Dynamic Choice Model of Urban Commercial Activity Patterns of Vehicles and People

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Intraurban commercial vehicle travel is a relatively underdeveloped aspect of urban travel demand modeling despite the large share of the weekday traffic stream represented by commercial movements. One problem is the proprietary nature of these data and the corresponding lack of behavioral understanding of how establishments schedule their trips. Even when such data have been made available, such as through establishment travel surveys, the large variation in firm size, commodities and services, and logistics practices makes it difficult to create a generalized decision framework. This work uses establishment survey data collected by the Ohio Department of Transportation to create an intraurban commercial vehicle model to be run in a disaggregate microsimulation environment and focuses on commercial movement patterns. The model generates entire daily patterns for workers who regularly travel as part of their jobs and creates tours through a dynamic choice process that incrementally builds tours, taking into consideration elapsed time and time of day in next-stop purpose and location choices. Activity durations are embedded in the utility equations of "stay" alternatives and provide internal consistency between the dimensions of activity purpose, duration, time of day, and location. Model formulation and estimation results are presented for the dynamic activity choice model component. The model system can reproduce observed commercial travel patterns found in the survey data and provide intuitively plausible interpretations for commercial travel behavior in the absence of more detailed knowledge of individual and firm operations.

The modeling of intraurban commercial vehicle movements has received much less attention than has the modeling of household personal movements despite the fact that intraurban commercial movements make up a large share of weekday traffic within urban areas (*1*). For example, separate weekday establishment surveys conducted in Calgary and Edmonton, Alberta, Canada, in 2000 and 2002, respectively, were consistent in finding that commercial vehicle movements composed 12% of all vehicle kilometers traveled in the two cities (*2*). About 60% of the stops were made with light vehicles, with provision of services accounting for 35% of trip purposes.

The 2003–2004 Ohio establishment survey data used in this research showed similar percentages: 37% of trip purposes were service related and nearly 70% percent of all commercial trips used light vehicles. The survey also revealed that 8.7% of the state's workforce had jobs in which local commercial travel was a daily component, for pickup and delivery of goods, for provision of services, for sales, or for meetings.

Despite these numbers, most commercial movement modeling has focused on freight movements over longer distances, using a commodity-based framework that considers the patterns of commodity flow translations to shipments, shipment routing (possibly involving consolidation and distribution and modes other than road vehicles), and the resulting allocations to vehicles and vehicle movements (*3, 4*). The result of efforts to enhance such an approach is an emphasis on logistics and fine-level categorizations of commodity types, with handling costs, vehicle capacities, less-than-load operations, and dead-hauling approaches becoming particular challenges (*5–8*). By comparison, there has been little enhancement of techniques for more practical urban-level considerations. Intraurban commercial movements are characterized by short-distance movements, more service than goods delivery, and a much greater emphasis on rapid than on cost-efficient response (*9, 10*).

Perhaps the most commonly used approach for modeling intraurban commercial vehicle movements is the synthesis of origin–destination matrices of commercial vehicle trips using Fratar or Furness expansion techniques (*11, 12*) or entropy maximization mathematical programming processes (*13*). These are comparatively straightforward, inexpensive treatments, but they lack policy responsiveness and have less-than-robust forecasts.

Another common approach for modeling intraurban commercial vehicle movements is the use of modified forms of the standard four-step model, with generation, distribution, and mode allocation of shipments or movement demands and network assignment of the resulting vehicles. Examples include work reported by Hutchinson (*14*) and List and Turnquist (*15*) and the processes designed for transferability in the *Quick Response Freight Manual* (*16*). Again, comparative ease of application and a sense of consistency with existing four-step personal travel models are advantages, yet all the problems inherent with the aggregate four-step approach remain. The emphasis on trips instead of tours is perhaps even more problematic with commercial movements, given the much greater number of trips per tour, the lack of an obvious primary stop, and the problem of less-than-load and empty vehicle movements.

Recently, use of microsimulation modeling to represent intraurban commercial movements has emerged. Stefan et al. (*17*) developed and applied a tour-based microsimulation of commercial vehicle movements for the city of Calgary. Logit choice models and sampling distributions are used in a Monte Carlo process to develop individual tours, including starting times, vehicle types, numbers and locations of stops, and stop durations for the full range of commercial vehicle movements observed in an establishment-based survey of commercial vehicle movements over 24 h. This approach departs from the explicit representation of shipments, thereby avoiding the challenges inherent with such an approach, and instead considers the patterns

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of commercial vehicle movements directly. The work described in this paper extends this tour-based microsimulation approach, enhancing the treatment of the temporal dimension and integrating it with activity and location choices.

This paper presents an activity-based model of commercial vehicle and person movements, developed as part of the Ohio statewide model project. Implemented in a microsimulation environment, the model uses a dynamic discrete choice formulation that steps each simulated worker through the day, constructing tours composed of stops for various purposes, and tracks elapsed time and time of day, adjusting probabilities accordingly. Activity durations are determined by the choice model through the timing of the decision to switch from the current activity to a new activity. A tour-based location choice model selects activity stop locations, with location choices made later in the tour increasingly sensitive to distance from the home establishment.

The advantage to this approach for policy analysis is that any type of alternative land use pattern or transportation system performance change that would affect the space–time separation of commercial activities would result in an array of responses that could include not only adjustments to trip lengths but also the frequency of commercial activity stops and their duration. With a semi-Markov process, activities are added sequentially and their timing and locations are resolved immediately, ensuring that the start time of activities, their duration, and the travel time required to connect them spatially are internally consistent throughout an entire day.

This model system was estimated and calibrated from establishment survey data collected by the Ohio Department of Transportation that are applied in an integrated package using Monte Carlo methods. The remainder of this paper describes the structure of the model system, with detailed discussion of the development of the dynamic activity choice model.

OVERVIEW OF DISAGGREGATE COMMERCIAL MODEL

The disaggregate commercial model (DCM) occupies one of four travel market niches in the Ohio statewide model system. The DCM was designed to capture that part of the commercial travel market that tends to be overlooked by freight-oriented models on one end of the spectrum and by household-based models at the other end. DCM reflects primarily an intrametropolitan commercial travel market, predominated by service provision, meetings, sales calls, and short hauls of goods.

The tours covered by the DCM are work-establishment based and must have at least one commercial stop, with no single trip allowed to exceed 50 mi. The 50-mi threshold is used to define travel market boundaries and is partially based on the establishment survey, in which fewer than 1% of trips exceeded 50 mi and those that did were usually between cities and did not include a return trip the same day. Commercial trips traveling farther than 50 mi are theoretically covered by an aggregate commercial model (ACM) if they are commodity based and by a person-travel–long-distance model (PT-LD) if they are service or professionally oriented business trips. The ACM is a separate commodity flow-based model that has greater resolution at the intercity scale. PT-LD covers non-commodity-oriented work travel and personal travel for trips greater than 50 mi. A fourth model, the household-based person transport is a tour-based microsimulation model, which accounts for local work-based tours with no commercial stops (e.g., lunch) as well as the familiar home-based work and nonwork travel.

The DCM travel market is further segmented by industry type and commercial activity purpose. The original North American Industrial Classifications are grouped as follows:

1. Industrial: agriculture and mining, construction, light manufacturing, heavy manufacturing, primary metals, and transportation equipment;
2. Wholesale;
3. Retail;
4. Transport handling; and
5. Service: government, education, health services, hotels and lodging, and other services.

The Ohio statewide model establishment survey evaluated 562 establishments statewide. With these data for model estimation and calibration, it is assumed that intraurban commercial travel behavior is relatively uniform throughout the state, which might not be true for certain subregions. To supplement the survey, a uniform classification of land use types was created at the level of the traffic analysis zone (TAZ) based on population and employment densities and compositions, which was essential for forecasting and transferring the model between subregions.

The survey included information about each establishment, including shipment and travel statistics. In addition, 24-h travel diaries were given to workers who traveled regularly as part of their jobs, typically at least once per day. The information provided is very similar to a household activity diary format, with activity purposes, starting and ending times, location coordinates, and related data.

Commercial activity purposes are grouped into five categories, defined as follows:

- Goods: the pickup or delivery of goods and materials;
- Services: the provision of services, such as real estate services, health care, public works, repair services, and recreation services;
- Meetings and sales: activities related to professional meetings or sales calls; and
- Other: work-related stops such as refueling vehicles and nonwork-related stops made as part of a work tour, such as breaks.

DCM was not designed to model fixed-route or patrol-type movements, which are referred to as “fleet” purposes. Examples of fleet purposes include taxis, mail trucks, school buses, garbage trucks, and police cruisers. Fleet movements require a different decision structure and were not well represented in the survey data.

Commercial vehicle use was identified for a worker’s entire day, implying the use of a single vehicle. The vehicle types included in the model were defined as follows:

- Light: automobiles, sport utility vehicles, and pickup trucks with four tires;
- Medium: six-tire dual-axle trucks; and
- Heavy: multiunit trucks and trucks with more than two axles.

The DCM model structure is presented in Figure 1 and is summarized in the following sections.

Traveler Generation

As indicated in Figure 1, the DCM first generates a list of traveling workers by industry type for each TAZ. Using a binary choice formulation, traveler generation selects a portion of the employees

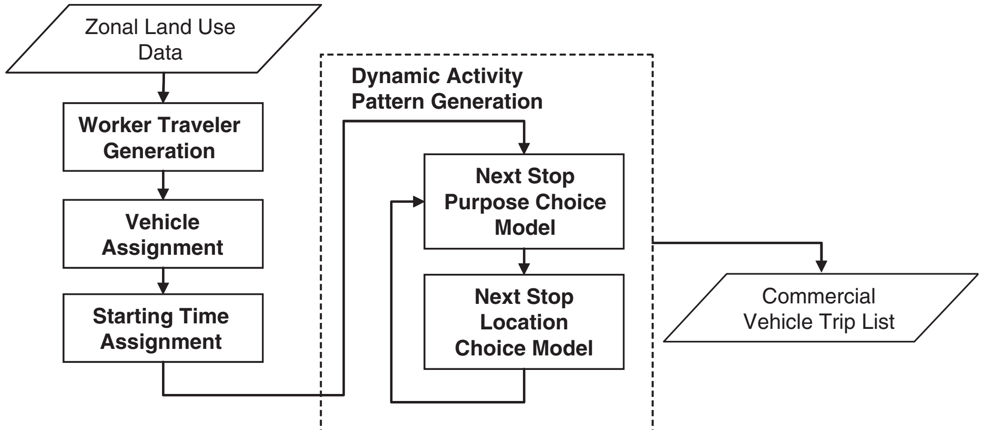

FIGURE 1 Structure of DCM.

in each industry within each TAZ to travel for the simulation day and creates individual traveler records for them. The propensity to travel is affected by industry type and TAZ land use demographics, with some interesting interactions. For example, service establishments located in industrial land uses and industrial establishments located in service land uses both have a greater propensity to include workers who travel.

Vehicle Assignment

For each traveling worker, a vehicle is assigned for the entire day. The establishment survey did not account for multiple vehicle types to be used by an individual during the same day. The type of vehicle assigned is based on a multinomial logit model, considering establishment type and TAZ land use type. Medium- and heavy-vehicle use tends to be more prevalent in industrial and wholesale land use types, whereas light-vehicle use tends to dominate office land use types, even if the offices are occupied by wholesale or manufacturing establishments.

Starting Time Assignment

Each traveling worker is assigned a starting time for the first departure from the establishment. These starting times are drawn from an empirical distribution of starting times for the first trip of the day, classified by industry and vehicle types. Heavy and medium vehicles tend to start their days earlier, because they are often used to make large deliveries before stores open.

Dynamic Activity Pattern Generation

From this point forward, DCM creates each traveler's daily activity pattern. An event simulation clock counts down in 5-min intervals, beginning with the assigned starting time. At each 5-min interval, the traveler has the choice to "stay" at the current activity or to "leave" to engage in an activity at a new location, one option being to return to the establishment. The choice of activity in the next time period is referred to as the next stop purpose model.

For the first activity of the day, the traveler does not have the option to "stay" at the establishment and must choose an activity purpose that will begin a new commercial tour, after which the worker has the option to remain at a current activity during a 5-min interval. If the worker chooses to return to the establishment, then the next activity location is known. If, however, the worker chooses to make a new commercial activity stop, the next stop location model is applied to choose a TAZ where it will take place.

Once the next activity location has been identified by the next stop location model, an expected travel time to the next stop is obtained from the travel time skims used to select the stop, stratified by vehicle type and time of day, and the simulation clock is advanced. Once the worker has reached the destination, the timing of the next activity's duration begins and control returns to the next stop purpose model, which again begins evaluating activity alternatives in 5-min intervals to build the tour. As time elapses, the probability of choosing to return to the establishment becomes greater and eventually is a near certainty.

The activity pattern generation process is carried out for each worker in turn until all workers have activity patterns. Every traveler generated in the traveler generation stage is guaranteed to make at least one activity stop and will eventually return to the establishment. The activity generation process will continue until midnight, unless the worker has not yet returned to the establishment. Those who started tours late in the day and do not finish before midnight, continue to be simulated until their tour is complete. The portion of the tour that takes place after midnight is "wrapped" around to the beginning of the day to capture the small portion of commercial movements that straddle midnight.

The remainder of this paper focuses on the development of the next stop purpose model, which uses a dynamic discrete choice process. There is a brief discussion about specific aspects of the next stop location model.

DYNAMIC ACTIVITY CHOICE MODEL FORMULATION

In the establishment survey travel diaries, each traveling worker's activity-travel choices are observed for a given survey day. To model these choices in an incremental fashion, one starts with an initial condition and then models the probabilistic transitions from one activity-travel episode to the next. The initial conditions that were set include the establishment type and location of the worker as well as the assigned vehicle type and time of first departure from the establishment. For each current activity state (e.g., "at establishment"), a choice is made for the next activity state. Formally, the probability of choosing one activity state over others can be expressed as follows:

$$\Pr\left(Y = k \middle| Y' = k'\right) \tag{1}$$

where the probability of choosing activity state k is conditional on the current state k', Y is a decision variable representing a choice to be made for the next time period, and Y' represents a choice already made for the current time period. In these data, however, only state changes are observed. The choice to remain at a current activity is not observed, but its start and end time are observed. There are two options. The first option, as followed by Stefan et al. (*17*), is to assume that the duration of the current activity is independent of the prospect of other activity alternatives, in which case it is a simple matter to generate an expected duration for the current activity, advance the simulation clock, and choose the next activity state. Alternatively, one can infer that, for the duration of the current activity, a continuous choice is being made to engage in the activity up to the point when there is greater perceived utility in switching to another activity state. The second option, the one pursued in this work, has the behavioral advantage of considering the influence of competing demands that might affect the duration of the current activity and has the practical advantage of integrating activity purpose choices and durations into a single decision structure.

To illustrate, these conditional probabilities can be arrayed in a matrix, which includes a "stay" alternative to represent the choice to continue in the current activity. As indicated in Table 1, the rows represent the starting activity state k' and the columns represent alternative destination states k. Each row is expected to sum to 1.0.

The cells of the matrix represent transition intensity rates. These rates imply that, for a given number of decision opportunities, there is some number of observed realizations of each choice. Formally, this can be written as follows:

$$\pi_{k'k}\left(t\right) = \frac{\sum_{t=1}^{T} I\left(Y_t = k \middle| Y_t' = k'\right)}{T_{k'}} \tag{2}$$

where

indicator function $I(*)$ = 1 if statement in parentheses is true and = 0 otherwise,
T = the maximum number of time periods, and
$T_{k'}$ = total number of time periods for which the starting activity was k'.

Using this logic, one can transform the dependent variable in this model to reflect the inference that a continuous choice is being made to "stay" at the current activity from its starting time to its ending time and that, at the ending time, a transition to a new activity begins. This period from the starting time of the current activity to its ending time, signaling the beginning of a new activity state, is referred to as a "cycle" (*18*).

Dependent Variable

For computational tractability, this continuous choice is recast in terms of a series of discrete events, or time intervals. Thus, for each observation in the diary data, the value of the decision variable is redefined to reflect the number of consecutive time periods when the worker was engaged in the current activity, up to and including the current time period. The observed choice of the next activity state takes place in an instant that is assigned to the following time period, when the worker leaves the current site. Formally, this relationship can be expressed as follows:

$$S_k = \frac{T_{k'}}{T_{k'} + 1} \qquad \text{for } k = k' \tag{3}$$

$$S_k = \frac{Y_k}{T_{k'} + 1} \qquad \text{for } k \neq k' \tag{4}$$

where $Y_k = 1$ indicates that the next activity purpose will be alternative k and $Y_k = 0$ if otherwise. The transformed dependent variable, S_k, represents the proportional share of decision opportunities, or time periods, for which activity state k is chosen over the cycle. It follows that

$$\sum_{k=1}^{K} S_k = 1 \tag{5}$$

where k represents the total number of activity states under consideration.

Travel time does not play a role in these calculations. Once a new activity has been chosen, it is assumed that no decisions are made during the course of travel, and the simulation clock is simply advanced to the arrival time at the new activity location. These cycles are referred to as observations, because each record in the data set represents one complete cycle, describing the duration of the current activity and the choice of the next activity. With this, it is possible to construct a likelihood function in which both the "stay" alternative

TABLE 1 Possible Activity State Transitions with Intensity Rates $\pi(k', k)$

	Destination Activity State k						
Starting Activity State k'	Stay at Current Activity	New Goods Stop	New Service Stop	New Other Stop	New Meeting Stop	Return to Establishment	Sum
At establishment	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	n/a	1.00
At goods stop	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	1.00
At service stop	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	1.00
At other stop	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	1.00
At meeting stop	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	$\pi(k', k)$	1.00

and the chosen next stop alternative contribute to the likelihood calculation through S_k as

$$L_n = \prod_{k=1}^{K}\left(P_{nk'k}\right)^{S_{nkk'}} \tag{6}$$

where the probability $P_{nk'k}$ of each alternative in observation n is a function of its utility (U). For simplicity, the familiar multinomial logit model of probabilistic choice is used, resulting in

$$P_{njk'} = \frac{\exp\left(U_{nk'j}\right)}{\sum_k \exp\left(U_{nk'k}\right)} \tag{7}$$

The indirect utility for a worker n in current activity state k' to choose activity state k for the next time period t_j may be expressed as follows:

$$U_{nk'k}\left(t_j\right) = \theta_{k'k} + \beta_k' X_n + \tau_k\left(t_j\right) + \epsilon_{k'k} \tag{8}$$

where

$\theta_{k'k}$ = transition constant that represents nominal rate of switching from state k' to state k;
X_n = time-invariant vector of variables representing attributes of the worker, such as vehicle type and establishment type;
β_k = vector of alternative-specific parameters to be estimated; and
ϵ = random error in the estimation of the utility function u

The time-varying portion of the utility function is represented in Equation 8 by the function $\tau_k(t_j)$, which may take on different forms and meanings depending on k.

Time-Varying Regressors

There are numerous ways that time can be represented in a dynamic choice context; however, this work focuses on the effects of time on the utility of state change alternatives. Specifically, time effects on utility were studied at three levels:

- Elapsed time of the current activity,
- Elapsed time of the current tour or work shift, and
- Time-period-specific effects.

To ease interpretation and avoid parameters with high correlations, an attempt was made to specify functions for alternatives for which there is both a positive and a theoretically defensible relationship between time and utility.

Stay Alternative

In this work, the "stay" alternative's utility considers the duration of the current activity, which is represented by the number of elapsed time periods since the activity began, $dt_{k'} = t_{k'j} - t_{k'0}$, but does not include the time used to travel to the activity location. The probability that the worker stays in the current activity at time period j, given that the activity must eventually end, can be expressed as the complement of the hazard rate h commonly used in survival analysis (*19*), such as

$$s\left(t_{ij}\right) = \Pr\left[T_i \neq j \middle| T_i \geq j\right] = \left(1 - h\left(t_{ij}\right)\right) \tag{9}$$

The best option, then, would be a functional form that approximates the probability density of activity durations found in the data, which are concave and right skewed. Through trial and error, the most robust function that could be estimated with linear parameters was the following expression:

$$\tau_k\left(t_j\right) = \delta_{k'}\left(dt_{k'}\right) + \gamma_{k'}\ln\left(dt_{k'}\right) \propto s_{k'}\left(t_{ij}\right) \tag{10}$$

in which $\delta_{k'}$ and $\gamma_{k'}$ are k'-specific parameters to be estimated with respect to the utility of the duration and natural log of duration, respectively. This function represents the time-varying utility of staying at the current activity for another time period.

New Activity Stop Alternatives

The utility of making a new activity stop is subject to a number of time-variant factors that are likely also to vary by activity purpose. For example, an establishment that seeks to pick up goods in the course of providing a service is subject to the business hours of its suppliers. To capture these relationships, time-period-specific indicator variables in the utility functions of new activity stop alternatives were specified, so that

$$\tau_k\left(t_j\right) = \alpha_{kp} I_p\left(t_j\right) \tag{11}$$

where α_{kp} is a vector of time-period–activity-specific parameters to be estimated and $I(t_j)$ equals 1 if t_j belongs to period p, and 0 otherwise.

Return to Establishment Alternative

Time-varying utility in the return-to-establishment alternative should consider the length of elapsed time of the current tour and even the duration of the worker's entire day. As elapsed time increases, the utility of returning to the establishment is expected to increase, potentially hastening the departure from activity stops at the end of a tour or the end of the day. To capture these relationships, the time-varying regressors were specified in the utility expression for the return-to-establishment alternative k^* as the linear effects of total elapsed time on the current tour dt and the additional increment of elapsed time since the worker started the day $t_j - t_0$. Thus,

$$\tau_k\left(t_j\right) = \varphi_{k^*}\left(dt\right) + \lambda_{k^*}\left(t_j - t_0 - dt\right) \tag{12}$$

where φ_{k^*} is a k^*-specific parameter on the utility of the total elapsed time on the current tour, and λ_{k^*} is a k^*-specific parameter on the utility of elapsed time since the worker began the shift, less the time spent on the current tour. These calculations incorporate travel time.

Rescaling Time

A critical issue in the specification of this model is the treatment of time by discrete periods, which makes it possible to estimate a model with a discrete choice formulation instead of a more computationally unwieldy model of continuous choice. From a model applications perspective, fewer time intervals require fewer computations, whereas a greater number of decision intervals would, in theory, provide finer resolution.

An additional consideration is the notion of decision maker sensitivity to time passage. This is reflected in the way the observed choice of next activity purpose is assigned a value equivalent to one decision period and this choice is weighted relative to the number of decision periods representing the duration of the current activity. For example, if the decision maker spends 30 min engaged in k' and 1-min decision intervals are used, then one obtains

$$S_{k'} = \frac{30}{30+1} = \frac{30}{31}$$

and

$$S_k = \frac{1}{30+1} = \frac{1}{31} \tag{13}$$

If 15-min intervals are used, then one obtains

$$S_{k'} = \frac{2}{2+1} = \frac{2}{3}$$

and

$$S_k = \frac{1}{2+1} = \frac{1}{3} \tag{14}$$

The contributions to the likelihood of the observation are drastically different under each scenario, an issue vetted in the initial stages of the estimation process. Through trial and error, it was found that a 5-min interval consistently provided the best fit to the data. Further, it was observed that establishment survey respondents tend to report times rounded to the nearest 5 min. Shorter time intervals tend to go unnoticed by respondents, whereas larger intervals can misrepresent very short-term decisions.

DYNAMIC ACTIVITY CHOICE MODEL ESTIMATION

The next stop purpose model was estimated with standard logit estimation software, with the dependent variable transformed into the proportions discussed previously. As indicated in Table 1, there are 29 elemental alternatives, representing the possible transitions from a current activity state to possible destination states. For any given observation, the availability of these alternatives is limited to groups of the six destination states, with the exception of an observation that begins at the establishment, for which the return-to-establishment alternative is unavailable.

Because the activity diary spanned 24 h, censoring of tours that began before the observation period ("left censored") or that concluded after the observation period ("right censored") must be handled differently. To avoid problems with initial conditions being unknown, left-censored tours were not used. Right-censored tours were used in the estimation up to the point of the last known activity choice, which is possible because one is looking ahead only one activity at a time. Because of relatively low numbers of observations for certain establishment types, a single model was estimated for all observations, with partial segmentation by establishment and vehicle types tested in the model specification and refinement process.

Model Fit

The estimation fit statistics obtained for the final model specification, which uses 9,588 observations, are as follows:

- Log likelihood at 0: −16,149,
- Log likelihood constants only: −8,754,
- Final log likelihood: −7,270,
- ρ^2 (relative to 0 coefficients): 0.550, and
- ρ^2 (relative to constants): 0.170.

The log likelihood obtained with the transition constants alone was substantial, resulting in a ρ^2 value of 0.380, indicating that the transition constants explain much of the choice variation. As discussed later, industry- and vehicle-specific parameters and time-varying regressors also help to explain the observed behavior, yielding a final ρ^2 value of 0.550. Coefficient estimates and t-statistics for transition constants and variables related to the "stay" alternative are presented in Table 2. Table 3 presents parameter estimates that apply to all starting activity types.

Transition Constants and Activity Durations

"Stay at the current activity" is the reference alternative in each case. Reading from left to right in Table 2, the transition constants indicate the utility of the new activity stop alternatives relative to remaining at the current activity. The second column represents the variables related to staying at the activity stop as a function of activity duration.

At Establishment

For activities beginning at the home establishment, the difference from the zero reference is only relevant once the worker has returned to the establishment and is contemplating a second tour. One of the new stop alternatives must be chosen for the first activity interval of the day and the return option is not available. As indicated in Table 2, the average worker appears to be making the first stop on a tour either a service stop or a goods stop, with meetings and other stops having less utility. Once the worker has returned to the establishment, the duration of the time spent back at the establishment begins, and the coefficients presented in Table 2 for the duration and log of duration result in a swiftly increasing utility for remaining at the establishment. If workers do not make a second tour within the first few time intervals after returning to the establishment, the odds say they will be finished for the day.

At Goods

Workers who start their day with a goods activity stop are more likely to make another goods stop immediately instead of staying more than one 5-min interval at the first stop, as represented by the positive coefficient on the new goods stop when the current stop is goods. If they do not make another goods stop, they are more likely to return to the establishment. This need to make another stop is offset by the utility of time spent at the current goods stop. The coefficients shown on the duration and log of duration at the goods stop allow the utility of staying to rise sharply in the first interval, peak in the second interval, and decline over several subsequent intervals. In addition, there was a significant, positive relationship between the duration of goods stops and wholesale workers, which most likely reflects the need to spend a greater amount of time at their customers' stores unloading multiple products.

TABLE 2 Estimated Parameters for Next-Stop Purpose Model: Specific to Starting Activity Types

	Stay at Current Activity*		New Goods Stop		New Service Stop		New Other Stop		New Meeting Stop		Return to Establishment	
	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
At establishment												
Transition constant			–2.690	–8.940	–2.645	–8.897	–4.503	–14.523	–4.769	–13.042		
Duration of stay at estab.	0.165	2.676										
LN duration at estab.	–0.678	–1.920										
At goods stop												
Transition constant			1.271	10.574	–2.180	–9.147	–1.314	–7.560	–4.862	–12.153	–0.748	–5.220
Duration of stay at goods	–0.042	–4.121										
LN duration at goods	1.927	21.286										
Wholesale stay at goods	0.769	5.342										
At service stop												
Transition constant			–2.531	–8.548	1.240	9.939	–1.983	–8.461	–4.734	–10.587	–1.262	–6.810
Duration of stay at service	–0.025	–3.330										
LN duration at service	1.677	16.727										
Industrial stay at service	0.300	2.542										
At other stop												
Transition constant			0.583	2.224	–0.155	–0.545	–0.345	–1.220	–3.218	–6.734	–0.589	–2.066
Duration of stay at other	–0.035	–1.856										
LN duration at other	1.903	9.322										
At meeting stop												
Transition constant			–2.277	–4.300	–1.764	–3.472	–1.324	–3.001	–1.540	–3.778	–0.842	–2.311
Duration of stay at meeting	–0.016	–0.806										
LN duration at meeting	1.454	7.092										
Wholesale stay at meeting	0.895	3.638										

*Reference case

TABLE 3 Estimated Parameters for Next Stop Purpose Model: All Starting Activity Types

	New Goods Stop		New Service Stop		New Other Stop		New Meeting Stop		Return to Establishment	
	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Worker's establishment type										
Industrial	–0.211	–2.245							0.499	3.489
Wholesale	0.857	6.107	–0.365	–2.832	–1.303	–4.131	1.333	7.444		
Retail			–0.609	–3.206					0.602	2.726
Transport handling			–1.746	–5.207	–0.861	–2.251				
Service*										
Worker's vehicle type										
Light	–0.154	–1.902					1.654	7.395		
Medium–heavy*										
Cumulative time										
Current tour									0.0045	2.542
Entire shift less current tour									0.0100	5.428
Time period										
Midnight to 3:00 a.m.			–1.479	–2.692			–1.242	–1.714		
3:00 a.m. to 6:00 a.m.										
6:00 a.m. to 7:00 a.m.										
7:00 a.m. to 8:00 a.m.			0.965	7.358						
8:00 a.m. to 9:00 a.m.			0.422	3.847						
9:00 a.m. to 10:00 a.m.							0.278	1.802		
10:00 a.m. to 11:00 a.m.							0.311	1.891		
11:00 a.m. to noon					0.688	3.264	0.562	3.301		
Noon to 1:00 p.m.					0.731	3.428				
1:00 p.m. to 2:00 p.m.			–0.337	–2.283						
2:00 p.m. to 3:00 p.m.									0.584	3.335
3:00 p.m. to 4:00 p.m.			–0.415	–1.979					0.625	3.36
4:00 p.m. to 5:00 p.m.									0.917	4.232
5:00 p.m. to 6:00 p.m.										
6:00 p.m. to 7:00 p.m.					1.214	3.928				
7:00 p.m. to 8:00 p.m.					1.103	3.154				
8:00 p.m. to 10:00 p.m.					1.242	4.031				
10:00 p.m. to midnight										

*Reference case

At Service

A similar relationship may be found by examining the estimated transition constants for people who start out with a service activity stop. They are much more likely to make subsequent service stops and the duration coefficients imply a similarly concave relationship between activity duration and utility, with service stops being longer on average than goods stops. Table 2 also indicates a significant positive relationship between industrial establishment types and the duration of the service stop, which probably indicates that workers spend a significant amount of time at customer sites performing repairs, construction, or maintenance.

At "Other"

For workers who make an "other" stop, which may include activities such as refueling a vehicle or taking a break, the most likely follow-up activity is a new goods stop, which might be correlated with the fact that workers who started out with goods stops are more likely to include an other stop on their tour than those who started out with different activity types. To avoid overlap with person transport models, other stops were limited to those that were for work purposes or that were part of a work tour. Consequently, there were relatively few other stop observations that met this qualification, forcing the authors to accept some nonsignificant coefficient estimates for other activity duration and for transition constants.

At Meeting

Table 2 indicates that workers whose first stop is a meeting or a sales call are more likely to return to the establishment than to make another stop. Meeting stops have the longest average duration. As indicated in Table 2, workers from wholesale establishments have significantly longer meeting and sales calls than workers from other establishment types. Again, this might reflect the complexity of wholesale activities.

Establishment and Vehicle Type Effects

Numerous establishment and vehicle type effects were tested. The significant effects were retained in the final model specification and are presented in Table 3. Limited by the survey sample size, this work focused on the main effects, making them generic across starting activity types.

Industrial

With the reference case being service establishments, the parameter estimates in Table 3 indicate that industrial establishments are significantly less likely to make new goods stops and significantly more likely to choose to return to the establishment, meaning they tend to have shorter tours. This, coupled with the tendency to make longer-duration service stops as mentioned previously, suggests that the type of commercial movements typical of industrial establishments are service oriented and focused on a single customer during each tour.

Wholesale

Wholesale establishment types showed the greatest difference from the other establishment types. As indicated in Table 3, relative to service establishments, wholesalers are significantly more likely to make goods and meeting stops and significantly less likely to make service or other stops. In general, they make more stops per tour and spend more time at each location than other establishment types.

Retail

As indicated in Table 3, relative to service establishments, retail workers were significantly less likely to make service stops and significantly more likely to return to the establishment, making the fewest stops per tour. Retail establishments make few large-item deliveries, most preferring to contract catalogue deliveries to transportation handling companies, with exceptions being restaurants, florists, and stores that sell home furnishings and appliances.

Transport Handling

Table 3 indicates that, relative to service establishments, transport handling workers are significantly less likely to make service and other stops. The type of commercial movements represented here for the transport handling sector are for-hire trucking and other delivery services that typically make less-than-truckload deliveries on a tight schedule, with little time left for other activity types. For the transport handling sector, the pickup and delivery of goods is actually a service they provide. The distinction used here between goods and services is an artificial one that was maintained for the purpose of combined model estimation with the other establishment types.

Service

Service establishments are the reference case in the model and therefore are not represented by parameter estimates in the tables. Service establishments include a wide variety of enterprises such as government services, public utilities, cable television, plumbers, automotive services, insurance adjusters, and others. The types of goods stops typical of service establishments are those that are required in the course of providing the service. For example, a tow truck might need to pick up a stranded vehicle, or a plumber might need to pick up supplies. Because of their diversity, service establishments share characteristics with many of the other establishment types and are thus less distinctive as a group, making them a better reference case.

Vehicle Types

Vehicle-specific effects were tested in many different places within the model specification, but only a few significant main effects were found in the choice of the next stop purpose. For example, it was hypothesized that larger vehicles spend more time loading and unloading than smaller vehicles; however, it was discovered that this effect was related specifically to wholesale establishment types, as discussed previously. As indicated in Table 3, workers who were assigned light vehicles were significantly less likely to make goods stops and significantly more likely to make meeting and sales stops. There was no significant difference in stop frequency between medium- and heavy-vehicle types.

Cumulative Duration and Time-of-Day Effects

Time-of-day effects appear in the model specification in two ways. First, in addition to the effects of individual activity durations, the effects of cumulative tour time and the elapsed time since the worker began the day (i.e., the first departure from the establishment) were tested. As indicated in Table 3, there is a positive effect between the elapsed time on a tour, which includes travel time between stops, and the propensity to return to the establishment. Further, there is an even stronger positive marginal utility of returning to the establishment for each minute elapsed since a worker began the day beyond the time spent on the current tour. Together, these two measures weigh elapsed time against the decision to make additional activity stops. A worker who can make several stops quickly is more likely make additional stops to fill out the workday, whereas a worker who spends several hours at a single stop will be less likely to make additional stops.

Time-of-day dummy variables were created for the 18 time periods shown in the first column of the bottom half of Table 3. In the estimation, the dummy variable was used to elicit time-varying effects on utility that were not captured by other variables in the model related to activity, tour, and work-shift duration. Their inclusion in the estimation also serves to remove any spurious correlation between observed choices and other explanatory variables that are actually attributable to time-of-day effects, such as typical business hours and lunch periods.

As indicated in Table 3, relative to all other activities, workers are significantly less likely to begin service or meeting stops during the first period of the day, 12 to 3 a.m. As the morning progresses, the estimation results in Table 3 show a propensity to make service stops during the hours of 7 to 9 a.m. New meeting stops are significantly more likely to take place during the late-morning hours, between the prime business hours of 9 a.m. and 12 p.m. In contrast, there appears to be a significant preference for making other stops either during the lunch hours of 11 a.m. to 1 p.m. or at night between 6 and 10 p.m. Being the times when most workers reach the end of their workdays, the hours between 2 and 5 p.m. show a significant positive effect on returning to the establishment.

DYNAMIC LOCATION CHOICE

Travel times and costs enter the DCM system through the next stop location model. In addition to the typical trip-length considerations, the space–time arrangement of activity stops partially determines the time available for activity stops, producing a lagged effect on subsequent activity choices. Because of space considerations, its properties are briefly discussed.

The next stop location model is a tour-based destination choice model, which uses a sequential approach to choosing activity locations for stops on the tour and is tightly integrated with the next stop purpose model. It is stratified by establishment types and stop purposes. It uses a utility equation function similar to other destination choice models with an impedance term accounting for vehicle-specific travel times and a "size" term representing the attractiveness value of alternative destination zones.

Another salient feature of its specification is the inclusion in the impedance portion of its utility function of a variable that represents the multiplicative interaction between the travel time back to the home establishment and the natural log of the duration of the tour. In estimation, this parameter proved to be significant and negative for all establishment types and trip purposes. Its behavioral impact is that the utility of locations nearer the establishment increases relative to locations more distant from the home establishment, and this effect intensifies as elapsed tour time increases. This specification not only complements the time sensitivity in the next stop purpose model but also constrains the return-to-establishment trip distances so that multistop tours do not meander too far from their origin before turning homeward.

CONCLUSIONS

This paper presents a novel method for modeling intraurban commercial movements, focusing on the generation of activity patterns using a dynamic discrete choice model formulation implemented in a microsimulation environment. The model formulation and estimation results demonstrate that the model is not only tractable but also produces intuitively sensible parameter estimates and behavior. The approach used here is generic enough to be applied to a wide variety of commercial establishment types and fills a void by characterizing intraurban commercial travel by observable travel patterns instead of attempting to fit this behavior into a one-size-fits-all theory. In doing so, some common behavioral tendencies have been identified across the dimensions of establishment types, vehicle usage, and trip purposes, and there is strong evidence from the persistence of the transition constants for general patterns of tour construction.

The DCM approach responds to unique spatiotemporal characteristics so that it is viewed to be transferable to other regions. Through specification of time-varying utility parameters, the model considers the duration of activity stops, total elapsed tour and work shift time, and exogenous time-of-day factors in construction of daily activity patterns. Realized travel times and the ability to reach clients, customers, and suppliers affect not only the location of commercial activity stops but also their frequency.

The DCM was calibrated against expanded survey data, which were made possible through built-in iterative calibration procedures. This made it possible to meet statewide target values for activity stop frequency by 18 time-of-day bins for five trip purposes simultaneously, including the return-to-establishment trip type, and by five establishment types; mean trip distances for all five trip purposes by establishment and three vehicle types; and traveler vehicle type usage frequency by establishment type.

Improvements to the current model might include a more rigorous study of perception differences in time passage to inform the creation of the dependent variable for dynamic activity choice. A larger number of survey responses would permit more detailed segmentation by starting activity, establishment, and vehicle type. Finally, identification of individual workers' occupations would help to inform the choice model.

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