10:16)=hh(j,15:21);
                person(i,17:23)=hh(j,8:14);
                person(i,24:27)=hh(j,25:28);
            elseif tempcount>0
                j=c;
            end
            j=j+1;
        end
    end
%End of updating person file

    [a,b]=size(person);
    [c,d]=size(hh);

    sortrows(hh,1);
    sortrows(person,[1,-35]);

%Updating sen and hhperno
    i=1;
    while i<a
        j=i+1;
        count=1;
        while j<a
            if person(i,1)==person(j,1)
                count=count+1;
                person(i,30)=1;
                person(j,30)=count;
                j=j+1;
            else
                j=a;
            end
        end
        i=i+count;
    end

person(:,31)=person(:,1)*100+person(:,30);

person(:,33)=person(:,32)*100+person(:,30);

end
%End of updating sen and hhperno
%End of making new households from
marraige
 %%%%%%%%%%%%%%%%%%%End of
marriage module%%%%%%%%

[a,b]=size(person);
[c,d]=size(hh);
%%%%%%%%%%%%%%Moving out
module%%%%%%%%%%%%%%%%%
%Household size and income distribution
calculation
    hhsize1=0;
    inc1=0;
    hhsize2=0;
    inc2=0;
    hhsize3=0;
    inc3=0;
    hhsize4=0;
    inc4=0;
```

```
hhsize5=0;
inc5=0;
hhsize6=0;
inc6=0;
hhsize7=0;
inc7=0;
hhsize8=0;
inc8=0;
for i=1:c
   if hh(i,3)==1
      hhsize1=hhsize1+1;
      inc1=inc1+hh(i,4);
   else if hh(i,3)==2
      hhsize2=hhsize2+1;
      inc2=inc2+hh(i,4);
      else if hh(i,3)==3
      hhsize3=hhsize3+1;
      inc3=inc3+hh(i,4);
         else if hh(i,3)==4
      hhsize4=hhsize4+1;
      inc4=inc4+hh(i,4);
            else if hh(i,3)==5
      hhsize5=hhsize5+1;
      inc5=inc5+hh(i,4);
               else if hh(i,3)==6
      hhsize6=hhsize6+1;
      inc6=inc6+hh(i,4);
                  else if hh(i,3)==7
      hhsize7=hhsize7+1;
      inc7=inc7+hh(i,4);
                     else if hh(i,3)>=8
      hhisze8=hhsize8+1;
      inc8=inc8+hh(i,4);

                        end
                     end
                  end
               end
            end
         end
      end
   end
end
   avinc1=inc1/hhsize1;
   avinc2=inc2/hhsize2;
   avinc3=inc3/hhsize3;
   avinc4=inc4/hhsize4;
   avinc5=inc5/hhsize5;
   avinc6=inc6/hhsize6;
   avinc7=inc7/hhsize7;
   if hhsize8==0
      avinc8=avinc7;
   else
      avinc8=inc8/hhsize8;
   end
%End of household size and inco
%%%%%%%%%%%%%%%%%%%%%%%%movi
ng out module%%%%%%%%%%%%
movingout=time
%Working with person file
temp=zeros(a,1);
   count=0;
   for i=1:a
      if i<=24
         if          person(i,4)>1          &&
sum(person(i,13:16))>2
            if person(i,35)==18
               temp(i)=1;
               count=count+1;
               x=person(i,4);
               for j=1:i+x;
                  if person(i,1)==person(j,1)
                     person(j,4)=person(j,4)-1;

autoratio=person(j,6)/(sum(person(j,12:16)))
;
                     if autoratio>0.5
                        person(j,6)=person(j,6)-
1;
                        person(i,6)=1;
                     else
                        person(j,6)=person(j,6);
                        person(i,6)=0;
                     end
                  end
               end
               person(i,44)=person(i,1);
```

```
            person(i,1)=person(a,1)+count;
            person(i,7)=0;
            if person(i,6)==1
               person(i,8)=0;
            else
               person(i,8)=-1;
            end
            person(i,9)=avinc1;
            person(i,10:12)=0;
            person(i,13:16)=0;
            y=rand;
            if y<=nnwrktot/nadulttot
               person(i,13)=1;
            elseif y>nnwrktot/nadulttot &&
y<=(nnwrktot+nstudtot)/nadulttot
               person(i,14)=1;
            elseif
y>(nnwrktot+nstudtot)/nadulttot &&
y<=(nnwrktot+nstudtot+nparttot)/nadulttot
               person(i,15)=1;
            elseif
y>(nnwrktot+nstudtot+nparttot)/nadulttot
               person(i,16)=1;
            end
            person(i,17:19)=0;
            for k=20:23
               if person(i,k-7)==1
                  person(i,k)=1;
               else
                  person(i,k)=0;
               end
            end
            person(i,30)=1;

person(i,31)=person(i,1)*100+person(i,30);

person(i,33)=person(i,32)*100+1;

person(i,36:42)=person(i,17:23);
            for k=1:7
               if person(i,35+k)==1
                  person(i,43)=k;
               end
            end
         end
      end
   elseif i>24 && i<a-24
      if person(i,4)>1 &&
sum(person(i,13:16))>2
         if person(i,35)==18
            temp(i)=1;
            count=count+1;
            x=person(i,4);
            for j=i-x:i+x;
               if person(i,1)==person(j,1)
                  person(j,4)=person(j,4)-1;
                  if sum(person(j,12:16))==0
                     autoratio=0;
                  else

autoratio=person(j,6)/(sum(person(j,12:16)))
;
                  end
                  if autoratio>0.5
                     person(j,6)=person(j,6)-
1;
                     person(i,6)=1;
                  else
                     person(j,6)=person(j,6);
                     person(i,6)=0;
                  end
               end
            end
            person(i,44)=person(i,1);
            person(i,1)=person(a,1)+count;
            person(i,7)=0;
            if person(i,6)==1
               person(i,8)=0;
            else
               person(i,8)=-1;
            end
            person(i,9)=avinc1;
            person(i,10:12)=0;
            person(i,13:16)=0;
            y=rand;
            if y<=nnwrktot/nadulttot
               person(i,13)=1;
```

```
            elseif y>nnwrktot/nadulttot &&
y<=(nnwrktot+nstudtot)/nadulttot
                person(i,14)=1;
            elseif
y>(nnwrktot+nstudtot)/nadulttot          &&
y<=(nnwrktot+nstudtot+nparttot)/nadulttot
                person(i,15)=1;
            elseif
y>(nnwrktot+nstudtot+nparttot)/nadulttot
                person(i,16)=1;
            end
            person(i,17:19)=0;
            for k=20:23
                if person(i,k-7)==1
                    person(i,k)=1;
                else
                    person(i,k)=0;
                end
            end
            person(i,30)=1;

person(i,31)=person(i,1)*100+person(i,30);

person(i,33)=person(i,32)*100+1;

person(i,36:42)=person(i,17:23);
            for k=1:7
                if person(i,35+k)==1
                    person(i,43)=k;
                end
            end
        end
    end
  elseif i>=a-24
    if          person(i,4)>1          &&
sum(person(i,13:16))>2
        if person(i,35)==18
            temp(i)=1;
            count=count+1;
            x=person(i,4);
            for j=i-x:a;
                if person(i,1)==person(j,1)
                    person(j,4)=person(j,4)-1;
autoratio=person(j,6)/(sum(person(j,12:16)))
;
                    if autoratio>0.5
                        person(j,6)=person(j,6)-
1;
                        person(i,6)=1;
                    else
                        person(j,6)=person(j,6);
                        person(i,6)=0;
                    end
                end
            end
            person(i,44)=person(i,1);
            person(i,1)=person(a,1)+count;
            person(i,7)=0;
            if person(i,6)==1
                person(i,8)=0;
            else
                person(i,8)=-1;
            end
            person(i,9)=avinc1;
            person(i,10:12)=0;
            person(i,13:16)=0;
            y=rand;
            if y<=nnwrktot/nadulttot
                person(i,13)=1;
            elseif y>nnwrktot/nadulttot &&
y<=(nnwrktot+nstudtot)/nadulttot
                person(i,14)=1;
            elseif
y>(nnwrktot+nstudtot)/nadulttot          &&
y<=(nnwrktot+nstudtot+nparttot)/nadulttot
                person(i,15)=1;
            elseif
y>(nnwrktot+nstudtot+nparttot)/nadulttot
                person(i,16)=1;
            end
            person(i,17:19)=0;
            for k=20:23
                if person(i,k-7)==1
                    person(i,k)=1;
                else
                    person(i,k)=0;
```

```
                end
            end
            person(i,30)=1;

person(i,31)=person(i,1)*100+person(i,30);

person(i,33)=person(i,32)*100+1;

person(i,36:42)=person(i,17:23);
            for k=1:7
                if person(i,35+k)==1
                    person(i,43)=k;
                end
            end
        end
    end
end
%end of working with person file

 dummyperson=person;
 k=0;

   for i=1:a
      if temp(i)==1
         k=k+1;
      for j=1:c
         if person(i,44)==hh(j,1)

dummyperson(i,22:39)=hh(j,22:39);
            hh(j,3)=hh(j,3)-1;
            if person(i,6)==1
               hh(j,6)=hh(j,6);
            end
            hh(j,17)=hh(j,17)-1;
            if hh(j,17)>0
               hh(j,10)=1;
            else
               hh(j,10)=0;
            end
         end
      end
      hh(c+k,1)=person(i,1);
      hh(c+k,2)=person(i,2);
      hh(c+k,3)=1;
      hh(c+k,4)=person(i,9);
      hh(c+k,5)=0;
      hh(c+k,6)=person(i,6);
      if hh(c+k,6)==0
         hh(c+k,7)=1;
      else
         hh(c+k,7)=0;

      end
         %%%%%%%%%%%%%%%%%%%%

utilt(c+k,1)=exp(-1.56263-0.6948*6*vehatr(1,2)/hh(c+k,4)*10000-0.09171*vehatr(1,3)/hh(c+k,4)+hh(c+k,3)*-0.17496);
 utilt(c+k,2)=exp(-0.8795-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)+-0.25982*hh(c+k,3)+hh(c+k,26));
 utilt(c+k,3)=exp(-.4484461-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4));
 utilt(c+k,4)=exp(.0299919-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)+sum(hh(c+k,20:21))*-0.1613351);
 utilt(c+k,5)=exp(-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)+0.192264*hh(c+k,25)-0.4836*sum(hh(c+k,41:42)));
 utilt(c+k,6)=exp(-1.155853-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)-0.2598117*hh(c+k,3));
 utilt(c+k,7)=exp(-0.9479952-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)-0.2598117*hh(c+k,3)+0.3345*sum(hh(c+k,41:42)));
 utilt(c+k,8)=exp(0.4083073-0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-0.09171*vehatr(2,3)/hh(c+k,4)-0.1749*hh(c+k,3)-0.0000134*hh(c+k,36));
```

```
 utilt(c+k,9)=exp(-0.1661281-
0.6948*6*vehatr(2,2)/hh(c+k,4)*10000-
0.09171*vehatr(2,3)/hh(c+k,4)-
0.0000165*hh(c+k,36)+0.46333*hh(c+k,15)
);

            utilt(c+k,10)=sum(utilt(c+k,1:9));
            % calculating the probabilites

utilt(c+k,11)=utilt(c+k,1)/utilt(c+k,10);

utilt(c+k,12)=utilt(c+k,2)/utilt(c+k,10);

utilt(c+k,13)=utilt(c+k,3)/utilt(c+k,10);

utilt(c+k,14)=utilt(c+k,4)/utilt(c+k,10);

utilt(c+k,15)=utilt(c+k,5)/utilt(c+k,10);

utilt(c+k,16)=utilt(c+k,6)/utilt(c+k,10);

utilt(c+k,17)=utilt(c+k,7)/utilt(c+k,10);

utilt(c+k,18)=utilt(c+k,8)/utilt(c+k,10);

utilt(c+k,19)=utilt(c+k,9)/utilt(c+k,10);

            for j=1:9

utilt(c+k,19+j)=sum(utilt(c+k,11:10+j));
            end

            if hh(c+k,6)==0
               p=1;
            elseif hh(c+k,6)==1
                p=2;
            elseif hh(c+k,6)==2
               p=3;
            elseif hh(c+k,6)>2
               p=4;
            end

            if hh(c+k,6)<4
                hh(c+k,6)=hh(c+k,6)+1;
```

```
   end
% assigning new vehicle type

for q=1:p
y=rand;
if y<utilt(c+k,20)
  hh(c+k,47+q)=1;
elseif y< utilt(c+k,21)
  hh(c+k,47+q)=2;
elseif y< utilt(c+k,22)
        hh(c+k,47+q)=3;
elseif y< utilt(c+k,23)
        hh(c+k,47+q)=4;
elseif y< utilt(c+k,24)
        hh(c+k,47+q)=5;
elseif y< utilt(c+k,25)
        hh(c+k,47+q)=6;
elseif y< utilt(c+k,26)
        hh(c+k,47+q)=7;
elseif y< utilt(c+k,27)
        hh(c+k,47+q)=8;
elseif y< utilt(c+k,28)
        hh(c+k,47+q)=9;
end

 hh(c+k,51+q)=trirnd(-6,0,7,1);
end
% assigning age of vehicle


% max age and max vehicle index
hh(c+k,56)=max(hh(c+k,52:55));
if hh(c+k,56)==hh(c+k,52)
   hh(c+k,57)=1;
elseif hh(c+k,56)==hh(c+k,53)
   hh(c+k,57)=2;
elseif hh(c+k,56)==hh(c+k,54)
   hh(c+k,57)=3;
elseif hh(c+k,56)==hh(c+k,55)
   hh(c+k,57)=4;
end

hh(c+k,8:14)=person(i,17:23);
hh(c+k,15:21)=person(i,10:16);
```

```
        hh(c+k,22:39)=dummyperson(i,22:39);
        hh(c+k,58)=1;
        end
    end


dummyperson=[];
%end of working with hh file
%%%%%%%%%%%%%%end of moving
out %%%%%%%%%%%%%%%%%%
%location, housing unit for new households

% update hh age
[c,d]=size(hh);
[a,b]=size(person);
for i=1:c
    hh(i,43)=hh(i,43)+1;
end
 [s,t]=size(hhhu);
 newhh=sum(hh(:,58));
 avahu=s;

 req=newhh-avahu;
 if req>0
     req=req ;
 else
     req=0;
 end

  % values for location choice
    for j=1:1074

houseval(j,20)=exp(0.476*houseval(j,19)+0.
351*houseval(j,18)-
0.071*houseval(j,2)+0.110/10000*houseval(
j,14)-
0.311*houseval(j,15)/houseval(j,5)+0.114*h
ouseval(j,10)/1000+0.0186*houseval(j,11)/1
000)-2.73/10000*logsumhh(j,2);
    end
    for j=1:1074

houseval(j,21)=houseval(j,20)/sum(houseval
(:,20));
    end


 % generate new homes in different zones

 for i=1:1074
    tazhhhu(i,60)=          houseval(i,21)*(-
891.69+21.51*sqrt(houseval(i,7))
+424.0541*tazcharhh(i,6)+732.589*tazchar
hh(i,5)+0.00000217*tazcharhh(i,20))/20;
    tazhhhu(i,61)=   houseval(i,21)*(-304.11-
0.1181*houseval(i,9)-
0.31*houseval(i,10)+17.52*houseval(i,2)+0.
00000695*tazcharhh(i,20))*3/20;
    tazhhhu(i,62)=
houseval(i,21)*(+29.97893-
3.133054*17.52*houseval(i,2)+0.0161271
*houseval(i,9)+0026705*houseval(i,10)+0.0
00000144*tazcharhh(i,20))*10/20;
    if  tazhhhu(i,60) <0
        tazhhhu(i,60)=0;
    end
    if  tazhhhu(i,61) <0
        tazhhhu(i,61)=0;
    end
    if  tazhhhu(i,62) <0
        tazhhhu(i,62)=0;
    end
 end


newbuilt=sum(tazhhhu(:,60))+sum(tazhhhu(
:,61))+sum(tazhhhu(:,62));
 reqrat=req/newbuilt;

  for i=1:1074
    tazhhhu(i,60)=
ceil(tazhhhu(i,60)*reqrat);
    tazhhhu(i,61)=
ceil(tazhhhu(i,61)*reqrat);
    tazhhhu(i,62)=
ceil(tazhhhu(i,62)*reqrat);
 end
```

```
newhu=sum(tazhhhu(:,60))+sum(tazhhhu(:,
61))+sum(tazhhhu(:,62));

 % update housing inventory
 sf=sum(tazhhhu(:,60));
 mf24=sum(tazhhhu(:,61));
 mfgt5=sum(tazhhhu(:,62));

[s,t]=size(hhhu);
k=1;
for i=1:1074
    k=1;
    [s,t]=size(hhhu);
   if tazhhhu(i,60)>0;
        for k=1:tazhhhu(i,60);
   hhhu(s+k,1)=i;
   hhhu(s+k,2)=1;
   hhhu(s+k,5)=1;
   hhhu(s+k,6)=trirnd(1300,1600,2200,1);
   tazcharhh(i,20)=tazcharhh(i,20)-
hhhu(s+k,6)*2.5;
   hhhu(s+k,7)=1;
        end
   end

     k=1;
    [s,t]=size(hhhu);
   if tazhhhu(i,61)>0;
        for k=1:tazhhhu(i,61);
   hhhu(s+k,1)=i;
   hhhu(s+k,3)=1;
   hhhu(s+k,5)=1;
   hhhu(s+k,6)=trirnd(500,800,1200,1);
   tazcharhh(i,20)=tazcharhh(i,20)-
hhhu(s+k,6)*1.5;
   hhhu(s+k,7)=2;
        end
   end
   k=1;
    [s,t]=size(hhhu);
   if tazhhhu(i,62)>0;
        for k=1:tazhhhu(i,62);
   hhhu(s+k,1)=i;
   hhhu(s+k,4)=1;
   hhhu(s+k,5)=1;
   hhhu(s+k,6)=trirnd(400,500,1200,1);
   hhhu(s+k,7)=3;
   tazcharhh(i,20)=tazcharhh(i,20)-
hhhu(s+k,6)*1.5;
        end
   end
end

val=zeros(c,13);

 % type choice model for new households
 for i=1:c
     if hh(i,58)>0
   val(i,1)=1;
   val(i,2)=exp(-
0.7597+0.4355*hh(i,26)+0.9691*hh(i,27)+0
.9691*hh(i,28)-0.1588*hh(i,3)-
0.698*(hh(i,21)+hh(i,20))-0.1180*hh(i,6)-
0.000025*hh(i,4));
   val(i,3)=exp(-
0.5637+0.7063*hh(i,26)+1.455*hh(i,27)+1.
455*hh(i,28)-0.2725*hh(i,3)-
0.4037*(hh(i,21)+hh(i,20))-0.1643*hh(i,6)-
0.000022*hh(i,4));
   val(i,4)=val(i,1)/sum(val(i,1:3));
   val(i,5)=val(i,2)/sum(val(i,1:3));
   val(i,6)=val(i,3)/sum(val(i,1:3));
     end
end
%alloting housing  unit type to housholds
sfall=0;
mf24all=0;
mfgt5all=0;
count=0;

sf=sum(hhhu(:,2));
 mf24=sum(hhhu(:,3));
 mfgt5=sum(hhhu(:,4));


for i=1:c
```

```
    if hh(i,58)>0
        count=count+1;
       x=rand;
       if x<=val(i,4)
           val(i,7)=1;
            sfall=sfall+1;
       elseif        x>val(i,4)        &&        x<=
(val(i,4)+val(i,5))
              val(i,8)=1;
              mf24all=mf24all+1;
       elseif  x> (val(i,4)+val(i,5))
            val(i,9)=1;
            mfgt5all=mfgt5all+1;
       end
    end
end

 isf=0;
 imf24=0;
 imfgt5=0;
 % adjust type according to availability
 if sfall>sf
    sfx=sfall-sf;
    sfr=sfx/sfall;
    isf=1;
 else
    sfx=sf-sfall;
    isf=0;
 end

  if mf24all>mf24
    mf24x=mf24all-mf24;
    mf24r=mf24x/mf24all;

 else
    mf24x=mf24-mf24all;
    imf24=0;
  end
  if mfgt5all>mfgt5
    mfgt5x=mfgt5all-mfgt5
    mfgt5r=mfgt5x/mfgt5all;
    imfgt5=1;
 else
    mfgt5x=mfgt5-mfgt5all;
    imfgt5=0;
  end

  % realloting housetype
  while     sf<sfall     ||     mf24<mf24all     ||
mfgt5<mfgt5all
    if sfall>sf
    sfx=sfall-sf;
    sfr=sfx/sfall;
    isf=1;
  else
    sfx=sf-sfall;
    isf=0;
  end

  if mf24all>mf24
    mf24x=mf24all-mf24;
    mf24r=mf24x/mf24all;
    imf24=1;
  else
    mf24x=mf24-mf24all;
    imf24=0;
  end
  if mfgt5all>mfgt5
    mfgt5x=mfgt5all-mfgt5;
    mfgt5r=mfgt5x/mfgt5all;
    imfgt5=1;
  else
    mfgt5x=mfgt5-mfgt5all;
    imfgt5=0;
  end
  if isf==1
   x=rand(sfall,1);
    k=1;
   for i=1:c
   if hh(i,58)>0
      if val(i,7)==1
        if x(k)<=sfr
            val(i,7)=0;
            sfall=sfall-1;
            if imf24==1
                val(i,9)=1;
                mfgt5all=mfgt5all+1;
            elseif imfgt5==1
```

```
            val(i,8)=1;
            mf24qall=mf24all+1;
          elseif
x(k)<sfr*(mf24x)/(mf24x+mfgt5x)
             val(i,8)=1;
             mf24all=mf24all+1;
          else
            val(i,9)=1;
            mfgt5all=mfgt5all+1;
          end
       end
      k=k+1;
     end
   end
  end


  end
   if imf24==1
   x=rand(mf24all,1);
   k=1;
   for i=1:c
   if hh(i,58)>0
     if val(i,8)==1;
      if x(k)<mf24r
         val(i,8)=0;
          mf24all=mf24all-1;
         if isf==1;
            val(i,9)=1;
            mfgt5all=mfgt5all+1;
         elseif imfgt5==1;
            val(i,7)=1;
            sfall=sfall+1;
         elseif x(k)<mf24r*sfx/(sfx+mfgt5x)
            val(i,7)=1;
             sfall=sfall+1;
         else
            val(i,9)=1;
            mfgt5all=mfgt5all+1;
         end
      end
        k=k+1;
     end
   end
   end
   end

   if imfgt5==1
      x=rand(mfgt5all,1);
    k=1;
   for i=1:c
   if hh(i,58)>0
      if val(i,9)==1;

      if x(k)<mfgt5r
         val(i,9)=0;
         mfgt5all=mfgt5all-1;
         if isf==1;
            val(i,8)=1;
             mf24all=mf24all+1;
         elseif imf24==1;
            val(i,7)=1;
             sfall=sfall+1;
         elseif x(k)<mfgt5r*sfx/(sfx+mf24x)
            val(i,7)=1;
             sfall=sfall+1;
         else
            val(i,8)=1;
            mf24all=mf24all+1;
         end
      end
       k=k+1;
      end

   end
   end
  end
  end % while loop end

 % location choice

hhhu=sortrows(hhhu,7);
xx=randperm(sfall);
k=1;
for i=1:c
   if hh(i,58)>0
      if val(i,7)==1
```

```
        hh(i,2)=hhhu(xx(k),1);
        hh(i,40)=1;
        hh(i,41:42)=0;
        hh(i,43)=hhhu(xx(k),5);
        hh(i,59)=hhhu(xx(k),6);
        hh(i,44)=1;
        hhhu(xx(k),8)=1;
        k=k+1;
        end
    end
end
xx=randperm(mf24all);
sf=sum(hhhu(:,2));
k=1;
for i=1:c
    if hh(i,58)>0
        if val(i,8)==1
        hh(i,2)=hhhu(sf+xx(k),1);
        hh(i,41)=1;
        hh(i,40)=0;
        hh(i,42)=0;
        hh(i,43)=hhhu(sf+xx(k),5);
        hh(i,59)=hhhu(sf+xx(k),6);
        hh(i,44)=1;
        hhhu(sf+xx(k),8)=1;
        k=k+1;
        end
    end
end

xx=randperm(mfgt5all);
mf=sum(hhhu(:,3));
k=1;
for i=1:c
    if hh(i,58)>0
        if val(i,9)==1
        hh(i,2)=hhhu(sf+mf+xx(k),1);
        hh(i,40)=0;
        hh(i,41)=0;
        hh(i,42)=1;
        hh(i,43)=hhhu(sf+mf+xx(k),5);
        hh(i,59)=hhhu(sf+mf+xx(k),6);
        hhhu(sf+mf+xx(k),8)=1;
        hh(i,44)=1;
        k=k+1;
        end
    end
end

[y,z]=size(hhhu);
count=0;
for i=1:y
    if hhhu(i-count,8)==1
        hhhu(i-count,:)=[];
        count=count+1;
    end
end

[c,d]=size(hh);

 % assign Taz characteristics to households

 for i=1:c
     if hh(i,58)>0
         taz=hh(i,2);
         hh(i,22:39)=tazcharhh(taz,2:19);
         hh(i,58)=0;

     end
 end

 % evaluate energy

   [c,d]=size(hh);
   hh(:,45:46)=zeros(c,2);
   % energy consumption electricity in kwh annual
   % natural gas in btu annual
   for i=1:c
       hh(i,45)= 14433.12-78788.77*priceel+0.25582*2974- 0.01937*1674 -2935.340*hh(i,28)-2935.340*hh(i,27)-2417.23*hh(i,26)-832.986*hh(i,42)-626.493*hh(i,41)+1514.025*hh(i,3)-19.64*hh(i,43)-1900.954*(hh(i,8))-1900.954*hh(i,9)-0.03744*hh(i,4)+0.000884*2964*hh(i,59);
       if hh(i,44)==1
```

```
        hh(i,46)=161.45-priceng*8666.8-
0.027*2974+0.04332*1674-
297.43*hh(i,42)-
55.0887*hh(i,41)+46.67*hh(i,3)-
42.46*hh(i,15)+0.00096*hh(i,4)+4.14*hh(i,
43)+hh(i,59)*1674*0.000014;
      else
        hh(i,46)=0;
      end

   end

  % evaluate co2
  co2elec(time)=sum(hh(:,45))*1.46;% in lbs
per year % generation coefficients
  co2ng(time)=sum(hh(:,46))*117.8;%      %
coefficient for natural gas not

%%%%%%%%%%%%% end of location
development                    model
%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%auto
ownership%%%%%%%%%%%%%%%%%%%
%
  [c,d]=size(hh);
    temp=zeros(c,9);
    utilt=zeros(c,28);
    for i=1:c
       temp(i,1)=exp(0);
       temp(i,2)=exp(-3.4683+
0.293547*hh(i,15)+0.3665*hh(i,47)+0.2856
*hh(i,17)+0.3217*hh(i,21)-
0.06589*hh(i,56));
       temp(i,3)=exp(-
4.7737+0.2678*hh(i,17)+0.1292*hh(i,56));
       temp(i,4)=exp(-3.5843-
0.5652+.0000114*hh(i,4));
       temp(i,5)=sum(temp(i,1:4));
       temp(i,6)=temp(i,1)/temp(i,5);

temp(i,7)=(temp(i,1)+temp(i,2))/temp(i,5);

temp(i,8)=(temp(i,1)+temp(i,2)+temp(i,3))/t
emp(i,5);
    end

    for i=1:c
       x=rand;
       if            x>temp(i,6)            &&
x<temp(i,7)%vehicle acquired
          hh(i,64)=1;
          acq=acq+1;
          %updating number of vehicles

          if hh(i,7)==0;
             hh(i,7)=1;
          end

            utilt(i,1)=            exp(-1.56263-
0.6948*3.25*vehatr(1,2)/hh(i,4)*10000-
0.09171*vehatr(1,3)/hh(i,4)+hh(i,3)*-
0.17496);
            utilt(i,2)=            exp(-0.8795-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+-
0.25982*hh(i,3)+hh(i,26));
            utilt(i,3)=            exp(-.4484461-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4));
            utilt(i,4)=exp(.0299919-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+sum(hh(i,20:21
))*-0.1613351);
            utilt(i,5)=exp(-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+0.192264*hh(i,
25)-0.4836*sum(hh(i,41:42)));
            utilt(i,6)=exp(-1.155853-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
0.2598117*hh(i,3));
            utilt(i,7)=exp(-0.9479952-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
```

```
0.2598117*hh(i,3)+0.3345*sum(hh(i,41:42)
));
            utilt(i,8)=exp(0.4083073            -
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-0.1749*hh(i,3)-
0.0000134*hh(i,36));
            utilt(i,9)=exp(-0.1661281-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
0.0000165*hh(i,36)+0.46333*hh(i,15));

            utilt(i,10)=sum(utilt(i,1:9));
            % calculating the probabilites
            utilt(i,11)=utilt(i,1)/utilt(i,10);
            utilt(i,12)=utilt(i,2)/utilt(i,10);
            utilt(i,13)=utilt(i,3)/utilt(i,10);
            utilt(i,14)=utilt(i,4)/utilt(i,10);
            utilt(i,15)=utilt(i,5)/utilt(i,10);
            utilt(i,16)=utilt(i,6)/utilt(i,10);
            utilt(i,17)=utilt(i,7)/utilt(i,10);
            utilt(i,18)=utilt(i,8)/utilt(i,10);
            utilt(i,19)=utilt(i,9)/utilt(i,10);

            for j=1:9

utilt(i,19+j)=sum(utilt(i,11:10+j));
            end

            if hh(i,6)==0
               j=1;
            elseif hh(i,6)==1
               j=2;
            elseif hh(i,6)==2
               j=3;
            elseif hh(i,6)>2
               j=4;
            end

         % assigning new vehicle type
         y=rand;
         if y<utilt(i,20)
               hh(i,47+j)=1;
         elseif y< utilt(i,21)
               hh(i,47+j)=2;
         elseif y< utilt(i,22)
               hh(i,47+j)=3;
         elseif y< utilt(i,23)
               hh(i,47+j)=4;
         elseif y< utilt(i,24)
               hh(i,47+j)=5;
         elseif y< utilt(i,25)
               hh(i,47+j)=6;
         elseif y< utilt(i,26)
               hh(i,47+j)=7;
         elseif y< utilt(i,27)
               hh(i,47+j)=8;
         elseif y< utilt(i,28)
               hh(i,47+j)=9;
         end

         % assigning age of vehicle

         hh(51+j)=trirnd(-6,0,7,1);
         % max age and max vehicle index
         hh(i,56)=max(hh(i,52:55));
         if hh(i,56)==hh(i,52)
            hh(i,57)=1;
         elseif hh(i,56)==hh(i,53)
            hh(i,57)=2;
         elseif hh(i,56)==hh(i,54)
            hh(i,57)=3;
         elseif hh(i,56)==hh(i,55)
            hh(i,57)=4;
         end
       hh(i,6)=hh(i,6)+1;
      elseif x>temp(i,7) && x<temp(i,8)
         dis=dis+1;
           hh(i,64)=2;
         % vehicle disposed
         % removing oldest vehicle from the
fleet
         if hh(i,6)>0
         p=hh(i,57);
         if p==1
           hh(i,47+p)=0;
           hh(i,51+p)=0;
           hh(i,6)=hh(i,6)-1;
           if hh(i,6)==0;
```

```
            hh(i,7)=1;
          end

hh(i,47+p:47+3)=hh(i,47+2:47+4);
           hh(i,51+p:51+3)=hh(i,51+2:51+4)
;
         elseif p==2
            hh(i,47+p)=0;
          hh(i,51+p)=0;
          hh(i,6)=hh(i,6)-1;
          if hh(i,6)==0;
            hh(i,7)=1;
          end

hh(i,47+p:47+3)=hh(i,47+3:47+4);

hh(i,51+p:51+3)=hh(i,51+3:51+4);
         elseif p==3
            hh(i,47+p)=0;
          hh(i,51+p)=0;
          hh(i,6)=hh(i,6)-1;
          if hh(i,6)==0;
            hh(i,7)=1;
          end

hh(i,47+p:47+3)=hh(i,47+4:47+4);

hh(i,51+p:51+3)=hh(i,51+4:51+4);
         elseif p==4
            hh(i,47+p)=0;
            hh(i,51+p)=0;
            hh(i,6)=3;

         end

         % max age and max vehicle index
        hh(i,56)=max(hh(i,52:55));
        if hh(i,56)==hh(i,52)
           hh(i,57)=1;
        elseif hh(i,56)==hh(i,53)
           hh(i,57)=2;
        elseif hh(i,56)==hh(i,54)
           hh(i,57)=3;
        elseif hh(i,56)==hh(i,55)
           hh(i,57)=4;
        end
       end

      elseif x>temp(i,8)
           hh(i,64)=3;
          trade=trade+1;
            % disposed a vehicle and got a
new vehicle
        if hh(i,6)>0
        % disposed vehicle details updates
          p=hh(i,57);
           if p==1
            hh(i,47+p)=0;
            hh(i,51+p)=0;
            hh(i,6)=hh(i,6)-1;
            if hh(i,6)==0;
              hh(i,7)=1;
            end

hh(i,47+p:47+3)=hh(i,47+2:47+4);
           hh(i,51+p:51+3)=hh(i,51+2:51+4)
;
          elseif p==2
             hh(i,47+p)=0;
            hh(i,51+p)=0;
            hh(i,6)=hh(i,6)-1;


hh(i,47+p:47+3)=hh(i,47+3:47+4);

hh(i,51+p:51+3)=hh(i,51+3:51+4);
          elseif p==3
             hh(i,47+p)=0;
            hh(i,51+p)=0;
            hh(i,6)=hh(i,6)-1;
            hh(i,47+p:47+3)=hh(i,47+4:47+4);
            hh(i,51+p:51+3)=hh(i,51+4:51+4);
          elseif p==4
             hh(i,47+p)=0;
             hh(i,51+p)=0;
             hh(i,6)=3;

           end
```

```
end


% new vehicle

utilt(i,1)= exp(-1.56263-
0.6948*3.25*vehatr(1,2)/hh(i,4)*10000-
0.09171*vehatr(1,3)/hh(i,4)+hh(i,3)*-
0.17496);
utilt(i,2)= exp(-0.8795-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+-
0.25982*hh(i,3)+hh(i,26));
utilt(i,3)= exp(-.4484461-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4));
utilt(i,4)=exp(.0299919-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+sum(hh(i,20:21
))*-0.1613351);
utilt(i,5)=exp(-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)+0.192264*hh(i,
25)-0.4836*sum(hh(i,41:42)));
utilt(i,6)=exp(-1.155853-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
0.2598117*hh(i,3));
utilt(i,7)=exp(-0.9479952-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
0.2598117*hh(i,3)+0.3345*sum(hh(i,41:42)
));
utilt(i,8)=exp(0.4083073 -
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-0.1749*hh(i,3)-
0.0000134*hh(i,36));
utilt(i,9)=exp(-0.1661281-
0.6948*3.25*vehatr(2,2)/hh(i,4)*10000-
0.09171*vehatr(2,3)/hh(i,4)-
0.0000165*hh(i,36)+0.46333*hh(i,15));

utilt(i,10)=sum(utilt(i,1:9));
% calculating the probabilites
utilt(i,11)=utilt(i,1)/utilt(i,10);
utilt(i,12)=utilt(i,2)/utilt(i,10);
utilt(i,13)=utilt(i,3)/utilt(i,10);
utilt(i,14)=utilt(i,4)/utilt(i,10);
utilt(i,15)=utilt(i,5)/utilt(i,10);
utilt(i,16)=utilt(i,6)/utilt(i,10);
utilt(i,17)=utilt(i,7)/utilt(i,10);
utilt(i,18)=utilt(i,8)/utilt(i,10);
utilt(i,19)=utilt(i,9)/utilt(i,10);

for j=1:9
utilt(i,19+j)=sum(utilt(i,11:10+j));
end

if hh(i,6)==0
j=1;
elseif hh(i,6)==1
j=2;
elseif hh(i,6)==2
j=3;
elseif hh(i,6)>2
j=4;
end

if hh(i,6)<4
hh(i,6)=hh(i,6)+1;
end
% assigning new vehicle type
y=rand;
if y<utilt(i,20)
hh(i,47+j)=1;
elseif y< utilt(i,21)
hh(i,47+j)=2;
elseif y< utilt(i,22)
hh(i,47+j)=3;
elseif y< utilt(i,23)
hh(i,47+j)=4;
elseif y< utilt(i,24)
hh(i,47+j)=5;
elseif y< utilt(i,25)
hh(i,47+j)=6;
elseif y< utilt(i,26)
hh(i,47+j)=7;
elseif y< utilt(i,27)
```

```
            hh(i,47+j)=8;
        elseif y< utilt(i,28)
            hh(i,47+j)=9;
        end
        % assigning age of vehicle

        hh(51+j)=trirnd(-6,0,7,1);
        % max age and max vehicle index
        hh(i,56)=max(hh(i,52:55));
        if hh(i,56)==hh(i,52)
           hh(i,57)=1;
        elseif hh(i,56)==hh(i,53)
           hh(i,57)=2;
        elseif hh(i,56)==hh(i,54)
           hh(i,57)=3;
        elseif hh(i,56)==hh(i,55)
           hh(i,57)=4;
        end


      end
    end


% This part of the code prepares data for the
Travel Demand Model.
hhtypeshares=xlsread('hhtypeshares.xls');
hhtypeshares(:,2:6)=0;
[c,d]=size(hh);
1
fueleco=[24.37  25.14  26.67  25.15  19.50
30.87 31.30 20.07 21.09];
households=zeros(c,7);
households(:,1:3)=hh(:,1:3);
households(:,6)=hh(:,4);
households(:,4)=hh(:,6);
hh(:,62)=zeros(c,1);
for i=1:c
   if hh(i,8)+hh(i,9)>0
      households(i,5)=1;
   end
   if hh(i,6)==0
   hh(i,62)=0;
   elseif hh(i,6)==1
      hh(i,62)=fueleco(hh(i,48));
   elseif hh(i,6)==2

hh(i,62)=2/(1/fueleco(hh(i,48))+1/fueleco(h
h(i,49)));
   elseif hh(i,6)==3

hh(i,62)=3/(1/fueleco(hh(i,48))+1/fueleco(h
h(i,49))+1/fueleco(hh(i,50)));
   elseif hh(i,6)==4

hh(i,62)=4/(1/fueleco(hh(i,48))+1/fueleco(h
h(i,49))+1/fueleco(hh(i,50))+1/fueleco(hh(i,
51)));
   end
end

for i=1:c
   if hh(i,62)<=20
      hh(i,63)= 1;
   elseif hh(i,62)<22
      hh(i,63)= 2;
   elseif hh(i,62)<24
      hh(i,63)= 3;
   elseif hh(i,62)<26
      hh(i,63)= 4;
   else
      hh(i,63)= 5;
   end
end


for i=1:c
   taz=hh(i,2);
   if hh(i,63)==1

hhtypeshares(taz,2)=hhtypeshares(taz,2)+1;
   elseif hh(i,63)==2

hhtypeshares(taz,3)=hhtypeshares(taz,3)+1;
   elseif hh(i,63)==3

hhtypeshares(taz,4)=hhtypeshares(taz,4)+1;
   elseif hh(i,63)==4
```

```
hhtypeshares(taz,5)=hhtypeshares(taz,5)+1;
   elseif hh(i,63)==5

hhtypeshares(taz,6)=hhtypeshares(taz,6)+1;
   end
end

[u,v]=size(hhtypeshares);
temp=zeros(u,1);
for i=1:u
temp(i)=sum(hhtypeshares(i,2:6));
if temp(i)>0
hhtypeshares(i,2)=hhtypeshares(i,2)/temp(i);
hhtypeshares(i,3)=hhtypeshares(i,3)/temp(i);
hhtypeshares(i,4)=hhtypeshares(i,4)/temp(i);
hhtypeshares(i,5)=hhtypeshares(i,5)/temp(i);
hhtypeshares(i,6)=hhtypeshares(i,6)/temp(i);
else

hhtypeshares(i,2)=0.2;
hhtypeshares(i,3)=0.2;
hhtypeshares(i,4)=0.2;
hhtypeshares(i,5)=0.2;
hhtypeshares(i,6)=0.2;
end

end

[c,d]=size(hh);
households_new=zeros(10*c,7);
for i=1:10
   households_new(c*(i-
1)+1:c*i,:)=households(:,:);
end

for j=1:10
   for i=1:c
   households_new(c*(j-
1)+i,1)=households(i)*10+(j-1);
   end
end

if time==5
   dlmwrite('hh_5.dat',hh);
   dlmwrite('person_5.dat',person);

dlmwrite('households_5.dat',households_ne
w);

dlmwrite('hhtypeshare_5.dat',hhtypeshares);
elseif time==10
   dlmwrite('hh_10.dat',hh);
   dlmwrite('person_10.dat',person);

dlmwrite('households_10.dat',households_ne
w);

dlmwrite('hhtypeshare_10.dat',hhtypeshares)
;
elseif time==15
   dlmwrite('hh_15.dat',hh);
   dlmwrite('person_15.dat',person);

dlmwrite('households_15.dat',households_ne
w);

dlmwrite('hhtypeshare_15.dat',hhtypeshares)
;
elseif time==20
   dlmwrite('hh_20.dat',hh);
   dlmwrite('person_20.dat',person);

dlmwrite('households_20.dat',households_ne
w);

dlmwrite('hhtypeshare_20.dat',hhtypeshares)
;
elseif time==25
   dlmwrite('hh_25.dat',hh);
   dlmwrite('person_25.dat',person);

dlmwrite('households_25.dat',households_ne
w);

dlmwrite('hhtypeshare_25.dat',hhtypeshares)
;
end
```

```
  yearcount=yearcount+1;
   empdata_initial=empdata;


% Updating firm size
   [m,n]=size(empdata);
   rand1=(1:m)';
   for i=1:m
      rand1(i)=rand;
      sizecat(i)=empdata(i,4);
   end
   for i = 1:m
      if empdata(i,2)==1
         j=empdata(i,4);
         if rand1(i)<=markov_basic(j,1)
            empdata(i,4)=1;
         elseif      rand1(i)>markov_basic(j,1)
&& rand1(i)<=sum(markov_basic(j,1:2))
            empdata(i,4)=2;
         elseif
rand1(i)>sum(markov_basic(j,1:2))        &&
rand1(i)<=sum(markov_basic(j,1:3))
            empdata(i,4)=3;
         elseif
rand1(i)>sum(markov_basic(j,1:3))        &&
rand1(i)<=sum(markov_basic(j,1:4))
            empdata(i,4)=4;
         elseif
rand1(i)>sum(markov_basic(j,1:4))        &&
rand1(i)<=sum(markov_basic(j,1:5))
            empdata(i,4)=5;
         elseif
rand1(i)>sum(markov_basic(j,1:5))        &&
rand1(i)<=1
            empdata(i,4)=6;
         end
      elseif empdata(i,2)==2
         j=empdata(i,4);
         if rand1(i)<=markov_retail(j,1)
            empdata(i,4)=1;
         elseif      rand1(i)>markov_retail(j,1)
&& rand1(i)<=sum(markov_retail(j,1:2))
            empdata(i,4)=2;
         elseif
rand1(i)>sum(markov_retail(j,1:2))        &&
rand1(i)<=sum(markov_retail(j,1:3))
            empdata(i,4)=3;
         elseif
rand1(i)>sum(markov_retail(j,1:3))        &&
rand1(i)<=sum(markov_retail(j,1:4))
            empdata(i,4)=4;
         elseif
rand1(i)>sum(markov_retail(j,1:4))        &&
rand1(i)<=sum(markov_retail(j,1:5))
            empdata(i,4)=5;
         elseif
rand1(i)>sum(markov_retail(j,1:5))        &&
rand1(i)<=1
            empdata(i,4)=6;
         end
      elseif empdata(i,2)==3
         j=empdata(i,4);
         if rand1(i)<=markov_education(j,1)
            empdata(i,4)=1;
         elseif
rand1(i)>markov_education(j,1)            &&
rand1(i)<=sum(markov_education(j,1:2))
            empdata(i,4)=2;
         elseif
rand1(i)>sum(markov_education(j,1:2))  &&
rand1(i)<=sum(markov_education(j,1:3))
            empdata(i,4)=3;
         elseif
rand1(i)>sum(markov_education(j,1:3))  &&
rand1(i)<=sum(markov_education(j,1:4))
            empdata(i,4)=4;
         elseif
rand1(i)>sum(markov_education(j,1:4))  &&
rand1(i)<=sum(markov_education(j,1:5))
            empdata(i,4)=5;
         elseif
rand1(i)>sum(markov_education(j,1:5))  &&
rand1(i)<=1
            empdata(i,4)=6;
         end
      elseif empdata(i,2)==4
         j=empdata(i,4);
```

```
        if rand1(i)<=markov_service(j,1)
            empdata(i,4)=1;
        elseif   rand1(i)>markov_service(j,1)
&& rand1(i)<=sum(markov_service(j,1:2))
            empdata(i,4)=2;
        elseif
rand1(i)>sum(markov_service(j,1:2))     &&
rand1(i)<=sum(markov_service(j,1:3))
            empdata(i,4)=3;
        elseif
rand1(i)>sum(markov_service(j,1:3))     &&
rand1(i)<=sum(markov_service(j,1:4))
            empdata(i,4)=4;
        elseif
rand1(i)>sum(markov_service(j,1:4))     &&
rand1(i)<=sum(markov_service(j,1:5))
            empdata(i,4)=5;
        elseif
rand1(i)>sum(markov_service(j,1:5))     &&
rand1(i)<=1
            empdata(i,4)=6;
        end
      end
   end

empdata(:,5)=empdata(:,2)*100+empdata(:,
4);
   for i=1:m
      j=empdata(i,4)-sizecat(i);
      if j~=0

        if empdata(i,4)==1
            empdata(i,3)=unidrnd(4);
        elseif empdata(i,4)==2
            empdata(i,3)=4+unidrnd(5);
        elseif empdata(i,4)==3
            empdata(i,3)=9+unidrnd(10);
        elseif empdata(i,4)==4
            empdata(i,3)=19+unidrnd(80);
        elseif empdata(i,4)==5
            empdata(i,3)=99+unidrnd(400);
        elseif empdata(i,4)==6
            if empdata(i,2)==1

%empdata(i,3)=499+poissrnd(1146);
                empdata(i,3)=500;
            elseif empdata(i,2)==2

%empdata(i,3)=499+poissrnd(547);
                empdata(i,3)=500;
            elseif empdata(i,2)==3

%empdata(i,3)=499+poissrnd(2019);
                empdata(i,3)=500;
            elseif empdata(i,2)==4

%empdata(i,3)=499+poissrnd(628);
                empdata(i,3)=500;
            % for size cat = 6 and sizes=(size-
500)
            % basic: mean=1146 (stdev=1288)
            % retail: mean=547 (stdev=653)
            %       education:       mean=2019
(stdev=4880)
            % service: mean=628 (stdev=727)
            end
        end
      end
      r=empdata(i,2);
      empdata(i,5+r)=empdata(i,3);
   end
% Firm size updated

%Birth Module
%empdata2=empdata;
   [m,n]=size(empdata);
   rand2=(1:m)';
   for i = 1:m
      rand2(i)=0;
   end
   for i = 1:m
      if empdata(i,5)==101
         rand2(i)=rand;
      elseif empdata(i,5)==102
         rand2(i)=2+rand;
      elseif empdata(i,5)==103
         rand2(i)=4+rand;
```

```
    elseif empdata(i,5)==104
        rand2(i)=6+rand;
    elseif empdata(i,5)==105
        rand2(i)=8+rand;
    elseif empdata(i,5)==106
        rand2(i)=10+rand;
    elseif empdata(i,5)==201
        rand2(i)=100+rand;
    elseif empdata(i,5)==202
        rand2(i)=102+rand;
    elseif empdata(i,5)==203
        rand2(i)=104+rand;
    elseif empdata(i,5)==204
        rand2(i)=106+rand;
    elseif empdata(i,5)==205
        rand2(i)=108+rand;
    elseif empdata(i,5)==206
        rand2(i)=110+rand;
    elseif empdata(i,5)==301
        rand2(i)=200+rand;
    elseif empdata(i,5)==302
        rand2(i)=202+rand;
    elseif empdata(i,5)==303
        rand2(i)=204+rand;
    elseif empdata(i,5)==304
        rand2(i)=206+rand;
    elseif empdata(i,5)==305
        rand2(i)=208+rand;
    elseif empdata(i,5)==306
        rand2(i)=210+rand;
    elseif empdata(i,5)==401
        rand2(i)=300+rand;
    elseif empdata(i,5)==402
        rand2(i)=302+rand;
    elseif empdata(i,5)==403
        rand2(i)=304+rand;
    elseif empdata(i,5)==404
        rand2(i)=306+rand;
    elseif empdata(i,5)==405
        rand2(i)=308+rand;
    else
        rand2(i)=310+rand;
    end
end
    birth1=(1:m)';
    for i = 1:m
        birth1(i)=0;
    end
    for i=1:m
        for j=0:5
            if rand2(i) > (2*j-1) && rand2(i) <
2*j+(Basic(j+1,4)/100)
                birth1(i)=j+1;
            end
        end
    end
    for i=1:m
        for j=0:5
            if rand2(i) > 100+(2*j-1) &&
rand2(i) < 100+2*j+(Retail(j+1,4)/100)
                birth1(i)=100+j+1;
            end
        end
    end
    for i=1:m
        for j=0:5
            if rand2(i) > 200+(2*j-1) &&
rand2(i) < 200+2*j+(Education(j+1,4)/100)
                birth1(i)=200+j+1;
            end
        end
    end
    for i=1:m
        for j=0:5
            if rand2(i) > 300+(2*j-1) &&
rand2(i) < 300+2*j+(Service(j+1,4)/100)
                birth1(i)=300+j+1;
            end
        end
    end
%birth2=xlswrite('birth1.0.xls',birth1);
%End of Firm Birth Module

% Updating Location Choice Module
% Travel time increases by 3% on all
routes/links
```

```
% Location Choice Scenario 1 & 2 and current scenario
   [m,n]=size(locchoice);
   [x,y]=size(logsum);
   if yearcount==1
%      if scenario==1
          logsum(:,2)=logsum(:,2)*1.00;      % Current Scenario
%      elseif scenario==2
%             logsum(:,2)=logsum(:,2)*0.75; % Scenario 1
%      elseif scenario==3
%             logsum(:,2)=logsum(:,2)*1.25; % Scenario 2
%      end
   else
   logsum(:,2)=1.03*logsum(:,2);
   end

   for i=1:x
      if logsum(i,5)==0
         logsum(i,6)=0;
      else

logsum(i,6)=log(logsum(i,5))/exp(.0896124*logsum(i,2)-.0238147*logsum(i,3));
      end
      if logsum(i,4)==0
         logsum(i,7)=0;
      else

logsum(i,7)=log(logsum(i,4))/exp(.1028167*logsum(i,2)-.0459523*logsum(i,3));
      end
   end
   locchoice(:,21)=0;
   locchoice(:,22)=0;
   for i=1:m
      for j=1:x
         if locchoice(i,1)==logsum(j,1)

locchoice(i,21)=locchoice(i,21)+logsum(j,6);

locchoice(i,22)=locchoice(i,22)+logsum(j,7);
         else
            locchoice(i,21)=locchoice(i,21);
            locchoice(i,22)=locchoice(i,22);
         end
      end
   end


locchoice(:,23)=0.507*log(locchoice(:,2))-3.142*locchoice(:,3)-1.495*locchoice(:,4)-0.816*locchoice(:,5)-0.004*locchoice(:,16)+0.00000131*locchoice(:,11)+0.011*locchoice(:,21)-0.010*locchoice(:,22);

%locchoice(:,23)=4.948+0.482*log(locchoice(:,2))-3.025*locchoice(:,3)-1.464*locchoice(:,4)-0.778*locchoice(:,5)+0.00000109*locchoice(:,11)+0.011*locchoice(:,21)-0.010*locchoice(:,22);
   locchoice(:,24)=exp(locchoice(:,23));


locchoice(:,25)=locchoice(:,24)/sum(locchoice(:,24));

   tazlocprob(:,22)=locchoice(:,25);

   for i=1:m

tazlocprob(i,21)=sum(tazlocprob(1:i,22));
   end
% Location Choice Module updated

%Location Choice Module for new born firms
   [m,n]=size(empdata);
   rand3=(1:m)';
   for i = 1:m
      rand3(i)=-1;
```

```
    end
    for i = 1:m
        if birth1(i)~=0
            rand3(i)=rand;
        end
    end
    [tazrow,tazcol]=size(tazlocprob);
    count=0;
    for i=1:m
        if rand3(i)~=-1
            count=count+1;
            if rand3(i)<tazlocprob(1,21)

empdata(m+count,1)=yearcount*100000+co
unt;

empdata(m+count,2:9)=empdata(i,2:9);

empdata(m+count,10:29)=tazlocprob(1,1:20
);
            else
                for j=2:tazrow
                    if rand3(i)<tazlocprob(j,21) &&
rand3(i)>tazlocprob(j-1,21)

empdata(m+count,1)=yearcount*100000+co
unt;

empdata(m+count,2:9)=empdata(i,2:9);

empdata(m+count,10:29)=tazlocprob(j,1:20)
;
                    end
                end
            end
        end
    end

%End of Location Choice Module for new
born firms

% Death/Exit Module
    [m,n]=size(empdata_initial);
    rand1=(1:m)';
for i = 1:m
    rand1(i)=0;
end
for i = 1:m
    if empdata(i,5)==101
        rand1(i)=rand;
    elseif empdata(i,5)==102
        rand1(i)=2+rand;
    elseif empdata(i,5)==103
        rand1(i)=4+rand;
    elseif empdata(i,5)==104
        rand1(i)=6+rand;
    elseif empdata(i,5)==105
        rand1(i)=8+rand;
    elseif empdata(i,5)==106
        rand1(i)=10+rand;
    elseif empdata(i,5)==201
        rand1(i)=100+rand;
    elseif empdata(i,5)==202
        rand1(i)=102+rand;
    elseif empdata(i,5)==203
        rand1(i)=104+rand;
    elseif empdata(i,5)==204
        rand1(i)=106+rand;
    elseif empdata(i,5)==205
        rand1(i)=108+rand;
    elseif empdata(i,5)==206
        rand1(i)=110+rand;
    elseif empdata(i,5)==301
        rand1(i)=200+rand;
    elseif empdata(i,5)==302
        rand1(i)=202+rand;
    elseif empdata(i,5)==303
        rand1(i)=204+rand;
    elseif empdata(i,5)==304
        rand1(i)=206+rand;
    elseif empdata(i,5)==305
        rand1(i)=208+rand;
    elseif empdata(i,5)==306
        rand1(i)=210+rand;
    elseif empdata(i,5)==401
        rand1(i)=300+rand;
    elseif empdata(i,5)==402
        rand1(i)=302+rand;
```

```
    elseif empdata(i,5)==403
        rand1(i)=304+rand;
    elseif empdata(i,5)==404
        rand1(i)=306+rand;
    elseif empdata(i,5)==405
        rand1(i)=308+rand;
    elseif empdata(i,5)==406
        rand1(i)=310+rand;
    end
  end
  death1=(1:m)';
  for i = 1:m
    death1(i)=0;
  end
  for i=1:m
    for j=0:5
      if rand1(i) > (2*j-1) && rand1(i) <
2*j+(Basic(j+1,5)/100)
        death1(i)=j+1;
      end
    end
  end
  for i=1:m
    for j=0:5
      if rand1(i) > 100+(2*j-1) &&
rand1(i) < 100+2*j+(Retail(j+1,5)/100)
        death1(i)=100+j+1;
      end
    end
  end
  for i=1:m
    for j=0:5
      if rand1(i) > 200+(2*j-1) &&
rand1(i) < 200+2*j+(Education(j+1,5)/100)
        death1(i)=200+j+1;
      end
    end
  end
  for i=1:m
    for j=0:5
      if rand1(i) > 300+(2*j-1) &&
rand1(i) < 300+2*j+(Service(j+1,5)/100)
        death1(i)=300+j+1;
      end
    end
  end
%death2=xlswrite('death1.0.xls',death1);
  i=1;
  count=0;
  while i<=m
    if death1(i)~=0
      empdata(i-count,:)=[];
      count=count+1;
    else
      empdata(i-count,:)=empdata(i-
count,:);
    end
    i=i+1;
  end

% End of Death/Exit Module

%Location Choice Module for relocating
firms
  reloc=tazlocprob;
  [x,y]=size(reloc);
  reloc=sortrows(reloc,22);
  utilindex=sum(reloc(x-10:x,22))/10;
  firmcount=sum(reloc(:,20));
  flag=round(firmcount*0.05);
  count=0;
  relocindex=ones(x,1);
  relocindex(:)=0;
  for i=1:x
    if count<(flag*3)
      count=count+reloc(i,20);
      relocindex(i)=reloc(i,1);
    end
  end

  [m,n]=size(empdata);
  temp(1:m,1)=0;
  for i=1:x
    for j=1:m
      if relocindex(i)==empdata(j,10)
        temp(j)=rand;
      end
    end
```

```
   end
   for i=1:m
      if temp(i)>0.067
         temp(i)=rand;
      else
         temp(i)=0;
      end
   end
   [tazrow,tazcol]=size(tazlocprob);
   for i=1:m
      if      temp(i)<tazlocprob(1,21)      &&
temp(i)>0

empdata(i,10:29)=tazlocprob(1,1:20);
      else
         for j=2:tazrow
            if   temp(i)<tazlocprob(j,21)   &&
temp(i)>tazlocprob(j-1,21)

empdata(i,10:29)=tazlocprob(j,1:20);
            end
         end
      end
   end
%
%End of Location Choice Module for
relocating firms

%Trip Generation Module
%empdata3(:,25=(n-5))=Trip              Gen
Percentage by TAZ
   [x,y]=size(tazlocprob);
   temptg=ones(x,1);
   double(temptg);
   for i=1:x

temptg(i)=tripgen(1)+tripgen(2)*tazlocprob(
i,2)*tazlocprob(i,3)+tripgen(3)*tazlocprob(i,
2)*tazlocprob(i,4)+tripgen(4)*tazlocprob(i,2
)*tazlocprob(i,5)+tripgen(5)*tazlocprob(i,20
)+tripgen(6)*tazlocprob(i,18)+tripgen(7)*ta
zlocprob(i,17)+tripgen(8)*tazlocprob(i,16)+
tripgen(9)*tazlocprob(i,15)+tripgen(10)*tazl
ocprob(i,14)+tripgen(11)*tazlocprob(i,13);
   end
   temptgsum=sum(temptg);
   temptg=(temptg/temptgsum)*100;
   tazlocprob(:,25)=temptg;
   if yearcount==5
      commtripgen=zeros(x,2);
      for i=1:x
         commtripgen(i,1)=i;
         commtripgen(i,2)=2*temptg(i);
      end
   end
%End of Trip Generation Module

%Updating FirmCount and Employment
Stats
%empdata4=empdata3;
   [m,n]=size(empdata);
   empdata(:,28)=0;
   empdata(:,29)=0;
   for i=1:m
      for j=1:m
         if empdata(i,10)==empdata(j,10)
            empdata(i,29)=empdata(i,29)+1;

empdata(i,28)=empdata(i,28)+empdata(j,3);
         else
            empdata(i,28)=empdata(i,28);
            empdata(i,29)=empdata(i,29);
         end
      end
   end

   % energy estimates:

   for i=1:m
      empdata(i,32)=669884.1-
2677204*priceelec+6.735*empdata(i,30)-
203.692*2974+0.00649*empdata(i,30)*297
4+2976.678*empdata(i,6)-
6050.721*empdata(i,31)+empdata(i,30)*1.6
98;
      empdata(i,33)=669884.1-
2677204*priceelec+6.735*empdata(i,30)-
203.692*2974+0.00649*empdata(i,30)*297
```

```
4+2976.678*empdata(i,7)-
6050.721*empdata(i,31)+empdata(i,30)*4.7
25;
      empdata(i,34)=669884.1-
2677204*priceelec+6.735*empdata(i,30)-
203.692*2974+0.00649*empdata(i,30)*297
4+2976.678*empdata(i,8)-
6050.721*empdata(i,31)+empdata(i,30);
      empdata(i,35)=669884.1-
2677204*priceelec+6.735*empdata(i,30)-
203.692*2974+0.00649*empdata(i,30)*297
4+2976.678*empdata(i,9)-
6050.721*empdata(i,31)+empdata(i,30)*6.7
66;
   end

   elecener(time,1)=sum(empdata(:,31));
   elecener(time,2)=sum(empdata(:,32));
   elecener(time,3)=sum(empdata(:,33));
   elecener(time,4)=sum(empdata(:,34));
   if time==5

xlswrite('f.empdata5.1jul.exp.xls',empdata);

xlswrite('f.commtripgen5.1jul.exp.xls',comm
tripgen);
   elseif time==10

xlswrite('f.empdata10.1jul.exp.xls',empdata)
;

xlswrite('f.commtripgen10.1jul.exp.xls',com
mtripgen);
   elseif time==15

xlswrite('f.empdata15.1jul.exp.xls',empdata)
;

xlswrite('f.commtripgen15.1jul.exp.xls',com
mtripgen);
   elseif time==20

xlswrite('f.empdata20.1jul.exp.xls',empdata)
;

xlswrite('f.commtripgen20.1jul.exp.xls',com
mtripgen);
   elseif time==25

xlswrite('f.empdata25.1jul.exp.xls',empdata)
;

xlswrite('f.commtripgen25.1jul.exp.xls',com
mtripgen);
   elseif time==30

xlswrite('f.empdata30.1jul.exp.xls',empdata)
;

xlswrite('f.commtripgen30.1jul.exp.xls',com
mtripgen);

xlswrite('f.empdata.energy1jul.xls',elecener)
;
   end
end
```