Micro-Simulation Models of Urban Regions: Anticipating Greenhouse Gas Emissions from Transport and Housing in Austin, Texas

Sumala Tirumalachetty
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
6.9 E. Cockrell Jr. Hall
Austin, TX 78712
sumala@mail.utexas.edu

Kara M. Kockelman
(Corresponding author)
Associate Professor and William J. Murray Jr. Fellow Department
of Civil, Architectural and Environmental Engineering The
University of Texas at Austin
6.9 E. Cockrell Jr. Hall
Austin, TX 78712
kkockelm@mail.utexas.edu

Saurabh Kumar Travel
Demand Forecaster
Cambridge Systematics, Inc.
9015 Mountain Ridge Drive, Suite 210
Austin, TX 78759
skumar@camsys.com

Presented at the 88th Annual Meeting of the Transportation Research Board, January 2009.

ABSTRACT

Anthropogenic greenhouse gas (GHG) emissions are largely attributable to household and firm travel and building decisions. This paper 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. A case study of the Austin, Texas region provides estimates of energy demands and CO2 emissions through the year 2030, as a function of several policies. Year 2005 population and point-based employment data coupled with a wide variety of other data sets are used. Lack of control totals for population forecasting creates issues, certainly, which is a key finding of this work. Scenario simulation results suggest an 81% increase in the Austin households and an evolution toward wealthier households, much larger firm sizes and a somewhat more efficient fleet of personal vehicles. GHG emissions from personal and commercial travel are predicted to nearly double in the business as usual case, but 74 percent and 60 percent under urban growth boundary and strict gas and road toll scenarios, respectively

(where the latter scenario assumes a $3-per-gallon gas tax increase and road tolls of 10 cents per vehicle-mile traveled).

INTRODUCTION AND MOTIVATION

Energy security and climate change are top issues in today's world and require immediate attention. The majority of anthropogenic GHG emissions are generated via transport of persons and goods plus building demands. 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).

Recently, U.S. gas prices have more than doubled (from $1.50 per gallon in January 2003 to nearly $4 in January 2008 [EIA 2008]). While travelers may adjust driving habits in the near run[1], over the long term, vehicle ownership and location choice decisions are more likely to shift. For example, for the first time in over two decades, share of new passenger cars increased by 2.4% in California between 2004 and 2006, reversing the decline seen since 1980 (CBO 2008).

In addition to transportation, households use electricity, natural gas and other sources of energy regularly for space conditioning and powering household devices. A closer 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 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. Managing urban sprawl to reduce VMT and GHG emissions could yield significant co-benefits of reduced pollution and congestion.

Microsimulation offers a convenient platform for anticipating these emissions at a disaggregate level. Several researchers have focused on behavior of the agents involved, especially households and, to a lesser extent, firms, and their land use and transport interactions (see, e.g. Miller et al. 1998, Timmermans 2003, Waddell et al. 2003, Salvini et al. 2005, and Maoh et. al. 2005). Hensher (2007) used an integrated transport, land use simulator to assess carbon emissions from the transportation sector. However, existing literature lacks studies on household and firm behavior in an integrated framework. Kumar and Kockelman (2008) focused on firm behavior and its interaction with land use and transport. This paper is an extension of the same, wherein households are tracked in conjunction with firms via a simulation model that forecasts future travel demand, location choices and changing demographic patterns (of households and firms), and the associated GHG emissions.

Microsimulation's key advantage stems from our desire to analyze the impacts of policies at the individual level. However, such advantages should be viewed in the context of added complexity

---

[1] Bomberg and Kockelman (2007) note from a survey of residents in Austin that trip chaining and driving at steadier speeds were the most common responses to the gas spike in 2005.

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 critical for 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), while 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).

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 (scaled up to 100%) and 100% of firms over time and space. The simulation approach seeks to tie 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 model of life-cycle transitions for households and firms has been estimated using a variety of available data sets. Lack of quality data is a serious issue for such studies. However, the aim of this study 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.

DATA DESCRIPTION

In the absence of panel data for the Austin households and firms area, this study develops a microsimulation model to forecast demographic and firmographic characteristics using various national and local, aggregate and disaggregate data sets and under various assumptions about life-cycle events. This section briefly describes these different data sets; more details on many can be found in Kumar (2007).

Household Data Sets

McWethy (2006) synthesized base year (2005) data using the Census 2000 5-percent Public Use Microdata Sample (PUMS) for Austin's three counties (Travis, Williamson and Hays), as the block-group level. Seven person types were defined: preschool children (0 – 4 years), pre-driving age school children (5 – 15 years), driving age school children (16 – 18 years), non-working adults, student adults, part-time working adults (1 – 39 hours of work per week) and working adults (40+ hours of work per week). In the year 2005, the average Austin household enjoyed an annual income of \$59,496 (σ = \$51,542) and owned 1.94 vehicles (σ = 0.95).

Other data sets of interest, primarily for household evolution are the National Vital Statistics Reports (NVSR) and the U.S. Panel Study of Income Dynamics (PSID)[2]. Information on TAZ level land use type and aggregate demographic data was obtained for the year 1997 from the

[2] The PSID is primarily sponsored by the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development and is conducted by the University of Michigan.

Capital Area Metropolitan Planning Organization (CAMPO). That data set also provides year-2007 estimates of all demographic attributes. Data from1997 and 2007 were used to impute TAZ–based population and jobs estimates for the year 2005. These data sets rely on a population-equivalent density (PED[3]) measure to classify TAZs as rural, suburban, urban, and CBD.

Data from the 1996-97Austin Travel Survey (ATS) was used to estimate parameters for the various travel demand models (described in detail in model specifications). More recent ATS data (from a 2005-2006 survey) were used to calibrate the vehicle ownership model which is rather central to this study (thanks to fuel economy). These are described here now.

Vehicle Ownership and Transactions Model

Nearly 1500 households from the Austin region participated in this survey. Data on 2007 model year purchase prices, 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 from 1342 households. The average number of vehicles per household is 1.91, which is slightly lower than the national average of 2.06 (NHTS 2001). Vehicles have been classified into nine broad classes: (1) luxury cars, (2) large car, (3) mid-size cars, (4) sub-compacts (5) compacts, (6) pickups, (7) sports utility vehicles (SUVs), (8) cross-over utility vehicles (CUVs), and (9) minivans. Pickup trucks accounted for 26% of all the vehicles in this household fleet, which is significantly higher than the national share of 18% (NHTS 2001). Passenger cars (luxury, large, mid size, small) constitute about 44% of the vehicle fleet, while minivans, SUVs, CUVs constitute the remainder.

Vehicle acquisitions and use models capture holdings in dynamic context, along with household level changes. Data from the Toronto Area Car Ownership Study (TACOS), a retrospective survey conducted by the University of Toronto (Roorda et. al. 2000), was used. TACOS contains information on household vehicle transactions over nine years (from 1990 to 1998). Miller et al (2003) use a mixed logit model for modeling vehicle transactions using TACOS data at the level of "decision making unit[4]". This study models vehicle transactions at the household level. Out of TACOS's 4096 household years, 79% neither lost nor acquired a vehicle in that year, 11% lost and gained at least a vehicle and 8% added a vehicle to their fleet and the remaining 2% lost or gave up a vehicle.

Development of New Housing Units

Parcel-level land use files for 2003 were provided by the City of Austin's Neighborhood Planning and Zoning Department (NPZD) for the area under its jurisdiction. For the base year, 2005, the Capital Area Council of Governments (CAPCOG) provided similar information for the three-county region. Housing units of various types (single family, 2 to 4-unit multi-family

---

[3] Austin's zone designations are based on a population-equivalent density (PED), equaling [ZonePop + (RegionalPop/RegionalEmp*ZoneEmp)]/(ZoneAcres). A zone with PED $\geq$ 15 is coded as CBD, 8 $\leq$ PED < 15 is coded as Urban, 1 $\leq$ PED < 8 is designated Suburban, and PED < 1 is defined as Rural.

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

structures, and 5+ multi-family structures) in all TAZs for years 2003 and 2005 were obtained from these files (by spatial joining operations), along with undeveloped land information. In this way, new housing units were located. Census figures for square footage age and type of dwelling units were also used, to assign existing households to specific housing units.

Businesses Data Sets

Point-location data for all firms in the three-county region was provided by the Texas Workforce Commission and geocoded by CAMPO. The study region, spread over 1074 TAZs contained 32,063 firms employing 655,722 full- and part-time workers in 2005. The Statistics of U.S. Businesses (SUSB) provides annual data on the number of firms, additions and losses of firms (births and deaths) for various employment size categories by industry. SUSB's firm data from year 1998 to 2004 were used to generate Markov transition matrices of firm growth. New firm birth and death data from year 2001-2002 and 2002-2003 were used to model firm births and deaths. Kumar and Kockelman' (2008) specifications and parameters were used.

Austin's 2006 Commercial Vehicle Survey data as acquired from the Texas Department of Transportation was used to estimate commercial trip generation and distribution models. Kumar (2007) provides a detailed description of various data sets used to model firm location, growth and travel behaviors.

Energy Demands by Households and Firms

Household energy demand was estimated using the 2001 Residential Energy Consumption Survey (RECS), conducted by the EIA. RECS provides information on the consumption of different kinds of energy sources including electricity, natural gas and fuel oil in residential housing units. 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 10,590 kWh and 44,865 BTUs, respectively. Based on National Center for Climatic Data (NCDC 2006) estimates HDD and CDD values for the region are 1674 and 2974; these values are assumed constant throughout the simulation period (though climate changes may actually impact them).

MODEL ESTIMATION

The synthetic household population can be taken through various life cycle transition models to predict the future. Figure 1 illustrates the complete microsimulation structure of household and firm synthesis and evolution. The transitions are applied annually based on a set of interwoven models. The set of rules for household evolution closely mimics Caliper's STEP2 model (Caliper Corporation 2003) for Clark County, as described below.

Base Year Population

As noted earlier a synthetic household population was generated using PUMS seeds, providing household and person records, along with household location TAZ and vehicle ownership and income. A multinomial logit (MNL) model of vehicle class holdings was used to assign vehicle type or classes to each household, based on the household size, number of workers, fuel price and vehicle prices, relative to income and neighborhood attributes (Table 1). Another MNL model was used to model the choice among single-family units and the two types of multi-family units mentioned earlier. The type of housing units is assigned by adjusting to the available housing units by Monte Carlo methods.

Household Transitions

Following Kumar (2007), household transition models anticipate births and deaths for each household. Using probabilities of death by age and gender from the U.S. National Vital Statistics Report, along with Monte Carlo simulation, dying individuals were identified and removed from the population. For child birth, marriage and divorce, binary logistic models were estimated using the 2005 wave of the U.S. PSID (Table 2). Income, a key determinant of several household decisions, is updated via a symmetric triangular distribution of annual percentage income increases (ranging, from -9% to +11% income growth per household per year). New households are formed by people moving into the region and young adults leaving home. The region's year-2005 net rate of increase in population (per year) is used through year 2035. This is done by drawing households randomly from the population and duplicating them, due to data constraints. New locations and housing units are assigned to these households based on a location choice model, based on several control factors (including logsum accessibility indices across all destination and mode choice). Of course, location choice depends on land prices, which are not specifically tracked, representing a short coming of the current specification. Demographics of out-migrating and in-migrating households could be quite different, however. Based on the observed frequency of 22 year old adults living alone, such persons were randomly selected to form new households

Auto acquisition and retirement decisions were predicted using a MNL model, estimated using the TACOS data (described earlier). When acquired, new vehicles classes are allocated based on an MNL model for ownership patterns, as described earlier.

Firm Transitions

The firm population is updated every year by running a sequence of sub-models. A model of firm death/exit is applied first, and exiting firms are removed from the population. This is followed by an expansion/contraction model for remaining firms in the population, based on a Markovian decision process. All existing firms are allowed to relocate based on utility differentials at their current location and the ten other TAZs offering the highest systematic utility values to that firm. New firms are added (based on the birth model) and their locations are chosen based on the location choice model using results from a Poisson regression model. Kumar and Kockelman (2007) provide a detailed description of the firm evolution models.

Travel Demand Model

Household and commercial trip counts are modeled as negative binomial random variables in order to account for over-dispersion (where the distribution's variance exceeds its mean) and latent heterogeneity (across zones) in trip counts, and an MNL model for destination choice is used for the trip distribution model. The choice set for estimation of the trip-distribution model consists of 30 randomly selected destinations plus the chosen destination. Household trips increase with household size, vehicles, and income. Commercial trips originating from each TAZ were regressed on the number of firms, CBD distance and others. Demographic attributes and firm and employment counts at all destination TAZs serve as explanatory variables, in the destination choice models, along with trip times and distances. External-internal and external- external trips were exogenous to the simulation model and added to the OD matrix for traffic assignment.

Emissions Estimates

Standard ordinary least squares regression was used to anticipate annual electricity and natural gas consumption by households. As shown in Table 3, age and type of housing unit, along with several household demographics, serve as key explanatory variables for both forms of energy demand. CO2 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).

Computing times when using microsimulation models is always a concern, and proved to be a challenge in this work. Since tracking 450,103 households over a span of 25 years is a tedious task, 10 percent of the households were sampled randomly for simulation purposes (and each was assumed to represent 9 others like it, in the same zone). A full run for the reduced population took 3 days on a standard desktop machine (3 GB RAM and 2.4 GHz processor).

MODEL RESULTS

Microevolution of all Austin firms and 10 percent of the regions households (then scaled up by a factor of 10) was carried out in MATLAB using yearly transitions. Travel demand modeling was performed externally once every five years, and three scenarios were evaluated: (1) a business as usual or BAU case (2) Imposition of an urban growth boundary (UGB) restricting location alternatives of all new households and firms 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, and (3) a pricing scenario, with gas prices set to $5 per gallon (rather than the $3/gallon base).

Table 4 shows population attributes for the simulation period for years 2015, 2030 and the base year (2005). Households and population are forecasted to grow by 81% and 61% respectively, over the 25-year period; average vehicle ownership (per household) is simulated to rise just 7%. Figure 2 illustrates the location patterns of households for the base year and in the 2030 BAU and UGB scenarios. As expected, the models predict greater household density in the centrally located zones when a growth boundary policy is implemented as compared to the normal growth scenario.

Figure 3 shows the firm density distribution for the base year 2005 and 2030. 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 5) with a steady increase in number of firms in all sectors. However, the increase in basic and retail firms is much less than that seen in education and service firms.

The base area had 4 million trips generating over 80 million VMT. Table 6 provides year 2030 predictions. VMTs generated under the three scenarios are reported in Table 6. In the business as usual case, VMT is predicted to double. Implementation of UGB restricts the rise in VMT (and travel's associated carbon emissions) to 74%, and the pricing scenario restricts it further (to a predicted 60% increase in VMT by 2030). The effect of the $3-per-gallon gas tax is somewhat apparent in the composition of year-2030 vehicles, as slight reductions in the shares of large cars and pickups allow for a higher percentage of small cars (compact and subcompact) and SUVs. The net result is an estimated doubling in transport-related GHG emissions for the BAU scenario, a 74% increase for UGB scenario, and a 60% increase when the gas tax and toll are introduced. Growing wealth really chips away at the opportunity for GHG savings; more stringent policies are needed than a $3 per gallon gas tax (as discussed in Kockelman et al. 2008).

Energy consumption for homes and businesses is forecasted to increase at a much lower rate than VMT (Table 7). Overall electricity consumption is estimated to increase by nearly 40% by 2030 in the business-as-usual and road-pricing/gas - scenarios, in contrast to 28% in the UGB scenario, mainly due to more multi-family units in the UGB case.

SUMMARY AND CONCLUSION

Households and firms are key agents of urban growth, and systems-based modeling techniques help anticipate their long-term location choices, building design decisions, and travel patterns, thereby facilitating analysis of a range of meaningful policies. This paper develops and demonstrates a microsimulation framework for tracking all these behaviors in an attempt to predict regional carbon emissions, and thus inform climate change policy. Perhaps most importantly, the work demonstrates that a microsimulation model of firms and households is feasible using largely existing datasets and standard desktop computing. The models predict greater spatial concentration than presently exists in the Austin region, with firms growing faster than is reasonable. Nevertheless, the UGB policy appears to be effective for curbing GHG emissions via both the transportation and residential sectors.

This work pulls together a variety of models estimated using multiple data sources, but − as is often the case in urban systems modeling − imperfect data give rise to many simplifying and sometimes heroic assumptions. Examples here include a constant in-migration rate for households, a Markovian transition process for firm changes, and a lack of supply constraints on built space for businesses. Certainly, panel data sets on individuals (persons and firms), vehicles land and buildings would resolve many of these issues. More detailed travel demand modeling (both commercial and personal, short distance and long distance) will also make a useful (and easy to undertake) enhancement. No control totals are specified here: population forecasting is entirely based on evolving processes – births, deaths, migration and relocation models. This kind of flexibility creates issues (i.e., jobs out numbering available workers and higher auto ownership levels) certainly, which is a key finding of this work. In the end, key challenges for accurate prediction seem to be the long-term behavior of Markovian processes underlying the firm transitions – resulting in relatively few, excessively large firms, along with a lack of understanding of how offices and other commercial buildings may respond to higher energy prices. Imposition of control totals and/or synchronization of the jobs and household count models would constrain the model somewhat, but help avoid certain unreasonable long-run estimates.

GHG emissions from transportation and residential sectors continue to rise, while offering multiple opportunities for carbon reductions. Taxes and tolls are likely policies, but must be designed carefully. Though both data and computing-intensive, microsimulation of urban systems provides a flexible tool for analyzing the impacts of various policy decisions along with demographic, environmental and other system changes. This work demonstrates that such tools are within our reach, and thoughtful model design and parameter estimation are likely key to their success.

REFERENCES

Bhat, C.R., and J. Y. Guo. 2004. A Mixed Spatially Correlated Logit Model: Formulation and Application to Residential Choice Modeling. Transportation Research Part B 38(2):147-168 2004.

Bina, M., D. Suescun, and K. Kockelman. 2006. Location Choice vis-à-vis Transportation: The Case of Recent Home Buyers. Proceedings of the 85th Annual Meeting of the Transportation Research Board, Washington, D.C. 12-15 January 2006.

Bomberg, M., and K. Kockelman. 2007. Traveler Response to the 2005 Gas price spike. Proceedings of the 86th Annual Meeting of the Transportation Research Board Washington D.C., 12-15 January 2007.

Brown M. A., F. Southworth, and T. K. Stovall. 2005. Towards a built climate friendly environment, Pew Center. http://www.pewclimate.org/docUploads/Buildings_FINAL.pdf Accessed 25th October 2007

Caliper Corporation. 2003. STEP2 for Clark County: Household Microsimulation for Transportation Policy Analysis prepared for Southern Nevada Regional Planning Coalition

CBO. 2008. Effect of Gasoline Prices on Driving Behavior and Vehicle Markets. http://www.cbo.gov/ftpdocs/88xx/doc8893/01-14-GasolinePrices.pdf Accessed 12th April 2008.

EIA. 2002. Updated State-level Greenhouse Gas Emission Coefficients for Electricity Generation 1998-2000 http://www.eia.doe.gov/pub/oiaf/1605/cdrom/pdf/e-supdoc.pdf Accessed 14th June 2008.

EIA. 2005. Voluntary Reporting of Greenhouse Gases Program (Fuel and Energy Source Codes and Emission Coefficients) http://www.eia.doe.gov/oiaf/1605/coefficients.html Accessed 20th June 2008.

EIA. 2006. Emissions of Greenhouse Gases in the United States for 2006. Report #: DOE/EIA-0573(2006) http://www.eia.doe.gov/oiaf/1605/ggrpt/pdf/enduse_tbl.pdf Accessed December 27, 2007.

EIA. 2008. Retail Gasoline Historical Prices Available at http://www.eia.doe.gov/oil_gas/petroleum/data_publications/wrgp/mogas_history.html, and accessed June 15, 2008.

Goulias, K. G., and R. Kitamura, 1992. Microsimulation for Travel Demand Forecasting: A Dynamic Model System of Household Demographics and Mobility. Institute of Transportation Studies Research Report, UCD-ITS-RR-92-4, University of California,Davis.

Kockelman, K., M. Thompson and C. Whitehead. 2008. Americas' Travel Choice and Their Relative Contributions to Climate Change: What Near-Term Behavioral Shifts Will Buy Us and Opportunities for Meeting Carbon Targets. Submitted for Presentation at the 88th Annual Meeting of the Transportation Research Board and Publication in the Transportation Research Record Series.

Kumar, S., 2007. Micro simulation of Household and Firm Behaviors: Coupled Models of Land Use and Travel Demand in Austin, Texas. Master's Thesis. Department of Civil Engineering, University of Texas at Austin.

Kumar,S. and K. M. Kockelman. 2008. Tracking the Size, Location and Interactions of Businesses : Micro-simulation of firm Behavior in Austin , Texas. Proceedings of the 87th Annual Meeting of the Transportation Research Board, Washington DC, 12-15 January 2008.

Maoh, H.F., Kanaroglou, P.S. and Buliung, R.N. 2005 Modeling the location of firms within an integrated transport and land-use model for Hamilton, Ontario. CSpA Working Paper 006. Centre for Spatial Analysis. McMaster University. Available at http://sciwebserver.science.mcmaster.ca/cspa/papers/CSpA%20WP%20006.pdf

Mannering, F., C. Winston, and W. Starkey. 2002. An Exploratory Analysis of Automobile Leasing by US Households. Journal of Urban Economics 52: 154-176.

McWethy, L. M. 2006. Comparing Microscopic Activity-Based and Traditional Models of Travel Demand: An Austin Area Case Study. Master's Thesis. Department of Civil Engineering, University of Texas at Austin.

Miller, E. J., and P. A. Salvini. 1998. The Integrated Land Use, Transportation,Environment (ILUTE) Modeling System: A Framework. Proceedings of the 77th Annual Meeting of the Transportation Research Board, Washington DC, 12-15 January 1998.

Miller, E.J., J.D. Hunt, J.E. Abraham and P.A. Salvini. 2004. Microsimulating Urban Systems. Computers, Environment and Urban Systems special issue, "Geosimulation:Object-Based Modeling of Urban Phenomena" 28: 9-44.

Mohammadian, A., and E. J. Miller. 2003. Empirical Investigation of Household Vehicle Type Choice Decisions. Transportation Research Record 1854: 99-106.

NCDC .2006. Comparative climatic data for the United States through 2006. National Climatic Data Center. Available at http://www1.ncdc.noaa.gov/pub/data/ccd-data/CCD-2006_fixed.pdf, and accessed February 18, 2008.

Polzin, S. E. .2006. The Case for Moderate Growth in Vehicle Miles of Travel: A Critical Juncture in U.S. Travel Behavior Trends Center for Urban Transportation Research, University of South Florida, National Household Travel Survey, U.S. Department of Transportation Available at http://nhts.ornl.gov/publications.shtml, and accessed July 5, 2008.

Roorda, M., A. Mohammadian, and E. J. Miller. 2000. Toronto Area Car Ownership Study: A Retrospective Interview and Its Applications. Transportation Research Record, 1719: 69-76.

Salvini, P.A., and E. J. Miller. 2005. ILUTE: An Operational Prototype of a Comprehensive Microsimulation Model of Urban Systems. Networks and Spatial Economics 5: 217-234.

Timmermans, H. 2003. The Saga of Integrated Land Use-Transport Modeling: How Many More Dreams Before We Wake Up? Presented at 10th International Conference on Travel Behaviour Research, Lucerne, Switzerland, 2003

Waddell, P.A., A. Borning, M. Noth, N. Freier, M. Becke, and G. Ulfarsson. 2003. Microsimulation of Urban Development and Location Choices: Design and Implementation of UrbanSim. Networks and Spatial Economics 3 (1): 43-67.

Ward's .2007. Ward's Automotive Yearbook. Ward's Communications, Detroit, MI.

Zhao, Y., and K. Kockelman. 2000. Household Vehicle Ownership by Vehicle Type: Application of a Multivariate Negative Binomial Model. Proceedings of the 81st Annual Meeting of the Transportation Research Board, Washington D.C.

List of Figures

List of Tables

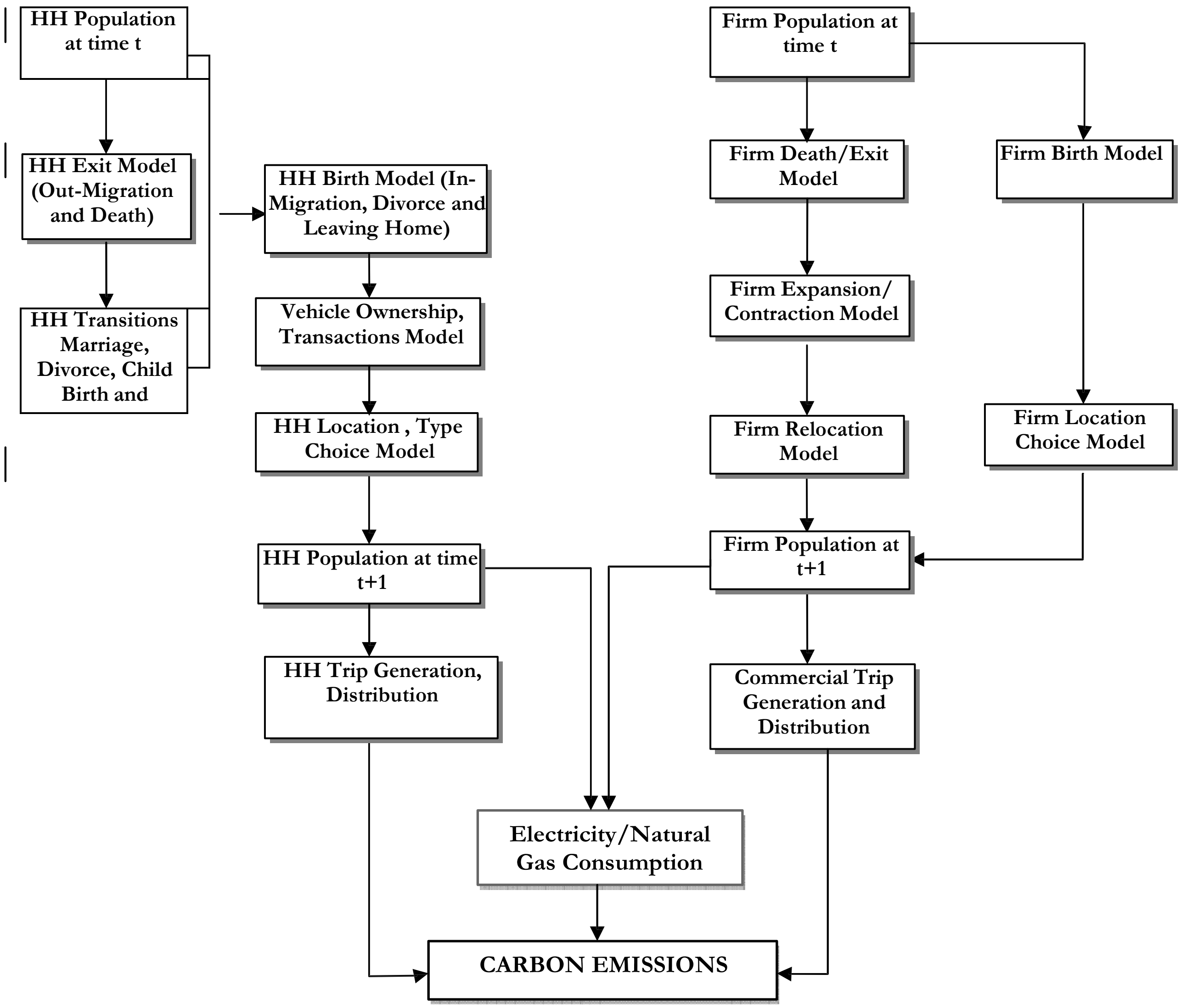

FIGURE 1 Overview of Simulation Framework

FIGURE 2 Household Density (a) Base year (2005) (b) 2030 BAU (c) 2030 UGB

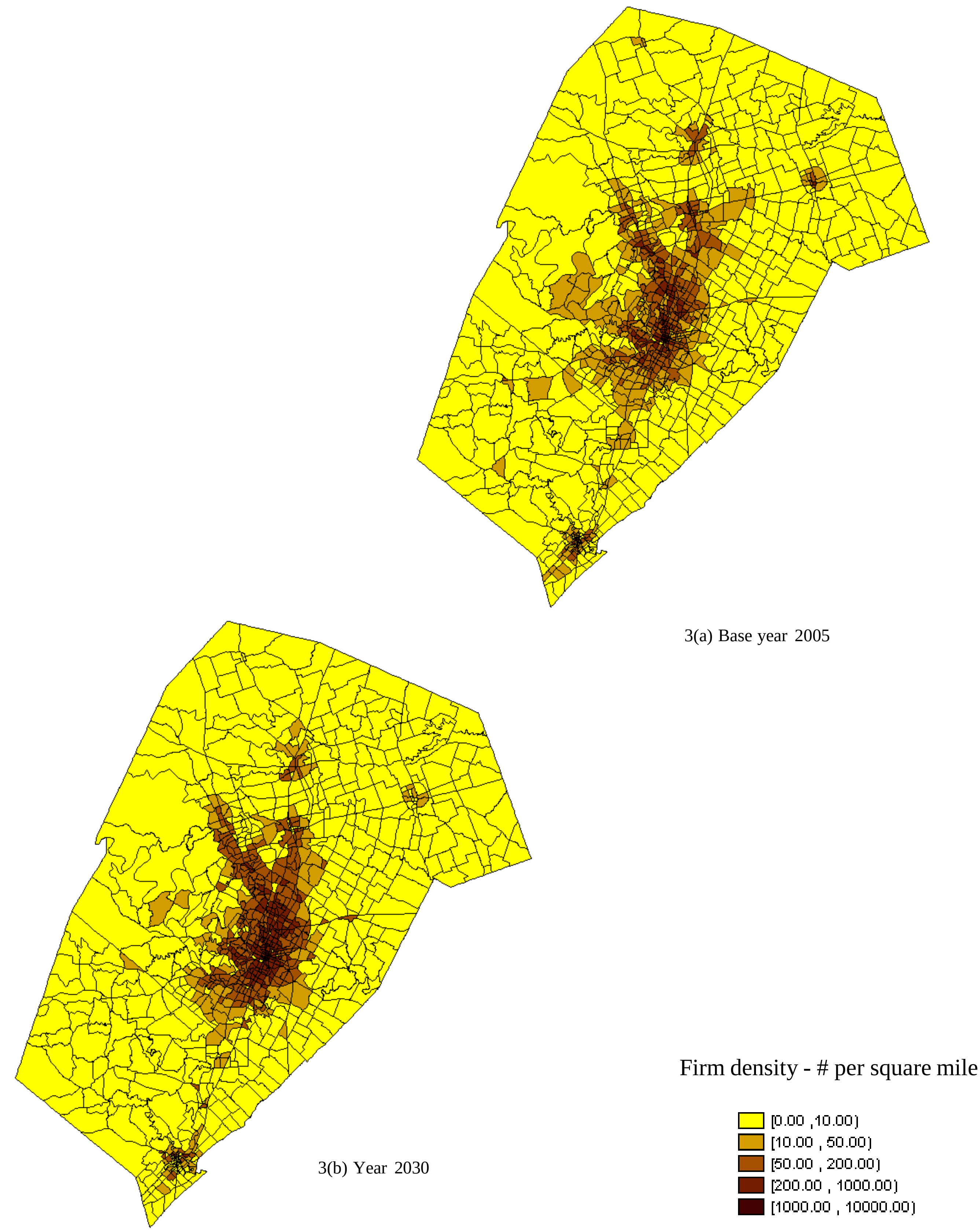

FIGURE 3 Firm Density (a) Base year (2005) & (b) 2030 for BAU scenario

TABLE 1 Vehicle Ownership Model

Variable	Coefficients	t-statistics
Fuel Price/Income x 10^4	-0.603	-2.46
Price of vehicle/Income	-0.104	-1.78
HH Size x (Sub-Compact, Compact, Mid Size Cars)	-0.221	-5.72
HH Size x (Large Cars , Luxury Cars)	-0.178	-4.70
Number of employees in HH x Mid size cars	0.122	1.99
High Income(>75k) x Luxury Cars	0.291	1.70
Age of House Head x Large Cars	0.024	3.88
No of Female Drivers x Sub-Compact Cars	0.307	3.83
Presence of Preschool children x Van	-0.463	-3.07
Rural x Pickups	0.178	1.58
Sub urban x Large Cars	0.200	1.39
Density of HH in zone x Small Car * 10^{-3}	0.009	1.71
Density of HH in zone x SUV *10^{-3}	-0.103	-1.53
Retail firms within 5 miles x SUV *10^{-4}	-0.125	-2.06
Retail firms within 5 miles x Van *10^{-4}	-0.093	-1.53
Multi Family Housing Unit x Pickup	-0.479	-3.05
Log Likelihood	-4649.22	
Pseudo R^2	0.0981	

Data Source: ATS 2006.

TABLE 2 Birth, Marriage and Divorce Models

Explanatory variable	Child Birth Model		Marriage Model		Divorce Model	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Constant	0.591	1.13	-1.869	-10.63	-1.437	-6.85
Household size			0.129	4.27	-0.281	-5.75
Age of household head			-0.032	-8.82	-0.028	-6.81
HH head's emp. status	0.666	1.89	0.027	2.63		
Age of mother	-0.110	-7.35				
Number of children	1.893	14.67				
Age of youngest child	-1.618	-10.81				
Pseudo r-square	0.4522		0.1409		0.1326	
No. of observations	2,127		3,504		4,028	

Data Source: 2005 U.S. Panel Study of Income Dynamics.

TABLE 3 Household Energy Consumption Model Parameter Estimates

Data Source: RECS 2001

	Natural Gas (BTU/year)		Electricity (kWh/year)	
	Coefficients	t-statistics	Coefficients	t-statistics
(Constant)	161.4	3.06	14433	23.64
$ /btu (natural gas) or $ /kwh (electricity)	-8666	-10.68	-78788	-24.63
Cooling Degree days(CDD) to base 65	-0.027	-2.451	0.255	1.687
Heating Degree days (HDD)to 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
Indicator for city			-2935	-12.62
Indicator for town			-2036	-7.661
Indicator for sub urban			-2417	-9.325
Indicator > 5 units dummy	-297.4	-14.86	-832.9	-3.533
Indicator 2-4 units dummy	-55.08	-2.394	-626.4	-2.22
Household Size	46.67	10.32	1514	19.25
No of kids	-42.46	-1.366	-1900	-4.779
No of persons > 65 years	46.69	4.372	-712.2	-5.78
Income ($ '000)	0.00096	3.74	0.037	11.95
Age of home	4.149	11.8	-19.46	-4.411
Total sqft − Basement and Garage areas	0.048	2.989	-1.136	-4.522
Total heated sqft* Northeast	0.104	5.383	-0.747	-3.124
Total heated sqft* West	0.049	3.023		
Total sqft * HDD	1.40E-05	3.612	1.47E-04	4.245
Total sqft*CDD			8.84E-04	15.02
R Square	0.48		0.50	

TABLE 4 Evolution of Austin's Population Attributes over Time

	Year 2005		Year 2015		Year2030	
# of Households	451,003		561,190		828,110	
# of Persons	1,148,177		1,402,970		1,970,900	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
HH size	2.55	1.47	2.5	1.39	2.38	1.23
Vehicles	1.94	0.95	2.06	0.9692	2.14	1.078
Income	$59,496	$51,542	$61,271	$52,279	$62,085	$53,268
Fraction of households with…						
Pre-School age children	0.15	0.36	0.18	0.38	0.15	0.36
Pre-driving children	0.23	0.42	0.22	0.41	0.18	0.38
Driving age children	0.06	0.24	0.05	0.22	0.05	0.21
Non-working adults	0.2	0.4	0.19	0.39	0.17	0.38
Student adults	0.15	0.35	0.15	0.36	0.14	0.35
Part-time working adults	0.34	0.47	0.32	0.47	0.28	0.45
Full-time working adults	0.68	0.47	0.66	0.47	0.63	0.48

TABLE 5 Evolution of Austin's Firm Attributes over Time

	2005		2030	
	No.	%	No.	%
No of Firms	32,063		42,176	
Basic	6,944	21.66	7,282	17.27
Retail	6,203	19.35	6,980	16.55
Educational	650	2.03	1,083	2.57
Service	18,266	56.97	26,831	63.62
Size of Firms				
1-4	16,641	51.90	15,102	35.80
5-9	5,815	18.13	9,454	22.42
10-19	4,153	12.95	6,171	14063
20-99	4,417	13.78	6,369	15.10
100 – 499	876	2.73	3,281	7.78
≥ 500	161	0.50	1,799	4.26

TABLE 6 Vehicle Fleet Composition Predictions (%)

	2005	Year 2030		
	BAU	BAU	UGB	Pricing *
VMT (per day)	112.3 million	223.9 million	195.1 million	180.2 million
Fleet Composition (%)				
Small Cars**	8.09%	8.53	8.94	8.83
Mid-Size Cars	17.24	17.27	17.66	17.68
Large Cars	7.42	6.86	6.97	6.77
Luxury Cars	13.62	12.78	12.91	12.90
Pickups	19.79	18.28	17.62	17.86
Passenger Vans	15.96	17.56	17.86	17.56
SUV/CUV	17.97	18.14	17.99	18.21

** Compact and sub-compact cars

TABLE 7 Predicted Residential Energy Consumption and Carbon Emissions in BAU scenario

	2005	2015		2030	
	Estimate	Estimate	% change from 2005	Estimate	% change from 2005
Total electricity consumed (‘000 kWh per year)	6,866,971	7,420,615,	8.06	9,517,468	38.60
Total lbs of CO2 from electricity (‘000 per year)	10,025,778	10,834,098	8.06	13,895,503	38.60
kWh energy per household per year	15,226	13,223	(-13.16)	11,493	(-24.52)
Total CCF of natural gas consumed (per year)	115,358,720	140,858,690	22.10	202,912,456	75.90
Total lbs of CO2 from natural gas (‘000 per year)	1,384,304	1,690,304	22.10	2,434,949	75.90
CCF of natural gas per household per year	255.78	251.00	(-1.87)	245.03	(-4.20)