Tracking the Size, Location and Interactions of Businesses: Microsimulation of Firm Behavior in Austin, Texas

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ABSTRACT

Firms are key drivers of urban growth along with households, yet data on businesses and commercial vehicle movements can be quite difficult to obtain. An understanding of firm behavior over time is critical in anticipating urban futures and addressing transportation, land use and other concerns. Firm birth and death, migration and location choice are defining events in a firm's life cycle, and a study of firm evolution requires estimating and applying models for each of these. Such an exercise is hindered primarily by a lack of quality micro-data for businesses. This paper proposes a basic framework for modeling firm demographics using a microsimulation approach. Year 2005 employment point data for the Austin, Texas region and 7 years of aggregate data from the Statistics of U.S. Businesses have been used to simulate firm entry, exit and evolution over time and space. A Markov process is used to anticipate firm growth and contraction, along with logit and Poisson models for firm location choice. Austin's commercial vehicle survey data are used to estimate commercial trip generation and distribution models, and applications of these are tied to forecasts of firm counts by location over time. Simulation results for both low- and high-growth scenarios suggest an increasing movement of firms towards central zones.

Keywords: Firmography, microsimulation, location choice, commercial vehicle movement, Markov transition process

INTRODUCTION

Policymakers, planners and researchers are interested in answering various questions raised by urbanization and infrastructure's ability to cope with added demands. Most research has focused on studying the behavior of 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, and Salvini et al. 2005). As key agents of urban development, households have been studied extensively, using sound behavioral specifications and data. The literature lacks similar studies tracking firm behavior (the focus of this study), owing to a lack of quality data (as compared to households) and greater variety (and thus uncertainty) in firm behavior (Elgar et al., 2006).

The demography of firms (firmography) may be key in understanding the process of urbanization and forecasting urban growth. Zones of high employment are major attractors and producers of personal and commercial trips. Since, commercial trips constitute a major portion of urban trips, an understanding of firm behavior should help improve transportation planning. Effect of demographic events in firms' life cycle on land use and urban travel patterns is also generating interest among urban planning agencies. Hence, this study aims to study the interaction of firm dynamics and transport infrastructure over time and spatial dimensions.

LITERATURE REVIEW

The study of firmography is multidisciplinary in nature involving economists (Evans, 1987), sociologists (Hannan et al. 1988 and Carroll and Hannan 2000), geographers (Van Dijk and Pellenbarg, 2000a), and transportation researchers (Khan et al. 2002, Wadell et al. 2003, Maoh et al. 2005, and Abraham and Hunt 2000), among others. Past studies have researched firmography from the viewpoint of a single discipline as well as from a multidisciplinary angle (Van Wissen, 2000). Key steps in the firmography process include firm birth, death, migration and location choices, as well as expansion and contraction. While migration and location choice decisions are of special interest to regional scientists, when studying spatial patterns (e.g., Pellenbarg and Steen 2003, and Dijk and Pellenbarg 2000a), firm birth, exit and growth patterns greatly interest economists, anthropologists, and others.

A common objective in firmographic studies is modeling the location choices of new firms and relocation decisions of existing firms. Neo-classical and behavioral schools of thought have proposed different theories to explain such location decisions (Hayter, 1997). Neo-classical theory assumes firms act as profit maximizers with perfect market information (see, e.g., Pellenbarg et al. 2002), while behavioral theory presumes firms are simply "satisficers" rather than maximizers (see, e.g., Brouwer et al. 2002). Past studies have modeled firms in both senses and have done market-segmentation analysis based on industrial sector and size (De Bok and Sanders 2005, Wadell et al. 2003, Khan et al. 2002, Elgar et al. 2006). For example, Bartik (1985), Coughlin et al. (1991), Friedman et al. (1992) and Head et al. (1995) used aggregate regions like U. S. states in U.S. as choice alternatives for firm location choice models. To account for agglomeration economies and labor market effects (which vary at much finer levels of spatial resolution), Hansen (1987) used cities in and around Sao Paulo, Brazil, and Woodward

(1992) used U.S. counties as choice alternatives. Guimaraés et al. (1998 and 2000) used municipalities in Puerto Rico and concelhos[1] in Portugal as choice alternatives.

Analysis of data at finer spatial scales results in larger choice sets, which can become impractical due to computational requirements (in popular analysis packages, like LimDep and STATA) and problems posed by the independence of irrelevant alternatives property (Ben-Akiva and Lerman 1984). To address such issues McFadden (1978) proposed the use of a random sample of choice alternatives, for estimation of the logit model, and showed it to result in consistent estimators. However, efficiency and replications are compromised (Train 1986). The stochastic nature of McFadden's approach also poses the problem of non-replication. Coughlin et al. (2000), Guimaraés et al. (2003) and many others have used Poisson regression to counter the complexities posed by a large set of choice alternatives and computational requirements. When locators are homogeneous, Poisson regression is a tractable econometric alternative to the conditional logit model, consistent with McFadden's (1974) maximization framework.

Relocation of existing firms is another aspect of location choice studied extensively in 1970s in Europe and U.K. (Pellenbarg et al. 2002). Data improvements and technological advances have improved the spatial resolution of these models, from a regional to more local levels of cities, but a study of firm mobility at the truly local scale remains neglected, to a large extent. Local firm movements affect local travel patterns and land use, as well as the local economy (Van Dijk and Pellenbarg 2000b). While most researchers have focused on factors affecting location choices of new firms, Lee (2006) used a binary probit model to examine the effect of firm and location specific factors on the relocation decision and Van Dijk and Pellenbarg (1999) used an ordered[2] logit model to study firm relocation patterns in Netherlands.

The modeling paradigm has changed considerably over the years, with more emphasis on individual agents. The basis for such a change in perspective is based on the assumption that tracking an individual's choices may lead to more behaviorally reasonable models and enhanced forecasting. Activity-based and microsimulation models of travel demand are starting to replace traditional aggregate models (e.g., Bhat et al's (2004) CEMDAP and the FHWA's (2006) TRANSIMS). Microsimulation provides the flexibility of modeling individual behaviors and aggregating results as needed. Disaggregate models provide footprints of behavior, while microsimulation tracks individual's transitions through space and time. Microsimulation models of land use include Miller et al's (2001) Integrated Land Use, Transport and Environment (ILUTE) model, Waddell et al's (2003) UrbanSim, Arentze and Timmermans' (2004) A Learning-Based Transportation Oriented Simulations System (ALBATROSS), and Moeckel et al's (2002) Integrated Land-Use Modeling and Transportation System Simulation (ILUMASS). ILUTE operates on a 100% sample of households and firms and simulates location choice as well as firmography and household demographics.

[1] As reasonably small administrative areas, Portugal's concelhos have an average area of 322.5 km^2.
[2] Firm propensity to move was expressed in percentages (0%, 0–10%, 10–25%, 25–50%, 50–75%, 75–90%, 90–100% and 100%) and used as the dependent variable in an ordered logit model.

Commercial trips[3] account for 10 to 15% of intra-urban vehicle trips (Hunt et al. 2004) and even higher share of inter-urban trips. Commercial trips also account for roughly 12 to 15% of VMT (Hunt et al. (2004) and Spear (2006)). The recent surge in microsimulation models of household travel would be well supplemented by similar models for commercial trips. Hunt et al. (2004, 2005) estimated a tour-based microsimulation model of commercial movements in the city of Calgary, Canada. Commercial trip patterns are strongly tied to firm location choices and this study highlights the same.

DATA DESCRIPTION

Point location data for all firms in the three-county Austin region was provided by the Texas Workforce Commission and geocoded by the Capital Area Metropolitan Planning Organization (CAMPO). In 2005 Hays, Travis and Williamson counties contained 32,063[4] firms employing 655,722 full- and part-time workers. The study region consists of 1,074 Traffic Analysis Zones (TAZs), and zone-level statistics for the year 2005 were imputed from CAMPO's 1997 and 2007 data sets. 57% of the firms belong to the service sector[5], and 26% of firms are single-worker firms. The average firm size is 20 workers, with a standard deviation is 155 owing mostly to the presence of a few, very large educational establishments[6]. Figure 1 shows the distribution of TAZs and firms by area type. Around 45% of Austin's TAZs are coded as rural[7]; these account for 85% of the three-county area but only 16% of firms and 12% of workers. In contrast, only 22% of the TAZs are coded as urban or CBD (accounting for a mere 3% of area yet 45% of the firms and 59% of workers).

The Statistics of U.S. Businesses (SUSB) provide annual data[8] on the number of firms and new birth and deaths for employment size of firm categories by location and industry. The data are a "snapshot" of firms at a point in time. SUSB's firm data from year 1998 to 2004 were used for generating Markov transition matrices of firm growth. 1998 to 2004 was a slow growth period for industries with a couple of years of recession. New firm birth and death data from year 2001-2002 and 2002-2003 were used for modeling firm births and deaths. While most of the industries witnessed slow rate of growth in 2001-2002, 2002-2003 showed higher growth rates.

The Texas Department of Transportation (DOT) provided commercial vehicle survey data for the region. In 2006, 342 vehicles were randomly selected from the study area's list of registered

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[3] Commercial vehicles were classified as trucks used for commercial or public agency-purposes with six or more tires and having a curb weight of 6,000 pounds or more.

[4] Addresses of 5 firms could not be mapped to the 3-county Austin region and hence were removed from the study population.

[5] The four sectors are Basic (manufacturing, construction, mining, transport services and utilities, forestry, fishing, recreation, and hunting and agricultural support), Retail (department stores, restaurants and hotels, retail and wholesale shops), Education (schools, colleges, and training institutes), and Service (information services, real estate, finance and insurance, professional and technical services, health, government services, and banks).

[6] The University of Texas at Austin, Texas State University and Austin Community College have 20,250, 4,884 and 3,390 workers in 2005, respectively.

[7] 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.

[8] The new birth and death data is available only for years 2001-2002 and 2002-2003 while aggregate number of firms in each size category and sector is available for 1998 through 2004.

commercial vehicles. These 342 vehicles were based in 113 TAZs and made 2,551 trips over the survey day.

MODEL SPECIFICATION

A microsimulation approach is used to simulate individual firm life cycles in an urban environment. Microsimulation is critical in tracking each decision maker over its life cycle and provides a better insight into firm behavior than forecasts made using aggregate cross-sectional data (Goulias and Kitamura, 1992). One key component of microsimulating firmography lies in estimating the statistical models of life cycle transitions. Lack of quality data is the biggest challenge in developing such a model. Of course any model of human behavior is an abstraction of reality and the uncertainty in business environments and behavioral dependence on various unpredictable and uncontrolled factors raises questions regarding interpretation of simulation results. Nonetheless, such modeling exercises can provide insights into how firms react to various changes in their urban environment and land use and transport components.

The basic structure for firm synthesis and evolution used here is shown in Figure 2. The firm population is updated every year by running through 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. All existing firms are allowed to relocate based on utility differential at their current location and ten most popular TAZs (based on levels of TAZ-specific systematic utility). New firms are added (based on the birth model) and their locations are chosen based on the location choice model. Commercial trip generation and distribution models are applied at time *t* based on the current firm population. Firm population and travel patterns are updated every year.

A lack of panel data necessitates the use of Markov decision process[9] for many submodules in the microsimulation process. Firms are modeled on a three-dimensional state space (*S*) of size, industry affiliation and location. Hence, the Markovian probability of any event in a firm's life cycle is dependent only on its current size (*s*), and industry affiliation (*i*). The Markovian series of states (over time) can be expressed as:

$$\Pr(S(t)=s_t,i_t)=\sum_{s_{t-1}}\sum_{i_{t-1}}\Pr(S(t)\mid S(t-1))\times\Pr(S(t-1)=s_{t-1},i_{t-1}) \qquad (1)$$

where $\Pr(S(t) \mid S(t\text{-}1))$ is one step (one year) transition probability from state at time t-1 to state at time *t*. Hence, the transition of a firm from state S_{t-1} to S_t depends on firm's existing state (S_{t-1}) and is independent of earlier states ($t' < t\text{-}1$).

Firm Death/Exit and Birth Model

SUSB estimates for U.S. firm death/exit (2001-2002 for low-growth and 2002-2003 for high-growth estimates), as a function of firm size category *s* and industry sector *i*, were used to randomly sample firms from the population for removal. Assumptions for the birth model are

[9] Assumption of a Markov transition process implies that firm history (e.g., how long a firm has existed or been in its size category) does not affect its future growth. While such assumptions limit data requirements, ideally they should be tested and improved upon, as needed.

similar to those for the death/exit model, in terms of the use of SUSB estimates and sampling. New firm attributes were (randomly) selected from the sample space (as defined by the existing firm population). Location information was provided each new-born firm simply by applying the firm location choice submodule (with a multinomial assignment based on random utility values).

Firm Expansion/Contraction Model

Using SUSB data on annual changes in firm counts (by industry sector and size) from years 1998 through 2004, a Markovian transition matrix was estimated via constrained least squares. SUSB data provide the aggregate proportions $y_j(t)$ and $y_i(t\text{-}1)$ of firms in size categories j and i over time. Using tenets of conditional probability and admitting an error term to account for differences between actual and estimated proportions of $y_j(t)$, the following stochastic equation expresses the relation between observed and estimated proportions (Lee et al. 1970, and Jones 2005):

$$y_j(t) = \sum_i y_i(t-1) p_{ij} + \varepsilon_j(t) \tag{2}$$

where $y_j(t)$ is the proportion of firms at time t in size category j, p_{ij} is the transition probability from size category i to j, and ε_j is the stochastic error term. This can be written in matrix notation as:

$$\mathbf{y} = \mathbf{Xp} + \boldsymbol{\varepsilon} \tag{3}$$

This can be expressed as a quadratic programming problem with the following objective function and linear constraints:

$$\underset{\{p_{ij}\}}{\text{Minimize}}\, f(\mathbf{p}) = \boldsymbol{\varepsilon}'\boldsymbol{\varepsilon} = (\mathbf{y} - \mathbf{Xp})'(\mathbf{y} - \mathbf{Xp})$$

$$\text{Subject to} \sum_i p_{ij} \le 1 \quad \forall i \quad \& \quad 0 \le p_{ij} \le 1 \quad \forall\ i, j \tag{4}$$

As an example, estimates of transition probabilities $\{p_{ij}\}$ resulting from this optimization are shown in Table 1, for basic firms. Using such Markovian transition probabilities and Monte Carlo sampling methods, firm and job counts are updated annually.

Firm Location Choice Model

While actual location choices are made at the parcel or building suite levels, it is very difficult to model location choice at such resolution due to computational and data availability issues. This study thus emphasizes firm location decisions at the TAZ level across the 3-county Austin region.

Let the utility derived by firm i by locating at TAZ j be given by:

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \tag{5}$$

Where β is a vector of unknown parameters to be estimated, X_j is a vector of explanatory variables associated with the choice alternative, and ε_{ij} is the error (stochastic) term. Under a random utility maximization framework and assuming a generalized extreme value type-I (Gumbel) distribution for ε_{ij}, this results in the following probabilities:

$$P_{ij} = \frac{e^{\beta X_{ij}}}{\sum_k e^{\beta X_{ik}}} \tag{6}$$

The log-likelihood of Austin's 32,063 firms' location choices in the year 2005 across the region's 1074 TAZs then takes the following form:

$$L = \sum_i^{32,063} \sum_j^{1,074} \delta_{ij} \log P_{ij} \tag{7}$$

where δ_{ij} equals 1 if firm i chooses to locate in TAZ j and 0 otherwise. After segmenting firms by sector (and not by size or other attributes) this study assumes that the firm location decision is based entirely on attributes specific to the zone alternatives. Essentially, the log-likelihood reduces to:

$$L = \sum_j \eta_j \log P_j \tag{8}$$

Where η_j is the number of firms choosing to locate in zone j and P_j is the probability of zone j being chosen by any single firm. If all firms choose their locations independently, equations (7) and (8) imply a Poisson model of firm counts, by zone. In the case of a Poisson probability for firm counts, the probabilities are as follows:

$$P(\eta_j, \lambda_j) = \frac{e^{-\lambda_j} \lambda^{\eta_j}}{\eta_j!} \tag{9}$$

Hence, the log-likelihood of firm counts across the 1074 zones takes the following form:

$$L = \sum_j^{1074} (-\lambda_j + \eta_j \log \lambda_j - \log \eta_j!) \tag{10}$$

Where $\lambda_j = \exp(\alpha + \beta X_j)$ (for consistency with equation (8)), so that equation (10) reduces to:

$$L = \sum_j \eta_j \log P_j + constant \tag{11}$$

The above expression differs from a logit's log-likelihood expression only in terms of its constant and hence, its maximization results in the same estimates for β (and similar standard errors for the β's). Guimaraés et al. (2003) compared logit model of location choice with Poisson regression model and concluded that logit model coefficients are equivalent (as long as one includes the full set of alternatives in the probabilities of the likelihood function).

This work's model of firm location choice model is estimated using the employment point data provided by CAMPO for the 3-county region. Logsums from a commercial trip distribution model serve as zonal accessibility indices. The accessibilities were computed as follows:

$$Access_i = \sum_j \frac{A_j}{e^{(\gamma_1 . time_{ij} + \gamma_2 . dist_{ij})}} \tag{12}$$

where A_j is the attribute under consideration (such as population or employment), $time_{ij}$ is the peak period travel time from zone i to zone j, $dist_{ij}$ is the distance between centroids of zone i and zone j, and γ_1 and γ_2 and are parameters from logit models of commercial trip destination choice. All new-born and relocating firms are assigned a zone according to probabilities from this model of firm location choice.[10]

Firm Relocation Model

Kroll et al. (1990) found that roughly 5% of firms relocate locally (within a county) every year. Relocating firms were selected randomly (with a sampling rate of 15%) from among the one-third of firms exhibiting the lowest systematic utilities, as estimated using the location choice model. New locations were assigned to these 15% of the low-utility firms based on firm-specific probabilities determined in the firm location choice model (using appropriately weighted Monte Carlo draws from a multinomial across all possible zones).

Commercial Trip Generation and Distribution Models

Commercial trip movements were modeled using trip generation and distribution models. A model of commercial trip generation was estimated using 2006 Austin Commercial Vehicle Survey data provided by the Texas DOT. The number of trips originating from each TAZ was regressed on firmographic and location attributes of the TAZ. Trip counts were modeled using a negative binomial regression (recognizing their integer nature, while allowing for overdispersion due to things like unobserved heterogeneity).

Trip distribution was modeled as a logit model, using the proportion of trips destined to a TAZ as the dependent variable. Demographic attributes and firm and employment counts at the destination TAZs serve as explanatory variables, along with trip times and distances.

MODEL RESULTS

Microsimulation of firm evolution was carried out using MATLAB. An initial population of 32,063 firms was taken through the series of models at one-year steps to forecast firm population, location and related trips 30 years into the future. Firm population profiles and commercial trip generation and attraction profiles were updated at the end of each one-year run of the simulation model for all TAZs.

[10] While separate location choice models were initially estimated for each of the four industries, the estimates were quite similar, so a single model of location choice is used here, without loss in generality.

Table 2 lists the results of Poisson regression model of firm location choices. Firms are more likely to locate near the CBD, everything else constant. Firms also are more likely to locate around other firms or in TAZs with better job accessibility, implying positive agglomeration effects. However, everything else constant, they appear to be less likely to locate in TAZs with high population accessibility, possibly due to congestion, higher land prices and zoning restrictions.

As discussed earlier commercial trip generation and destination choice models were estimated for the region using 2006 commercial vehicle survey data. Trip counts originating from a TAZ follow a negative binomial distribution, and produce a high overdispersion parameter, of $\alpha =$ 3.161[11]. Table 3 shows the results of this model. Signs and magnitudes of coefficients are as expected: Commercial trip production falls with distance from the CBD. Urban and suburban zones are the biggest generators of commercial trips, ceteris paribus. However, trip counts show a very low elasticity with respect to number of firms in the zone. Table 4 shows the results of the logit model of commercial trip distribution, including a pseudo[12] r^2 value of 0.180 (which is a very reasonable fit for a logit model of disaggregate trip data). Commercial trips tend to be destined to outer zones (away from the CBD) as suggested by positive coefficient on the distance-from-CBD variable. As expected, peak-period travel time has a negative coefficient.

Assuming year 2001/2002 rates of firm exit, birth and growth/contraction for different sectors and sizes, Figure 3 illustrates simulated changes in firm size by sector over time, for the low-growth scenario. These results suggest a steady increase in service firms while other sectors exhibit are predicted to endure losses in firm numbers, with this trend stabilizing over time. Large firms (> 100 workers) show a sharp increase at the cost of smaller firms initially, but this trend also stabilizes.

Of course, every simulation is different, and it is important to get a sense of the simulation's own variability. 25 runs of each scenario were performed, and these exhibit less than 10% variation (from lowest simulated value to highest value) in the total number of firms in different categories for both scenarios by the year 2035. Much greater variation in firm counts generally is evident at the level of individual zones, due to their smaller size and the discrete nature of firm existence and location choice. However, in congested parts of the region, a 10% variation can remain. For example, in the high-growth scenario, CBD zones are estimated to end up with a total of 3,612 to 3,927 firms, while in the low-growth scenario, these numbers vary between 2,884 and 3,118 (versus 2,163 firms in the year 2005).

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[11] Negative binomial distributions can be written as follows:

$$\Pr(Y = k \mid \lambda, \alpha) = \frac{\Gamma(k+\alpha^{-1})}{k!\Gamma\alpha^{-1}}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\alpha^{-1}+\lambda}\right)^{k}$$

where E[Y] = λ, Var(Y) = $\lambda(1+\lambda\alpha)$, and α is called the overdispersion parameter.

[12] McFadden's Likelihood Ratio Index also referred to as a pseudo-R^2: $r^2 = 1 - \frac{\ln \hat{L}(\text{full})}{\ln \hat{L}(\text{intercept})}$ where $\hat{L}(\text{full})$ is estimated likelihood for model with predictors and $\hat{L}(\text{intercept})$ is for the no-information model (with only constant terms).

Employment counts in each category, larger firms, and educational firms showed relatively higher variance than others. Markov transition probabilities developed from all years of the SUSB data set appear skewed towards larger firms (possibly due to smaller sample sizes in this size group), producing strong growth in large firm sizes at the expense of smaller firms.

Figure 4 illustrates changes in firm size and sector profiles over time for the high-growth scenario. The simulation implies a steady increase in number of firms in all sectors. However, the increase in basic and retail firms is much less pronounced than in that seen in education and service firms.

Figure 5 shows the changes in the spatial distribution of firms and employment over time. The models predict greater spatial concentration than presently experienced in the Austin region, since firms are expected to favor urban and CBD zones, in both the high- and low-growth scenarios. Such inward movement seems unlikely and is probably due to the use of cross-sectional data sets for calibration of the location choice model (rather than use of panel sets and a dynamic model focused on location changes). A model of land development also would be very useful in this context, in order to synchronize demand with supply. This will be a useful model feature to incorporate in the future.

CONCLUSIONS AND EXTENSIONS

This paper presents a modeling framework for tracking events in firm life cycles using data from Austin, Texas. Microsimulation is a powerful tool, but models are only as good as the data that underlie them. A lack of quality business data is a severe handicap in modeling firm behavior effectively, throughout the world. The results of this study provides a good starting point for developing such models and offer insights into the effects of various attributes on firm behavior.

This paper uses Poisson regression as an alternative to logit models, facilitating the estimation of location choice models at finer spatial resolution. Microsimulation of firm size and location choices was carried out by industry sector. Certain Markovian process assumptions to model such changes were necessitated by data constraints but can be easily relaxed within the modeling framework once longitudinal data on individual firms becomes available. A major limitation of this paper is the use of SUSB data for Texas to model firm evolution, birth and death patterns, when Austin may not be a representative of entire Texas.

With availability of high-quality data, microsimulation can help forecast the future effectively while formulating policies for directing and managing urban growth. These models of firm behavior may serve as a valuable supplement to household simulation models; together such agents dominate urban travel and land use patterns. Moreover, an appreciation of commercial vehicle movements can be very useful in mitigating urban congestion, especially in industrially and commercially developed areas. The approaches used here permit close examination of various policy and infrastructure scenarios.

Key extensions of this study include integration of models of household behavior, and iteration with models of travel demand, in order to appreciate changes in location access and attractiveness over time. Recognition of the land development process and supply interactions also is critical for system forecasting. Use of dynamic data to avoid pitfalls in interpretation of cross-sectional models of location choice may also be key.

Firms and households are the two most important drivers of urban growth, and an integrated model explaining both household and commercial travel patterns will provide policy makers a handy tool to design policies to sustain economic and social systems while combating problems of congestion and sprawl. The work seeks to facilitate adoption of freight modeling methods by MPOs and others.

REFERENCES

Abraham, J. E., and J. D. Hunt. 2000. Firm Location in the MEPLAN Model of Sacramento. *Transportation Research Record,* 1685: 187-198.

Arentze, T.A., and H. J. P. Timmermans. 2004. A Learning-Based Transportation Oriented Simulation System. *Transportation Research B,* 38: 613-633.

Bartik, T. 1985. Business Location Decisions in the United States: Estimates of the Effects of Unionization, Taxes, and Other Characteristics of States. *Journal of Business and Economic Statistics* 3: 14–22.

Ben-Akiva, M., and S. R. Lerman. 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. The MIT Press, Cambridge.

Bhat, C.R., J. Y. Guo, S. Srinivasan, and A. Sivakumar. 2004. A Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns. *Transportation Research Record,* 1894: 57-66.

Brouwer, A. E., I. Mariotti, and J. N. van Ommeren. 2002. The Firm Relocation Decision: A Logit Model. Paper presented at the *42nd ERSA conference,* Dortmund, Germany.

Carroll G. R., and M. T. Hannan. 2000. *The Demography of Corporations and Industries.* Princeton University Press, Princeton.

Coughlin, C., J. Terza, and V. Arromdee. 1991. State Characteristics and the Location of Foreign Direct Investment within the United States. *this REVIEW* 73: 675–683.

Coughlin, C., and E. Segev. 2000. Location Determinants of new Foreign-owned Manufacturing Plants. *Journal of Regional Science,* 40(2): 323-351.

De Bok, M. and F. Sanders. 2005. Firm Location and the Accessibility of Locations: Empirical Results from the Netherlands. Proceedings of the 84th Annual Meeting of Transportation Research Board*,* Washington DC.

De Bok, M., and M. Bliemer. 2005. Using Firm Demographic Microsimulation for Land Use and Transport Scenario Evaluation: Model Calibration. Presented at the 45th European Regional Science Association Congress, Amsterdam, 23-27 August.

Elgar, I., and E. J. Miller. 2006. A Conceptual Model of Small Office Firm Location. Proceedings of the 85th Annual Meeting of the Transportation Research Board, Washington DC, 22-26 January.

Evans, D. 1987. The Relationship between Firm Growth, Size and Age: Estimates for 100 Manufacturing Industries. *Journal of Industrial Economics* 35: 567–581.
FHWA. 2006. TRANSIMS Home Page. URL: http://tmip.fhwa.dot.gov/transims/. Accessed 10th October 2006.

Firm Size Data. Office of Advocacy, U. S. Small Business Administration. URL: http://www.sba.gov/advo/research/data.html#us. Accessed 10th July 2007.

Friedman, J., D. Gerlowski, and J. Silberman. 1992. What Attracts Foreign Multinational Corporations? Evidence from Branch Plant Location in the United States. *Journal of Regional Science* 32: 403–418.

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.

Guimaraés, P., O. Figueirdo, and D. Woodward. 2000. Agglomeration and the Location of Foreign Direct Investment in Portugal. *Journal of Urban Economics* 47: 115–135.

Guimaraés, P., O. Figueirdo, and D. Woodward. 2003. A Tractable Approach to the Firm Location Design Problem. *The Review of Economics and Statistics* 85(1): 201–204.

Guimaraés, P., and R. Lindrooth. 2005. Dirichlet-Multinomial Regression. *Economics Working Paper* Archive at WUSTL, Econometrics, 0509001. http://ideas.repec.org/p/wpa /wuwpem/0509001.html/. Accessed 18th April 2007.

Guimaraés, P., R. Rolfe, and D. Woodward. 1998. Regional Incentives and Industrial Location in Puerto Rico. *International Regional Science Review* 21(2): 119–138.

Hannan M. T., G. R. Carroll, S. D. Dobrev, and J. Han. 1988. Organizational Mortality in European and American Automobile Industries Part I: Revisiting the Effects of Age and Size. *European Sociological Review* 14: 279-302.

Hansen, E. 1987. Industrial Location Choice in Sao Paulo, Brazil: A Nested Logit Model. *Regional Science and Urban Economics* 17: 89–108.

Head, K., J. Ries, and D. Swenson. 1995. Agglomeration Benefits and Location Choice: Evidence from Japanese Manufacturing Investments in the United States. *Journal of International Economics* 38: 223–247.

Hayter, R. 1997. *The Dynamics of Industrial Location. The Factory, The Firm and The Production System*. New York: Wiley.

Hunt, J. D., D. S. Kriger, and E. J. Miller. 2005. Current Operational Urban Land Use–Transport Modelling Frameworks: A Review. *Transport Reviews* 25(3): 329–376.

Hunt, J. D., K. J. Stefan, and J. E. Abraham. 2003. Modeling Retail and Service Delivery Commercial Movement Choice Behaviour in Calgary. Paper presented at the 10th International Conference on Travel Behaviour Research, Lucerne, 10-15 August. http://www.ivt.baug.ethz.ch/allgemein/slides/hunt.pdf. Accessed 25th April 2007.

Hunt, J. D., K. J. Stefan, A. T. Brownlee, J. D. P. McMillan, A. Farhan, K. Tsang, D. Atkins, and M. Ishani. 2004. A Commercial Movement Modelling Strategy for Alberta's Major Cities. Paper prepared for presentation at the 2004 Annual Conference of the Transportation Association of Canada, Québec City, Québec.

Jones, M. T. 2005. Estimating Markov Transition Matrices Using Proportions Data: An Application to Credit Risk. *IMF working paper*, Monetary and Financial Systems Department. http://www.imf.org/external/pubs/ft/wp/2005/wp05219.pdf. Accessed 10th April 2007.

Khan, A.S., J.E. Abraham, and J.D. Hunt. 2002. A System for Microsimulating Business Establishments: Analysis, Design and Results. *Access to Activities and Services in Urban Canada: Behavioral processes that condition equity and sustainability,* Laval University, Quebec City.

Kroll, C., and J. Landis. 1990. Housing Prices, Other Real Estate Factors and the Location Choice of Firms. *Fisher Center for Real Estate & Urban Economics*. http://repositories.cdlib.org/iber/fcreue/reports/0990. Accessed 26th April 2007.

Lee, T. C., G. G. Judge, and A. Zellner. 1970. *Estimating the Parameters of the Markov Probability Model From Aggregate Time Series Data*. Amsterdam: North Holland.

Lee, Y. 2006. Relocation Patterns in U.S. Manufacturing. *Working Paper 06-24*, Federal Reserve Bank of Cleveland. www.clevelandfed.org/research. Accessed 9th January 2007.

Maoh, H. F., and P. S. Kanaroglou. 2005. Agent-Based Firmographic Models: A Simulation Framework for the City of Hamilton. Proceedings of *PROCESSUS Second International Colloquium on the Behavioural Foundations of Integrated Land-use and Transportation Models: Frameworks, Models and Applications,* Toronto. http://www.civ.utoronto.ca/sect/traeng/ilute/processus2005/PaperSession/Paper08_Maoh-Kanaroglou_Agent-basedFirmographicModels_CD.pdf. Accessed 8th November 2006.

McFadden, D. 1974. Conditional Logit Analysis of Qualitative Choice Behavior. (pp. 105–142), in P. Zarembka (Ed.). *Frontiers in Econometrics*, New York: Academic Press.

McFadden, D. 1978. Modeling the Choice of Residential Location. (pp. 75–96), in A.

Karquist, L. Lundqvist, F. Snickars, and J. Weibull (Eds.). *Spatial Interaction Theory and Planning Models.* Amsterdam: North-Holland.

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.

Miller, E. J., and P.A. Salvini. 2001. The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling system: Description & Current Status. Chapter 41, in D. Hensher (ed.) *The Leading Edge in Travel Behaviour Research*, Amsterdam: Pergamon, 711-724.

Moeckel, R. 2005. Simulating Firmography. Fourth Oregon Symposium on Integrating Land Use and Transportation Models, 15-17 November. http://www.oregon.gov/ODOT/TD/TP/docs/Modeling/4symp/1117_1045.pdf. Accessed 5th November 2006.

Moeckel, R., C. Schurmann, and M. Wegener. 2002. Microsimulation of Urban Land Use. Proceedings of the 42nd European Congress of the Regional Science Association, Dortmund, 27-31 August. http://www.ersa.org/ersaconfs/ersa02/cd-rom/papers/261.pdf. Accessed 5th November 2006.

Nerella, S., and C.R. Bhat. 2004. Numerical Analysis of Effect of Sampling of Alternatives in Discrete Choice Models. *Transportation Research Record* 1894: 11-19.

Pellenbarg, P. H., and P. J. M. Van Steen. 2003. Spatial Perspectives on Firm Dynamics in the Netherlands. *Tijdschrift voor Economische en Sociale Geografie,* 94(5): 620-630.

Pellenbarg, P. H., L. J. G. Van Wissen, and J. van Dijk. 2002. Firm Relocation: State of the Art and Research Prospects. *SOM Research Report 02D31*, University of Groningen. http://som.eldoc.ub.rug.nl/FILES/reports/themeD/2002/02D31/02D31.pdf. Accessed 15th December 2006

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.

Spear, B. D. 2006. Freight Modeling in Urban Areas – State of the Practice. www.trb.org/Conferences/2006/FDM/Spear.pdf. Accessed 10th November 2007.

Stefan, K. J., J. D. P. McMillan, and J. D. Hunt. 2004. An Urban Commercial Vehicle Movement Model for Calgary. Proceedings of the 84th Annual Meeting of the Transportation Research Board, Washington DC.

Timmermans, H. 2003. The saga of integrated land use-transport modeling: How Many More Dreams Before We Wake Up? Conference Keynote Paper at the 10th International Conference on Travel Behaviour Research, Lucerne, 10-15 August. http://www.ivt.baug.ethz.ch/allgemein/pdf/timmermans.pdf. Accessed 10th October 2006.

Train, K. 1986. *Qualitative Choice Analysis: Theory, Econometrics , and an Application to Automobile Demand.* Cambridge, Massachusetts: The MIT Press.

Van Dijk, J., and P. H. Pellenbarg. 2000a. Spatial Perspectives on Firm Demography. *Papers in Regional Science* 79: 107-110.

Van Dijk, J., and P. H. Pellenbarg. 2000b. Firm Relocation Decisions in The Netherlands: An Ordered Logit Approach. *Papers in Regional Science* 79: 191-219.

Van Wissen, L. J. G. 2000. A Micro-Simulation Model of Firms: Applications of Concepts of the Demography of the Firm. *Papers in Regional Science* 79: 111-134.

Van Wissen, L. J. G. 2002. Demography of the Firm: A Useful Metaphor? *European Journal of Population* 18: 263–279.

Waddell, P., 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.

Woodward, D. 1992. Locational Determinants of Japanese Manufacturing Start-Ups in the United States. *Southern Economic Journal* 58: 690–708.

LIST OF TABLES AND FIGURES

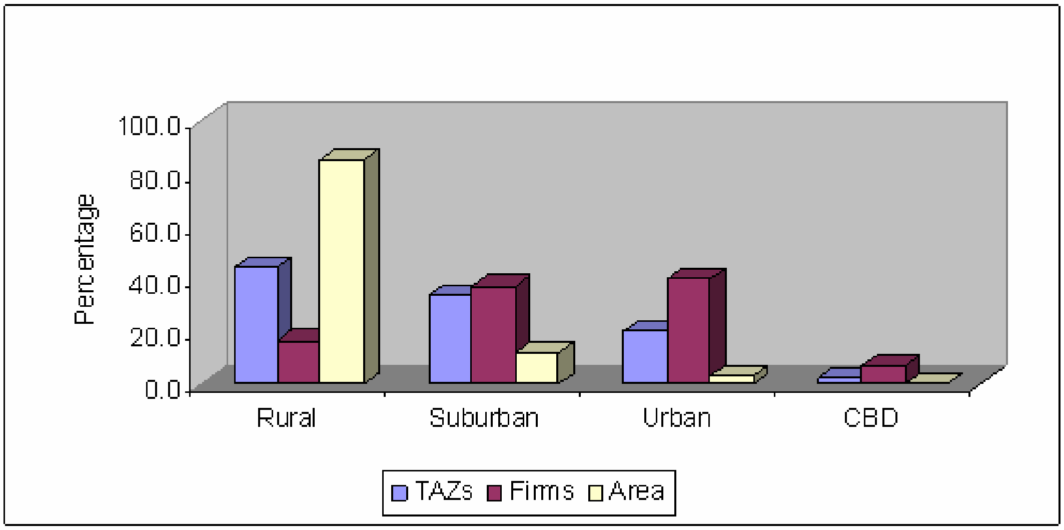

Figure 1: 2005 Distribution of TAZs (Number and Enclosed Area) and Firms by Area Type

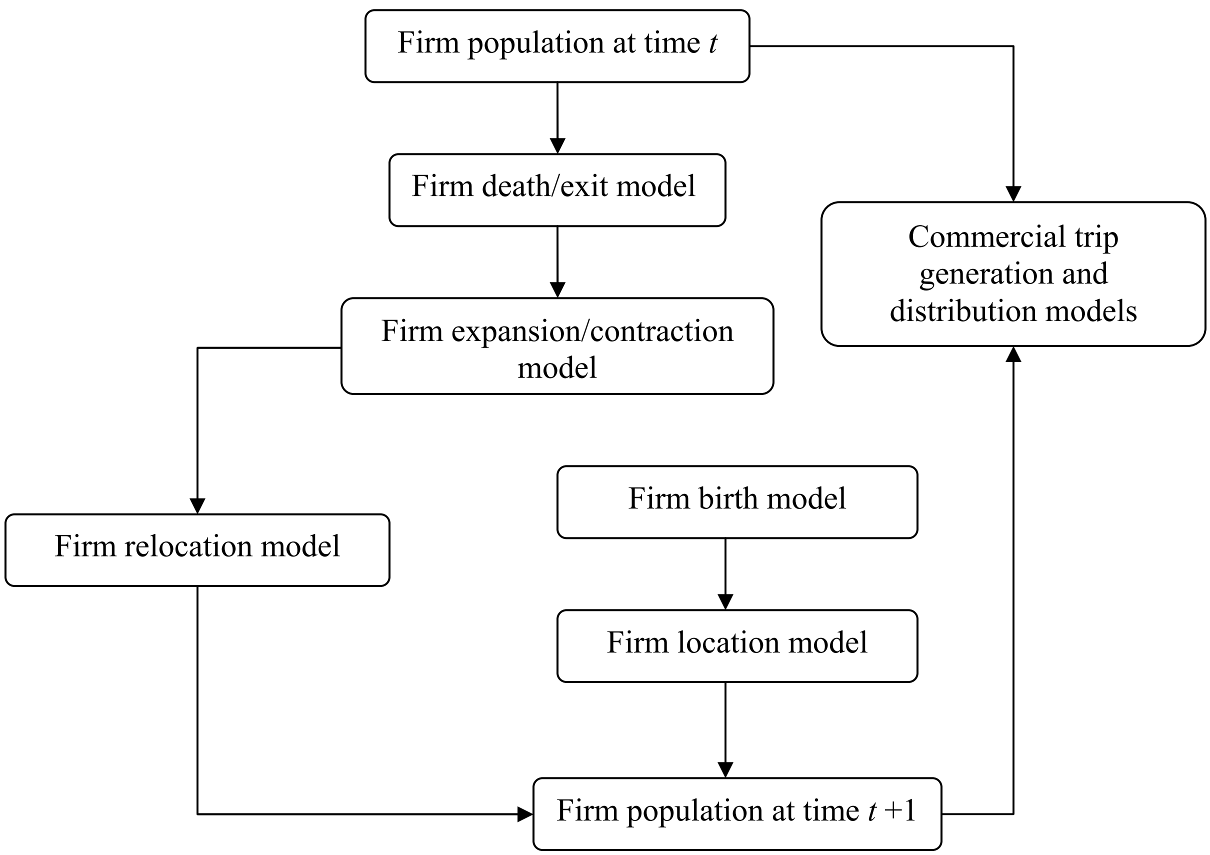

Figure 2: Flowchart for Model of Firm Behaviors
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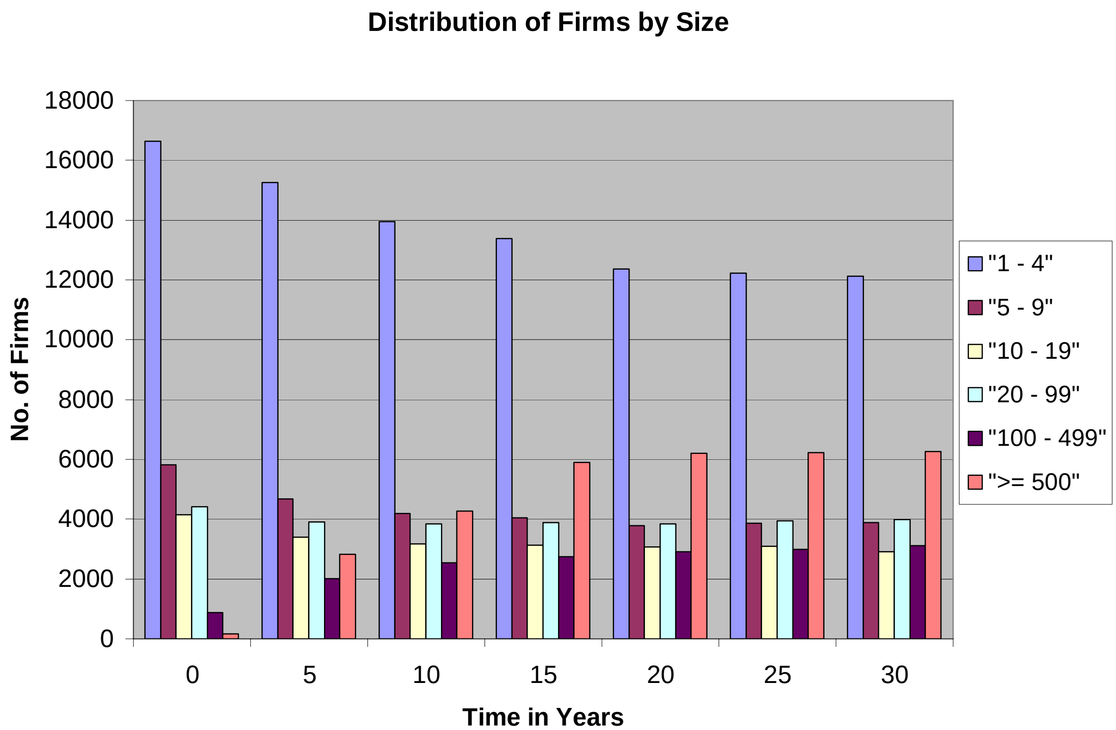

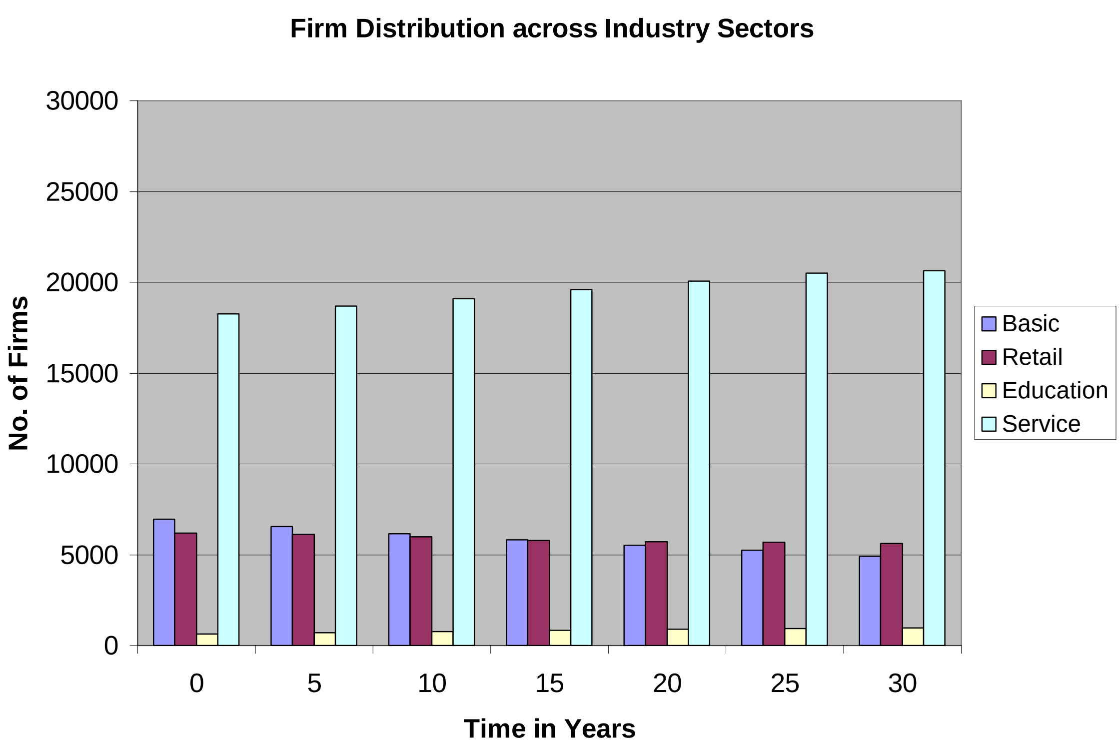

Figure 3: Firm Size Profile and Distribution of Firms across Industries
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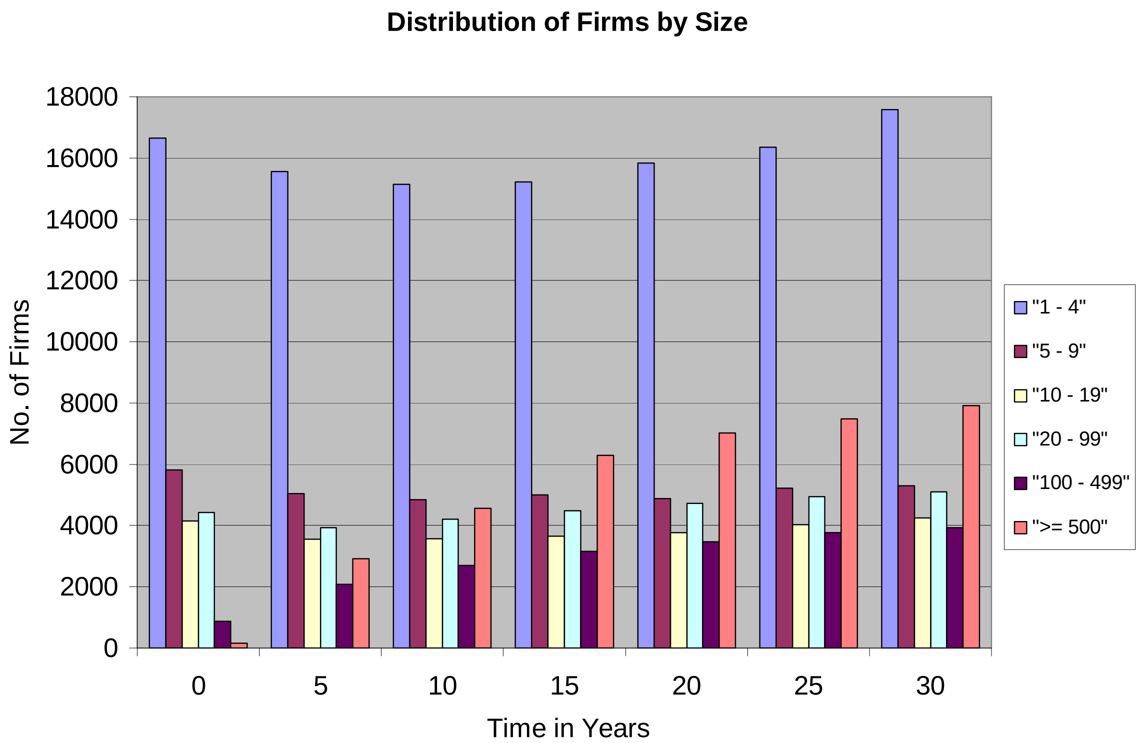

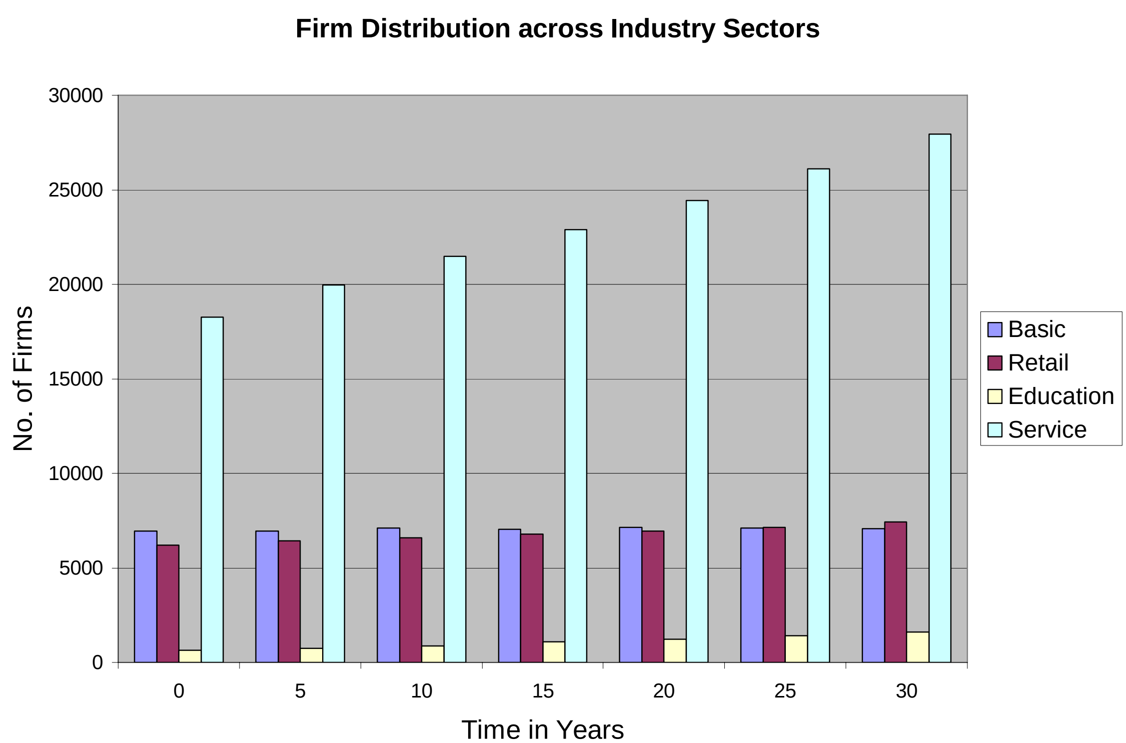

Figure 4: Firm Size Profile and Distribution of Firms across Industries (High-growth Scenario)

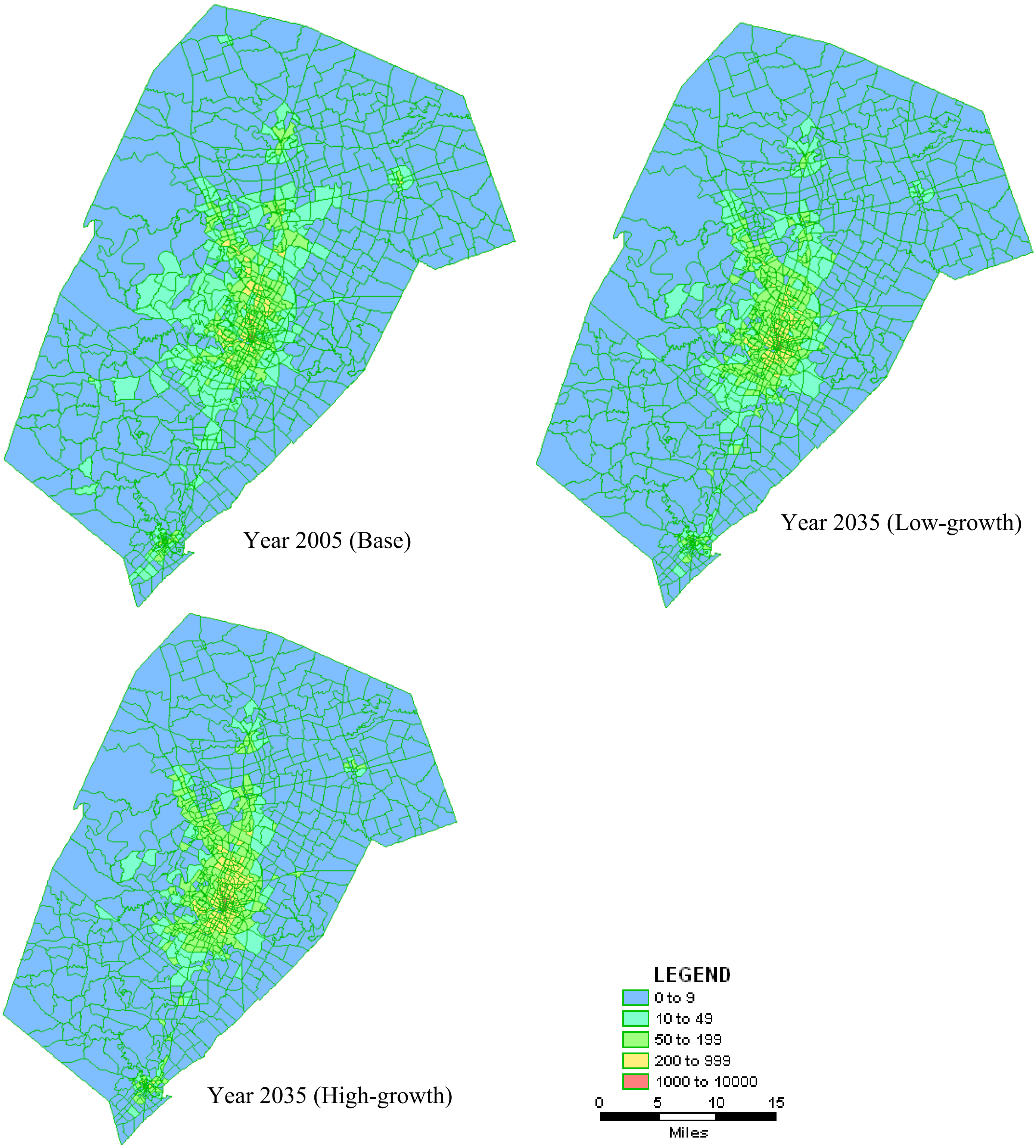

Figure 5: Firm Density by Location in Year 2005 and Forecasts for Year 2035

Table 1: Markov Transition Probability Estimates for Basic Firms

	1-4 employees	**5-9**	**10-19**	**20-99**	**100-499**	**≥ 500**
1-4 employees	0.880	0.073	0.021	0.015	0.004	0.008
5-9	0.090	0.779	0.068	0.052	0.011	0.001
10-19	0.039	0.052	0.769	0.096	0.018	0.025
20-99	0.007	0.011	0.069	0.818	0.047	0.048
100-499	0.008	0.008	0.012	0.059	0.760	0.153
≥ 500	0.022	0.001	0.003	0.005	0.080	0.890

Table 2: Poisson Regression Model of Firm Location Choice

	Poisson Model	
	Coefficients	**t-statistics**
Constant	4.948	105.18
ln(area)	0.482	61.86
Rural*	-3.025	-73.65
Suburban*	-1.464	-47.82
Urban*	-0.778	-30.31
Distance to CBD	-	-
Median HH Income	1.09E-06	4.93
Job Access	0.011	40.35
Population Access	-0.010	-36.77
log-likelihood (null)	-23,817	
log-likelihood (model)	-12,319	
Pseudo r^2 (McFadden's LRI)	0.483	
No. of observations	1,074	

* CBD is base area type.

Table 3: Negative Binomial Model of Commercial Trip Generation by TAZ

	Coefficients	t-statistics	Elasticity
Constant	0.921	6.02	-
ln(Area)	0.316	5.50	1.026
Suburban	0.691	4.41	2.566
Urban	0.984	4.66	4.476
Distance to CBD	-0.028	-4.00	-0.092
No. of Firms	0.006	3.42	0.018
Alpha (Overdisp. param.)	3.161	16.32	-
log-likelihood (null)	-4,945.78		
log-likelihood (model)	-2,143.50		
Pseudo r^2 (McFadden's LRI)	0.567		
No. of Observations	1,074		

Note: CBD is the base area type. Elasticities for indicator variables are based on a discrete change in *x*, from 0 to 1.

Table 4: Logit Model of Commercial Trip Distribution

	Coefficients	t-statistics
Area x Rural Indicator	0.024	4.97
Area x Suburban	-0.426	-13.2
Area x Urban	-1.193	-10.69
Sqrt(HH)	0.006	3.58
Median HH Income	-6.60E-06	-5.91
No. of Firms	0.0005	2.05
Distance to CBD	0.007	2.7
Peak Drive Time	-0.075	-51.44
log-likelihood (null)	-11,441	
log-likelihood (model)	-9,377	
Pseudo r^2 (McFadden's LRI)	0.180	
No. of Observations	2,551	