

**BUSINESS AND SITE SPECIFIC TRIP GENERATION MODEL FOR TRUCK
TRIPS**

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ABSTRACT

This research was motivated by the recognition that recent developments in supply chain management have altered the mechanism of truck trip generation (TTG) at the individual facility level. It developed TTG models for retail stores at the disaggregate level that incorporate supply chain strategies of individual businesses. It assumed that TTG is an outcome of strategic and operational business decisions. Detailed data sets from two furniture chains were used to develop and validate binary logit models with several alternative specifications. The empirical results validated the potential of building a disaggregate TTG model at the individual store level. Inclusion of location and store type dummy variables improved model's predictive power. The comparison between ITE Trips generation and the best models from this research found that a commonly used independent variable - the number of employees – is a poor predictor of TTG at furniture chains, often resulting in severe overestimation of truck trips.

INTRODUCTION

The motivation of this study came from the recognition that the recent trends in the increase of truck traffic on major highways and urban areas, and the adoption of sophisticated logistics and supply chain management (SCM) strategies by private businesses have influenced the truck dominance in freight movements. A recent estimate predicts the truck dominance in goods movement will increase in the near future. The proportion of urban interstates that carry more than an average of 10,000 trucks per day is expected to increase to 69 percent in 2020 from 27 percent in 1998 (FHWA, 2004). Another estimate predicts the volume (tons) of freight transported by trucks will grow by over 75 percent over the next 15 years (FHWA, 2002). According to the 2002 Commodity Flow Survey (CFS), trucks moved 64 percent of the nation's commercial freight, measured by value, and 58 percent of tonnage (U.S. Bureau of Transportation Statistics, 2004). Most certainly, such dependence on trucks has contributed to ever-increasing levels of congestion, and has created additional expansion needs for roadways and freight-related facilities.

In addition to these trends, the rapid adoption of SCM by private businesses has changed the goods movement behavior to more consumer-, location, and individual business- specific arrangements of delivery frequency. In other words, the paradigm of goods movements has shifted from manufacturer- or supplier-led shipments (push logistics) of mass-produced items to consumer-led and demand-responsive shipments (pull logistics). Therefore, at the individual business level, the number and type of freight truck trips within a given time period can be regarded as “an outcome of a series of business decisions about products, sales, locations, delivery times, and frequencies (Iding et al., 2002)” as well as social and market conditions in which businesses operate. Such changes imply that the existing demand model at the geographically aggregate model may not be able to cope with new changes that occur at more and more disaggregate level.

As the first step toward incorporating the recent trends, this research focused on the developing the most important step of the truck trip demand modeling, Truck Trip Generation (TTG). The goal of this study is to build a predictive model at the individual retail store level that reflects supply chain strategies. The study assumes that TTG is directly related to businesses' decision-making behavior with respect to

SCM and logistics strategies adopted, with the goal of profit maximization. Thus, the businesses in a similar sector would share the similar TTG characteristics.

For this study, two data sets from Furniture Chains A and B. Using these data, TTG models for Furniture Chain A were built and validated the Furniture Chain B data set. The final models were also compared to TTG rate for furniture stores presented in ITE Trip Generation (2003). The study found the importance of store-specific characteristics on producing reliable TTG estimates. It also found one of the commonly used independent variables – number of employees – may not be an appropriate predictor at the disaggregate level.

The paper begins with the discussion on the background on TTG studies. Then, the research framework is illustrated. After the discussion on the data collection and database building, the research results are presented with tables. The validation results and the predictive power of the selected models are presented. Finally, the paper concludes with addressing the implications and suggestions of the study with the comparison between our models and an ITE model.

BACKGROUND

The TTG analysis is performed to estimate the number of trucks coming in and out of a study area or a facility. Existing models for TTG are mostly based on aggregate-level data. In addition, those aggregate data tend to be proxies of economic activities such as land use type, number of employees, and gross floor space that do not capture the effects of supply chain strategies. For example, the studies by Slavin (1974), Brogan (1979), and, more recently, Tadi and Balbach (1994) used types of land uses as the important indicator of TTG. As a result, existing models only indicate the relative importance of trip generators at a general level and are not suited to analyze the impacts of SCM that can be highly variable at the disaggregate level.

Since these types of models do not consider the heterogeneous characteristics within a land use (e.g. regional retail center), they are subject to aggregation errors that have limited their applicability to other regions. The issues associated with the transferability of TTG model were indirectly addressed by Holguin-Veras and Lopez (2002). Their study calibrated the TTG model for marine container terminals based on a nationwide survey of twenty-one container terminals in four regions. They found the number of

boxes, the size of terminals, and the number of berths as the good indicators of TTG. However, statistically significant differences in the regional patterns of trip generation were also found. Klodzinski and Al-Deek (2003) proved that a TTG model could be transferred to another site if the study subjects are similar in their characteristics. They successfully applied the Artificial Neural Network (ANN)-based TTG model for the Port of Miami to three ports in Florida: the Port of Jacksonville, the port of Tampa, and Port Canaveral.

The results of the literature review revealed that, in general, the experiences with aggregated-level models showed that they are likely to produce inconsistent outputs in terms of accuracy and transferability; indicating such approach cannot accurately capture the relationships between the activities at different business facilities and the amount of freight truck trips. This problem is exacerbated as the businesses have adopted even more sophisticated logistic management strategies in the last two decades. For example, the growing concerns on flexible production decisions propelled by the development of JIT and e-commerce (or e-economy) have changed the shipment patterns of goods movement.

The literature review failed to identify any past efforts that clearly addressed the TTG of major retail outlets at the individual store level. However, the research on supply chain management (SCM) strategies in the management science field offers some useful insights. A supply chain is a network that consists of the information regarding production, services, sales, financial resources, and demand (Mentzer et al., 2001). Trucks' movements in a supply chain are subject to the choices of shipping schedules, methods, and time tables (Gaither and Frazier, 1999). A conceptual model, "GoodTrip model" by Boerkamps et al. (2000), provided a good insight into the relationships between freight movements and the interactions between various actors in a supply chain. The authors argued that the incorporation of behavioral aspects of businesses and consumers would yield a more reliable model of a goods distribution system. Even though their model did not specifically deal with truck trips, it recognized the importance of the behavioral patterns that can only be captured at the disaggregate level.

RESEARCH FRAMEWORK

This research frames TTG with a perspective on the relationships between truck trips and economic activities. At the individual business level, the number and type of freight truck trips within a given time period can be regarded as "an outcome of a series of business decisions about products, sales,

locations, delivery times, and frequencies (Iding et al., 2002)” as well as social and market conditions in which businesses operate. Therefore, the main assumption is that TTG is directly related to businesses’ decision-making behavior with respect to SCM and logistics strategies adopted, with the goal of profit maximization.

In a supply chain, transporting mode is a medium of the commodity flows that are based on various business decisions on production and sales of commodities. Strategic, tactical, and operational decisions are critical components of SCM decision making (Winser, 2003; Miller and de Matta, 2003). Based on the decision hierarchy of a supply chain, a business makes various decisions on inventory, distribution, production, sales, and replenishment or routing schedule to retail chains. In this process, an efficient transportation system is a critical component of supply chain performance (Bowersox et al, 2002). Transportation decisions are partly dictated by the factors such as the conditions of various markets (e.g. labor, real estate, energy, and products and services being sold), consumer preferences, and government regulations. Consequently, truck trips connecting suppliers, firms, and customers are influenced by the complex interaction among those decisions, factors and constraints. Thus, it is obvious that the planning and control of the system critically affect the number of truck trips. Estimating TTG based on activity-related variables of a firm’s supply chain and logistics strategy will provide a comprehensive framework that is based on the reality.

The literature review provided a high-level understanding of the relationship between the business decisions, supply chain systems, and TTG. Nevertheless, the more detailed knowledge of the day-to-day operations of the businesses was needed to formulate actual models. In order to obtain necessary information, preliminary interviews with the experts from a manufacturing plant, a trucking company, and two logistics and supply chain solution providers were conducted.

The resulting framework for the retail businesses is illustrated in Figure 1. The small box on the top of the figure implies that the most important factor of freight truck demand is consumer demand for different types of goods. The demand for truck trips will be best estimated at the individual facility level since the number of truck trips is influenced by the way in which the facility operation is responsive to consumer demand. However, the inclusion of numerous commodities in a model is probably not feasible in most cases since the trade-off between the data requirement and the marginal improvement in the accuracy

may not be favorable. Instead, it is assumed that there are four types of commodities: fast-moving and slow-moving goods in terms of the velocity of inventory turns and weigh-out and cube-out goods in terms of size and weight concerns on shipments.

The bottom of the middle box shows the variables that need to be considered in a TTG modeling process. The variables are classified as long-term factors and short-term factors. The long-term factors include such variables as physical constraints of a facility and human resources. In this model, these variables are tested in order to see if they are useful predictors for a long-term TTG forecast. On the other hand, the short-term factors are associated with daily operations of a business. Such variables as replenishment schedule and sales information are the most important variables. The variation of sales volume over time will show the seasonal variations in the business operation that may be related to the number of truck trips.

Three boxes on the bottom of the Figure 1 are suppliers of commodities. As noted earlier, there are several different shipment patterns between a retail store and suppliers or DCs. Only three types of inbound shipments to a retail store are assumed.

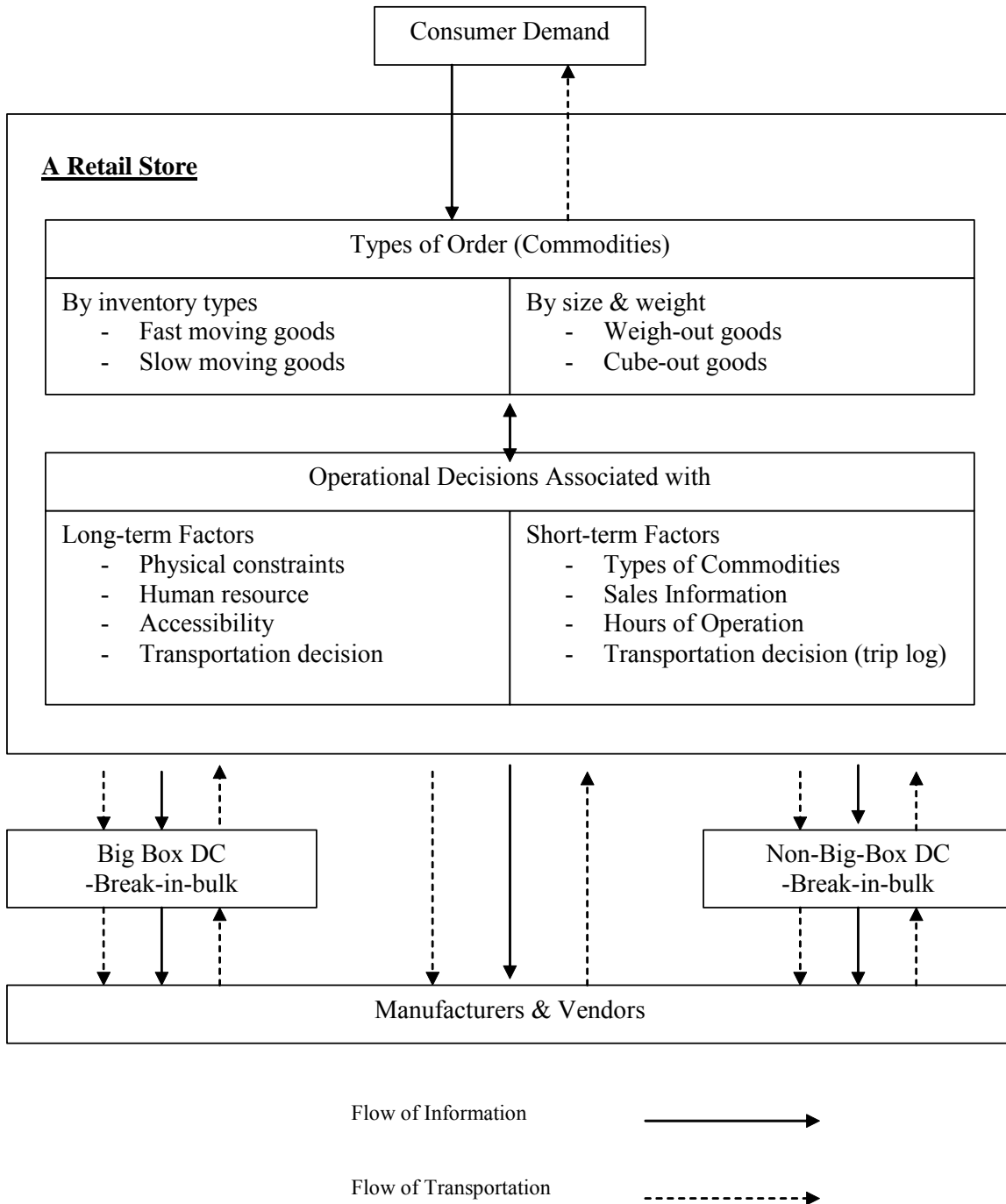


FIGURE 1. CONCEPTUAL MODEL OF TRUCK TRIP GENERATION

The conceptual model of TTG for a store in Figure 1 is simply expressed as to identify the possible variables to be collected for building a predictive model.

- $TTG = f(\text{Commodity sold, Logistics decision making variables})$

The left hand side is represented as truck movements between DCs and retail stores that are critical information. The right hand side has two variables. Commodity sold is simply the volume of sales by stores. Since the sales volume is a direct reflection of store performance and consumer demand, it would allow a researcher to estimate more realistic TTG. However, sales data are not easy to obtain. Instead, the study assumes that socio-economic characteristics such as the number of household by income class, median household income, or aggregated income of a market shed would be the proxies for consumer demand.

If the variables that capture the logistics decisions of a firm were known, a precise estimation of TTG would also be possible. Since logistics decisions cannot be observed, the study makes an assumption that store-related information such as the number of employees, and physical characteristics (e.g. size, location) reflect the firm's logistics decisions. In addition, the firm also makes a decision on store types and size, sales prediction, locations choice based on socio-economic characteristics within a market shed.

In summary, the following assumptions are generated from the conceptual model illustrated in Figure 1.

- (1) TTG is a direct function of sales volume and logistics decisions.
- (2) Since the volume of sales is difficult to obtain, socio-economic characteristics of a market shed are assumed to be the proxies of consumer demand on commodities.
- (3) Because the firm's logistics decisions are hard to observe, socio-economic characteristics of a market shed and store-specific information are assumed to capture them.

DATA

The conceptual model requires detailed information on the supply chain system of an individual store. Thus, the research team put much effort to collect as detail data as possible. Since no public data is available for individual business level, the research team collected the data either by the distribution of survey questionnaire, phone call, or store visit. Eight nine data points from two furniture chains – Furniture Chains A and B - were collected. The data set for Furniture Chain A was provided by the chain's distribution center (DC) that covers 76 stores in 18 Midwestern and Eastern states. The data set contained the detailed information such as routing schedule, store characteristics, store location characteristics and the amount of furniture delivered for all 76 chain stores. The data from Furniture Chain B were collected by visiting individual stores in Chicago area. Unlike Furniture Chain A, only delivery frequency information could be collected using this method. The purpose of this approach was to complement the data obtained by the main survey, and examine whether the stores in the same sector received the similar number of weekly deliveries with other factors being equal. In addition, the data points can be used to validate the performance of the TTG. The collected data from both chains showed that some stores received one delivery per week and other stores received two deliveries per week. This replenishment schedule was consistent all year round, suggesting that these chains used a highly standardized delivery schedule.

Since neither approach provided sufficient information on the variable such as the number of employees, sales volume, and store size, such data were purchased from InfoUSA, a company that specializes in business and consumer information. For socioeconomic information, the 2000 Census (U.S. Census Bureau, 2005^a) and the 2001 National Household Travel Survey (NHTS) were used (U.S. Department of Transportation, 2004).

The database was built in a multiple process. First, individual store information including store types, locations, addresses, employees, store size, and sales volume were geocoded in GIS and superimposed on a layer of census block group. Based on the 75 percentile of the shopping distance of urban residents in the US contained in the 2001 NHTS (since most stores in the dataset are located in urbanized area defined by the Census (U.S. Census Bureau, 2005^b)), a 6-mile buffer of the hypothetical market area was built around each store. The buffer was used to generate various socioeconomic data for the population within the market shed from the 2000 Census data at the block group level. Depending on

the aerial distance between a store and the centroid of each Census block group, four weights – (1) no weight; (2) Inverse of distance; (3) Inverse of distance squared; and Inverse of distance cubed - were assigned to each data points. Finally, the merged dataset was collapsed at the individual store level.

MODELING STRATEGY

Although the number of truck trips is obviously count data, neither Poisson model nor negative binomial model could be used because it has very narrow range – only one or two – and no zero values. For this reason, the binary logit model was chosen for building a predictive model for two furniture chains. The logit regression is arguably the most well known technique for analyzing discrete choice situations. It assumes that the probability of choosing one alternative over another is a function of the independent variables. For this research, it is assumed that the number of deliveries that a store receives is determined by the decisions that the Furniture Chain A has made as a part of the business operation strategy. While it is not possible to model the operation strategy directly, it is hypothesized - as previously mentioned - that it can be approximated by store-specific and socioeconomic variables.

The models were developed in the four-step procedure. The first step built a model using only the store-specific information. Then, the models only with the socioeconomic variables were constructed in the second step. To account for the different travel distances between the store and various points within the market area, four different weighting schemes were used. Thus, four separate models were developed in this step. In addition, the independent variables for a model were first selected by factor analysis, and, then, the various combinations of independent variables were examined until the models satisfying the selection criteria, which will be discussed later, were found. In the third step, the independent variables from the first and second steps are considered at the same time to build the best model for each weight type. Finally, the selected models from the previous three steps were compared to select the best model. In the first two steps, two separate models were built for store-specific information and socioeconomic information. In addition, the selected independent variables were combined in the third step. These processes were conducted to identify the importance of store-specific information as indicator variables.

It should be noted that the data for this study were not sampled. In other words, the observations in the Furniture Chain A data set represent the population (i.e., all the stores covered by the DC). There was

no stochastic variation in the dependent variable and in many of the independent variables. In other words, there was no sampling error associated with this data set. Thus, no hypothesis test was performed. Instead, the model selection was based on the pre-selected criteria mentioned below.

Since the prediction is the primary goal of this research, the criteria indicating the predictive power of a model were considered important. First of all, redundancy among independent variables should be avoided. Second, the signs of the regression coefficients should be reasonable. Third, sensitivity and specificity of the model were taken into consideration. Sensitivity is the probability of correct predictions of positive events (coded as 1), which is two weekly trips for this research. On the other hand, specificity is the probability of correct predictions of negative events (coded as 0), which is one weekly trips for this research. These measure the ability of the model to replicate both majority and non-majority responses. In addition, the overall probability of correct predictions is considered. Fourth, the receiver operating characteristic (ROC) is considered. The ROC curve shows the relationship between the probability of correct classification of positive events (sensitivity) and the probability of incorrect classification of negative events (1-specificity). When ROC is 1, it indicates a perfect predictive power, while ROC of 0.5 indicates no predictive power. All these criteria were considered in selecting the models.

Once a model satisfied the predefined model selection criteria and it was validated against the baseline dataset, it should be applied against a distinct set of data to test the transferability and predictive capabilities.

MODELING RESULTS

Models with Store Information

As mentioned previously, the first step of the modeling was to build a model only with store specific information. Four types of store-specific information were available - the number of employees, annual sales volume, store location characteristics and store types. The hypotheses, as specific to these variables, are:

- (1) Number of employee (*employee*) is positively related to trip frequency.
- (2) Sales volume (*sales*) has a positive impact on trip frequency.
- (3) Off-mall based stores (*mall 1*) tend to receive two weekly deliveries.

(4) Compared to combo type store (*stchar 1*), other types – conventional (*stchar 2*) and outlet stores (*stchar 3*) – are less likely to receive two weekly deliveries.

Table 1 compared five different models in order to examine the importance of location characteristics and store types. The first three models were built to test if *employee* and *sales* variables are sufficient to construct a model for this dataset. Although these three models did not violate the aforementioned hypothesis, their predictive powers were disappointing. More specifically, pseudo R-squared values were closed to zero. Sensitivities for these models were extremely low. Specificities were predicted well in all three models, which automatically increased the probability of overall correct classification. Considering the dominance of negative events (one weekly deliveries – 74 percent of stores), the high level of specificity was not surprising. Lastly, ROC scores showed adequate, but not excellent, predictive powers of the models.

TABLE 1. LOGIT REGRESSION WITH STORE INFORMATION

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Employee and sales	Employee only	Sales only	All variables (Adding location and store dummies)	Location and store types only
Employee	0.0352	0.0805		-10.52388	
Sales	0.0347		0.0506	0.0538	
mall1				0.6583	0.2406
stchar2				-109.0505	-3.8885
stchar3				-107.6011	-3.6354
Constant	-2.0525	-1.8837	-1.9961	104.6751	2.0086
Pseudo R2	0.0211	0.0137	0.0199	0.4536	0.2853
Sensitivity	7.14% (1/14)	0.00% (0/14)	7.14% (1/14)	50.00% (7/14)	50.00% (9/18)
Specificity	100.00% (44/44)	97.73% (43/44)	100.00% (44/44)	100.00% (44/44)	98.04% (50/51)
Pr(Correct Classificatin)	77.59% (45/58)	74.14% (43/58)	77.59% (45/58)	87.93% (51/58)	85.51% (59/69)
ROC	0.5909	0.5950	0.5698	0.8969	0.7696
n = number of obs.	58	58	58	58	69

Model 4 was constructed by adding the dummy variables for store location and types to Model 1 in order to examine the influence of store characteristics. Sensitivity indicated that 50 percent of two

weekly trips were correctly reproduced. Overall probability of correct classification was almost 90 percent. In addition, the ROC was close to 0.9, indicating a high predictive power. However, the negative coefficient for employee, which has no plausible justification, excluded this model from the consideration for the final model. The last model only used dummy variables. It showed high sensitivity and overall classification rate. ROC is higher than the first three models.

What should be noted here is the influence of store location and types for predicting the delivery frequency. Compared to the first three models, all aspects of the predictive power were superior for the last two models. In addition, *mall 1* was more likely to receive two deliveries per week. Compared to *stchar1*, *stchar2* and *stchar3* stores were less likely to receive two weekly deliveries. This implies that the availability of information on location and store types may help predict the frequency of truck trips very well. The data shown in the cross-tabulation (Table 2) supported this finding. The number in each cell represents the share among the stores with the characteristics indicated by the column and row headings that receive two deliveries per week. For example, the figure in the “combo/off-mall” cell indicates that 87.5 percent of combo stores located in off-mall location received two weekly deliveries. The row total (the last column) showed that 34 percent of the stores in an off-mall location received two weekly deliveries, whereas it was only 17 percent for the stores in a mall location. As such, column totals (the last row) showed that 90 percent of combo stores, 14 percent of conventional stores and 20 percent of outlet stores received two weekly deliveries. The table indicated that combo stores were highly likely to receive two delivery trips compared to other two store types. Furthermore, if a store was both combo and mall located, then it received two delivery trips without exception. It should be noted that location and store types could be easily observed, while employee and sales information are not easy to obtain.

TABLE 2. PERCENTAGE OF STORE WITH TWO WEEKLY DELIVERY TRIPS

		Store Types			Total
		Combo	Conventional	Outlet	
Location	Off-mall	0.875	0.176	0.200	0.343
Characteri	Mall	1.000	0.125	0.000	0.176
Total		0.900	0.143	0.200	0.261

Models with Socioeconomic Information

The next step tried to build binary logit models without using store types and locations to investigate whether it is possible to predict that truck trip frequencies without such information. As mentioned before, factor analysis was conducted to guide the independent variable selection. After examining a number of potential combinations of independent variables, four models, one for each of four weighting schemes, were developed and examined. Two models, shown in table 3 were identified as the best models. Since the third and fourth weights did not yield a satisfactory prediction, they were discarded. The descriptions of the independent variables are as follows:

- *Employee* = number of employees by stores
- *Highincome* = high income population
- *Med_age* = median age
- *Sqmincome* = square of median household income
- *Sales* = annual sales volume by stores
- *W1pop00_sqmi* = inverse of distance weighted population density per square mile
- *W1lowincome* = inverse of distance weighted low income population
- *W1med_age* = inverse of distance weighted median age
- *W1aincome* = inverse of distance weighted aggregate income

TABLE 3. TWO BEST MODELS WITHOUT STORE CHARACTERISTICS

Variables	Model 6 (Weight I)	Variables	Model 7 (Weight II)
employee	0.0679	sales	0.0808
highincome	0.0466	w1pop00_sqmi	0.0853
med_age	0.1546	w1lowincome	-0.0676
sqmincome	0.0023	w1med_age	-0.0514
Constant	-9.5737	w1aincome	0.0828
Pseudo R2	0.1378	Constant	-2.0692
Sensitivity	35.71% (5/14)	Pseudo R2	0.1911
Specificity	100.00% (44/44)	Sensitivity	21.43% (3/14)
Pr(Correct Classificatin)	84.48% (49/58)	Specificity	97.73% (43/44)
ROC	0.7192	Pr(Correct Classificatin)	79.31% (46/58)
		ROC	0.7695

Model 6 represents the unweighted model; Model 7 is the model with the inverse of distance weight. Neither model violated the hypotheses stated in a previous section. Although Model 7 had better pseudo R-squared and ROC, Model 6 was deemed superior overall. Since the purpose of this effort was to derive the best model for prediction, much emphasis was given to sensitivity and the overall probability of correct prediction. However, compared to the models with only store dummy variables (Model 5 in Table 1), both models had less predictive power.

TABLE 4. TWO BEST MODELS INCLUDING STORE CHARACTERISTICS

Variables	Model 8	Variables	Model 9
employee	0.1242	employee	
sales		sales	0.0012
mall1	0.9558	mall1	0.0858
stchar2	-22.4117	stchar2	-22.0636
stchar3	-22.4725	stchar3	-21.0442
highincome	0.0537	w1pop00_sqmi	0.0862
med_age	0.4602	w1lowincome	-0.0647
sqmincome	0.0134	w1med_age	-0.0487
		w1aincome	-0.0101
Constant	-3.7462	Constant	18.1270
Pseudo R2	0.5602	Pseudo R2	0.5076
Sensitivity	57.14% (8/14)	Sensitivity	64.29% (9/14)
Specificity	97.73% (43/44)	Specificity	100% (44/44)
Pr(Correct Classification)	87.93% (51/58)	Pr(Correct Classification)	91.38% (53/58)
ROC	0.9221	ROC	0.9042

Combined Model

The third step was to combine store specific information to the best model with socioeconomic information. Table 4 summarizes two such models. Model 8 was built by adding store types and location characteristics to Model 6; Model 9 was constructed by including store types and location characteristics to model 7. In terms of pseudo R-squared, model 8 was superior, while Model 9 showed a better overall percentage of correct predictions. Model 9 correctly estimated about 91 percent of observations, while model 8 successfully classified about 88 percent. In addition, sensitivity and specificity figures for Model 9

were slightly better. On the other hand, the ROC was better for Model 8. The sensitivity values for the models indicate a weakness in correctly identifying the stores that receive two deliveries per week. These models were able to identify only between 55 percent and 65 percent of those stores. Therefore, if these models are used in practice, the TTG will likely to be underestimated.

TABLE 5. VARIANTS OF MODELS 8 AND 9

Weight I				Weight II			
Variables	Model 8	Model 10 (Without employee)	Model 11 (Without types)	Variables	Model 9	Model 12 (Without sales)	Model 13 (Without types)
N	58	69	58	N	58	69	58
employee	0.1242		0.1003	employee			
sales				sales	0.0012		0.0102
mall1	0.9558	1.0281	1.1691	mall1	0.0858	-0.1501	1.0340
stchar2	-22.4117	-5.7744		stchar2	-22.0636	-4.2704	
stchar3	-22.4725	-4.1760		stchar3	-21.0442	-3.9247	
highincome	0.0537	0.0491	0.0541	w1pop00_sqmi	0.0862	0.0648	0.0829
med_age	0.4602	0.6261	0.2423	w1lowincome	-0.0647	-0.0804	-0.0579
sqmincome	0.0134	0.0212	0.0040	w1med_age	-0.0487	-0.0287	-0.0547
				w1aincome	-0.0101	0.0022	0.0972
Constant	-3.7462	-27.4889	-14.6557	Constant	18.1270	2.4357	-3.0178
Pseudo R2	0.5602	0.4893	0.2131	Pseudo R2	0.5076	0.4079	0.2182
Sensitivity	57.14% (8/14)	61.11% (11/18)	35.71% (5/14)	Sensitivity	64.29% (9/14)	66.67% (12/18)	21.43% (3/14)
Specificity	97.73% (43/44)	96.08% (49/51)	93.18% (41/44)	Specificity	100% (44/44)	98.04% (50/51)	95.45% (42/44)
Pr(Correct Classification)	87.93% (51/58)	86.96% (60/69)	79.31% (46/58)	Pr(Correct Classification)	91.38% (53/58)	89.86% (62/69)	77.59% (45/58)
ROC	0.9221	0.9096	0.7825	ROC	0.9042	0.8355	0.8052

As found previously, the existence of store characteristics are critical in building store level TTG model. Models 8 and 9 were only marginally improved compared to Model 5. To compare the influence of store-related variables, several variants of Models 8 and 9 were built, which is displayed in Table 5. For example, by comparing Model 8 with its variant without the *employee* variable, it was possible to determine its contribution to the predictive power of the TTG model. The analyses showed that the number of employee and sales did not play a critical role in predicting the delivery frequency by trucks. While removing those variables from the TTG models reduced pseudo R-squared and ROC, the accuracy of the prediction, measured by the values on the bottom four rows in the table, decreased only slightly, or in some cases, improved. In fact, the sensitivities of Models 8 and 9 actually improved slightly when *employee* and *sales* were removed.

The importance of store types was found again. The pseudo R-squared dropped considerably when the dummy variables for store types were removed from the models. Predictive power, especially the correct classification of two deliveries per week stores, also was decreased by a wide margin.

Validation and Transferability

One of the objectives of this study is to test the developed TTG model for validation using another set of data. Eleven stores of Furniture Chain B in Chicago area were tested. Like furniture chain A, some stores of furniture chain B received one weekly delivery; and others received two weekly deliveries. Three store-specific variables were available, *stchar1* (off-mall) *employee* and *sales*. However, all stores were located in off-mall location, meaning that any models with store types (Models 8, 9, 10, and 12) could not be used for validating the model. Instead, models 6 and 7 in Table 3 and Models 11 and 13 in Table 5 were tested for validating models.

TABLE 6. VALIDATION AND TRANSFERABILITY ANALYSIS

		Model 6	Model 7	Model 11	Model 13
		Weight I	Weight II	Weight I	Weight II
Furniture Chain A	Sensitivity	35.71% (5/14)	21.43% (3/14)	35.71% (5/14)	21.43% (3/14)
	Specificity	100.00% (44/44)	97.73% (43/44)	93.18% (41/44)	95.45% (42/44)
	Pr(Correct Classification)	84.48% (49/58)	79.31% (46/58)	79.31% (46/58)	77.59% (45/58)
Furniture Chain B	Sensitivity	33.33% (2/6)	83.00% (5/6)	66.67% (4/6)	100% (6/6)
	Specificity	20.00% (1/5)	40.00% (2/5)	0.00% (0/5)	20% (1/5)
	Pr(Correct Classification)	27.27% (3/11)	63.64% (7/11)	36.36% (4/11)	63.64% (7/11)

The prediction results, summarized in Table 6, showed that while all four models performed at approximately the same level for Furniture Chain A, the differences became apparent when they were applied to Furniture Chain B. As for the overall percentage of correct predictions, the models that included weighted socioeconomic variables outperformed unweighted ones. The former classified approximately 64 percent of the delivery frequencies for Furniture Chain B stores, while the latter succeeded only about 30

percent of time. Another notable result was that, in contrast to the cases for Furniture Chain A, the models generally overestimated the two deliveries per week stores. While all four models in general produced decent sensitivity values, their ability to correctly identify one delivery per week stores was disappointing. This phenomenon was most likely related to the fact that all of Furniture Chain E stores in the dataset were off-mall types. One plausible interpretation is that while the location type was one of the factors that were used by Furniture Chain A to determine the replenishment frequency, this is not the case for Furniture Chain B. Furniture Chain A may be using some other criteria that are not captured by the models in Table 6. Thus, the evidence indicates that the transferability of the models from Furniture Chain A to Furniture Chain B must be questioned, even though they are close competitors that sell similar merchandise.

FINDINGS

Since the dependent variable for the Furniture Chain A dataset had only two outcomes, binary logit model was the most appropriate for this study. Store location and store types were the most influential variables for TTG models. Inclusion of those variables always improved model's predictive power. Although the models that included the store type variable could not be validated using the Furniture Chain B dataset, it is reasonable to expect that such model would outperform the four models that were tested. It should be noted that location and store types are characteristics that are easily observable while many of the variables that were examined in this study can not be obtained easily. The number of employees, which was often used as the predictor of trip generation, showed a positive association with the delivery frequency. However, it had only a marginal effect on the predictive power of the TTG models. Socioeconomic characteristics of the market shed, while providing some improvement in the performance of the TTG models, were far less important than the store type and location.

CONCLUSION: IMPLICATIONS AND SUGGESTIONS

This research proposed a new approach to the truck trip generation (TTG) modeling. Unique features of the proposed model, compared against existing TTG models, are: 1) it was developed at individual facility level, and 2) it was designed to capture the effects of supply chain strategies on the truck trip generation.

The findings presented in this report underscored various shortcomings of existing methods. As shown in Table 7, the ITE method severely overestimated the number of truck trips, while the TTG models for this study produced reasonably accurate estimates.

TABLE 7. COMPARISON OF TTG MODELS VERSUS ITE TRIP GENERATION METHOD

	Furniture Chain A		Furniture Chain B	
Number of Stores	58		11	
Actual Number of Trips	72		17	
	Number of Trips Predicted by Model	Percent Actual Trip	Number of Trips Predicted by Model	Percent Actual Trip
Model 11	66	91.67	20	117.65
Model 13	63	87.50	21	123.53
Model 6	63	87.50	17	100.00
Model 7	62	86.11	20	117.65
ITE (based on number of employees)	1120	1555.56	291	1711.76

The study found that commonly used independent variable like the number of employees was a poor predictor of the TTG for furniture stores. Although this study covered only two furniture chains, this was consistent for both cases. Consequently, it is reasonable to suspect that current traffic studies and infrastructure planning activities that rely on independent variables at the geographically aggregate level contain a large margin of error. Furthermore, for small-scale traffic studies, collecting such information may be rather wasteful since one can predict the TTG potential of a facility by simply asking the supply chain strategies of prospective tenant or collecting data on similar facilities operated by the tenant.

Empirical data, although limited, validated the potential of building a disaggregate TTG model at the individual store level. Inclusion of location and store type dummy variables usually improved model's predictive power, often dramatically. It should be noted that store location and types are physical characteristics that are easily observed, while the identification of attributes such as floor space, the number of employees, or sales is more difficult to obtain. Since current data collection approaches that rely on land use information or development plans are not effective in gathering the aforementioned type of data, a whole new data collection strategy must be developed to support new TTG models.

The successful development of the new generation of TTG models will rest on the availability of data. Although a considerable amount of resources were spent on data collection, we did not obtain sufficient number of datasets to cover broad types of retailers. In addition, the validation and the evaluation of the transferability of the model were limited by the data availability. Considering the proprietary nature of the data required to build the TTG models, it is our opinion that the development of the new generation models cannot be carried out without strong support from the public sector and also industry participants and trade organizations. If individual companies could provide neutral trade associations or third parties with truck trip data a more robust analysis could be more meaningful.

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