Access to Destinations

Access to Destinations:
How Close is Close Enough?
Estimating Accurate Distance Decay Functions
for Multiple Modes and Different Purposes

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16. Abstract (Limit: 200 words)

Existing urban and suburban development patterns and the subsequent automobile dependence are leading to increased traffic congestion and air pollution. In response to the growing ills caused by urban sprawl, there has been an increased interest in creating more "livable" communities in which destinations are brought closer to ones home or workplace (that is, achieving travel needs through land use planning). While several reports suggest best practices for integrated land use-planning, little research has focused on examining detailed relationships between actual travel behavior and mean distance to various services. For example, how far will pedestrians travel to access different types of destinations? How to know if the "one quarter mile assumption" that is often bantered about is reliable? How far will bicyclists travel to cycle on a bicycle only facility? How far do people drive for their common retail needs?

To examine these questions, this research makes use of available travel survey data for the Twin Cities region. A primary outcome of this research is to examine different types of destinations and accurately and robustly estimate distance decay models for auto and non-auto travel modes, and also to comment on its applicability for: (a) different types of travel, and (b) development of accessibility measures that incorporate this information.

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Access to Destinations: How Close is Close Enough? Estimating Accurate Distance Decay Functions for Multiple Modes and Different Purposes

Final Report

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Executive Summary

Existing urban and suburban development patterns and the subsequent automobile dependence that is associated with them are leading to increased traffic congestion and air pollution. In response to the growing ills caused by urban sprawl, there has been an increased interest in creating more "livable" communities in which destinations are brought closer to one's home or workplace (that is, achieving travel needs through land use planning). While several reports suggest best practices for integrated land use-planning, little research has focused on examining detailed relationships between actual travel behavior and mean distance to various services. For example, how far will pedestrians travel to access different types of destinations? How can we know if the "one quarter mile assumption" that has become conventional wisdom in planning and designing communities is reliable? How far will bicyclists travel to cycle on a bicycle only facility? How far do people drive for their common retail needs? This research provides evidence on these and other closely related questions.

The approach taken in this research is to estimate sets of distance-decay functions to describe the impedance of travel distance or time across the transportation network. The concept of distance-decay, used widely in geography and spatial interaction modeling, including many transportation forecasting models, can be interpreted as measuring either the impedance to travel through a network or the willingness of individuals to travel various distances to access opportunities. An important feature of this work is the explicit effort to extend the set of distance-decay functions to as many combinations of modes and trip purposes as available data permit. The set of modes that are considered of interest in this study are auto (single-occupant and shared ride), public transit, bicycling and walking. The data sets used in the analysis include a general-purpose travel survey for the Twin Cities region, an on-board survey of users of the regional public transit system, and a survey of users of joint-use trail facilities in Hennepin County. Together, these data sets allow for a fairly comprehensive look at travel behavior by various modes and trip purposes.

The findings of the research, particularly as they relate to non-motorized modes (walking and bicycling), provide evidence that can supplement existing rules-of-thumb for pedestrian and bicyclist behavior. The findings suggest, for example, that substantial shares of pedestrian travel (perhaps one-quarter to one-third) exceed the often-cited threshold of one-quarter mile. Moreover, this finding appears to be invariant to trip purpose. Unless the segment of the population who reported these pedestrian trips are substantially different from those who either did not make utilitarian trips by the pedestrian mode or did not think to report them, this may be a welcome finding for pedestrian planning as it indicates a greater willingness to walk than is generally thought to be the case.

Results for bicycle travel data reveal a substantial difference in travel distances by trip purpose. Primary activities such as work and school often involved very long bike trips (up to 20-30 KM) for those who chose this mode. In contrast, more discretionary trips (e.g. for shopping, entertainment or recreation purposes) tended to be substantially shorter in length. It would be desirable for future studies of these types of behavior to target bicycling specifically in order to provide a large enough sample to further substantiate these findings.

The public transit trips examined in this study reveal significant differences in travel behavior across several types of stratification. Type of service (local bus, express bus, light rail), access mode and trip purpose all appear to affect trip length. The origin-destination data examined in this study allowed for a disaggregation of trips by segment (access, egress, and line-haul), which presents opportunities to ask further questions about how travelers view the relative importance of different parts of their trip (e.g. access).

Lastly, an important purpose of this research is to demonstrate how the decay curves for different travel modes and trip purposes can be used to provide measures of accessibility. While the calculation of accessibility measures for auto and transit modes are relatively straightforward using conventional travel demand models, we show how the use of a more disaggregate zonal structure using Census geography can allow for the generation of non-motorized accessibility measures at a spatial scale more closely aligned with actual bicycle and pedestrian travel behavior. While the results reported here are restricted to a relatively small sample area, the techniques should be scalable to larger geographic areas given full spatial data sets and appropriate computational hardware.

Chapter 1
Introduction

At the heart of much contemporary interest in transportation and community planning is the notion that cities can and should be modified to influence travel behavior. More specifically, increases in the density and mix of activities at various locations, along with improvements to the provision and aesthetics of facilities for travel, are intended to foster greater use of public transit and non-motorized modes (bicycling and walking) of travel.

In most large metropolitan regions these ideas have filtered through to practice in the form of planning documents and inclusion in ongoing planning processes. The Metropolitan Council of the Twin Cities, for example, has produced its own such document intended to provide a guide for local units of government seeking to produce transit-oriented forms of development (*Guide for Transit-Oriented Development*, 2006). Many of these documents proscribe the geometric dimensions of the development in terms of catchment areas for local retail and service establishments, typically defined in terms of a particular walking distance or time (e.g. ¼ to ½ mile or 5 to 8 minutes). Yet empirical evidence on which to substantiate these guidelines remains scarce. We do not know whether individuals might be willing to travel farther than these thresholds, implying a potentially larger catchment area, or how the barrier of distance affects the propensity to travel to desired local destinations.

This study seeks to produce evidence of people's actual travel behavior, especially with reference to travel by public transit and non-motorized modes. Travel behavior is examined for several types of trip purposes (work, school, shopping, restaurant trips, recreation, etc.) to understand individuals' willingness to travel a given distance to reach common destinations. The tool to be used to understand individual's willingness to travel is that of *distance decay functions*. Distance decay is a concept that is familiar to conventional transportation planning practice as an integral part of methods to model the distribution of trips throughout urban space. The key element of distance decay functions is a parameter that describes the spatial reach of trips by a particular mode for a particular purpose (e.g. home-based work trips by auto). This parameter is typically interpreted in terms of travelers' willingness to travel a given distance, or alternatively as a measure of impedance to travel that characterizes transportation networks and the distribution of activities that they serve. In planning practice, trip purposes are highly aggregated in order to expedite the process of travel forecasting. Little is known, then, about how far people will travel to reach a variety of destinations, and whether there are potentially significant differences between types of destinations.

The following sections of the study introduce the concept of distance decay in greater detail and survey some of the literature on travel by various modes and for specific purposes. Then, the data sources employed in the study are introduced and distance decay functions are estimated for auto (single-occupant and shared ride), walking, bicycling and public transit modes. Next, a discussion section identifies some of the study's limitations and indicates the potential use of the results in terms of measuring accessibility by various modes. Lastly, a concluding section recaps the findings of the study and suggests some next steps.

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Chapter 2
Literature Review

The Importance of Distance Decay Functions

The study of distance decay functions for various transportation modes and destinations provides a good starting point for understanding travel behavior associated with each mode. The parameters of distance decay functions provide a measure of the spatial extent of travel that each mode provides. Disaggregating the modal trips by purpose permits comparison of the distribution of trips by work and various non-work purposes for each mode.

Empirically estimated distance decay functions also provide evidence that can be used to examine various claims about travel behavior and support planning activities. For example, the recent interest in land use planning circles in creating "livable" communities has centered around loosely-held assumptions about individuals' propensity to walk to reach certain destinations. A general rule of thumb is that people will walk up to one-quarter of a mile to reach most destinations (Untermann, 1984). Little information is available as to whether some people are willing to walk further and if so, how much further. Also, there is little evidence concerning the effect of distance relative to the type of activity being pursued, the attractiveness of the destination (or destinations) being considered, and characteristics of the trip makers themselves.

Engaging in these direct behavioral inquiries leads naturally to another important application of distance decay functions, that is, their use as the basis for calculating measures of accessibility. Accessibility measures for motorized modes are often readily available, given the abundance of data on their use and their application to various planning activities. Similar measures are rarely calculated for walking and cycling trips since they are less frequent activities and represent a rather small share of overall urban travel. However, given data on the spatial distribution of trips and crude measures of attractiveness for various destinations, one could derive measures of accessibility provided by non-motorized modes. These types of measures could be used to illustrate the impacts of planning initiatives designed to promote the use of non-motorized modes or to increase the concentration of activities near a given location.

The following sections outline the formulation and use of distance decay functions, including their connection to transportation planning models and the development of accessibility measures. Some empirical studies incorporating distance decay concepts are reviewed to give a sense of the variety of possible applications. The estimation of distance decay functions is then briefly discussed, along with the approach to be applied in the current study.

Distance Decay Function Development

Distance decay functions are of particular interest in transportation and land use planning activities because of their historic association with gravity models, a form of spatial interaction model conventionally used to forecast trip distribution in transportation planning models. In general, the unconstrained gravity model for forecasting interactions between zonal units (e.g. traffic analysis zones) in an urban region might take the form (Fotheringham & O' Kelly, 1989):

$$T_{ij} = kv_i{}^{\mu}w_j{}^{\alpha}c_{ij}{}^{-\beta} \tag{1}$$

where T_{ij} represents the number of trips between zones i and j, v_i and w_j are variables conveying information about the attraction or intensity of origin and destination zones, and c_{ij} is a function representing the cost of travel between zones. The function c_{ij} is the distance decay function component of the gravity model and represents the deterrence or impedance to travel or interaction between locations due to distance, when all other determinants of interaction are held constant (Fotheringham, 1981). In a distance decay function, the parameter β is of great importance, since it specifies the level of deterrence or impedance to travel created by distance. Alternatively, this parameter may be interpreted as the *willingness* of individuals to travel between locations, given the conditions of the transportation network and the distribution of activities. In the gravity model presented above, the distance decay function is presented as a power function. Alternatively, the function can be specified as the inverse of distance or with the more common specification of a negative exponential function exp(-*bx*), where *x* is a variable representing distance. Regardless of the mathematical expression used, the distance decay function is intended to convey the decline in interaction as spatial separation increases, hence the typical use of a monotonically decreasing function.

For purposes of trip distribution modeling, analysts sometimes may simplify the gravity model by assuming that origins and destinations are known, which may be the case for some habitual types of trips (e.g. journey to work or school). This reduces the structure of the gravity model to the estimation of its decay or deterrence function. Separate functions will often be estimated for different trip purposes before being reintroduced to a forecasting model (Bates, 2000)

The distance decay parameter is often studied over time because of its characteristic of being dynamic and changing in response to transportation network development and changes in urban spatial structure. For example, Luoma, Mikkonen and Palomaki (1993) present evidence of the decline in the distance decay parameter over time as a result of increasing travel speeds and more fully-developed networks. Further work (Mikkonen & Luoma, 1999) sought to decompose the reasons for the observed change in gravity model parameters over time.

Applications of Distance Decay Concepts

Distance decay functions have found widespread use in transportation planning activities due to their relative simplicity and ability to describe a range of phenomena. Among the more common uses have been the empirical estimation of transit service areas via pedestrian access (Hsiao, Lu, Sterling, & Weatherford, 1997; Levinson & Brown-West, 1984; Lutin, Liotine, & Ash, 1981; Upchurch, Kuby, Zoldak, & Barranda, 2004; Zhao, Chow, Li, Ubaka, & Gan, 2003). as well as auto access (Farhan & Murray, 2006). Researchers studying pedestrian behavior in central business districts have also found distance decay relationships to be a useful organizing principle to describe pedestrian movement. Rutherford (Rutherford, 1979) estimated a gravity model of pedestrian trip distribution for the Chicago CBD using distance as an impedance factor, while Seneviratne (1985) used survey data from the Calgary CBD to estimate "critical distances" for walking in CBDs. Both of these studies are a bit dated, though they illustrate nicely the effects of distance on pedestrian travel patterns.

While the concept of distance decay is able to provide a rough proxy for the effect of travel cost on travel decisions, many researchers have noted the incomplete nature of distance as a predictor of spatial choice and travel behavior. Some attempts have been made to provide trip distribution models that account for the attraction characteristics of various destinations (Daly, 1982), (Bhat, Govindarajan, & Pulugurta, 1998), competition among destinations (Fotheringham, 1983), and intervening opportunities (Goncalves & Ulyssea-Neto, 1993). Others have sought to explain disaggregate spatial choices, such as consumers' shopping choice behavior, in terms of aspatial, general attributes (McCarthy, 1980), (Wrigley & Dunn, 1984), (Timmermans, 1996). One particularly interesting study by Beckmann et al. (Beckmann, Golob, & Zahavi, 1983a), (Beckmann, Golob, & Zahavi, 1983b) attempts to explain the spatial distribution of trips as elliptical "travel probability fields", which incorporate elements of urban spatial structure and the effects of residential location on travel patterns.

The results of many of these studies suggest that qualitative, aspatial factors may exert a significant amount of influence on travel behavior, interacting with the effects of urban structure to produce observed spatial choices and travel patterns. Individuals typically do not behave like physical objects, being drawn deterministically to the nearest activities. Nonetheless, given the limited policy tools available to change behavioral patterns, urban planners have stressed the importance of bringing potential destinations into greater proximity of residences. These measures seek to reduce overall travel or increase non-motorized mode shares by reducing the impedance of distance and increasing the quantity and variety of nearby destinations. Designing and testing such a strategy requires some formulation of the systematic relationship between transportation and land use. This relationship most often finds its expression in the form of the concept of accessibility.

The Relationship to Accessibility

The influence of distance on travel in urban areas is modified by the spatial structure of activities. This is the effect of accessibility, and it is believed to influence multiple dimensions of travel behavior, including the spatial distribution of trips. Defining an appropriate measure to capture the locational and behavioral aspects of accessibility has been a matter of much discussion in the transportation planning literature.

A review of accessibility measures by Handy and Niemeier (Handy & Niemeier, 1997) suggests three general categories of measures: gravity-based measures, cumulative opportunity measures, and behavioral measures. Gravity-based measures, as their name implies, are derived from the gravity model of spatial interaction. In deriving gravity-based measures of accessibility, destination opportunities, such as employment, are weighted by the cost of their interaction. This cost is usually specified by the distance decay function component of the gravity model, often taking on the familiar negative exponential form. Thus, a measure of Hansen (Hansen, 1959) accessibility (in reference to the seminar paper by Walter Hansen), which is based on the gravity model, could be specified as:

$$A_{ik} = \sum_j W_{kj} f_{ij} \tag{2}$$

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where *i* and *j* are subareas, W_k is a total population of opportunities, W_{kj} is a sub-population of opportunities (Harris, 2001). The function f_{ij} represents the cost of travel as an impedance to interaction, and can be specified as:

$$f_{ij} = \exp(-bC_{ij}) \qquad\qquad\qquad (3)$$

where *f* is the impedance function, with *b* as a non-negative parameter, and *C* a generalized cost variable, which can be replaced simply with distance or travel time. While this general formulation of accessibility is based on the unconstrained case of the gravity model, it can be easily extended to the single and double constraint varieties of the gravity model (Harris, 2001).

The cumulative opportunity measure of accessibility, perhaps best characterized by Wachs and Kumagai (Wachs & Kumagai, 1973), seeks to describe the accessibility of a location in terms of the number of opportunities that can be reached within a specified period of time. This method of measurement does not, however, discount measures of opportunity over distance (Krizek, 2005), and it is sensitive to the choice of demarcation area (Baradaran & Ramjerdi, 2001). Despite these limitations, the cumulative opportunity measure continues to be used due to its ease of comprehension and less data-intensive structure.

A third class of measures identified by Handy and Niemeier (Handy & Niemeier, 1997) are behavioral accessibility measures, alternatively referred to as a utility-based surplus approach (Baradaran & Ramjerdi, 2001). Based on utility theory and disaggregate travel choice models, behavioral measures allow for individual preference and perceived utility, as opposed to an aggregate approach with an assumption of uniform preferences across all individuals (Ben-Akiva & Lerman, 1979). Behavioral measures consider accessibility to be a function of the attributes of a destination and the cost of travel, as revealed by consumer choices. Since this measure of accessibility can be defined in terms of monetary units, it can be more easily used for comparison purposes.

More recent attempts at measuring accessibility have emphasized a movement toward disaggregate measurement of accessibility and the incorporation of constraints on travel behavior. In particular, interest in activity-based analysis of travel and time geography have yielded accessibility measures that account for the temporal dimension of activities and multipurpose activity behavior through the use of space-time prisms. Accessibility measures based on these considerations are referred to as constraints-based measures (Baradaran & Ramjerdi, 2001).

Distance Decay and Accessibility Measures

Distance decay functions are central to determining accessibility measures, particularly those based on gravity model formulations. Since these models specify access as a declining function of separation, the distance decay or impedance parameter will impact accessibility by either increasing or decreasing the degree of separation between two locations. Recall from equation (3) that travel impedance can be specified as a negative exponential function. Again, the variable C_{ij} represents a generalized cost measure that can include time, money, distance or other forms of cost, and is modified by a parameter *b*. When *b* is relatively small, impedance is low and accessibility is high. The inverse of accessibility can then be viewed as an average cost (of access) and can be specified as:

$$c_{ik} = -\ln(a_{ik})/b \tag{4}$$

where c is the average cost of accessing activity k from location i, given b. This average approaches 0 as b becomes large, and becomes large as b approaches 0. Therefore, b represents a measure of *unwillingness* to travel. Also, the b coefficient is negative, since C_{ij} is a measure of disutility. Hence, it is analogous to accessibility derived from multinomial logit models, using the logsum approach (Harris, 2001).

As a practical matter, public authorities with responsibility for transportation planning approach their work with the general goal of improving accessibility vis-à-vis mobility improvements. That is, they seek to lower the cost of travel by all modes, and hence the impedance to movement, by providing mobility-enhancing improvements to existing networks. However, Handy (Handy, 2005) argues that competition among travel modes and feedback mechanisms involved in modal investments (particularly those oriented toward auto travel) might imply that mobility improvements and accessibility improvements are not necessarily complementary. The implication is that while mobility by auto has generally improved over time, mobility, and hence accessibility, by non-auto modes has declined. If this assessment is in fact true, it most likely means that planning for accessibility will require different goals and methods than those currently in place.

As far as planning methods are concerned, a good place to start would be with a thorough understanding of individuals' current travel behavior by all modes, drawn from observations of actual behavior. This information can form the foundation of more elaborate accessibility measures. It is here that the study of distance decay functions can be quite useful.

Estimation of Distance Decay Functions

Like other transportation models, distance decay functions must be estimated from sample data. Similar to other spatial interaction models, there are two primary methods for estimating a distance decay function: linear regression using ordinary least squares on a transformed decay function and estimation of a nonlinear model using maximum likelihood estimation (MLE) techniques.

Ordinary Least Squares

Consider again the unconstrained gravity model in equation (1). This model is in power function form, though an exponential decay or impedance function can just as easily be used and often is in practice. While these two model forms are inherently non-linear, they can be transformed into a linear-in-parameters form by taking the natural logarithm of both sides. The logarithmic transformation of equation (1) has the form (Fotheringham & O' Kelly, 1989):

$$\ln T_{ij} = \ln k + \mu \ln v_i + \alpha \ln w_j - \beta \ln c_{ij} \tag{5}$$

If we choose an exponential decay function, the model takes on the form:

$$\ln T_{ij} = \ln k + \mu \ln v_i + \alpha \ln w_j - \beta c_{ij} \tag{6}$$

Furthermore, if we ignore the production and attraction variables and estimate the decay function directly, we get a simple expression of the form:

$$\ln T_{ij} = \ln k - \beta c_{ij} \tag{7}$$

Each of these equations can be estimated by ordinary least squares methods. However, while the other parameters in the model will be unbiased and consistent, the estimate of k, produced as $e^{\ln k}$, will be underestimated unless the model fit is perfect (Heien, 1968), (Haworth & Vincent, 1979). Fotheringham and O'Kelly (Fotheringham & O' Kelly, 1989) offer a procedure for correcting this bias.

Maximum Likelihood Estimation

Gravity models and their associated decay functions can also be estimated without transformation by maximum likelihood estimation techniques. The unconstrained gravity model can be estimated via maximum likelihood if it is assumed that interactions are the outcome of a Poisson process (Flowerdew & Aitkin, 1982). Similar estimation examples are given by Sen (Sen, 1986) and Sen and Matuszewski (Sen & Matuszewski, 1991). Algorithms for maximum likelihood estimation include the Newton-Raphson procedure, among others (Batty, 1976).

Current Application

In this study, the distance decay functions for various combinations of mode and trip purpose are used to relate the number of trips to distance, which serve as a proxy for travel cost. Most distance decay functions are estimated as part of a gravity model, such as the formulation in equation (6), with travel time or some other function of generalized cost as predictors, and the number of trips stratified by time duration interval as a dependent variable. The dependent variable used here is the *percent* of trips in each distance interval, with the percent of trips expressed as a function of increasing distance. Observations of distance values are taken by selecting the midpoint of each distance interval. The percent is computed by simply dividing the number of trips in each interval by the total number of trips by a given mode for a given purpose. Hence, the distance decay function for each mode and activity combination can be written as:

$$P_{mk} = \alpha \exp(\beta x) \tag{8}$$

where P_{mk} denotes the percentage of trips of mode m and purpose k at a given distance x. Using the percentage of trips, rather than the absolute number, allows for a more standardized comparison among activities within a given mode and ensures that the decay function will not be sensitive to the number of available observations. One may also note that using the percentage of trips instead of the number of trips as the dependent variable does not affect the impedance

parameter, β, since this only reflects a scale transformation of the decay function. The value of the α parameter is scaled accordingly, however.

The following section provides empirical estimates of distance decay functions for each available mode and trip purpose.

Chapter 3
Distance Decay Function Estimates

Distance decay functions are estimated for five modes: walking, bicycling, public transit, single-occupant auto, and shared ride (defined as auto with two or more occupants). For each mode a subset of six different trip purposes are used, contingent upon data availability. The six trip purposes are work, shopping, school or school-related activities, restaurant trips, entertainment, recreation or fitness trips, and trail access trips, which are defined only for the bicycle mode. For each mode, a summary figure is produced, with all trip purposes for a single mode plotted on the same axes. Figures for individual combinations of mode and trip purpose are provided in Appendix A with estimated curves, sample sizes, and an R^2 measure of goodness-of-fit. Note that the sample sizes listed on these figures do not correspond directly to the number of points plotted on each figure. This occurs because the distance decay curves are estimated from points representing the distance *intervals* for each mode and purpose, along with their associated trip frequencies. The number of points plotted to estimate a decay function for each mode is held constant across trip purposes, and is roughly proportional to the sample size for the trip purpose with the least number of observations. This explains why many of the curves for the auto modes are estimated with only 15 points, while there are typically several hundred observations for each trip purpose.

Data Sources

Travel Behavior Inventory

The primary source of data for the estimation of distance decay functions was the Metropolitan Council's 2000 Travel Behavior Inventory (TBI). Conducted approximately every 10 years, the TBI includes a home interview component, during which travel diary data are collected from participating households in additional to socioeconomic and demographic data. The primary purpose of the TBI is to collect travel data from which the submodels of the regional travel demand forecasting model system can be updated, though the data also supports many of the Council's transportation planning activities.

The home interview survey component of the TBI was conducted by telephone with a randomly selected set of households between April and September of 2001. Households were recruited from the seven core counties of the Twin Cities region, along with a smaller sample from the 13 adjacent 'collar' counties. The sample was stratified by geography in order to provide a proper geographic distribution of samples. Counties within the seven-county core of the region were sampled independently in order to maintain proportion with their 1990 U.S. Census household counts. Counties in the 13-county 'collar' were clustered and sampled together without distribution requirements. Sample selection was also managed to ensure adequate representation of households with respect to household size and vehicle ownership strata. A total of 8,961 households were recruited to participate in the survey, of which 6,219 provided complete 24-hour travel diaries. These travel diaries yielded data on over 40,000 trips, including travel by motorized and non-motorized modes. Trips were classified based on trip

purpose and data were collected regarding type of activity at each trip origin and destination, with 17 different activity types identified.

Transit On-Board Survey

Given the relatively small percentage of travelers who use public transit modes (bus, rail and demand-response services), data from the TBI survey were rather limited in their ability to describe travel behavior by transit. Fortunately, a more detailed on-board survey of transit users was authorized by the Metropolitan Council and conducted in 2005. These data were collected primarily to update the mode choice submodel of the Council's forecasting model system and include data on trip origins and final destinations, as well as points of access and egress from transit stops and stations. The inclusion of this data set allowed for a more highly disaggregated analysis of transit use, including stratification by trip purpose, access mode and type of service.

The on-board survey was conducted with a stated goal of completing 22,000 valid surveys for the transit system. Targets were set to collect minimum samples based on service type (local, express, and commuter bus, light rail) and peak/off-peak strata. The on-board survey data were more limited in terms of their treatment of trip purpose, since the objective of the survey was simply to identify characteristics relevant to travel forecasting models. Trip purposes identified in the survey were limited to general purposes of work, school (K-12), college/university, shopping and 'other'.

Trail User Survey

Data on bicycle use reported in the TBI data were also rather limited, necessitating the use of supplementary data sources to either confirm the results produced from the TBI or to replace them where existing data were insufficient or missing. A survey of bicycle use conducted by Hennepin County along three major bicycle trails provided one such source of supplementary data. The trail user survey was an intercept survey administered by County staff located at 13 points along the Midtown Greenway, Kenilworth and Southwest LRT trails. In addition to user counts, staff collected survey data items concerning respondents' activities on the trail, frequency of trail use, residential location, general activity level and satisfaction with the trail system. In all, approximately 3,000 surveys were collected. These data were particularly useful for calculating distance decay functions for bicycle access to major trail facilities.

Non-Motorized Pilot Program (NMPP) Survey

An additional source of data covering travel by non-motorized modes was provided by a recent survey conducted by the Active Communities/Transportation (ACT) research team at the University of Minnesota as part of an evaluation of The Non-motorized Transportation Pilot Program (NMPP), a program to increase walking and bicycling authorized under the most recent federal surface transportation bill. The NMPP program authorized grants to four communities (Minneapolis, MN, Colubmia, MO, Sheboygan, WI, and Marin County, CA) to promote non-

motorized mode use and required a follow-up evaluation to determine the program's efficacy. As part of the interim evaluation, a survey was conducted in each of the four communities along with a control community (Spokane, WA) between September 2006 and January 2007, to gauge rates of walking and cycling.

Since the focus of the survey was on behavior by users of non-motorized modes and public transit, these groups were sampled using quota sampling techniques in order to ensure a minimum number of responses from each stratum. More frequent users of walking, cycling and public transit modes were identified through their responses to a question in a self-mailer that preceded the administration of the survey regarding elapsed time since their last instance of use of a particular mode. These respondents were then asked to participate in a longer telephone survey, during which much of the data regarding their travel behavior was collected. The survey also contained questions that asked about a recent "reference" trip, in which the respondent was asked to provide information about trip distance, destination type, user perception, and other trip-specific data. A total of approximately 1,500 complete surveys were returned, roughly 300 from each study region.

Statistical Summaries

A set of statistical summaries for each distance decay function is provided in Appendix B. There are five tables, each covering a specific mode and providing estimation results for the set of decay functions relating to each trip purpose.

For each trip purpose there is a set of three different estimates. Originally, the distance decay curves were fitted using Microsoft Excel's curve fitting module and specifying an exponential form. The output from this module includes estimates of the relevant parameters, along with an (unadjusted) goodness-of-fit statistic, R^2. While these summary measures are provided, along with a graphical display, there are no estimates of variance included for the fitted exponential function and no summaries of residuals from which to extract such information. It is important to note that the impedance parameters are estimated from sample data, and hence take on a sampling distribution. In many transportation planning applications, this uncertainty is ignored and is a source of forecast error. In the present study it is even more important to quantify this uncertainty, since the curves estimated for non-motorized modes are based on limited sample sizes and represent a cross-section of the population with varying propensities to bike or walk.

To provide variance estimates for the decay function parameters and a check against the original estimates, two other sets of estimates are reported. The estimates labeled *regression* represent linear least-squares estimates of the distance decay functions, using the transformation described in equation (7). For this set of estimates, the α parameter is transformed using its natural logarithm, and must be exponentiated in order to provide the actual mean value estimate. The estimates labeled *curve fitting* represent parameter estimates obtained using the curve fitting module in SPSS version 13.0 statistical software. This module estimates the non-linear, exponential decay function directly, rather than the transformed version, which results in more precise estimates of the scaling (α) parameter.

The curve-fitting module estimates the decay function by least-squares techniques using the Levenberg-Marquardt algorithm, a minimization algorithm that minimizes a function (e.g. the sum of squared residuals) over a space of the function's parameters. The algorithm

interpolates between the Gauss-Newton algorithm and the gradient descent method (Marquardt, 1963). The sum of squared residuals is minimized by iteratively selecting a damping parameter, λ, to minimize a function representing the "neighborhood" around the vector of parameters. Convergence is usually assumed to have been achieved when the reduction in the sum of squares reaches some pre-defined limit. The algorithm requires the user to supply initial values for the estimates of the parameters.

The regression and curve-fitting summaries provide parameter estimates along with their standard errors and associated t-statistics. In addition, model summaries for the bivariate regressions representing the decay functions are listed. These include the coefficient of determinantion (R^2), the F-statistic for tests of overall model significance, and the sample size used to estimate distance decay functions for each mode and trip purpose.

Walking

Distance decay curves for the walking mode are presented in Figure 1. From the figure it is apparent that most walking trips cover distances of less than 3 kilometers (km), or roughly 1.86 miles. The curves take on similar forms for work, shopping, and restaurant trips, while entertainment, recreation and fitness trips tend to cover longer distances. This result reflects the more discretionary nature of entertainment or recreation trips and their lack of strict time constraints within the course of an individual's daily activity schedule. Curves fitted for recreation trips using TBI and NMPP data are summarized in Table 1 of Appendix B. The distance decay parameters derived from each data set are relatively similar ($\approx$ -0.77 and -0.69), though the variance of the parameter estimated from the TBI data is marginally higher, due to a slightly smaller sample.

Curves fitted for individual trip purposes are provided in Figures A.1 through A.4 in Appendix A. These curves appear to fit the data quite well, according to the summary statistics provided with each curve. Impedances for walking trips are especially high, with impedances for all trip purposes except for entertainment, recreation and fitness falling within the range of -1.0 to -2.0. These impedances reflect the rather limited speeds attainable by pedestrian travel. However, an interesting result is that a surprising number of trips are made at distances up to and even exceeding 1 km (0.6 mile). This result is consistent across trip purposes, suggesting that individuals may be willing to walk considerably greater distances than the ¼ mile threshold considered a standard in planning practice, in order to pursue common activities such as shopping and restaurant trips.
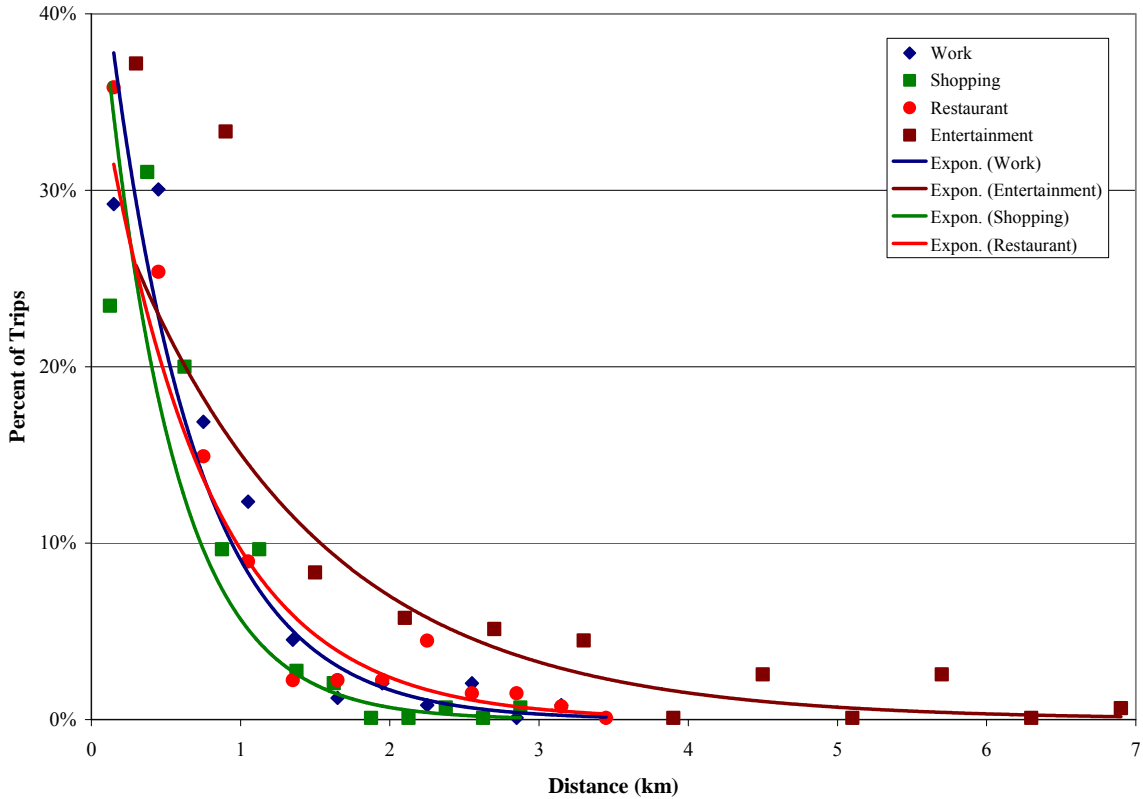
Figure 1. Distance Decay Curves for Walking Trips

Bicycling

Distance decay curves for bike trips are provided in Figure 2. Bicyclists are willing to travel much longer distances than pedestrians, largely due to higher average speeds attainable by bicycle. Entertainment, recreation and fitness trips appear to cover the greatest average distances with some trips reaching 30 to 40 km (18.6 to 24.8 miles). Work trips by bike are the next longest type of trip, with most trips falling within a range of about 20 km. Bike trips for work, shopping, or access to bicycle trail facility tend to be shorter on average, with the majority of trips falling within 10 km (6.2 miles). Trip purpose is an important factor in determining the length individuals are willing to travel by bicycle.

Distance decay curves for individual trip purposes by bike are presented in Figures B.1 through B.5 in Appendix A. It becomes more clear that some of the curves estimated for the bicycle mode are constrained by limited data. Sample sizes for curves estimated for work, shopping, and entertainment, recreation and fitness trips are all below 70 observations. It is clear that bicycling trips are a rather rare behavior that is hard to capture and describe accurately within the context of general purpose travel surveys. In contrast, the distance decay function estimated for trail access trips has a much larger sample size, since the data upon which this curve was estimated come from a specialized survey of bicycle trail user behavior.
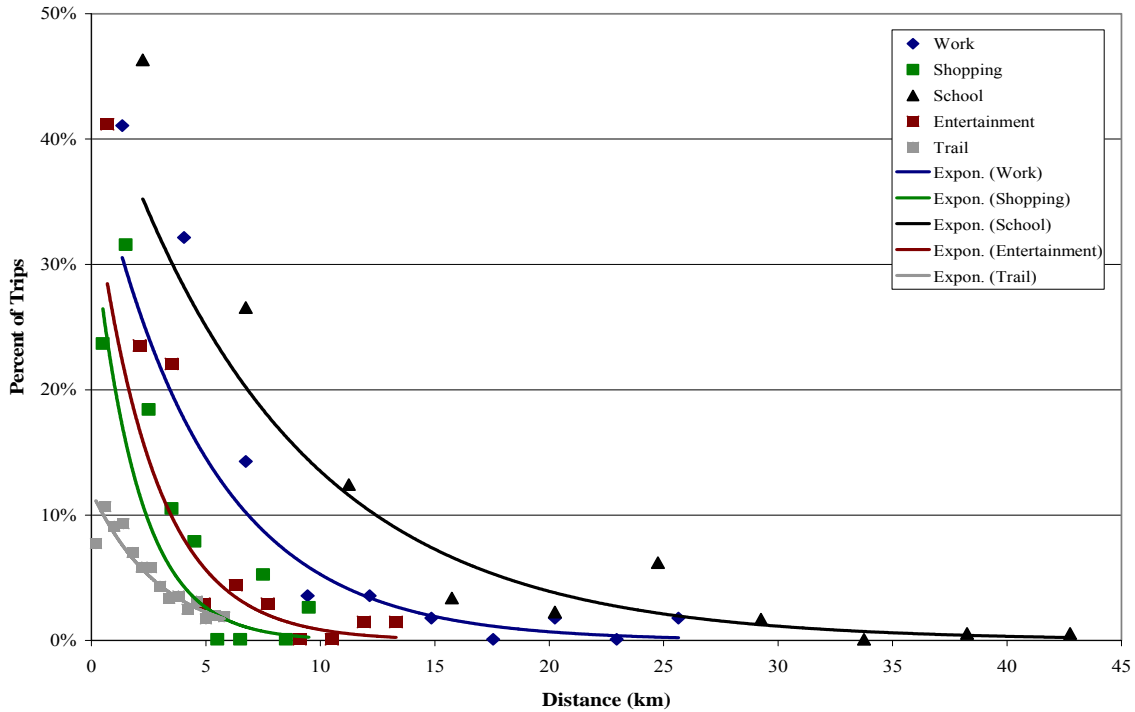
Figure 2. Distance Decay Curves for Bicycling Trips

Transit

Analysis of travel behavior by users of public transit modes is more difficult, since trips are comprised of separate collection, line-haul and distribution segments, often made by different modes. In addition, different types of transit service (local and express bus, light rail) have different operating characteristics, the most important being speed. Ideally, one would like to account for all of these sources of variability in describing the travel behavior of transit users, but data limitations preclude this level of detail. Instead, we begin with aggregate descriptions of distance decay functions for transit users, then seek to disaggregate to the greatest degree possible by trip purpose, access mode (walk and auto), and service type. Furthermore, we focus our attention on home-based trips that do not require transfers in order to limit the uncertainty in travel distance calculations where multiple routes exist between origins and destinations.

Trip Purpose

As with the pedestrian and bicycle modes, the disaggregation of trips by purpose is of primary interest in this study. The on-board rider survey data used to estimate decay functions for transit trips contained a more limited range of trip purposes that the Travel Behavior Inventory. Trip purpose analyses were therefore mostly limited to trips for work, shopping and college or university educational purposes.   A summary of the distance decay curves for transit trips made for these purposes is provided in Figure 3.
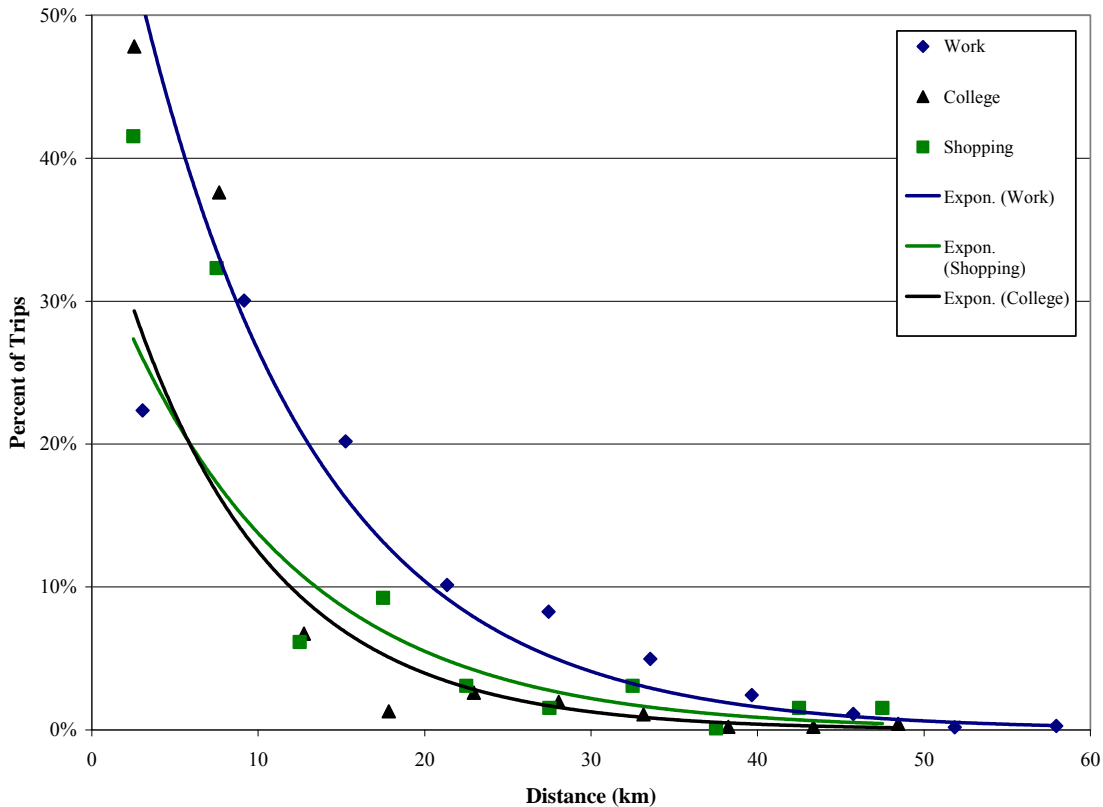
14

Figure 3. Distance Decay Curves for Transit Trips by Purpose

As one would expect, work trips tend to be longer-distance trips, covering distances of 50 or more KM with some regularity. Trips for shopping or college purposes were shorter and broadly similar in terms of responding to the effects of distance. Summaries of the fitted curves are provided in Table 3 of Appendix B, while the individual curves are displayed in Figures C.1 through C.3 of Appendix A. Using aggregate trip purpose data does obscure some of the underlying differences in the characteristics of travel for each purpose, though. On one hand, many of the transit users making trips identified as being for college or university purposes may include students, many of whom live relatively short distances from campus and make short daily commute trips by bus. These are counterbalanced by students (and some faculty or staff) who commute longer distances using the network limited-stop and express bus routes directly serving the university. These types of trips would show up as the less frequent observations in the long tail of the decay curve. A related issue is the effect of access mode and service type on trip length. Many transit work trips are longer than other types of transit trips because travelers are using higher-speed services such as express bus and light rail, allowing greater distance to be covered without much additional travel time. In addition, more of the users of these types of services are likely to use auto as an access mode, increasing overall trip speeds.

This latter effect can be examined by disaggregating the trips by both access mode and trip purpose. Given the hypothesis that travelers have a more or less fixed budget of travel time, transit users who access transit by walking to a station or stop would be expected to make shorter trips, since they are in principle trading off access (and perhaps also egress) time against time

spent on the line-haul portion of the trip (i.e. time spent in-vehicle), thus generating shorter overall distances. This hypothesis is borne out by comparison of the distance decay parameters for trips with walk and auto access by trip purpose in Table 4 of Appendix B. One can also confirm these differences visually by examining the curves for trips by walk and auto access presented in Figures 4 and 5. Trips with walk access for shopping and college purposes are generally confined to distances of less than 20 KM, while work trips are as longer as 35 KM. By contrast, trips with auto access tend to be longer, with overall distances of up to 50 KM for college trips and nearly 60 KM for work trips.
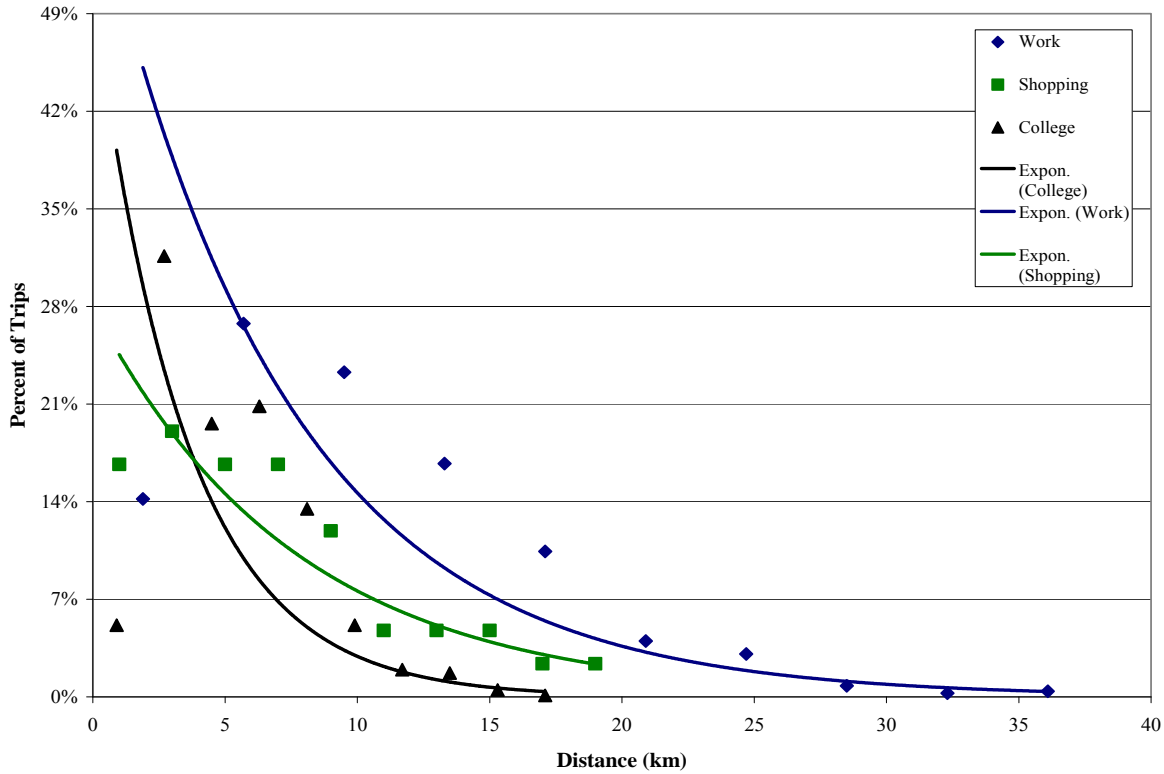
Figure 4. Distance Decay Curves for Transit Trips by Purpose with Walk Access

Transit trips with auto access trips also appear to have a distance threshold (in the range of 5-10 KM) below which users will not use this combination of access and line-haul modes. This finding also indicates that a negative exponential curve is not appropriate for capturing the distance decay effect for this type of trip. Figure 5 plots the exponential curves in addition to points that trace out the shape of the curves using predictions from a more general decay function of the form:

$$f(x) = (\alpha)x^{\mu} \exp(-\beta x) \tag{9}$$

Figure 5. Distance Decay Curves for Transit Trips by Purpose with Auto Access

where α, μ and β are parameters to be estimated. This form has been referred to as a 'combined' function (Ortuzar & Willumsen, 2001). It is unimodal and approaches zero as the cost or impedance variable x does. The parameters of the fitted curves using this specification are listed in the Appendix B statistical summaries under the label "combined" for each trip purpose. The combined function app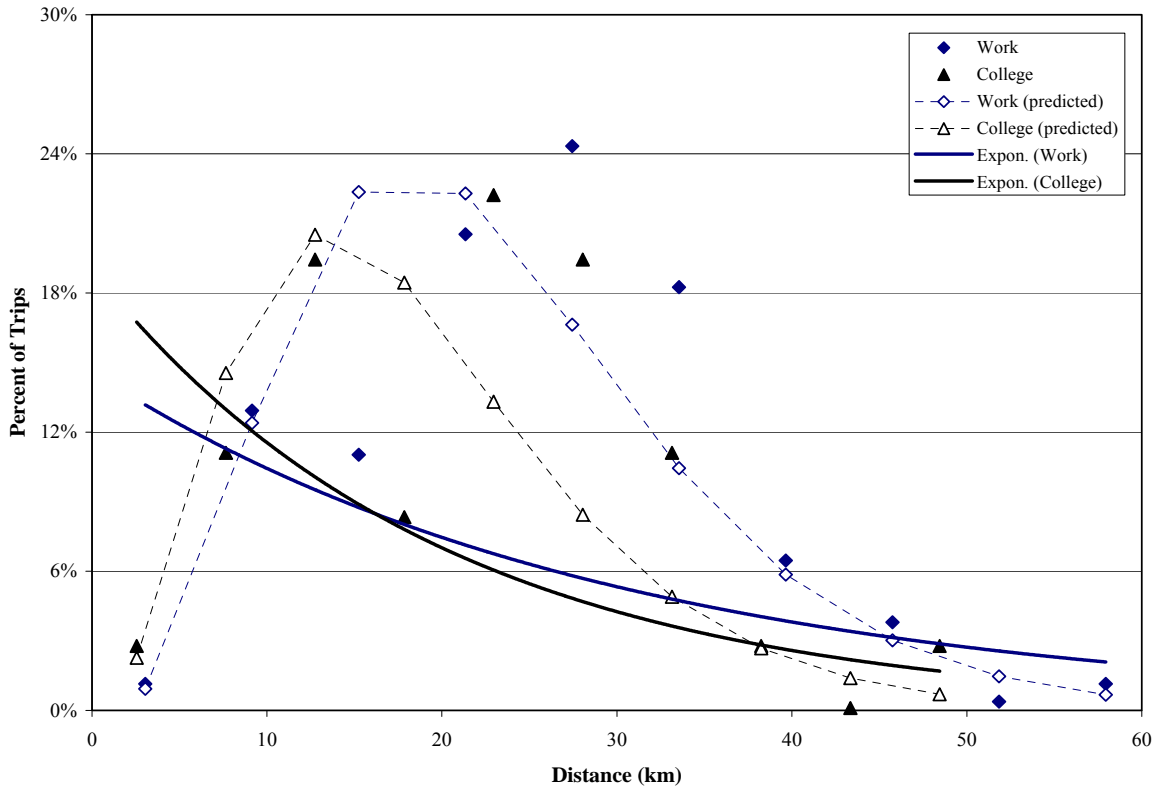ears to be a better fit for transit trips with auto access, and indeed is a suggested form for trip distribution functions applied to auto trips or any type of travel where short trips are not common (Kanafani, 1983).

Service Type

Another useful way to disaggregate transit trips in order to isolate the effects of speed on distance is to stratify trips by service type. The detailed data available from the on-board survey of transit users permits this type of analysis. Users are stratified according to three major service types: express bus, light rail and local bus.

The curves fit for transit trips by service type are shown in Figure 6. Again, there appear to be threshold effects for each of the service types, though they are more pronounced for express and light rail trips. The summaries for each of the fitted curves in Table 5 of Appendix B indicate that, particularly for express and light rail trips, the combined function again provides a markedly better fit to the data.

17
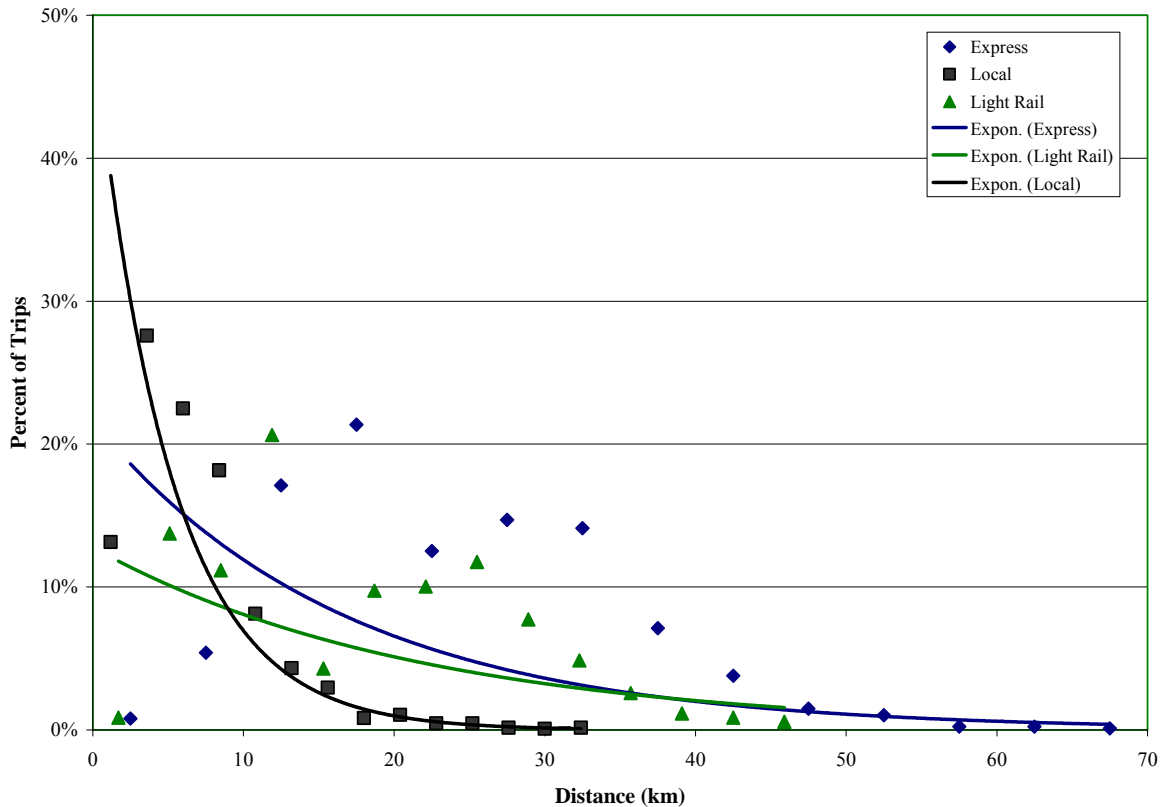
Figure 6. Distance Decay Curves for Transit Trips by Service Type

The deviation of the data from the negative exponential curve form becomes more apparent when the individual curves are viewed in isolation (Figures C.4 through C.6 in Appendix A). Trips by local bus appear to be considerably shorter than express bus and light rail. This can be partly accounted for by the different operating speeds of the services, but also by the tendency of express bus services (and to a smaller extent, light rail services) to be used extensively for work trips, which tend to be longer than average regardless of mode.

While the negative exponential form does not fit the distribution of total trip distances very well, it does describe well the distance decay effect for access modes by themselves. Summaries of these curves disaggregated by service type are provided in Table 6 of Appendix B.

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Auto

Drive Alone

As Figure 7 indicates, single-occupant trips by auto are considerably longer than trips by non-motorized modes and also longer than most transit trips. Decay curves for most trip purposes are strikingly similar, with the exception of work trips which, as one would expect, cover a greater distance. For non-work trip purposes by solo drivers, distances of up to 30 km or so are fairly common, while work trips appear to routinely extend beyond 40 km.
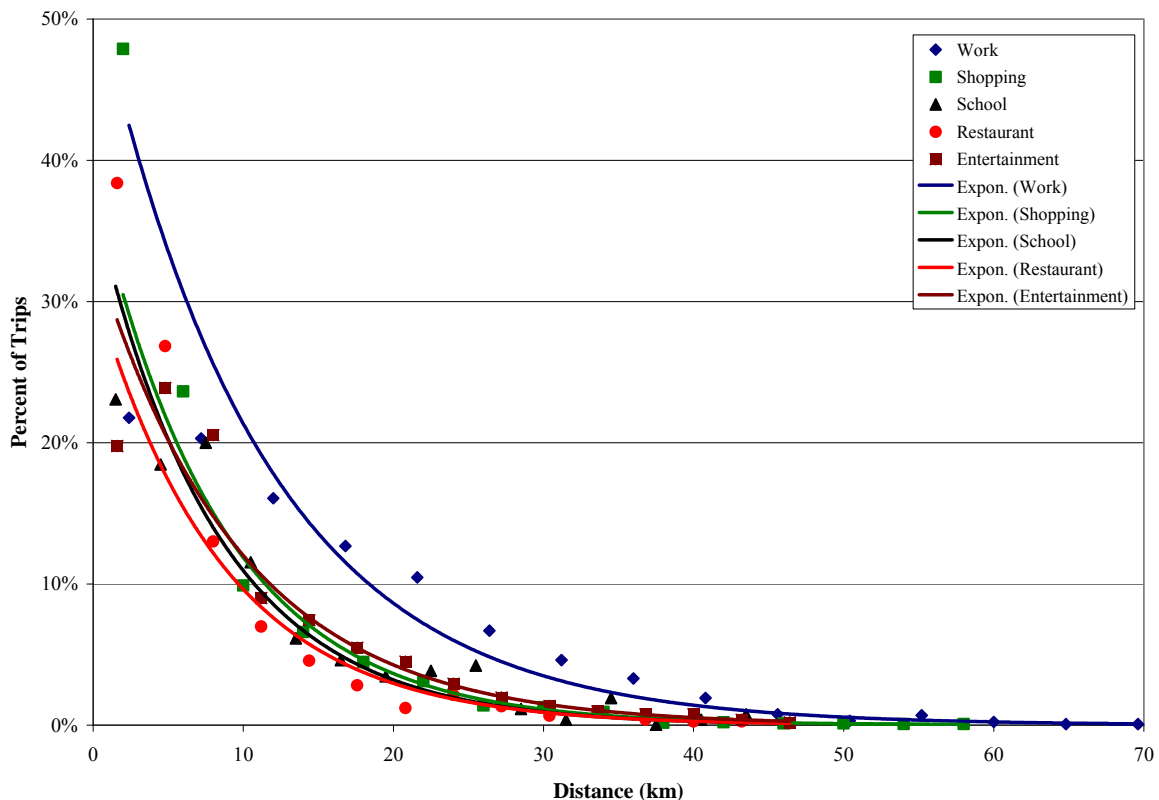
Figure 7. Distance Decay Curves for Single-Occupant Auto Trips

Additional comparisons are permitted by examining the estimated impedance parameters (β) in Table 7 of Appendix B. While drive alone trips for non-work purposes tend to have impedance values slightly above 0.1 in magnitude, work trips tend to indicate a lower impedance, closer to 0.09. By contrast, impedance values for bike trips range from 0.12 for school-related trips to over 0.50 for shopping trips. As noted above, impedances for walking trips are greatest, with values ranging form 1.0 to 2.0. The relative magnitudes of these values indicate the importance of modal speeds in determining the spatial extent of travel by each mode.

Shared Ride Trips

Shared ride trips describe all auto trips taken with two or more occupants. This includes regular carpools, as well as any other arrangement involving one or more occupants, such as parents taking their children along on shopping trips or to school. Figure 8 displays the distance decay curves for shared ride trips.

Estimates of impedance parameters for shared ride trips are largely similar to those for single-occupant auto trips, though there is not as much of a noticeable difference between work and non-work trips. Work and entertainment, recreation and fitness trips tend to be slightly longer on average than other types of trips, as is evident in Figure 8. Most trips cover distances of up to 30 km, with some work and recreation trips approaching and exceeding 40 km.

Health Care Decay Function

In addition to the travel survey data collected to estimate decay functions for most trip purposes, a special data set was provided for clinic trips that allow for inferences regarding health care access-related travel. The data were collected from 32 clinics in the Twin Cities metropolitan area, representing over 170,000 clinic visits. A five percent random sample was
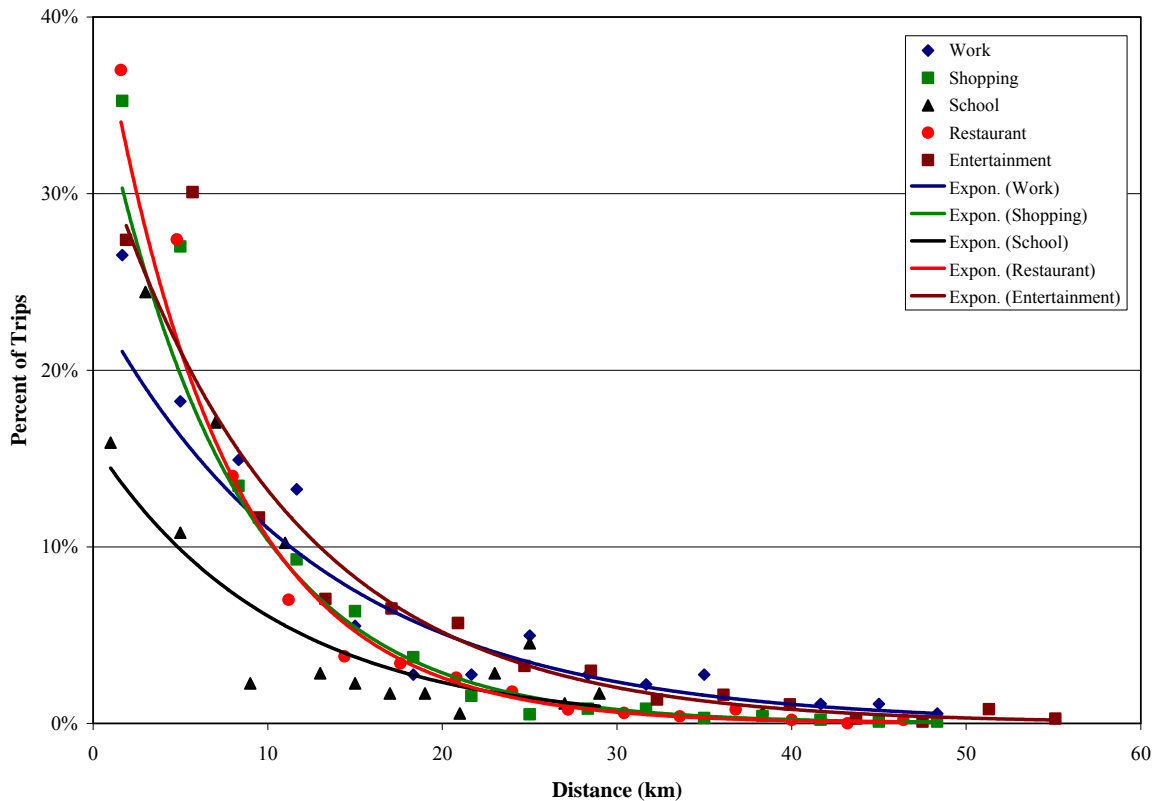

Figure 8. Distance Decay Curves for Shared Ride Auto Trips

drawn from these data, yielding over 8,500 observations. Each record contained the address of the clinic, along with the zip code of the trip maker, allowing for the calculation of a minimum distance path from the zip code centroid to the facility. A major limitation of these data, however, is the fact that no information was obtained on choice of mode. Therefore, the decay curves represent a pooling of trips by all modes, though the inclusion of a large number of longer-distance trips suggests a dominance by auto travel.

Figure 9 displays the negative exponential decay function fitted to the health care data. Overall, the fit is quite good, except for short distance trips (less than 10 km). The fit is improved slightly if the combined function is employed, allowing for the smaller number of trips that are made over very short distance (see Table 9 of Appendix B).

The equation shown on the figure:

$$y = 0.525e^{-0.11x}$$
$$R^2 = 0.980$$
$$N = 8,554$$
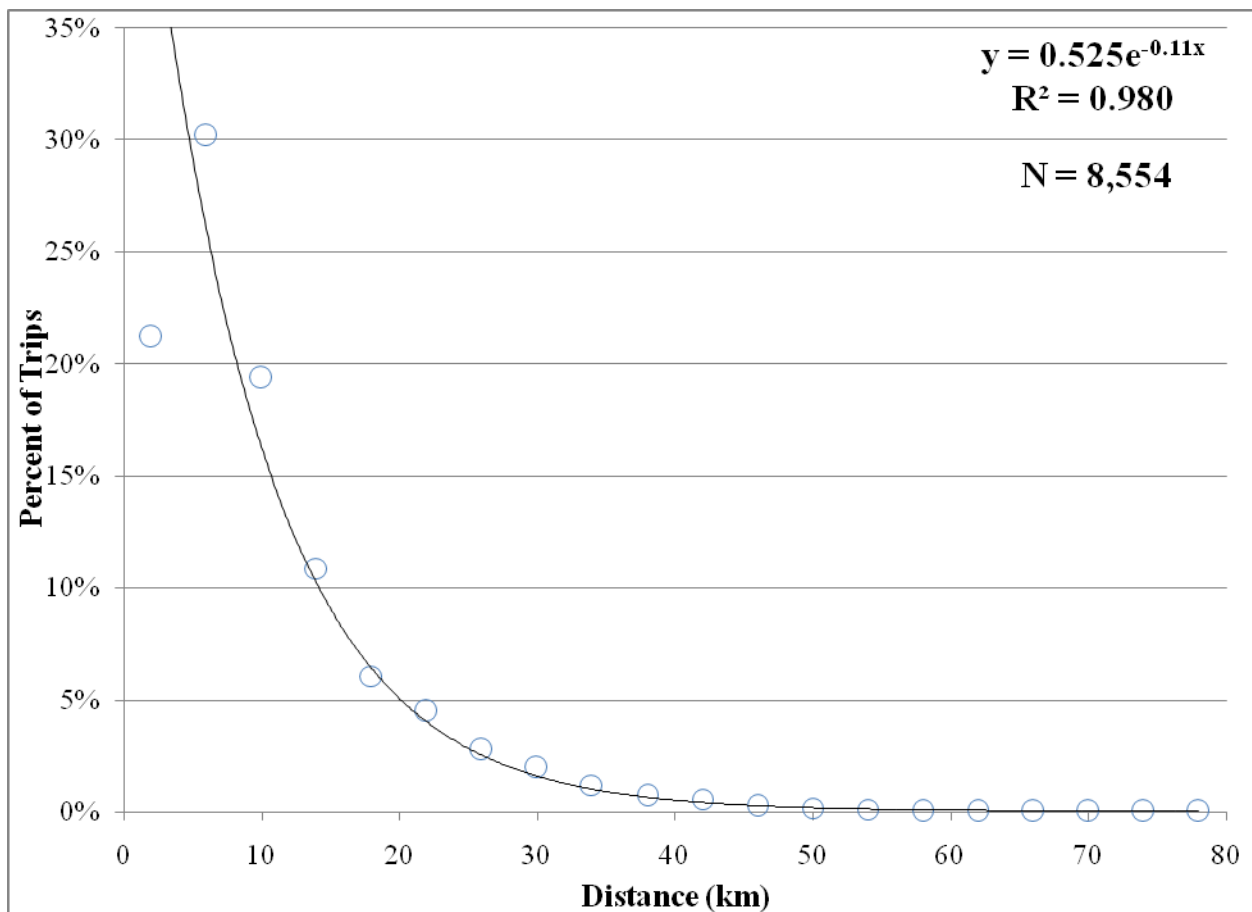
Figure 9. Distance Decay Curve for Health Care Trips

The fitted curve for the health care data indicates that the majority of health care-related trips are less than 20 km in length. The presence of a small number of very long trips probably represents individuals who either live at the metropolitan fringe, far from the nearest clinic, or require special treatment that can only be accessed at a few, highly specialized and geographically dispersed facilities. It should be noted, again, that these trips represent clinic visits, which are likely to represent more routine treatments. This is qualitatively different from access to hospitals, for which trip frequencies are likely to be less, but for which access is more critical.

Chapter 4
Travel Time Decay Functions

As a check against the accuracy of the distance decay functions estimated using data on trip distance, a second set of functions were estimated using travel time as the impedance variable. This is an important step, since our previous procedure involving travel distance does not allow for validation of either the chosen travel path (assumed to be minimum distance) or the trip speed. One drawback of using travel time data, however, is that the sample is limited to the Travel Behavior Inventory data, since the other data sets do not collect data on trip duration. Also, data on travel time is self-reported in the TBI, indicating that the accuracy of the data is subject to the bounds of human perception and cognition.

Walking

A couple of things stand out when observing the distance decay functions for walking using travel time as an impedance measure. The first is the considerably smaller impedance parameter estimates, with all parameters taking values of 0.10 or less. This is merely a function of the units used in the analysis (minutes as opposed to kilometers), so the relative magnitudes of the parameter values should be roughly consistent across trip purposes. The second is the remarkable amount of consistency between trip purposes, which is indicated by the comparison of fitted curves in Figure 10. Only a small fraction of trips are longer than 30 minutes in duration, with an absolute upper limit near one hour. Trips for recreation, exercise and fitness purposes appear to have the greatest duration, followed closely by school and work-related trips. Shopping and restaurant trips tend to be the shortest, though not by much. Curves fitted for individual trip purposes are provided in Figures F.1 through F.5 in Appendix A, and statistical output for these curves is provided in Table 10 of Appendix B.

Bicycling

Distance decay curves for bicycle trips exhibit less uniformity and a weaker fit than those fitted for walking trips using travel time. Figure 11 contains the fitted curves and indicates that the simple negative exponential functions that fit the distance data reasonably well do not approximate as well the effect of travel time on the propensity to travel. In particular, the negative exponential curves tend to overpredict trips of a shorter duration, while underpredicting some of the longer trips in the 25 to 60 minute range. This is reflected in the fit of the individual curves, as shown in Figures G.1 through G.4 of Appendix A, and as summarized in Table 11 of Appendix B. Also suggestive is the improved explanatory power of the combined function, which allows for a non-monotonic shape and appears to better fit the distribution of travel time data. Work trips still appear to be the longest trips, followed by recreation, school and shopping trips, though this relationship is blurred by the poor fit of the curves at more extreme values. Again, most trips appear to be less than 30 minutes in length, with almost none greater than 60 minutes.
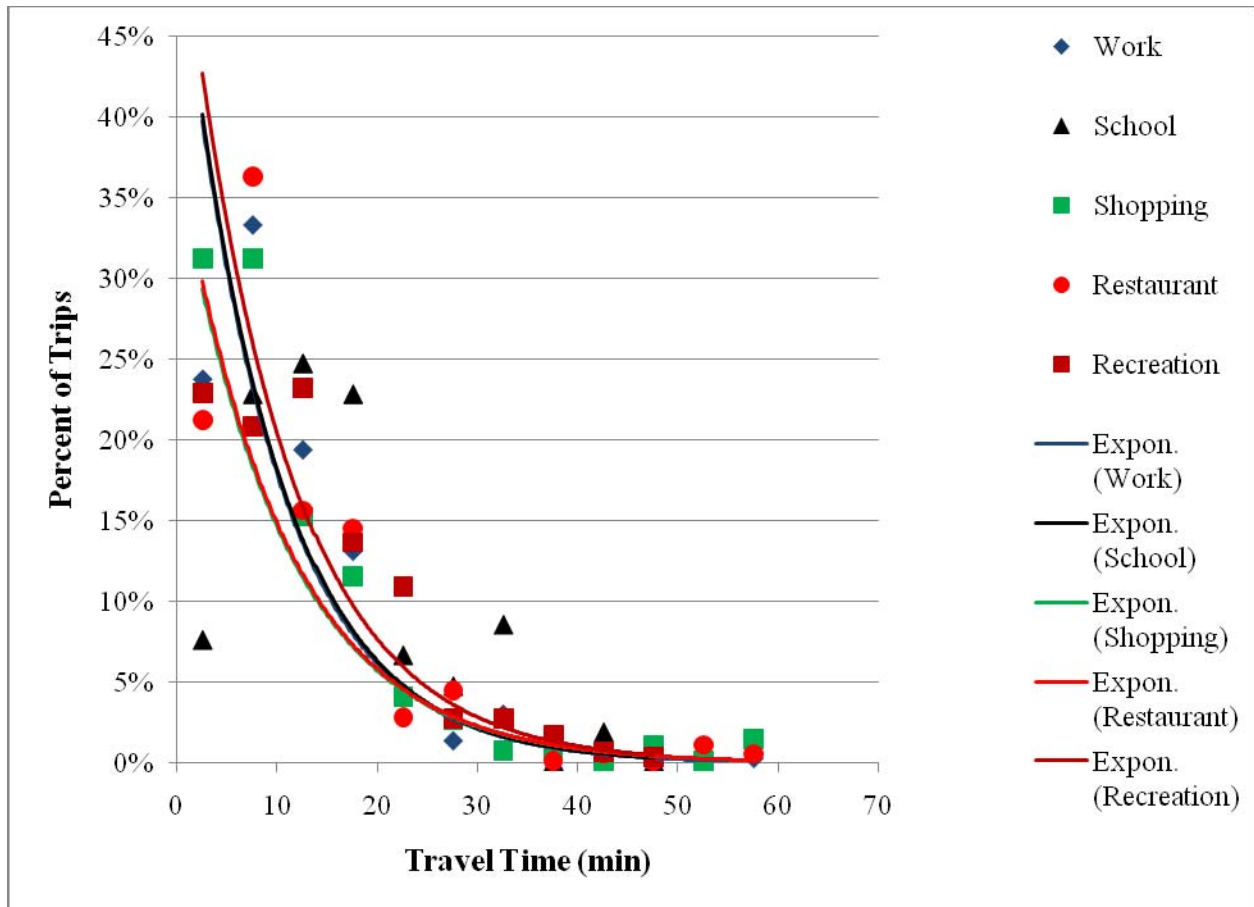
Figure 10: Distance Decay Curves for Walking Trips (Travel Time)

Transit

The lack of fit of the negative exponential curve to the travel time data becomes most apparent when trips taken by public transit are examined. The limited number of non-work trips by public transit in the data set restrict the analysis to work and shopping trips. The individual curves for each of these trip purposes are provided in Figures H.1 and H.2 of Appendix A. Imposing the negative exponential specification on these data result in an equation with almost no explanatory power; in fact, imposing an exponential curve form on the shopping trip data results in the estimation of a positive coefficient for the travel time variable, certainly a counterintuitive result.
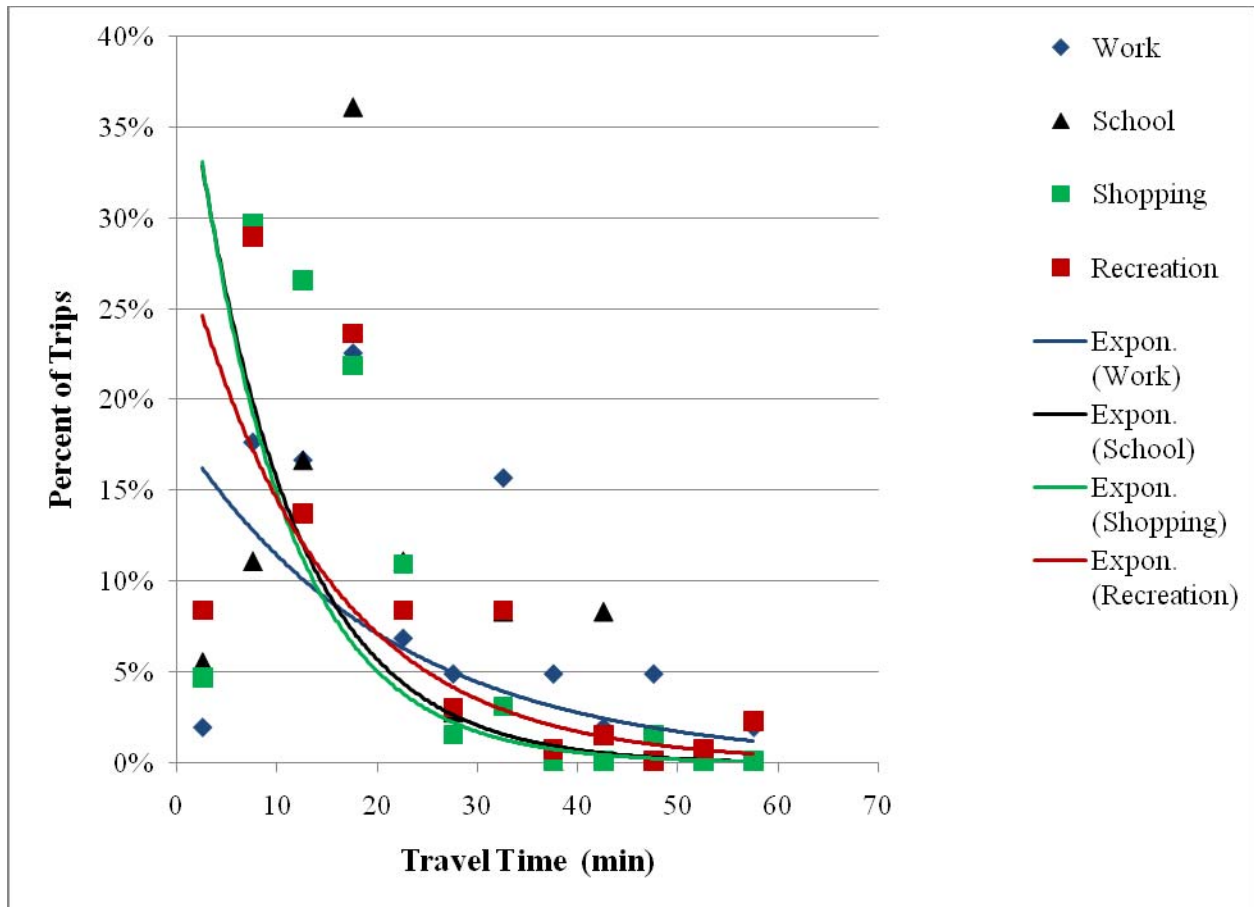
Figure 11. Distance Decay Curves for Bicycle Trips (Travel Time)

The data for work and shopping trips by transit are plotted in Figure 12, along with curves for each trip purpose using predicted values from the combined function. While the transit data do exhibit a degree of variability that is not present for the other modes (particularly for work-related trips), the combined function provides a greatly improved fit, as can be visualized in Figure 12 and confirmed by the summaries in Table 12 of Appendix B. As was discussed in the interpretation of the distance-related transit decay functions, transit travel can vary on many dimensions, such as service type and access mode, which is then reflected in the more scattered nature of the travel time data for transit trips. Figure 12 also shows that there is a minimum threshold for the duration of transit trips of somewhat less than 10 minutes. This reflects the fact that transit trips incur a certain fixed time cost, relating to stop or station access and waiting times.

Figure 12. Distance Decay Curves for Public Transit Trips (Travel Time)

Chapter 5
Discussion

This section reviews some of the limitations the study faced and identifies further uses of the estimated distance decay functions.

Limitations

Sample Size

Perhaps the greatest limitation of the study was the inability to obtain workable sample sizes for various combinations of modes and trip purposes. General purpose travel surveys such as the TBI's home interview survey tend to yield small numbers of trips by public transit and non-motorized modes, given the rarity of these 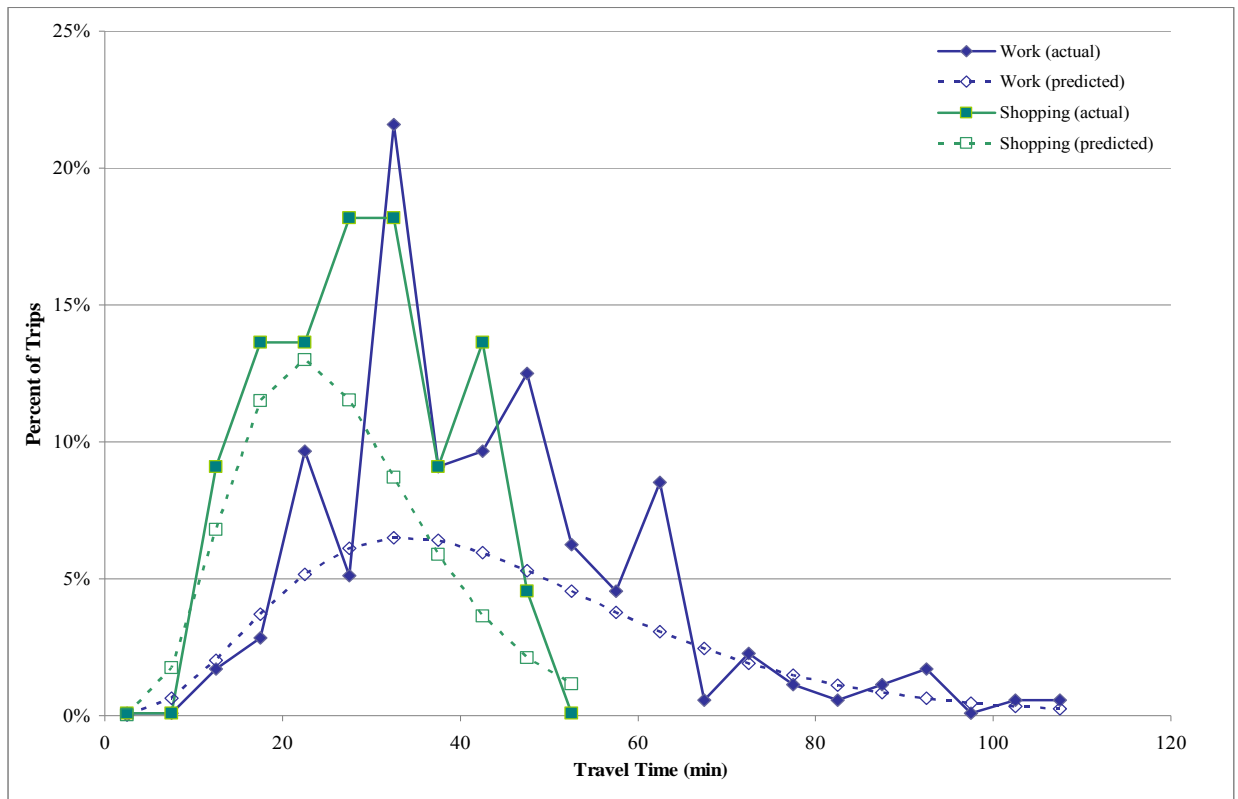behaviors. While this data source provided a large number of potential trip purposes (17 were identified in the data set), disaggregating trips by mode and purpose greatly limited the sizes of the samples that could be obtained from them. Public transit trips for purposes other than work were represented only in small numbers.

Further limiting the sample sizes used in the analysis was the quality of the data available. Usable records in each data set had to be geocodable, including all trip origins and destinations. In addition, records in the transit on-board survey needed to have boarding and alighting points properly located and geocoded. Inaccurate or inappropriate survey responses, including reporting of unrealistic trip distances or speeds, further thinned the data sets. As a consequence, many of the parameters of the estimated decay functions retained high amounts of variance, as is reported in the statistical summaries.

The other three data sources used in the study were specialized surveys designed to capture behavior by specific modes. While these surveys were able to target certain modes and provide a larger number of observations, they also tended to be limited in terms of the trip purposes identified in the survey instrument. This was especially the case for the transit on-board survey, whose primary purpose was to collect data suitable for modeling purposes. It would seem that a study designed to provide greater depth than the current work would need to design and implement a special survey instrument, combined with specialized sampling techniques, rather than relying on existing secondary sources of data.

Focus on Home-Based Trips

Since emphasis in this study is placed on understanding how far individuals will travel to reach various destinations and how this might help to structure measures of accessibility, most interest is centered around individuals accessing activities relative to their home location. Thus, non-home based trips are not examined as extensively in this study. This may not be as much of a problem for travel by non-motorized modes, since multi-stop trips by these modes tend to be less common (Ye, Pendyala, & Gottardi, 2007). However, the treatment of transit trips

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significantly limited our understanding of transit travel behavior. By constraining the trips used in the analysis to those that did not require transfers, a significant number of trips were missed. These excluded trips may have had characteristics dissimilar from those that were studied. One possibility is that they represented longer trips than those studied (in terms of time, distance or both). Another is that a significant number of light rail trips were missed, since many rail users must transfer at either their boarding or alighting point during a trip.

No Multi-Stop Trip Chains

Among the most fundamental concepts of travel behavior analysis is the idea that individuals' travel behavior is structured in both space and time and faces numerous constraints (Ettema & Timmermans, 1997; McNally, 2000). Activities are typically organized into trip chains or tours in order to be carried out with reference to some primary activity (work, school, etc.). Since the secondary data sources used in the analysis all contain trip-based data sets, the resulting analysis must make the rather strong (and unrealistic) assumption that all trips are carried out independently of one another.

Estimation of Distance Decay Functions

In more conventional analyses of travel demand or other applications where predictions of spatial interaction are required, distance decay functions are typically estimated as part of a more general gravity-type model (see Section 2) containing variables that represent the attractiveness of origins and destinations. The decay functions are estimated along with these terms because of the close relationship between the impedance parameter and the spatial structure of the study region (Sheppard, 1995). The impedance parameter is, in principle, a function of both the utility of the transportation network and the spatial distribution of activities around a given location. Hence, estimating distance decay functions without reference to these variables could introduce a considerable amount of bias into the decay function parameters. The possible extent of this bias is difficult to determine *a priori*.

Applications of the Distance Decay Functions

In addition to providing valuable information about the willingness of individuals to travel to reach various destinations, the distance decay functions estimated in this study can be used as inputs to further types of analysis. One possible application is the study of multimodal, multipurpose accessibility. Using the decay functions estimated for the various mode-purpose combinations, Song (1996) shows how the negative exponential function can be introduced into a gravity-type accessibility measure to yield an accessibility equation of the form:

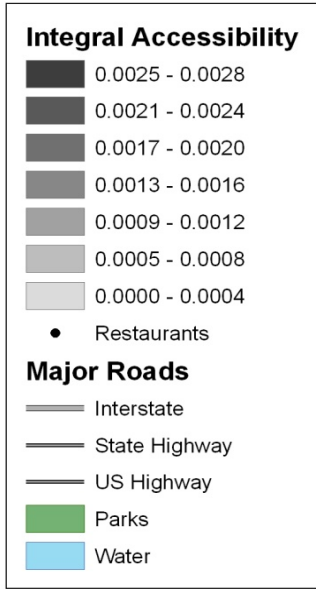$$A_i = \frac{\sum_{j \neq i} E_j \exp(-\beta x)}{E} \tag{10}$$

where A_i represents the accessibility at zone i, E_j is a measure of opportunities (here we can use employment) at zone j, E represents all opportunities available in the region, and the negative exponential decay function is as defined as before. In this manner, accessibility measures can be calculated for all modes, or as a single measure with a weighted sum to represent the probabilities of using each mode. In addition to calculating regional, gravity-based measures of accessibility, smaller-scale measures of neighborhood accessibility (Handy & Clifton, 2001; Krizek, 2003) can also be calculated using cumulative opportunities formulations (Wachs & Kumagai, 1973) and information about the range of each mode from the estimated distance decay curves. These types of measures have rarely been evaluated for non-motorized modes, hence the construction of such measures from the distance decay functions provided in this study represent a significant achievement.

To illustrate the procedures used to produce estimates of non-motorized accessibility, we completed some sample accessibility calculations for a small study area in South Minneapolis. The study area is bounded on the west by Lyndale Avenue, on the north by Franklin Avenue, on the east by the Mississippi River, and on the south by 50th Street. This area contains approximately 1,600 Census block groups, which represent the unit of analysis. The accessibility values calculated for each block group are *integral* accessibility measures (Song 1996), where the activities in each destination zone, discounted by their associated impedance value, are summed across destinations and normalized by dividing by the total activities in the study area. This method provides a measure that can be easily interpreted and compared across zones on the same zero to one scale. Thus, in each case, accessibility is expressed as a decimal indicating proximity to destinations in each location. In the case of each accessibility calculation, an attractiveness measure is constructed for each block group by summing the level of retail sales at each establishment within the block group. Impedance measures are introduced by calculating the shortest path through the network between each block group pair, then using this value to discount activities at the destination using the functional form described previously.

Figure 13 presents maps displaying measures of accessibility to restaurant destinations for the walking mode. Again, the maps show the same measures calculated using time and distance as alternate measures of travel impedance. Consistent with the findings described earlier, they show a high degree of correlation. Areas near clusters of restaurant destinations are shown to have high levels of accessibility, with a gradual decline as one moves away from these clusters.

Figure 14 presents a pair of maps showing accessibility to shopping destinations by bicycle with distance and time impedance measures. In this case, destinations are spread more evenly throughout the study area, leading to higher overall accessibility values in each zone. Retail establishments appear to align themselves along linear corridors, reflecting the historical network of streetcar routes in South Minneapolis. One particularly large corridor is found along Lake Street, a major east-west route that lies at the center of the swath of high accessibility shown in both maps. This high-accessibility location results from a combination of clustering of activities and proximity to the Midtown Greenway, a grade separated off-street bicycle facility highlighted in green on the map.

Walking
Integral Accessibility to
Restaurant Destinations:
Using Distance & Time
Impedance Parameters

Integral Accessibility

■	0.0025 - 0.0028
■	0.0021 - 0.0024
■	0.0017 - 0.0020
■	0.0013 - 0.0016
■	0.0009 - 0.0012
■	0.0005 - 0.0008
□	0.0000 - 0.0004
•	Restaurants

Major Roads

	Interstate
	State Highway
	US Highway
■	Parks
■	Water
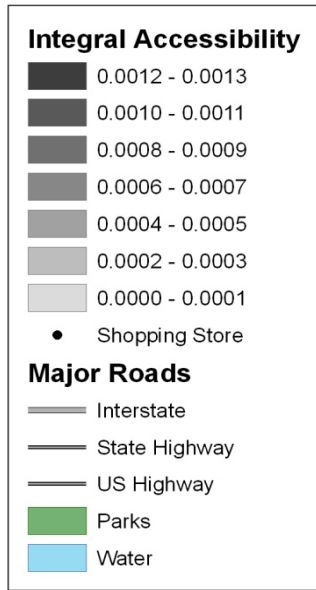
Data Source: Metropolitan Council,
Lawrence Group, Dunn & Bradstreet,

0   0.5   1   2 Kilometers

0   0.5   1   2 Miles
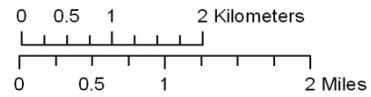
Projection: GCS North America 1983

Time Impedance

Distance Impedance

Figure 13. Walk Accessibility to Restaurants

29
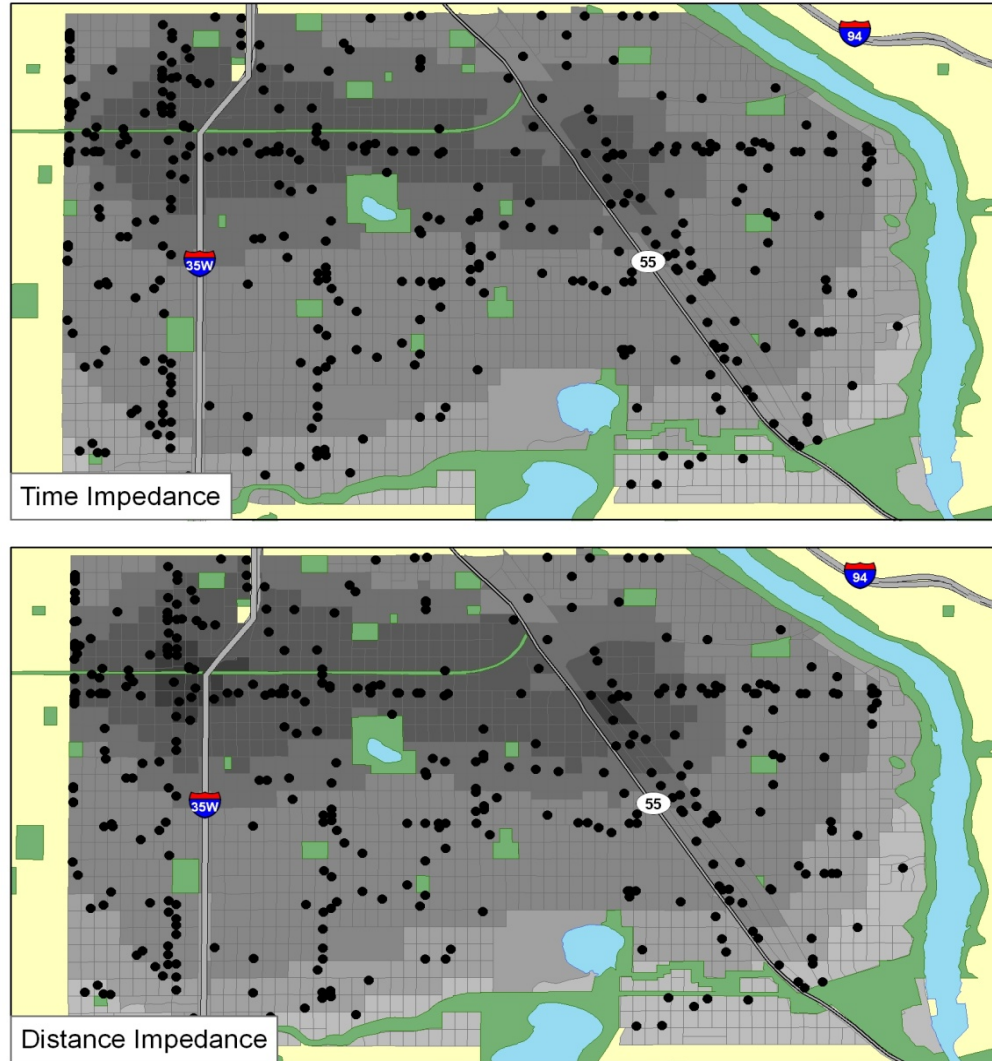
Figure 14. Bicycle Accessibility to Shopping

These examples demonstrate the applicability of accessibility measures to non-motorized modes and the importance of spatial scale when measuring non-motorized accessibility. The use of block-level data allow for the identification of local clusters of activity, which translate into pockets of higher accessibility. With the same sets of data available at the regional level, it should be possible to scale these types of calculations up to produce region-wide measures of accessibility by non-auto modes.

Chapter 6
Conclusion

The evidence presented in this study is intended to address a perceived need in the field of transportation planning, especially with respect to non-auto modes, though relevant information about auto travel is also presented. The evidence focuses on one particular aspect of travel behavior, namely the spatial distribution of trips by mode and trip purpose. The findings are intended to supplement traditional rules-of-thumb regarding planning for travel by walking and bicycle modes.

The findings suggest, for example, that substantial shares of pedestrian travel (perhaps one-quarter to one-third) exceed the often-cited threshold of one-quarter mile. Moreover, this finding appears to be invariant to trip purpose. These results are based on available reported trips from actual travel diaries. Unless the segment of the population who reported these pedestrian trips are substantially different from those who either did not make utilitarian trips by the pedestrian mode or did not think to report them, this may be a welcome finding for pedestrian planning.

Results for bicycle travel data revealed a substantial difference in travel distances by trip purpose. Primary activities such as work and school often involved very long bike trips (up to 20-30 KM) for those who chose this mode. In contrast, more discretionary trips (e.g. for shopping, entertainment or recreation purposes) tended to be substantially shorter in length. It would be desirable to future studies of these types of behavior to target bicycling specifically in order to provide a large enough sample to further substantiate these findings.

The public transit trips examined in this study reveal significant differences in travel behavior across several types of stratification. Type of service (local bus, express bus, light rail), access mode and trip purpose all appear to affect trip length. The origin-destination data examined in this study allowed for a disaggregation of trips by segment (access, egress, and line-haul), which presents opportunities to ask further questions about how travelers view the relative importance of different parts of their trip (e.g. access). As mentioned previously, though, the analysis of transit trips presented here was limited to those making one or fewer transfers. Future work should extend this to multiple-transfer trips using transportation planning packages with a significant transit travel modeling component.

A notable finding across the different travel modes was that a range of functional forms can and should be used to measure travel impedance. We have suggested a couple of these alternatives in earlier sections; a thorough examination of the literature on the practice of travel demand modeling would likely turn up even more. Different modes tend to have different characteristics that are reflected in their decay or impedance functions. The most glaring examples are auto and transit travel, which both tend to have certain minimum thresholds in terms of travel time or distance. Thus, when comparing across modes or trip purposes, a good guideline to follow would be to fit multiple curves using different functional forms to find the most appropriate form.

Lastly, we have also demonstrated how the decay curves for different travel modes and trip purposes can be used to provide measures of accessibility. While the calculation of accessibility measures for auto and transit modes are relatively straightforward using conventional travel demand models, we have shown how the use of a more disaggregate zonal structure using Census geography can allow for the generation of non-motorized accessibility

measures at a spatial scale more closely aligned with actual bicycle and pedestrian travel behavior. While our results were restricted to a relatively small sample area, the techniques should be scalable to larger geographic areas given full spatial data sets and appropriate computational hardware.

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Appendix A
Distance Decay Functions by Mode and Purpose

$$y = 0.4862e^{-1.6817x}$$
$$R^2 = 0.8564$$
$$N = 243$$
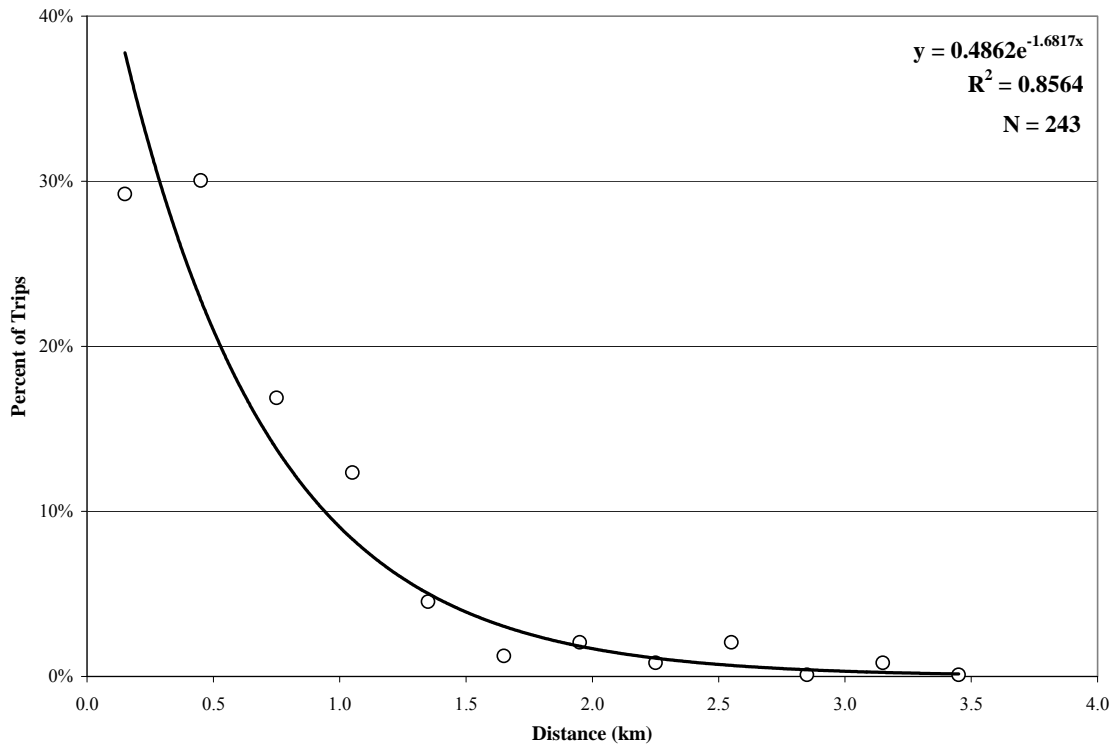
Figure A-1. Walk Work Trips

$$y = 0.4694e^{-2.1098x}$$
$$R^2 = 0.7488$$
$$N = 145$$
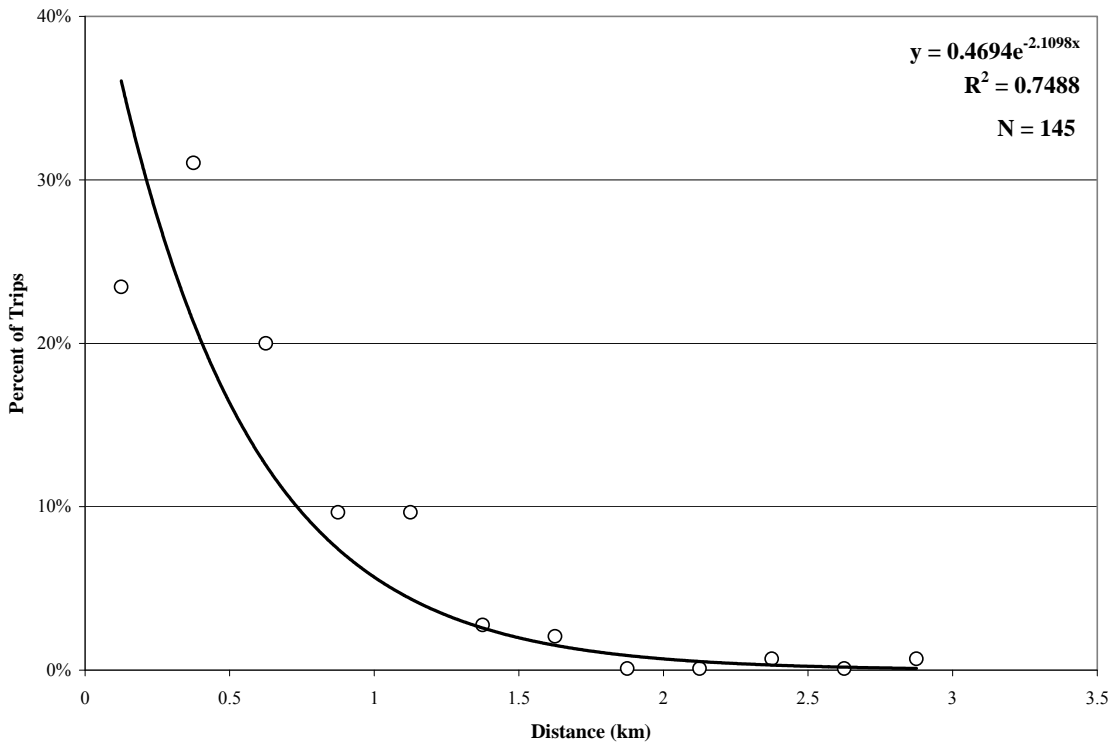
Figure A-2. Walk Shopping Trips

Figure A-3. Walk Restaurant Trips

The plot shows data points with fitted curve:

$$y = 0.3878e^{-1.3919x}$$
$$R^2 = 0.8499$$
$$N = 134$$
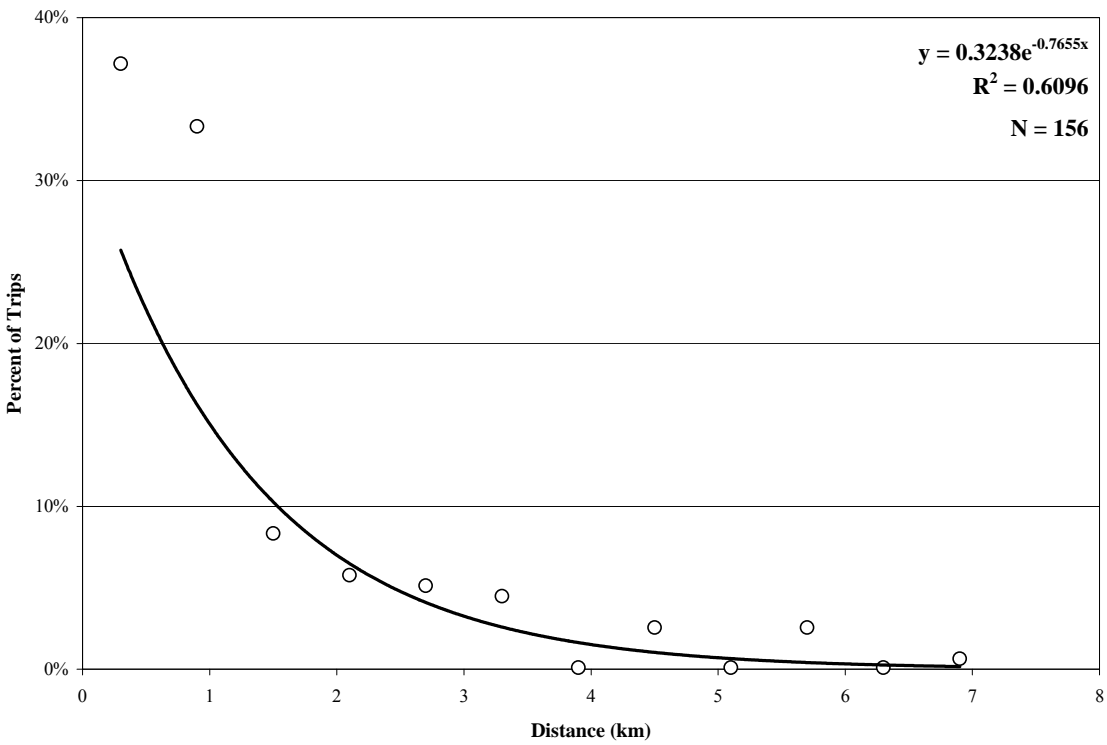
Figure A-4. Walk Entertainment, Recreation and Fitness Trips

The plot shows data points with fitted curve:

$$y = 0.3238e^{-0.7655x}$$
$$R^2 = 0.6096$$
$$N = 156$$
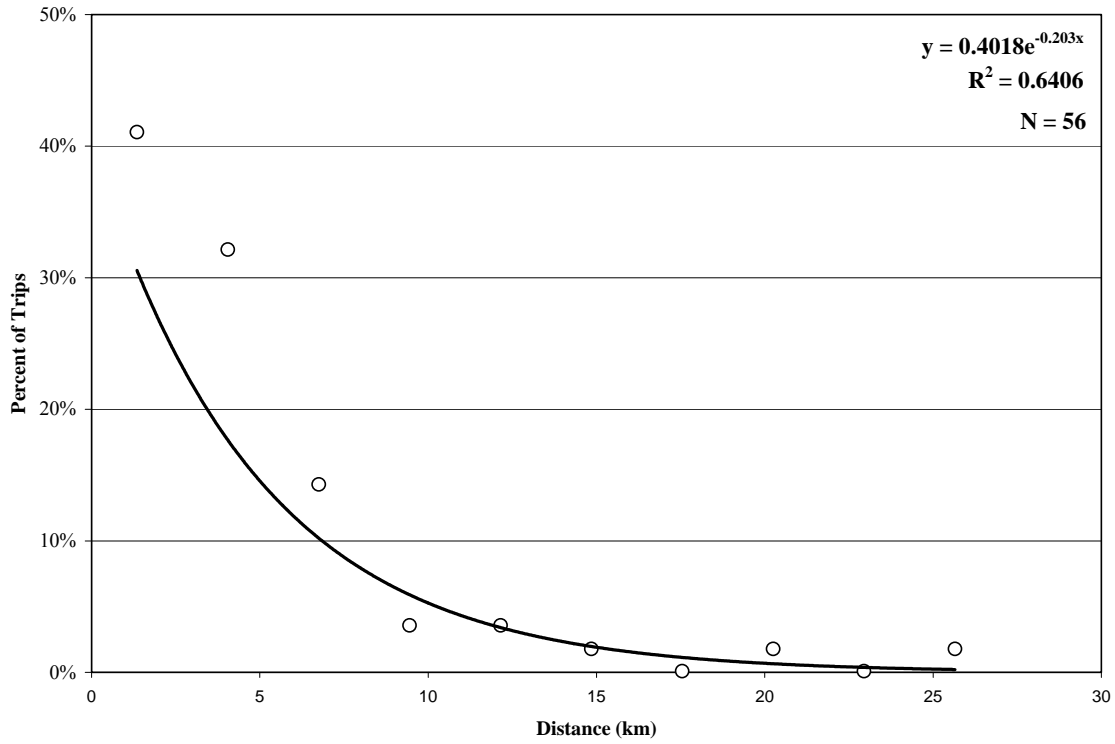
Figure B-1. Bike Work Trips

$$y = 0.4018e^{-0.203x}$$
$$R^2 = 0.6406$$
$$N = 56$$

Figure B-2. Bike Shopping Trips

$$y = 0.3422e^{-0.5131x}$$
$$R^2 = 0.4303$$
$$N = 38$$
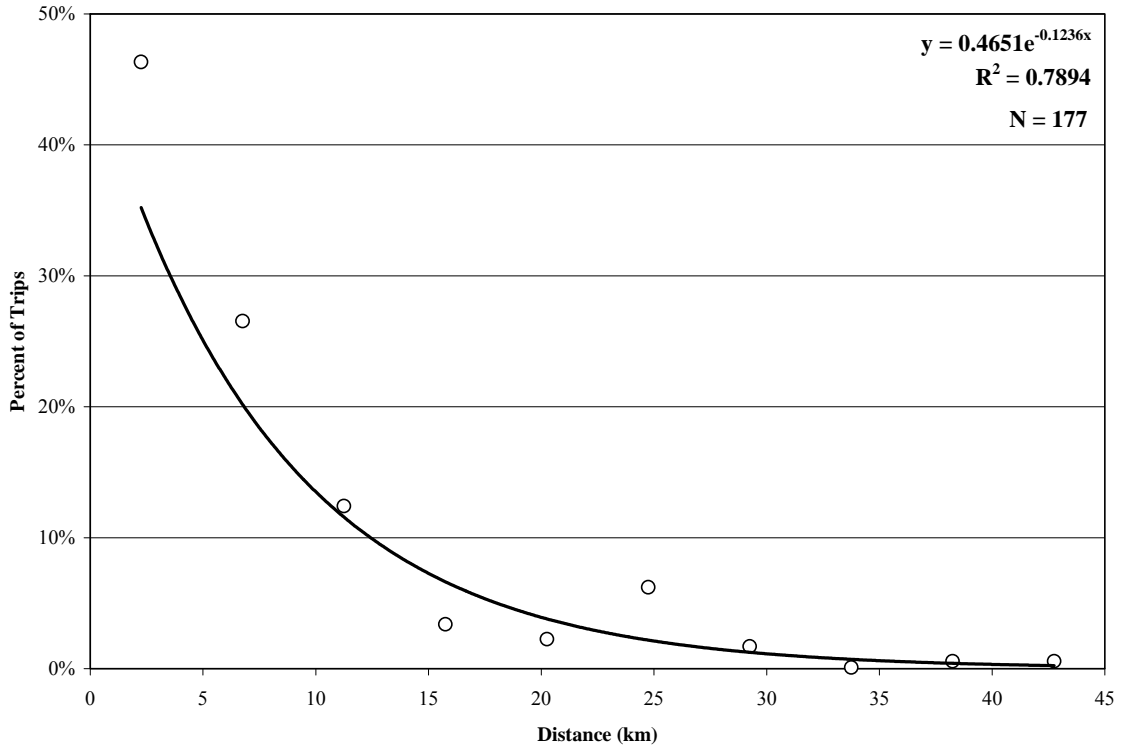
Figure B-3. Bike School or School-Related Trips
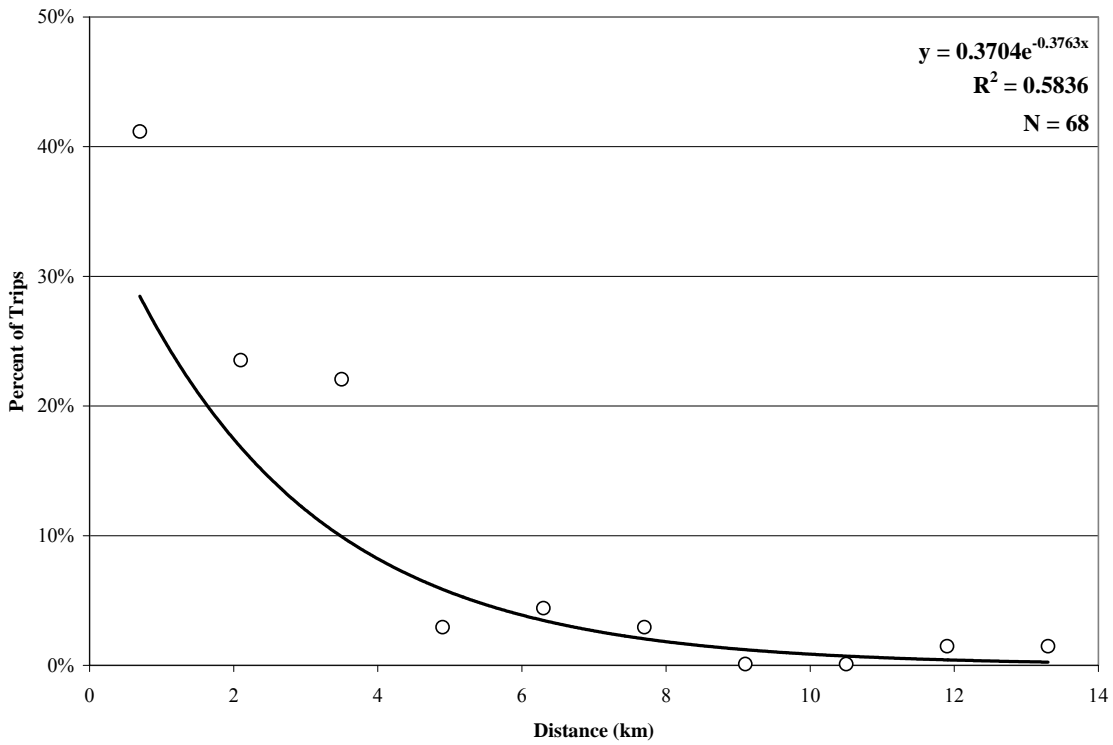
Figure B-4. Bike Entertainment, Recreation and Fitness Trips
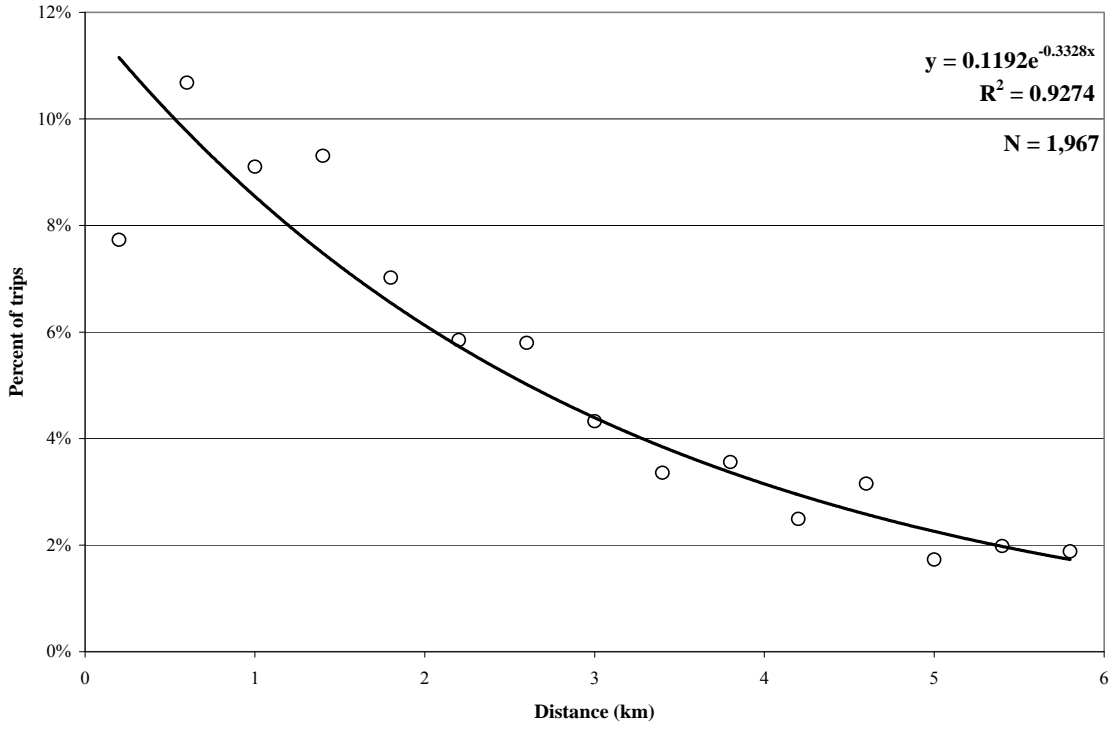
Figure B-5. Bike Trail Access Trips
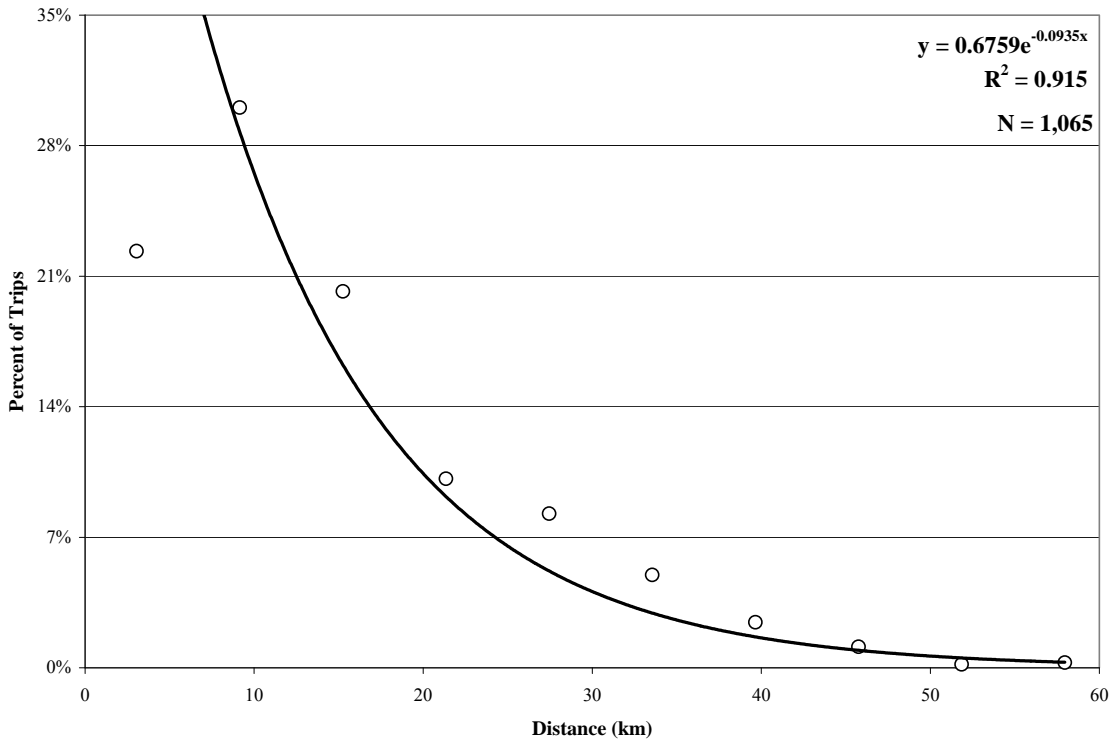
Figure C-1. Transit Work Trips
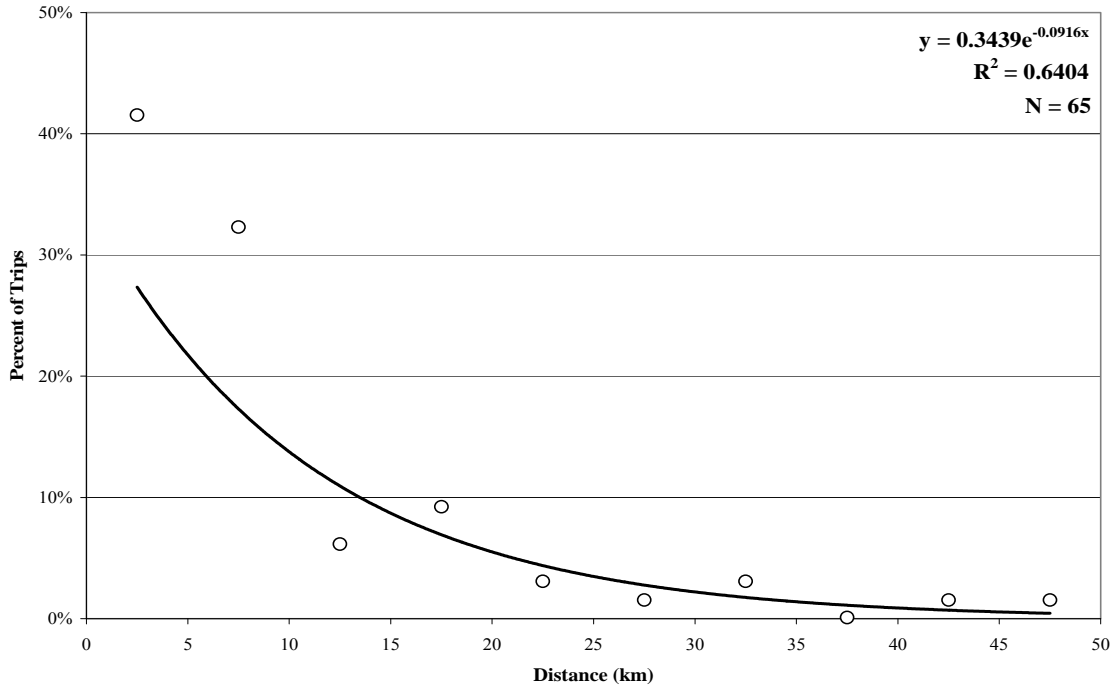
Figure C-2. Transit Shopping Trips
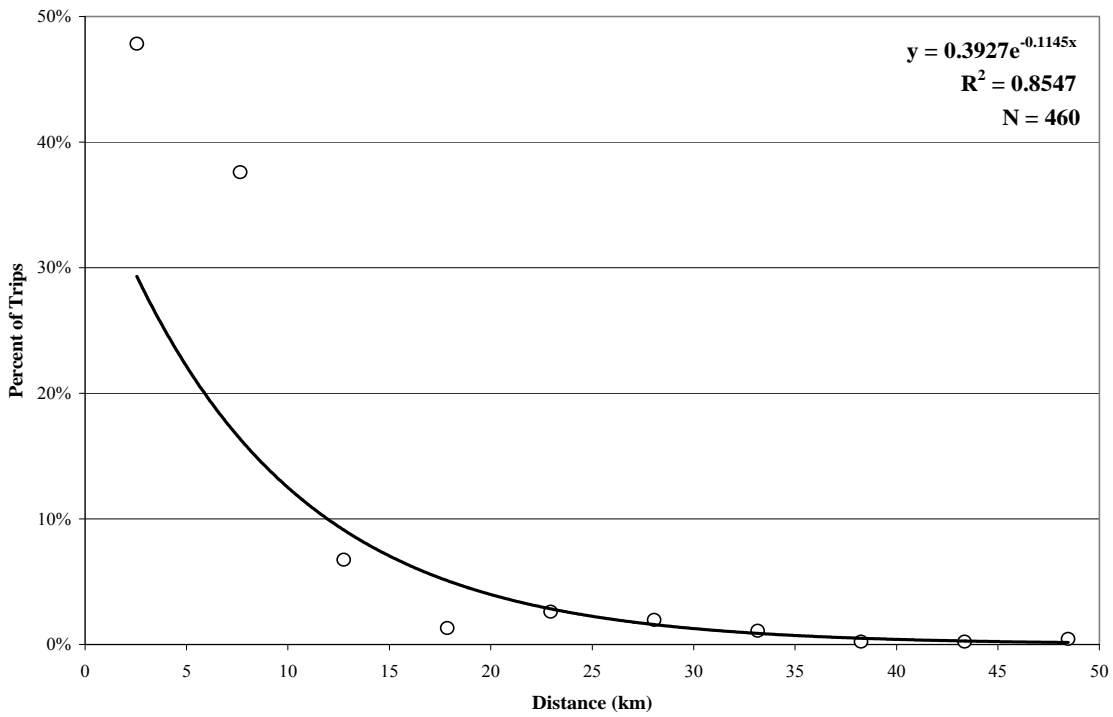
Figure C-3. Transit College and University Trips
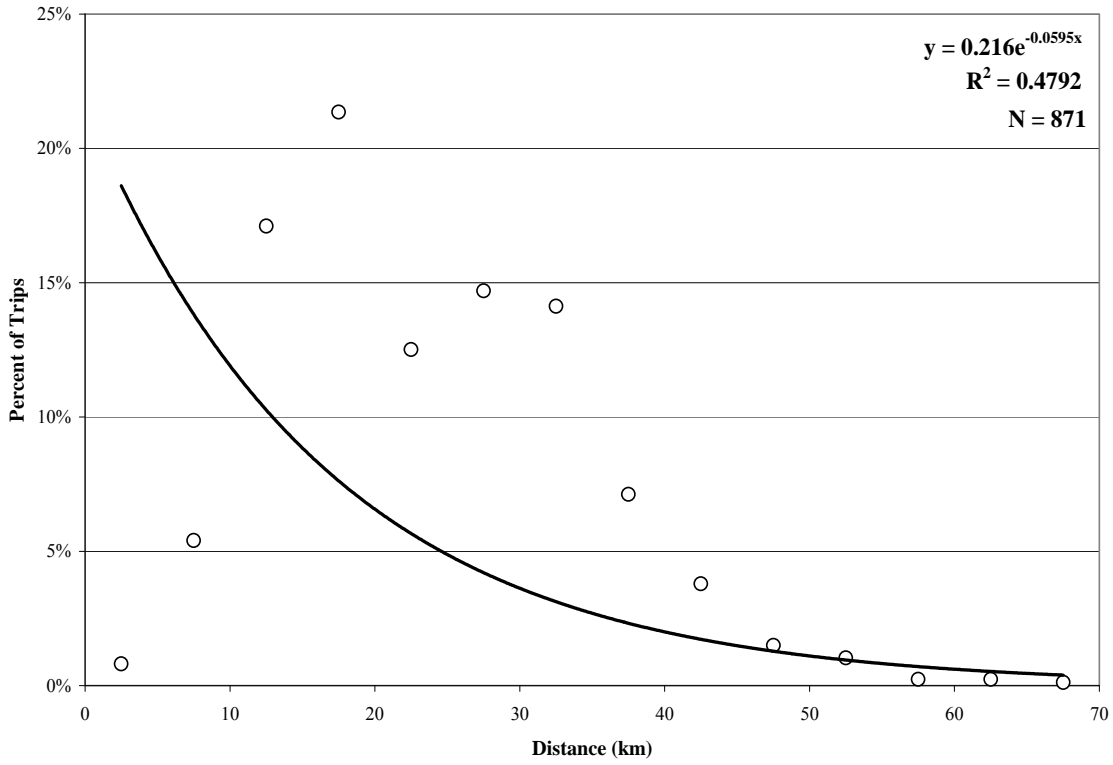
Figure C-4. Transit Trips by Express Bus
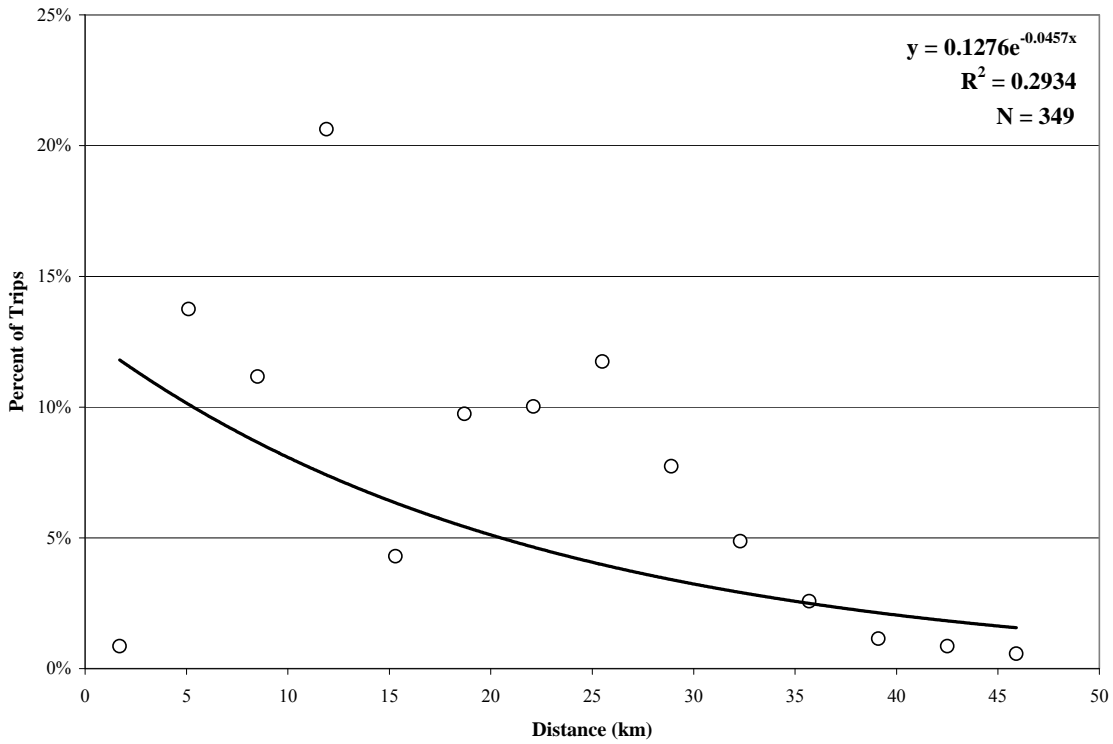
Figure C-5. Transit Trips by Light Rail
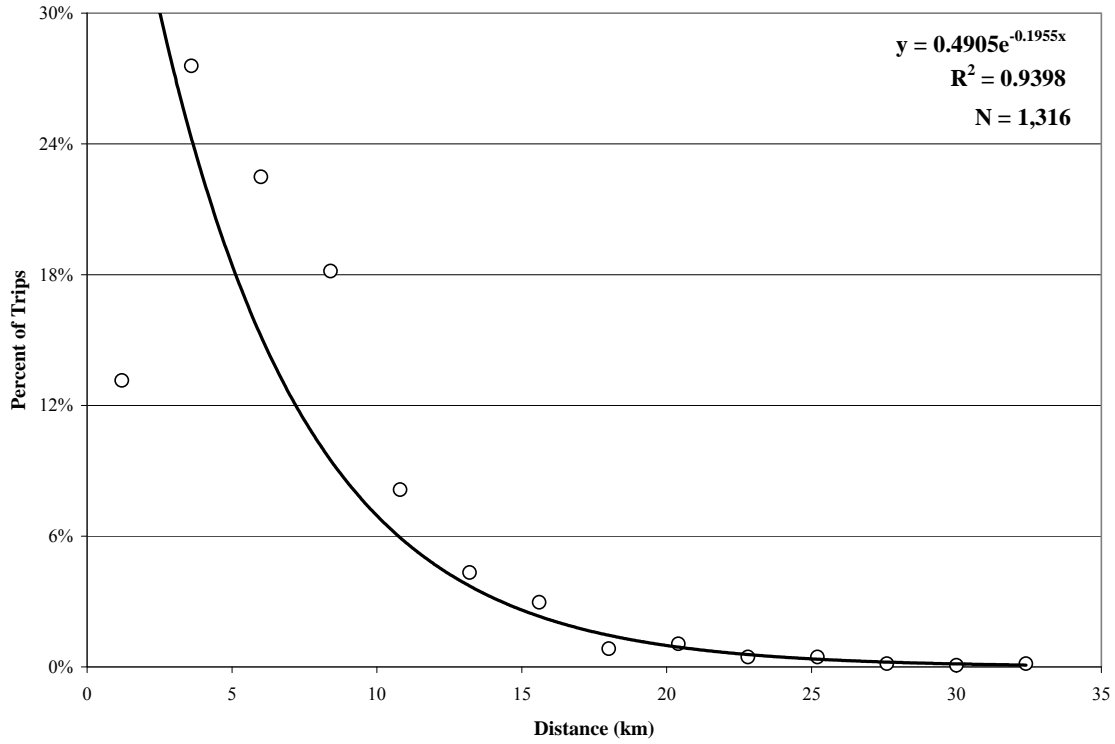
Figure C-6. Transit Trips by Local Bus

$y = 0.4905e^{-0.1955x}$

$R^2 = 0.9398$

$N = 1,316$
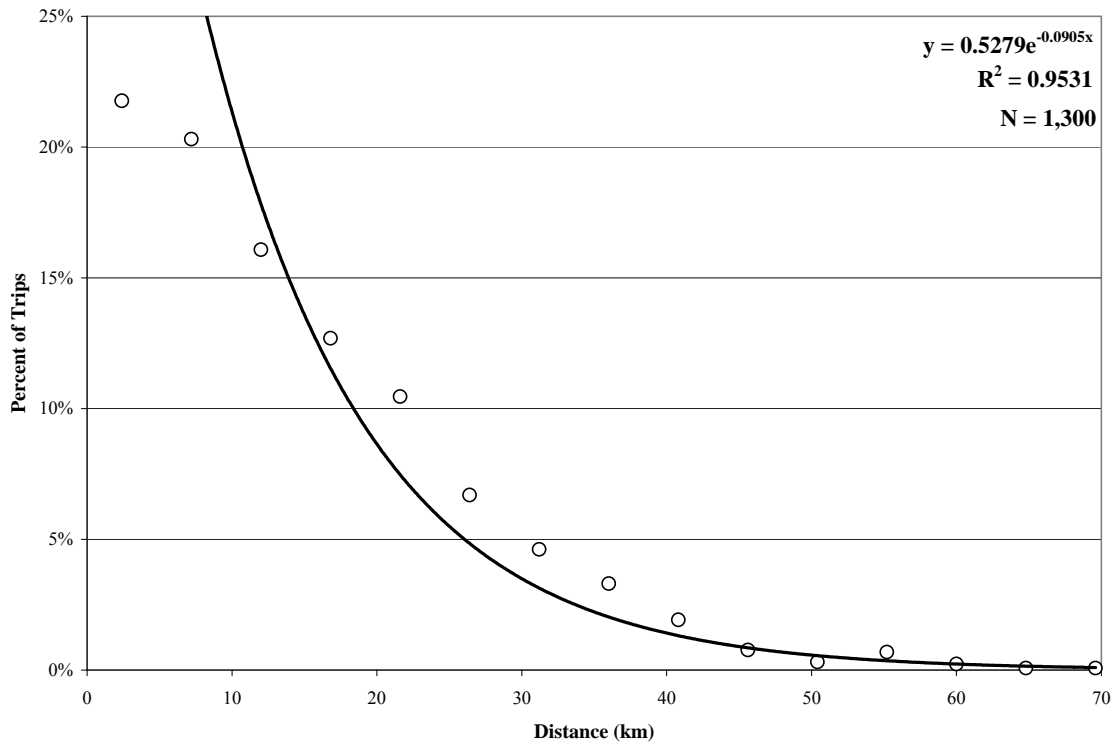
Figure D-1. Drive Alone Work Trips

$y = 0.5279e^{-0.0905x}$

$R^2 = 0.9531$

$N = 1,300$
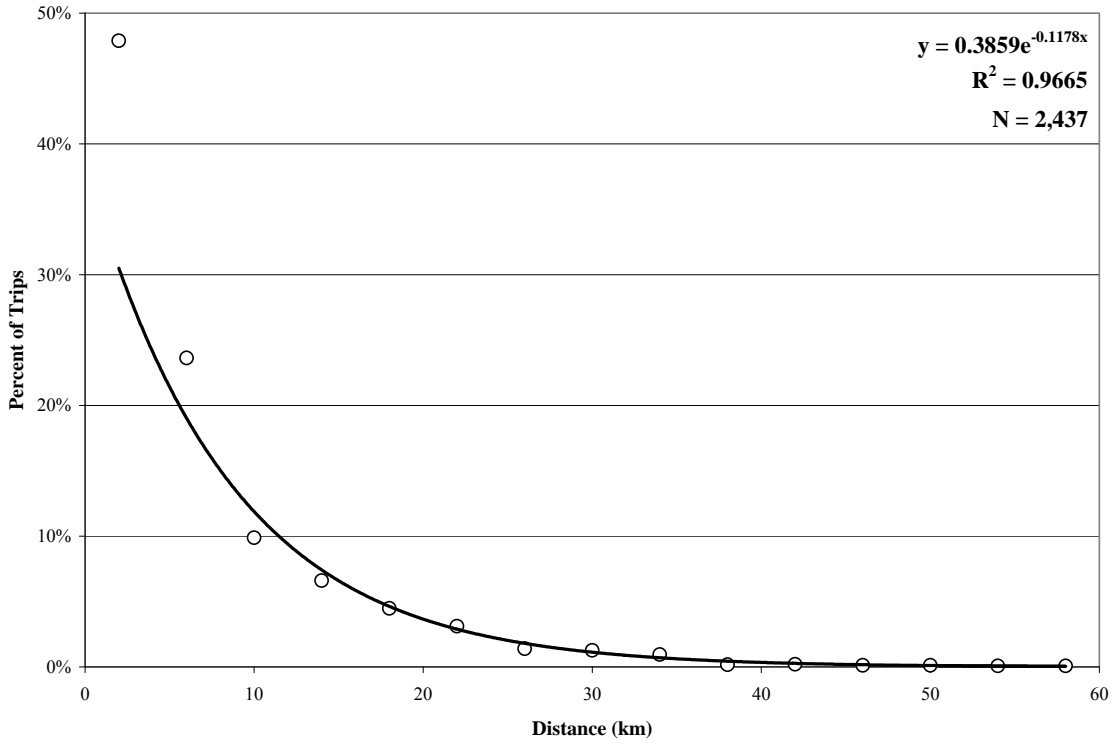
Figure D-2. Drive Alone Shopping Trips

$$y = 0.3859e^{-0.1178x}$$
$$R^2 = 0.9665$$
$$N = 2,437$$
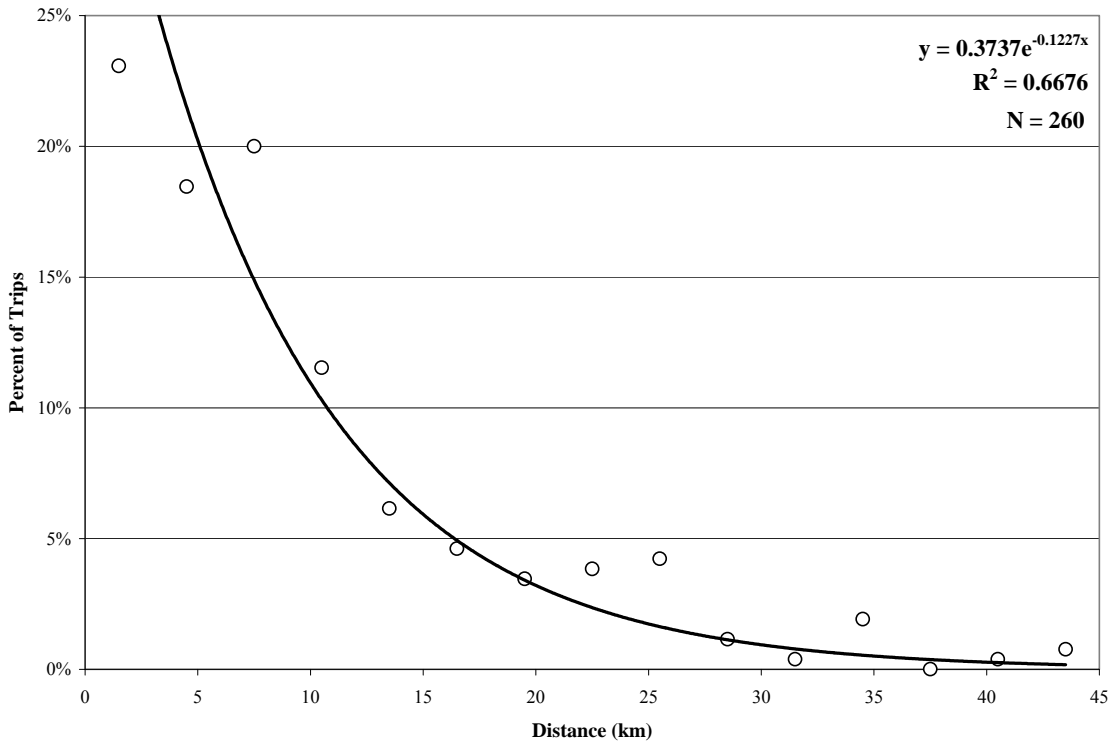
Figure D-3. Drive Alone School or School-Related Trips

$$y = 0.3737e^{-0.1227x}$$
$$R^2 = 0.6676$$
$$N = 260$$

$$y = 0.3129e^{-0.1178x}$$
$$R^2 = 0.9618$$
$$N = 745$$
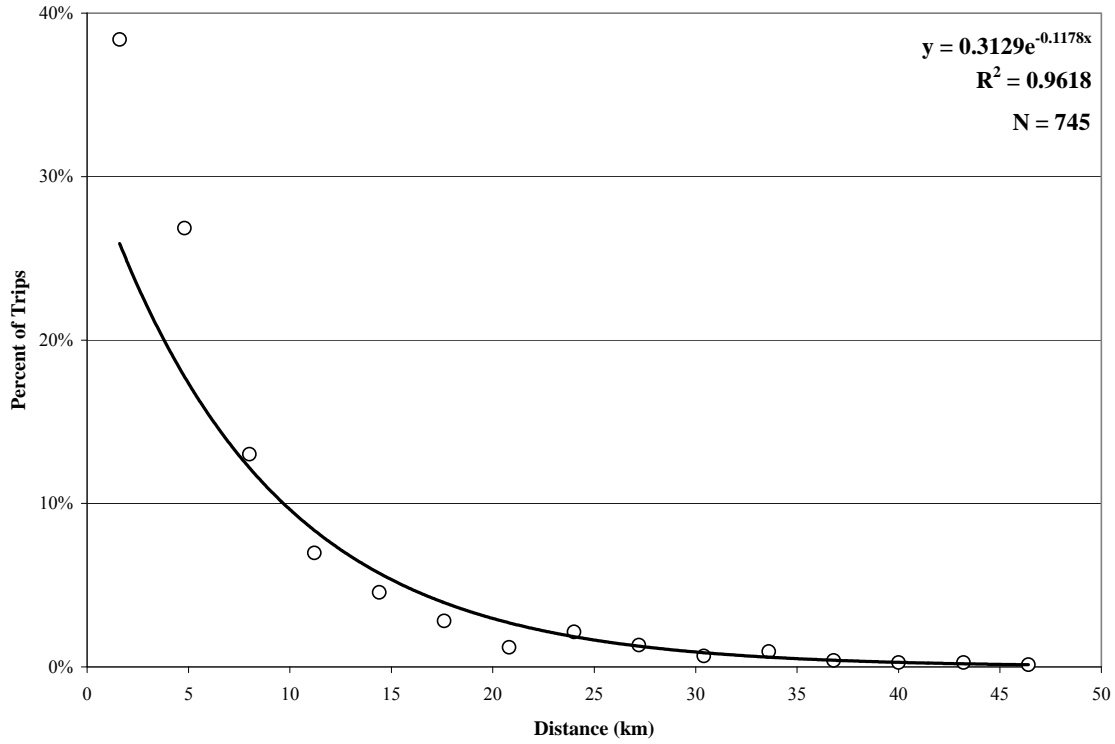
Figure D-4. Drive Alone Restaurant Trips

$$y = 0.3388e^{-0.1035x}$$
$$R^2 = 0.9812$$
$$N = 511$$
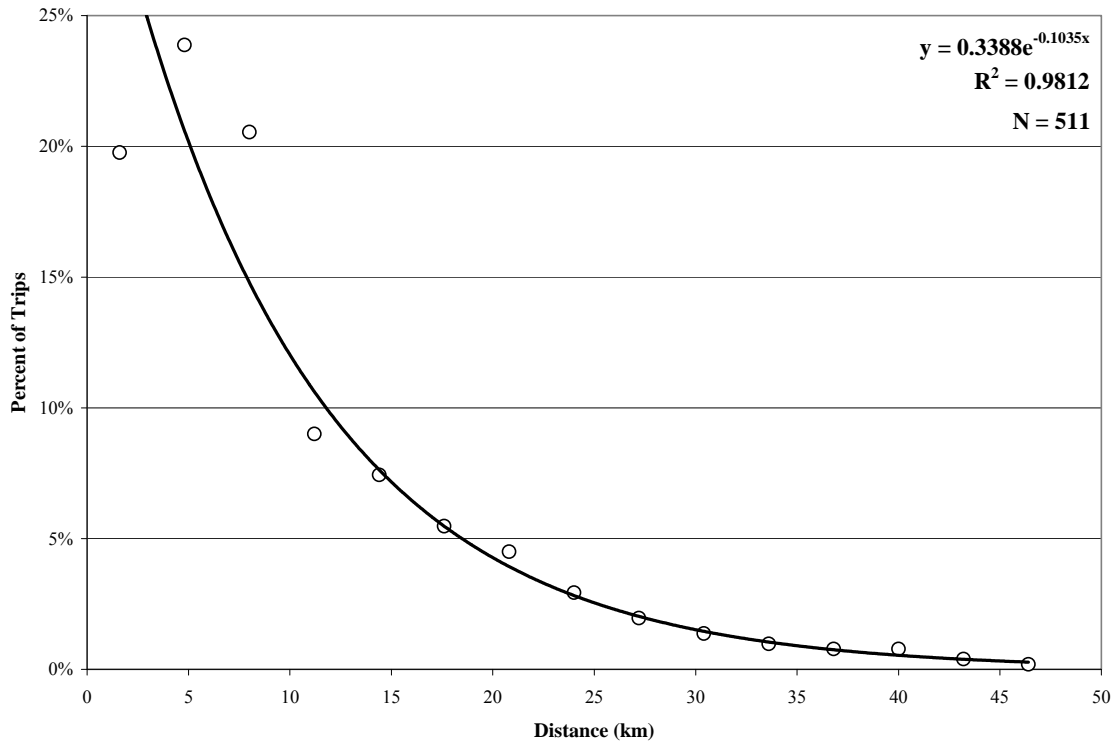
Figure D-5. Drive Alone Entertainment, Recreation and Fitness Trips

A-10
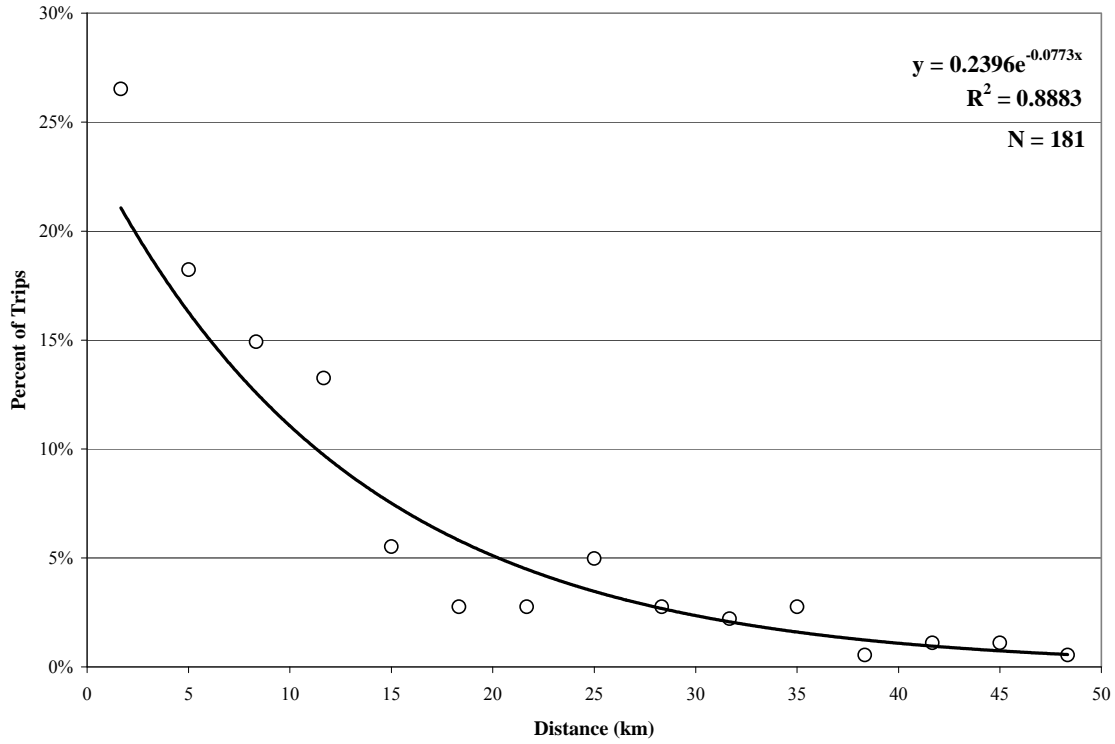
Figure E-1. Shared Ride Work Trips

$$y = 0.2396e^{-0.0773x}$$
$$R^2 = 0.8883$$
$$N = 181$$
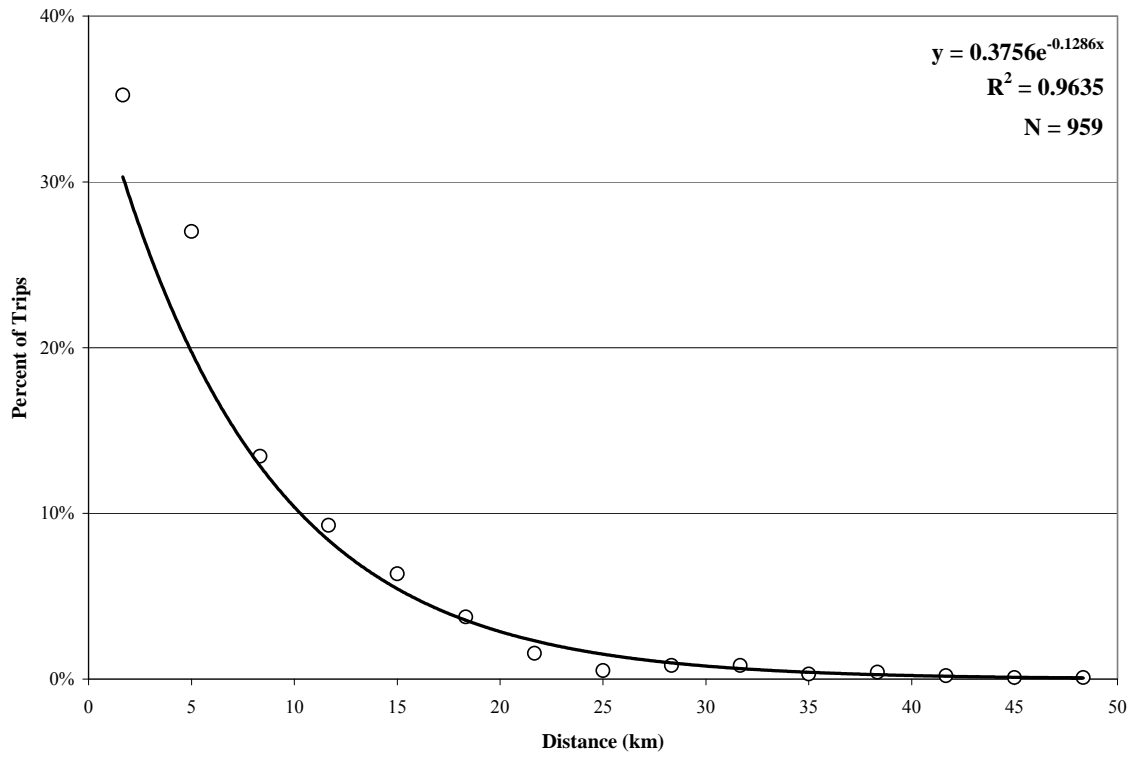
Figure E-2. Shared Ride Shopping Trips

$$y = 0.3756e^{-0.1286x}$$
$$R^2 = 0.9635$$
$$N = 959$$
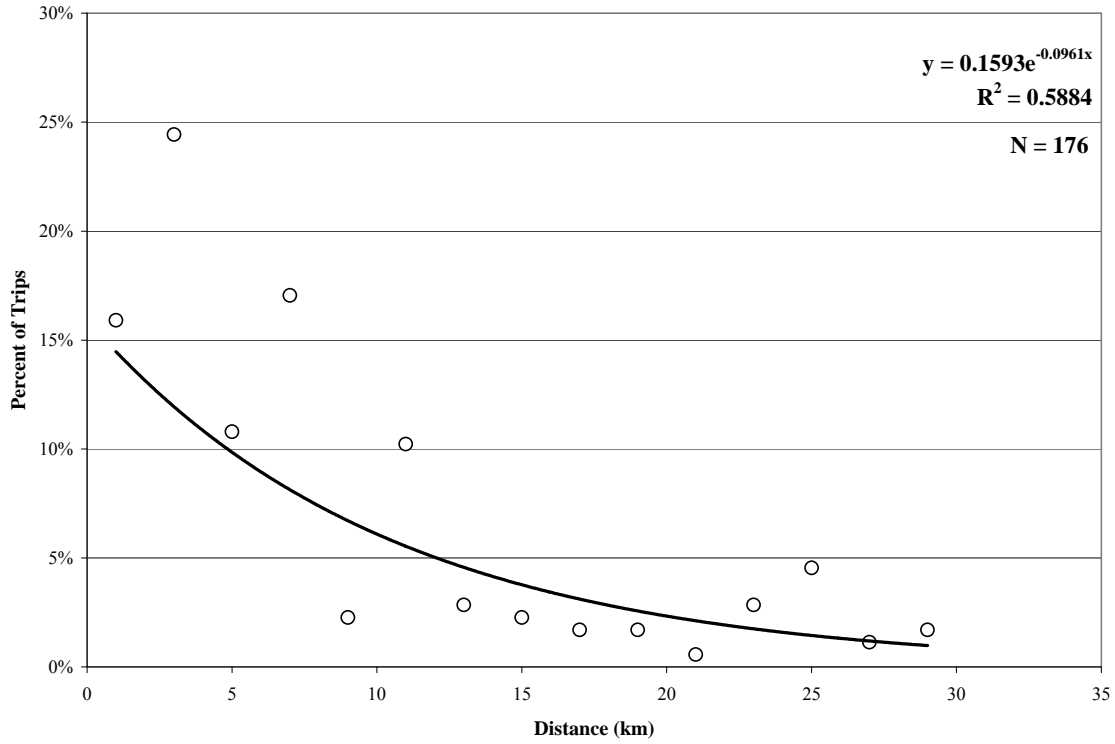
Figure E-3. Shared Ride School or School-Related Trips
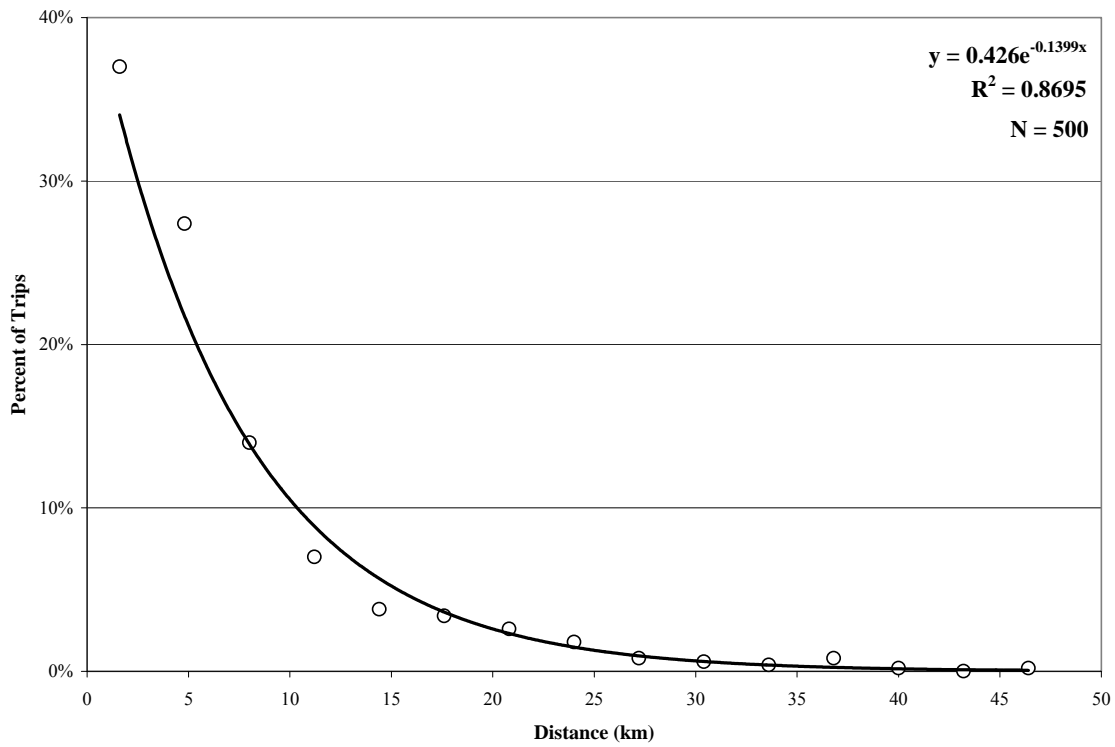
Figure E-4. Shared Ride Restaurant Trips
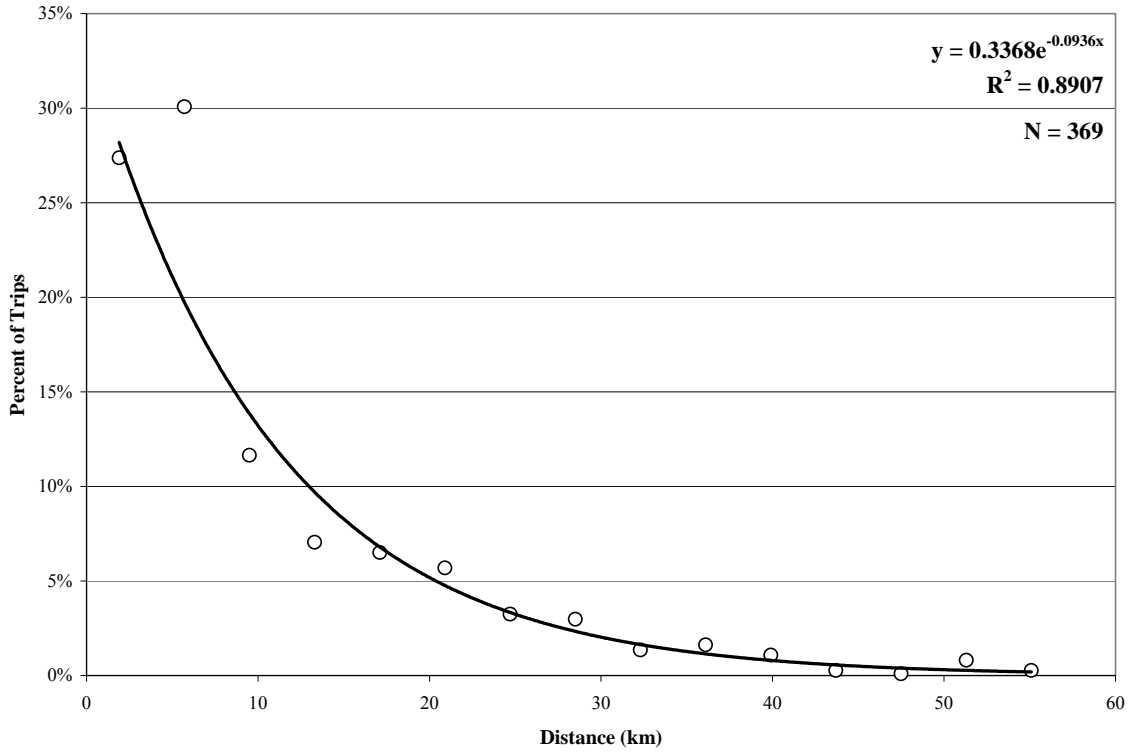
Figure E-5. Shared Ride Entertainment, Recreation and Fitness Trips

$y = 0.3368e^{-0.0936x}$
$R^2 = 0.8907$
$N = 369$
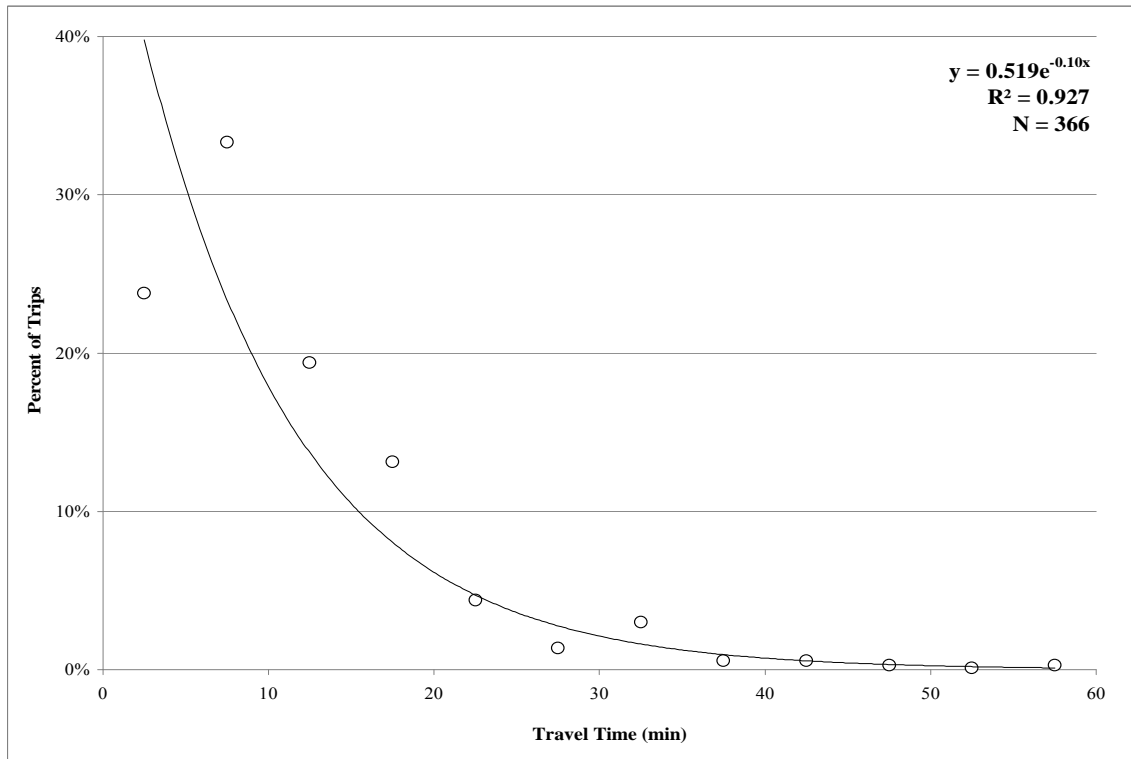
Figure F-1. Walking Work Trips

$y = 0.519e^{-0.10x}$
$R^2 = 0.927$
$N = 366$
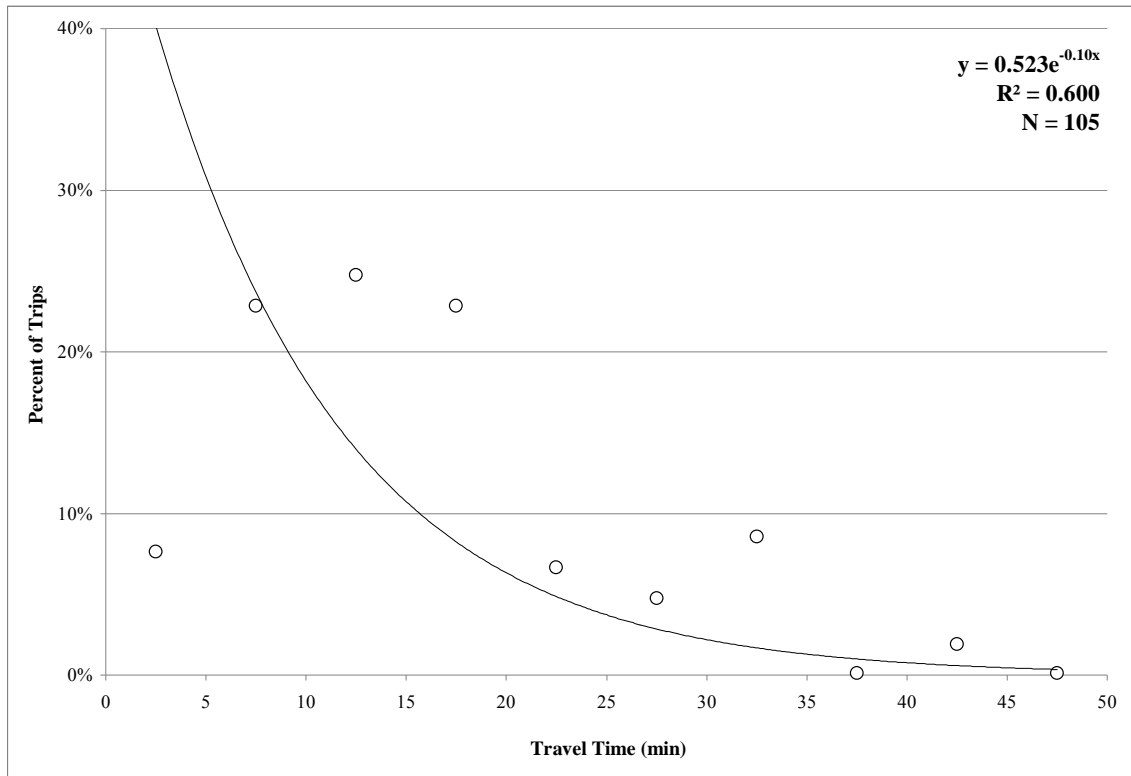
Figure F-2. Walk School or School-Related Trips

$y = 0.523e^{-0.10x}$
$R^2 = 0.600$
$N = 105$
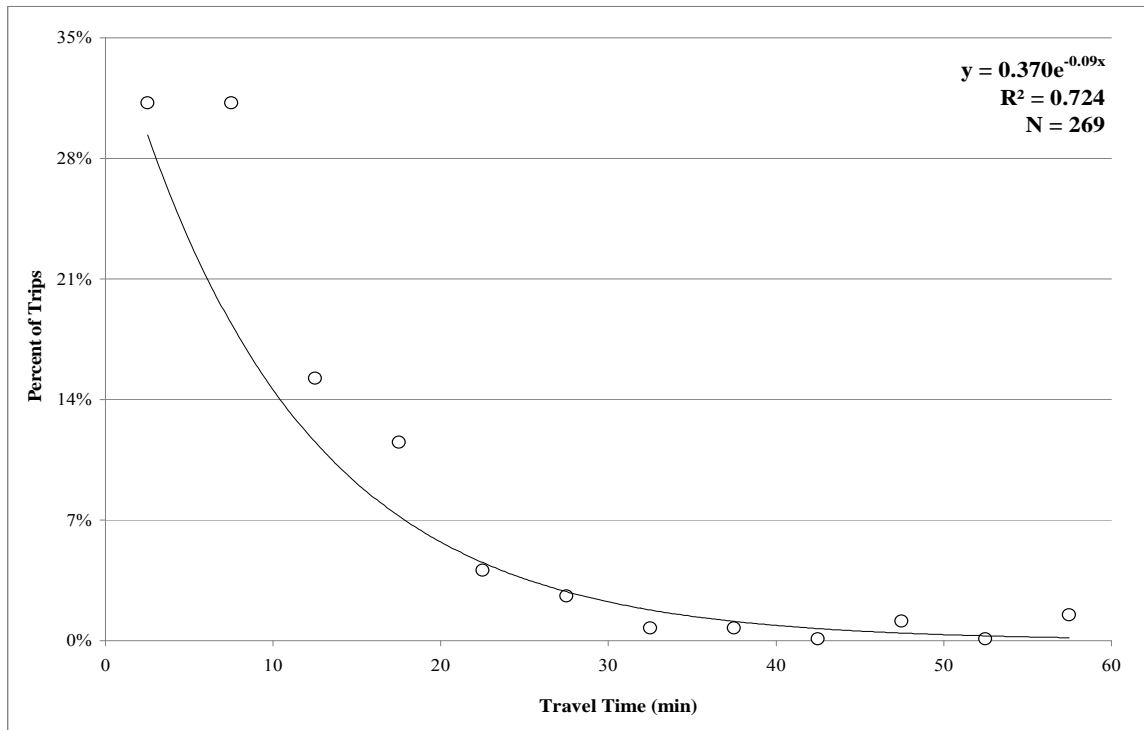
Figure F-3. Walk Shopping Trips

$y = 0.370e^{-0.09x}$
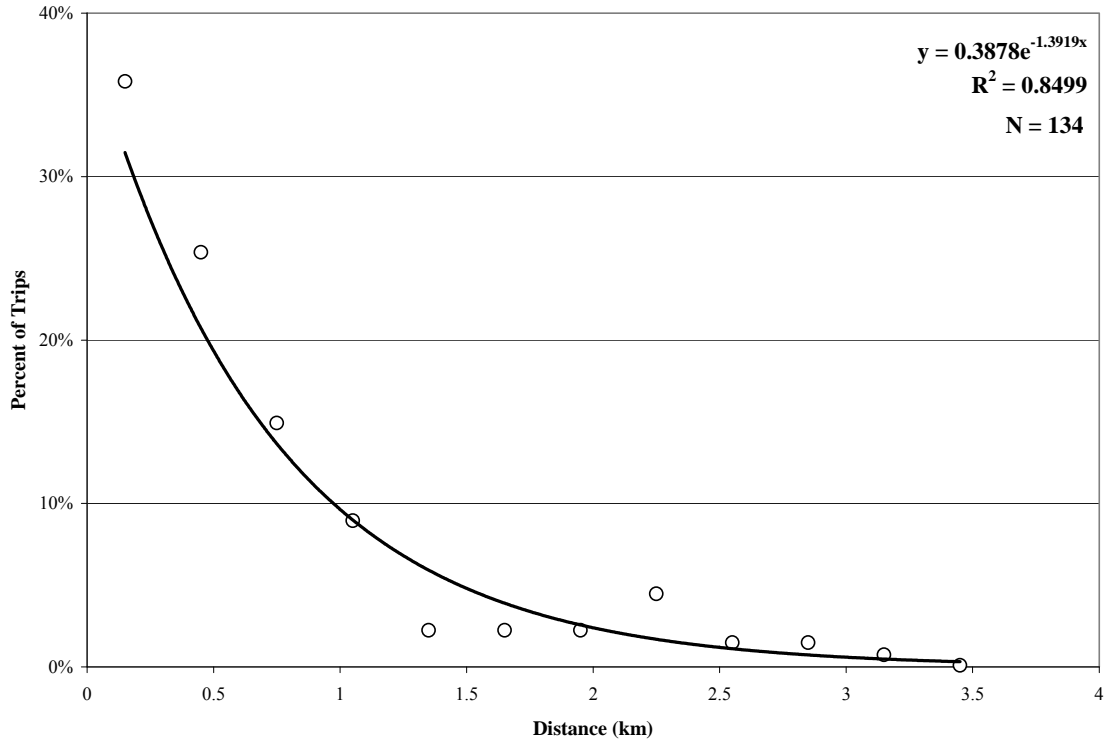$R^2 = 0.724$
$N = 269$
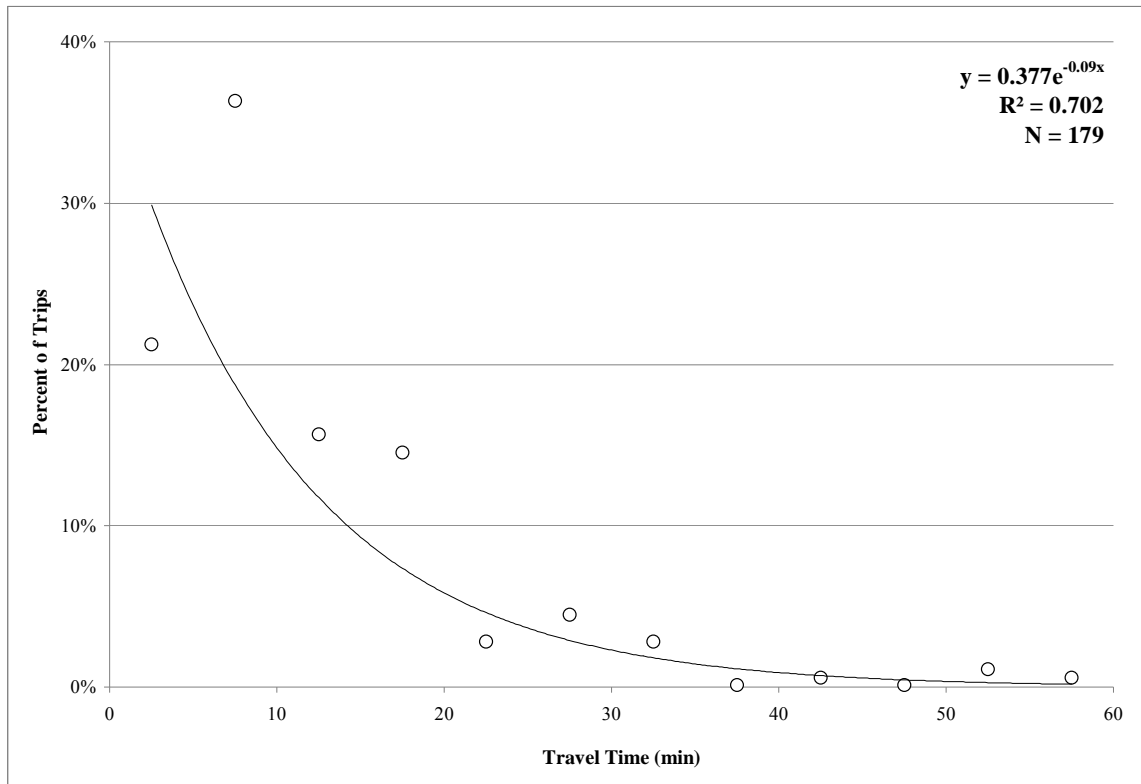
Figure F-4. Walk Restaurant Trips
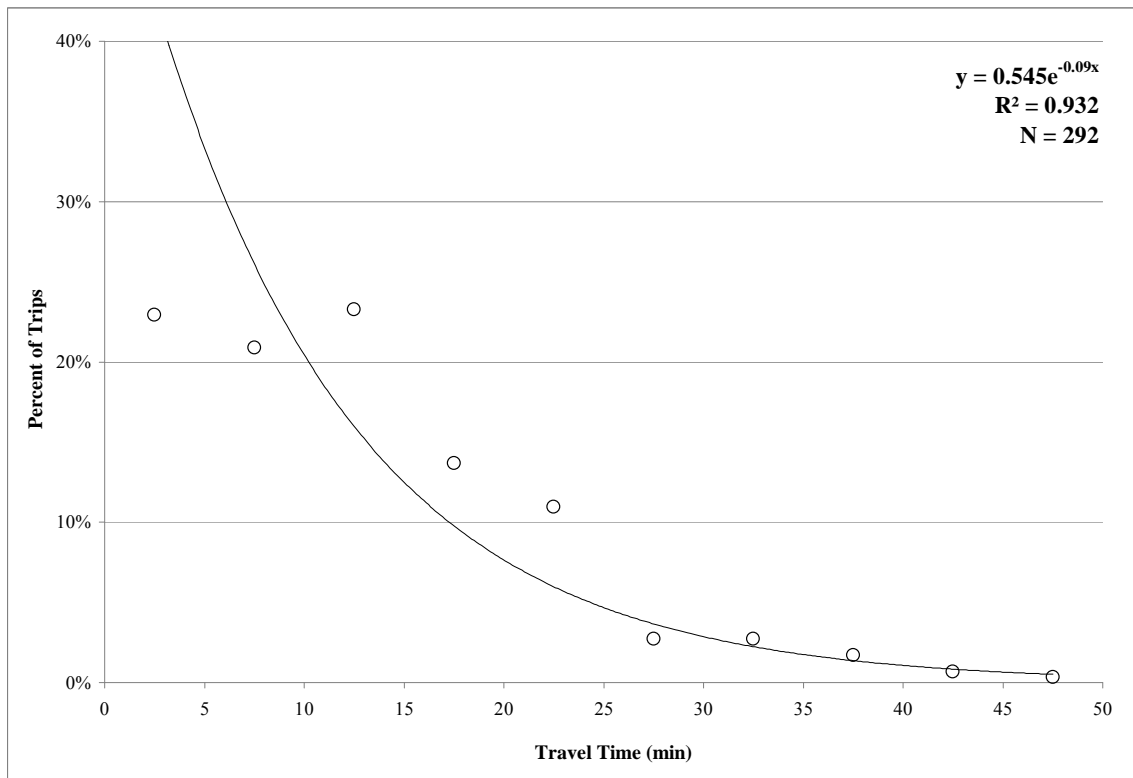
Figure F-5. Walk Entertainment, Recreation and Fitness Trips
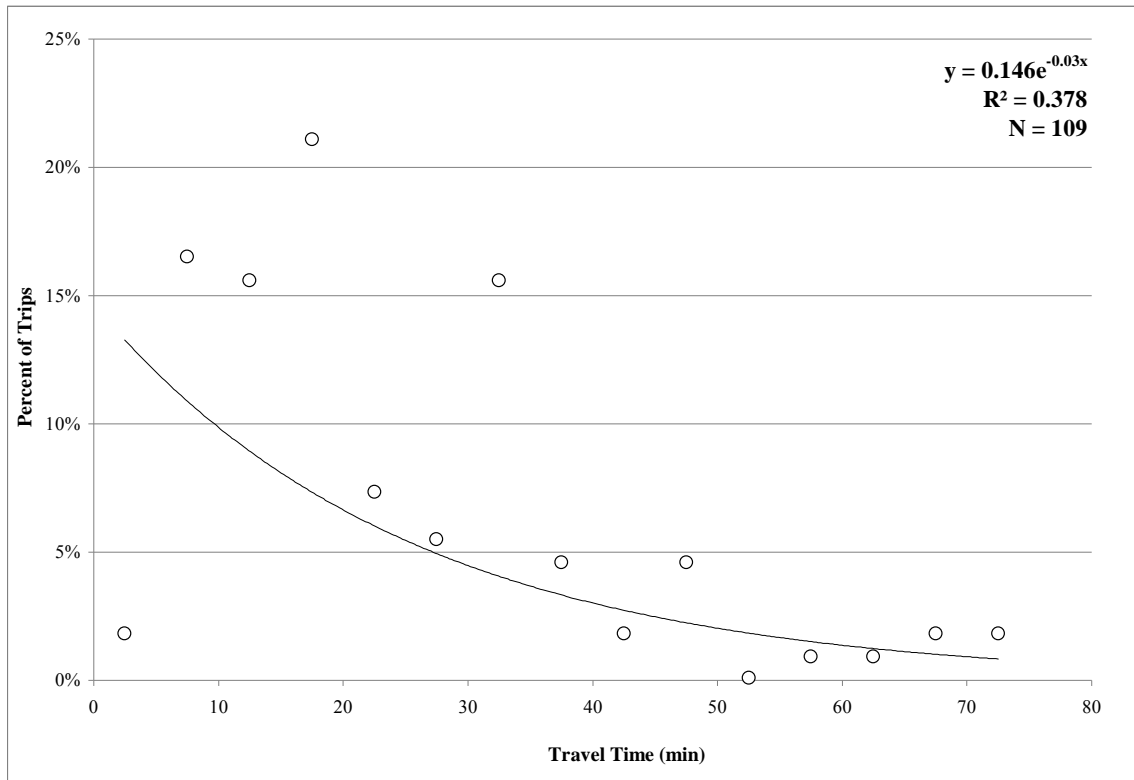
Figure G-1. Bike Work Trips

$y = 0.146e^{-0.03x}$
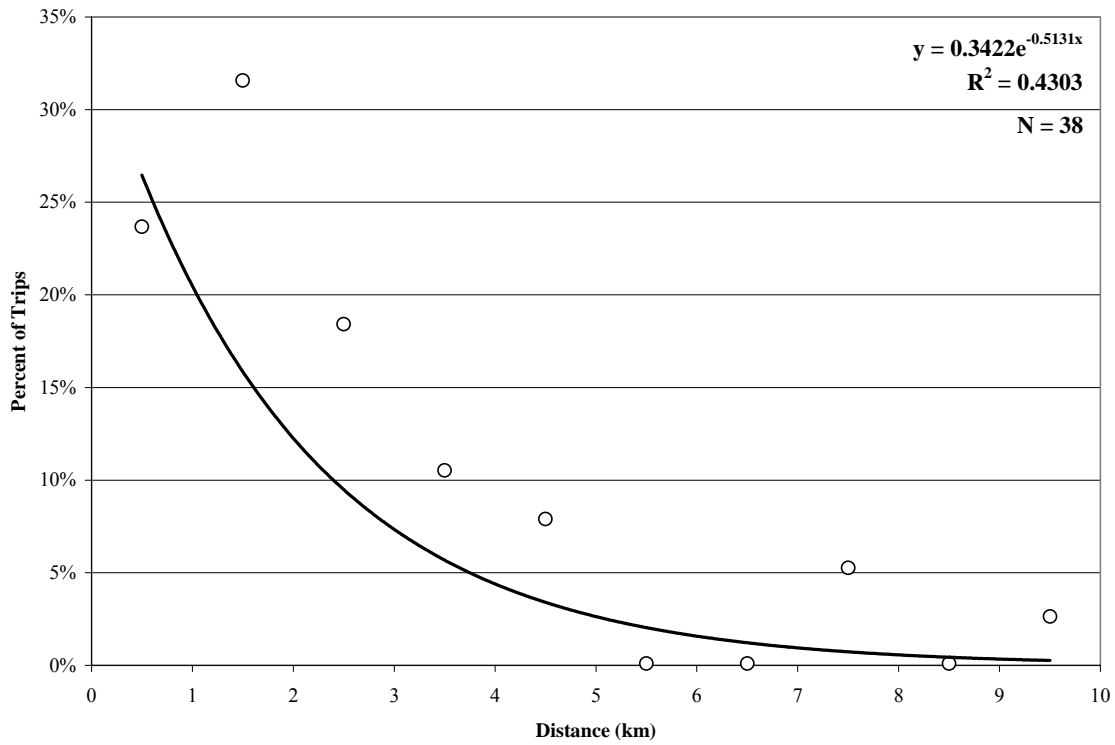$R^2 = 0.378$
$N = 109$
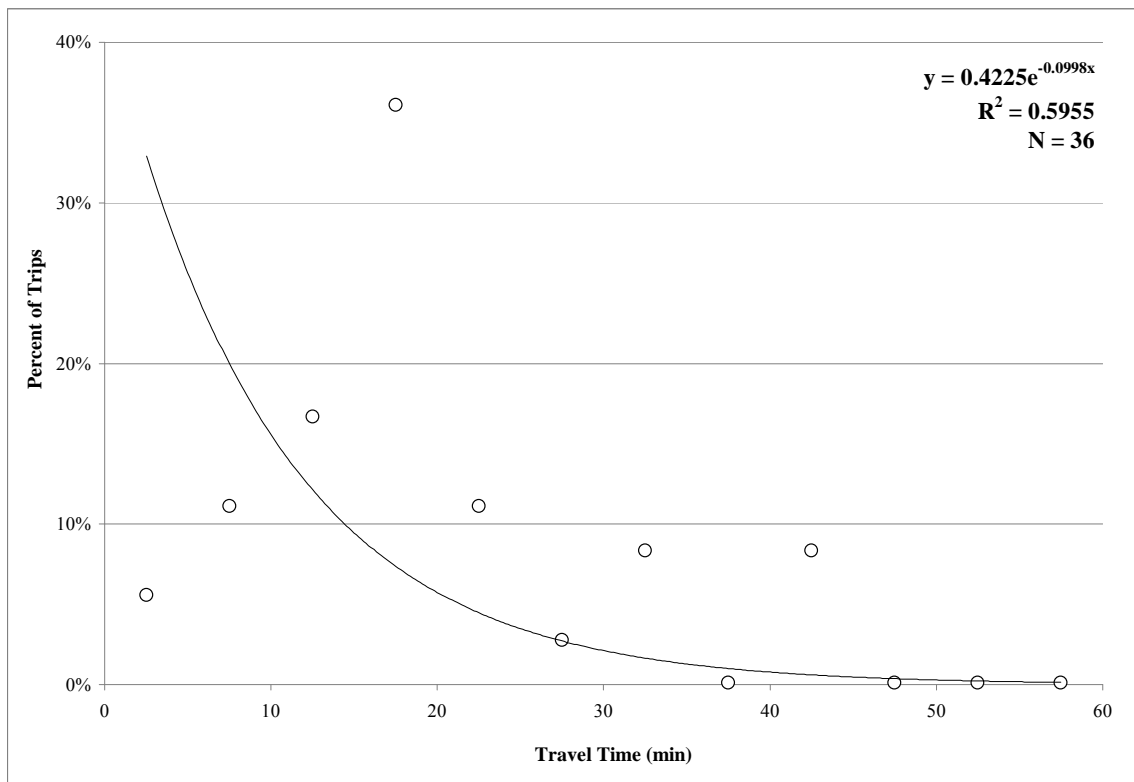
Figure G-2. Bike School or School-Related Trips

$y = 0.4225e^{-0.0998x}$
$R^2 = 0.5955$
$N = 36$

A-16
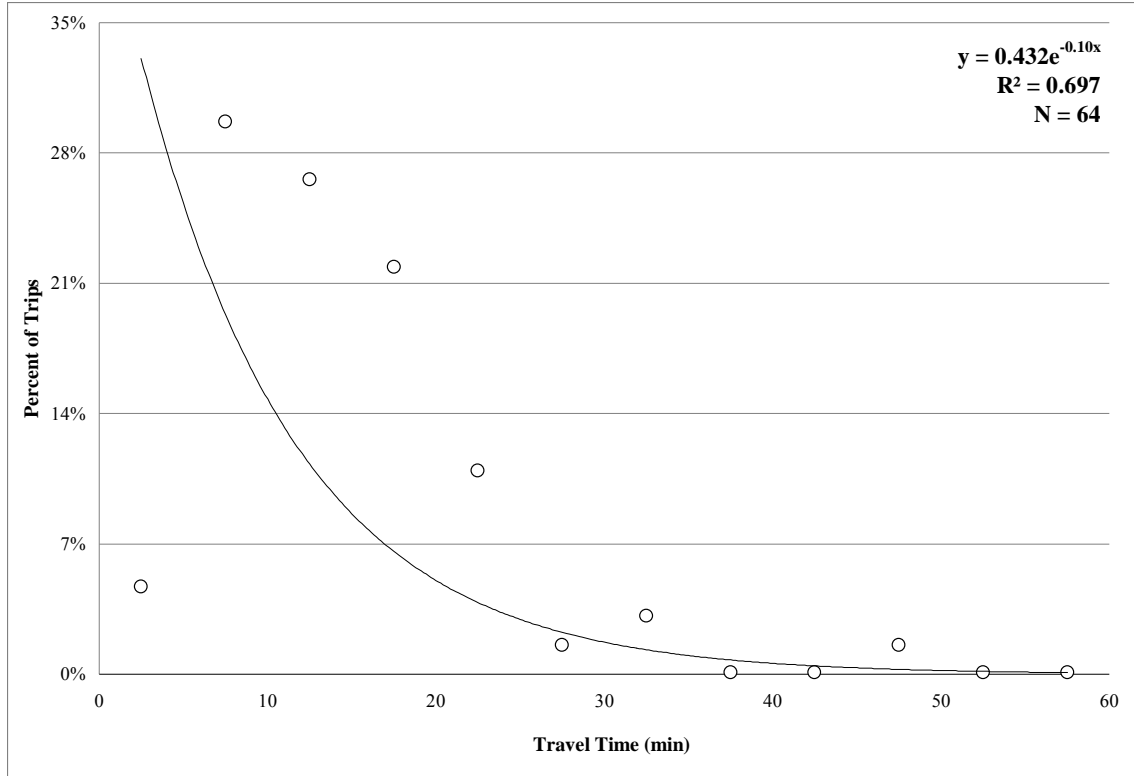
Figure G-3. Bike Shopping Trips
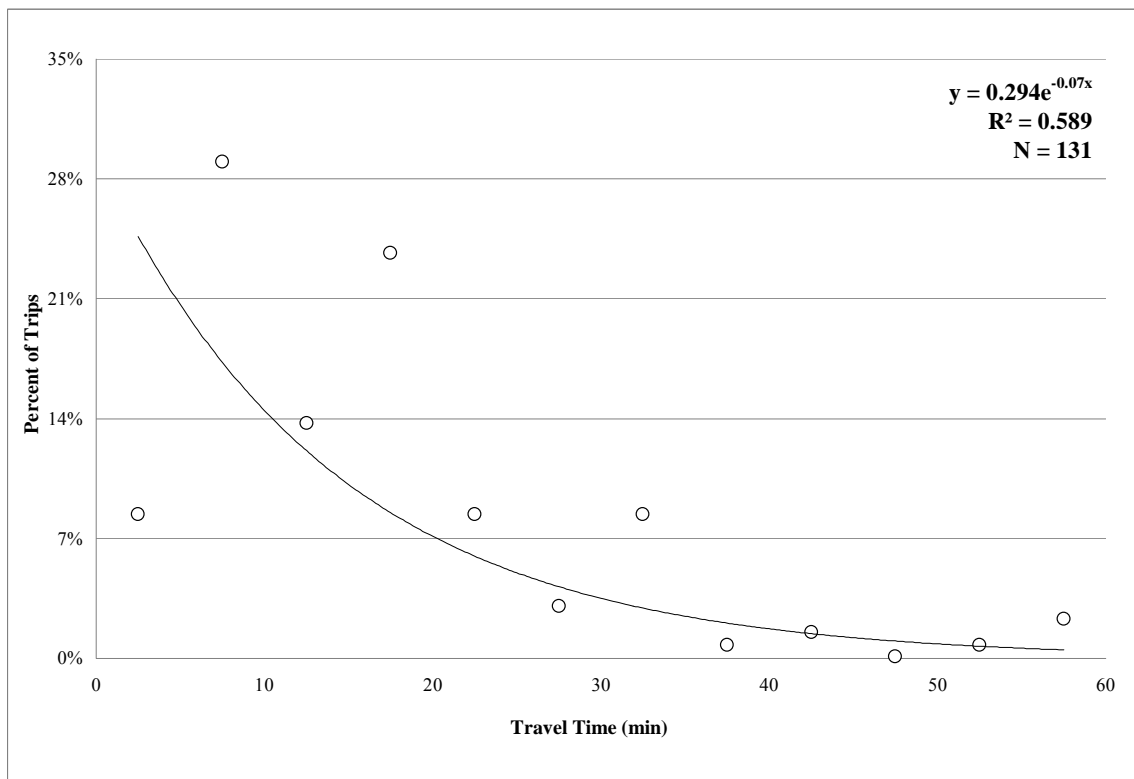
Figure G-4. Bike Entertainment, Recreation and Fitness Trips
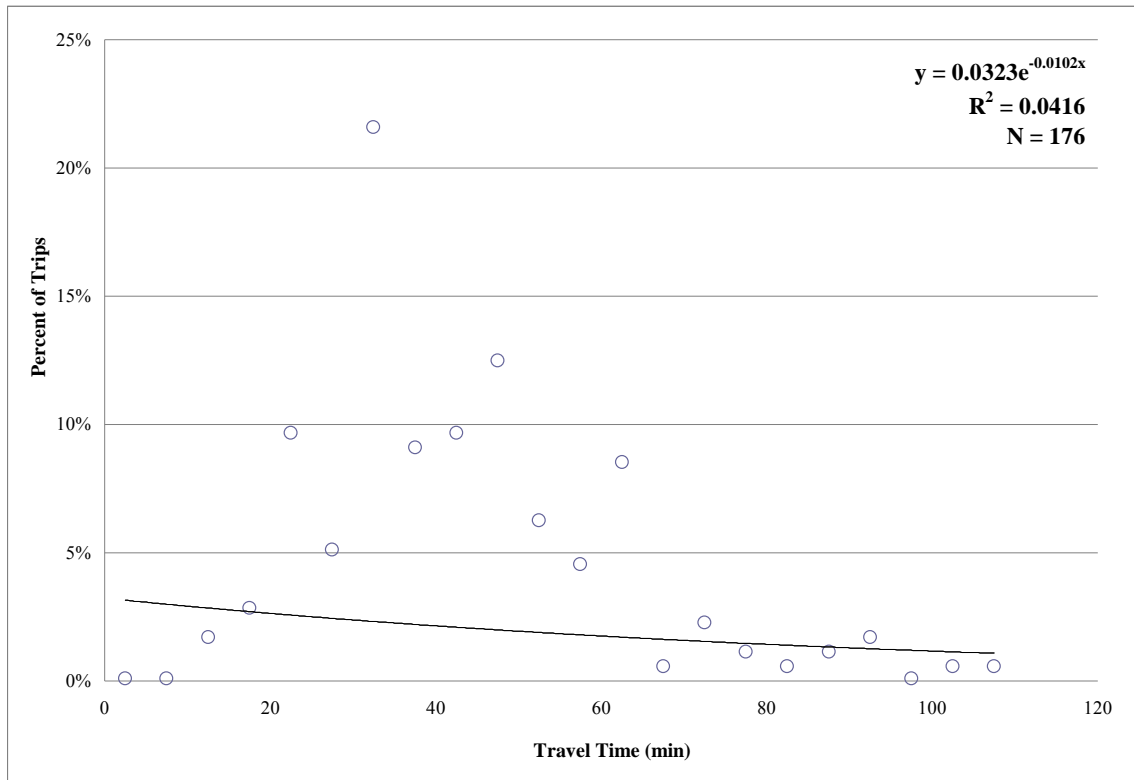
Figure H-1. Transit Work Trips

The chart shows data with fitted equation:
$$y = 0.0323e^{-0.0102x}$$
$$R^2 = 0.0416$$
$$N = 176$$

X-axis: Travel Time (min)
Y-axis: Percent of Trips
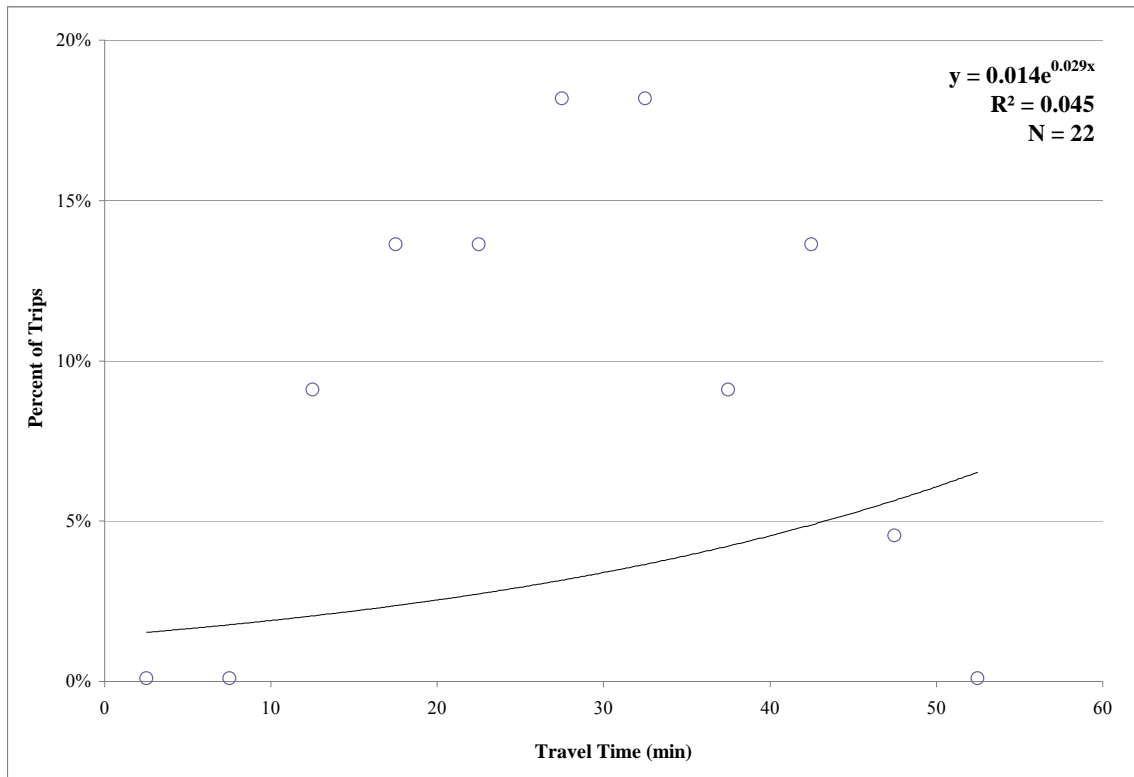
Figure H-2. Transit Shopping Trips

The chart shows data with fitted equation:
$$y = 0.014e^{0.029x}$$
$$R^2 = 0.045$$
$$N = 22$$

X-axis: Travel Time (min)
Y-axis: Percent of Trips

Appendix B
Statistical Summaries of the Estimated Distance Decay Functions

Table 1. Distance Decay Functions for Walking Trips by Trip Purpose

	Distance				Constant				Model Fit		
	β	S.E.	t	sig.	α	S.E.	t	sig.	(adj.) R^2	F	N
Work Trips											
Excel	-1.682				0.486				0.856		243
Regression	-1.683	0.219	-7.685	0.000	-0.723	0.454	-1.593	0.143	0.841	59.284	243
Curve Fitting	-1.683	0.219	-7.685	0.000	0.486	0.220	2.209	0.052	0.841	59.284	243
Shopping Trips											
Excel	-2.110				0.469				0.749		
Regression	-2.106	0.388	-5.428	0.000	-0.756	0.671	-1.127	0.286	0.721	29.474	145
Curve Fitting	-2.106	0.388	-5.428	0.000	0.469	0.315	1.489	0.167	0.721	29.474	145
Restaurant Trips											
Excel	-1.392				0.388				0.850		134
Regression	-1.397	0.186	-7.511	0.000	-0.946	0.385	-2.457	0.034	0.835	56.710	134
Curve Fitting	-1.397	0.186	-7.511	0.000	0.388	0.150	2.587	0.027	0.835	56.710	134
Recreational Trips											
TBI											
Excel	-0.766				0.324				0.610		156
Regression	-0.769	0.193	-3.984	0.003	-1.119	0.803	-1.394	0.193	0.574	15.830	156
Curve Fitting	-0.769	0.193	-3.984	1.003	0.327	0.262	1.248	0.241	0.574	15.830	156
NMPP											
Excel	-0.688				0.499				0.797		104
Regression	-0.687	0.122	-5.619	0.000	-0.695	0.529	-1.314	0.225	0.773	31.571	104
Curve Fitting	-0.687	0.122	-5.619	0.000	0.499	0.264	1.891	0.095	0.773	31.571	104

Table 2. Distance Decay Functions for Bicycle Trips by Trip Purpose

	Distance				Constant				Model Fit		
	β	S.E.	t	sig.	α	S.E.	t	sig.	(adj.) R^2	F	N
Work Trips											
Excel	-0.203				0.402				0.641		56
Regression	-0.203	0.054	-3.759	0.005	-0.910	0.838	-1.086	0.309	0.594	14.190	56
Curve Fitting	-0.203	0.054	-3.759	0.005	0.402	0.337	1.193	0.267	0.594	14.190	56
Shopping Trips											
Excel	-0.513				0.342				0.430		38
Regression	-0.514	0.209	-2.459	0.039	-1.071	1.203	-0.890	0.399	0.360	6.059	38
Curve Fitting	-0.514	0.209	-2.459	0.039	0.343	0.412	0.833	0.430	0.360	6.059	38
School Trips											
Excel	-0.124				0.465				0.789		177
Regression	-0.122	0.023	-5.304	0.001	-0.780	0.591	-1.320	0.223	0.756	28.854	177
Curve Fitting	-0.122	0.023	-5.304	1.001	0.458	0.271	1.690	0.129	0.756	28.854	177
Recreational Trips											
TBI											
Excel	-0.376				0.370				0.584		68
Regression	-0.375	0.113	-3.319	0.011	-1.003	0.911	-1.101	0.303	0.527	11.034	68
Curve Fitting	-0.375	0.113	-3.319	0.011	0.367	0.334	1.099	0.304	0.527	11.034	68
NMPP											
Excel	-0.228				0.544				0.927		87
Regression	-0.229	0.022	-10.387	0.000	-0.604	0.318	-1.899	0.094	0.922	107.892	87
Curve Fitting	-0.229	0.022	-10.387	0.000	0.546	0.174	3.141	0.014	0.922	107.892	87
Trail Trips											
Excel	0.333				0.119				0.927		1967
Regression											
Curve Fitting											

Table 3. Distance Decay Functions for Transit Trips by Trip Purpose

	Distance (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R2	F	N
Work Trips												
Excel	-0.094			0.676						0.915		1065
Regression	-0.093	0.010	-9.467	-0.405	0.345	-1.174				0.908	89.633	1065
Curve Fitting	-0.093	0.010	-9.467	0.667	0.230	2.902				0.908	89.633	1065
Combined	-0.143	0.018	-7.875	-2.350	0.690	-3.406	1.110	0.369	3.012	0.954	94.564	1065
College Trips												
Excel	-0.115			0.393						0.855		460
Regression	-0.116	0.017	-6.953	-0.902	0.493	-1.828				0.840	48.343	460
Curve Fitting	-0.116	0.017	-6.953	0.406	0.200	2.027				0.840	48.343	460
Combined	-0.062	0.042	-1.483	0.675	1.205	0.560	-1.002	0.706	-1.419	0.858	28.241	460
Shopping Trips												
Excel	-0.092			0.344						0.640		65
Regression	-0.092	0.024	-3.811	-1.060	0.697	-1.522				0.600	14.527	65
Curve Fitting	-0.092	0.024	-3.811	0.346	0.241	1.435				0.600	14.527	65

Table 4. Distance Decay Functions for Transit Trips by Access Mode and Trip Purpose

	Distance (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R2	F	N
Walk Access												
Work Trips												
Excel	-0.139			0.588						0.869		747
Regression	-0.138	0.019	-7.433	-0.544	0.406	-1.338				0.858	55.252	747
Curve Fitting	-0.138	0.019	-7.433	0.581	0.236	2.461				0.858	55.252	747
Combined	-0.248	0.026	-9.504	-2.446	0.470	-5.203	1.496	0.328	4.567	0.959	106.610	747
College Trips												
Excel	-0.286			0.507						0.719		408
Regression	-0.285	0.063	-4.509	-0.685	0.656	-1.045				0.682	20.327	408
Curve Fitting	-0.285	0.063	-4.509	0.504	0.331	1.524				0.682	20.327	408
Combined	-0.699	0.053	-13.132	-2.082	0.268	-7.768	2.662	0.316	8.412	0.967	134.184	408
Shopping Trips												
Excel	-0.130			0.280						0.898		42
Regression	-0.130	0.015	-8.379	-1.275	0.179	-7.139				0.885	70.207	42
Curve Fitting	-0.130	0.015	-8.379	0.279	0.050	5.599				0.885	70.207	42
Combined	-0.195	0.034	-5.712	-1.571	0.207	-7.586	0.469	0.226	2.075	0.919	51.755	42
Auto Access												
Work Trips												
Excel	-0.034			0.146						0.184		263
Regression	-0.033	0.025	-1.323	-1.937	0.882	-2.196				0.077	1.751	263
Curve Fitting	-0.033	0.025	-1.323	0.144	0.127	1.134				0.077	1.751	263
Combined	-0.188	0.031	-6.080	-7.892	1.175	-6.716	3.399	0.628	5.415	0.797	18.635	263
College Trips												
Excel	-0.050			0.190						0.225		36
Regression	-0.050	0.033	-1.522	-1.658	0.964	-1.721				0.128	2.317	36
Curve Fitting	-0.050	0.033	-1.522	0.191	0.184	1.038				0.128	2.317	36
Combined	-0.191	0.072	-2.641	-5.719	2.087	-2.740	2.579	1.223	2.109	0.390	3.881	36

Table 5. Distance Decay Functions for Transit Trips by Service Type

	Distance (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R2	F	N
Local Bus Trips												
Excel	-0.196			0.491						0.940		1316
Regression	-0.186	0.014	-13.238	-0.799	0.272	-2.933				0.931	175.250	1316
Curve Fitting	-0.186	0.014	-13.238	0.450	0.123	3.670				0.931	175.250	1316
Combined	-0.243	0.031	-7.857	-1.539	0.442	-3.480	0.666	0.332	2.005	0.945	111.679	1316
Express Bus Trips												
Excel	-0.060			0.216						0.479		871
Regression	-0.062	0.018	-3.369	-1.492	0.738	-2.021				0.443	11.350	871
Curve Fitting	-0.062	0.018	-3.369	0.225	0.166	1.354				0.443	11.350	871
Combined	-0.199	0.012	-16.727	-7.717	0.530	-14.570	3.373	0.267	12.647	0.961	160.828	871
Light Rail Trips												
Excel	-0.046			0.128						0.293		349
Regression	-0.046	0.020	-2.258	-2.054	0.555	-3.703				0.240	5.099	349
Curve Fitting	-0.046	0.020	-2.258	0.128	0.071	1.803				0.240	5.099	349
Combined	-0.185	0.024	-7.755	-5.449	0.594	-9.175	2.326	0.364	6.398	0.824	31.498	349

Table 6. Distance Decay Functions for Transit Trips by Access Mode and Service Type

	Distance (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R^2	F	N
Walk Access												
Local Bus												
Excel	-2.199			0.413						0.900		1120
Regression	-2.150	0.258	-8.324	-0.912	0.447	-2.041				0.884	69.281	1120
Curve Fitting	-2.150	0.258	-8.324	0.402	0.180	2.238				0.884	69.281	1120
Express Bus												
Excel	-2.393			0.384						0.827		613
Regression	-2.347	0.351	-6.684	-0.982	0.608	-1.616				0.799	44.673	613
Curve Fitting	-2.347	0.351	-6.684	0.375	0.228	1.646				0.799	44.673	613
Light Rail												
Excel	-1.919			0.591						0.850		185
Regression	-1.932	0.280	-6.905	-0.511	0.484	-1.056				0.838	47.675	185
Curve Fitting	-1.932	0.280	-6.905	0.600	0.290	2.065				0.838	47.675	185
Auto Access												
Local Bus												
Excel	-0.175			0.421						0.668		40
Regression	-0.175	0.044	-4.016	-0.866	0.627	-1.379				0.627	16.129	40
Curve Fitting	-0.175	0.044	-4.016	0.421	0.264	1.594				0.627	16.129	40
Express Bus												
Excel	-0.135			0.453						0.954		161
Regression	-0.136	0.011	-12.785	-0.778	0.221	-3.524				0.948	163.448	161
Curve Fitting	-0.136	0.011	-12.785	0.459	0.101	4.530				0.948	163.448	161
Light Rail												
Excel	-0.113			0.375						0.834		140
Regression	-0.113	0.018	-6.352	-0.972	0.340	-2.863				0.814	40.35	140
Curve Fitting	-0.113	0.018	-6.352	0.378	0.128	2.945				0.814	40.35	140

Table 7. Distance Decay Functions for Drive Alone Trips by Trip Purpose

	Distance				Constant				Model Fit		
	β	S.E.	t	sig.	α	S.E.	t	sig.	(adj.) R^2	F	N
Work Trips											
Excel	-0.091				0.528				0.953		1300
Regression	-0.088	0.005	-17.600	0.000	-0.685	0.216	-3.171	0.007	0.954	288.930	1300
Curve Fitting	-0.088	0.005	-17.600	0.000	0.504	0.109	4.624	0.000	0.954	288.930	1300
Shopping Trips											
Excel	-0.118				0.386				0.967		2437
Regression	-0.117	0.006	-19.500	0.000	-0.969	0.222	-4.365	0.001	0.960	333.671	2437
Curve Fitting	-0.117	0.006	-19.500	0.000	0.379	0.084	4.512	0.001	0.960	333.671	2437
School Trips											
Excel	-0.123				0.374				0.668		260
Regression	-0.122	0.024	-5.083	0.000	-0.991	0.624	-1.588	0.136	0.639	25.755	260
Curve Fitting	-0.122	0.024	-5.083	0.000	0.371	0.232	1.602	0.133	0.639	25.755	260
Restaurant Trips											
Excel	-0.118				0.313				0.962		745
Regression	-0.119	0.007	-17.000	0.000	-1.146	0.186	-6.161	0.000	0.957	312.158	745
Curve Fitting	-0.119	0.007	-17.000	0.000	0.318	0.059	5.390	0.000	0.957	312.158	745
Recreational											
Excel	-0.104				0.339				0.981		511
Regression	-0.103	0.004	-25.750	0.000	-1.089	0.110	-9.900	0.000	0.980	675.393	511
Curve Fitting	-0.103	0.004	-25.750	0.000	0.336	0.037	9.081	0.000	0.980	675.393	511

Table 8. Distance Decay Functions for Shared Ride Trips by Trip Purpose

	Distance				Constant				Model Fit		
	β	S.E.	t	sig.	α	S.E.	t	sig.	(adj.) R^2	F	N
Work Trips											
Excel	-0.077				0.240				0.888		181
Regression	-0.076	0.007	-10.857	0.000	-1.439	0.213	-6.756	0.000	0.884	107.508	181
Curve Fitting	-0.076	0.007	-10.857	1.000	0.237	0.050	4.740	0.000	0.884	107.508	181
Shopping Trips											
Excel	-0.129				0.376				0.964		959
Regression	-0.130	0.007	-18.571	0.000	-0.965	0.202	-4.777	0.000	0.961	345.595	959
Curve Fitting	-0.130	0.007	-18.571	0.000	0.381	0.077	4.948	0.000	0.961	345.595	959
School Trips											
Excel	-0.096				0.159				0.588		176
Regression	-0.096	0.022	-4.364	0.001	-1.833	0.380	-4.824	0.000	0.566	19.236	176
Curve Fitting	-0.096	0.022	-4.364	1.001	0.160	0.061	2.623	0.021	0.566	19.236	176
Restaurant Trips											
Excel	-0.140				0.426				0.870		500
Regression	-0.140	0.015	-9.333	0.000	-0.853	0.416	-2.050	0.061	0.859	86.610	500
Curve Fitting	-0.140	0.015	-9.333	1.000	0.426	0.177	2.407	0.032	0.859	86.610	500
Recreational Trips											
Excel	-0.094				0.337				0.891		369
Regression	-0.093	0.009	-10.333	0.000	-1.100	0.295	-3.729	0.003	0.883	106.367	369
Curve Fitting	-0.093	0.009	-10.333	1.000	0.333	0.098	3.398	0.005	0.883	106.367	369

Table 9. Distance Decay Functions for Health Care Trips (no mode specified)

	Distance (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R2	F	N
Health Care												
Excel	-0.110			0.525						0.980		8,554
Regression	-0.118	0.004	-29.256	-0.612	0.187	-3.275				0.978	855.913	8,554
Curve Fitting	-0.118	0.004	-29.256	0.542	0.101	5.350				0.978	855.913	8,554
Combined	-0.132	0.009	-14.636	-1.342	0.474	-2.833	0.374	0.225	1.663	0.980	471.291	8,554

Table 10. Distance Decay Functions for Walking Trips with Time Impedance

	Travel Time (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R^2	F	N
Work Trips												
Excel	-0.100			0.519						0.927		366
Regression	-0.106	0.010	-10.853	-0.671	0.338	-1.983				0.914	117.782	366
Curve Fitting	-0.106	0.010	-10.853	0.511	0.173	2.957				0.914	117.782	366
Combined	-0.116	0.026	-4.480	-1.016	0.927	-1.096	0.202	0.502	0.403	0.906	54.037	366
Shopping Trips												
Excel	-0.090			0.370						0.724		269
Regression	-0.094	0.018	-5.104	-0.999	0.635	-1.574				0.695	26.046	269
Curve Fitting	-0.094	0.018	-5.104	0.368	0.234	1.576				0.695	26.046	269
Combined	-0.063	0.048	-1.333	0.091	1.710	0.053	-0.638	0.926	-0.689	0.678	12.576	269
School Trips												
Excel	-0.100			0.523						0.600		105
Regression	-0.106	0.031	-3.464	-0.645	0.880	-0.733				0.550	12.002	105
Curve Fitting	-0.106	0.031	-3.464	0.524	0.461	1.136				0.550	12.002	105
Combined	-0.231	0.069	-3.372	-4.114	1.907	-2.157	2.243	1.133	1.980	0.670	10.150	105
Restaurant												
Excel	-0.090			0.377						0.702		179
Regression	-0.093	0.019	-4.804	-0.985	0.667	-1.477				0.667	23.076	179
Curve Fitting	-0.093	0.019	-4.804	0.373	0.249	1.499				0.667	23.076	179
Combined	-0.081	0.051	-1.588	-0.576	1.840	-0.313	-0.240	0.996	-0.241	0.633	10.480	179
Recreation												
Excel	-0.090			0.545						0.932		292
Regression	-0.100	0.010	-10.264	-0.586	0.280	-2.096				0.921	105.352	292
Curve Fitting	-0.100	0.010	-10.264	0.556	0.156	3.575				0.921	105.352	292
Combined	-0.153	0.016	-9.261	-2.052	0.458	-4.478	0.947	0.272	3.481	0.967	131.933	292

Table 11. Distance Decay Functions for Bicycle Trips with Time Impedance

	Travel Time (β)			*Constant (α)*			*Shape (μ)*			*Model Fit*		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R^2	F	N
Work Trips												
Excel	-0.030			0.146						0.378		109
Regression	-0.040	0.014	-2.821	-1.922	0.609	-3.156				0.332	7.956	109
Curve Fitting	-0.040	0.014	-2.821	0.146	0.089	1.642				0.332	7.956	109
Combined	-0.088	0.032	-2.721	-4.317	1.574	-2.742	1.255	0.768	1.633	0.408	5.822	109
Shopping Trips												
Excel	-0.100			0.432						0.697		64
Regression	-0.107	0.022	-4.791	-0.836	0.776	-1.077				0.666	22.953	64
Curve Fitting	-0.107	0.022	-4.791	0.434	0.336	1.288				0.666	22.953	64
Combined	-0.182	0.053	-3.425	-3.542	1.912	-1.852	1.585	1.036	1.531	0.706	14.190	64
School Trips												
Excel	-0.100			0.422						0.595		36
Regression	-0.100	0.026	-3.845	-0.858	0.899	-0.954				0.556	14.785	36
Curve Fitting	-0.100	0.026	-3.845	0.424	0.381	1.112				0.556	14.785	36
Combined	-0.199	0.059	-3.370	-4.450	2.124	-2.095	2.104	1.150	1.829	0.640	10.799	36
Recreation												
Excel	-0.07			0.294						0.589		131
Regression	-0.071	0.019	-3.785	-1.226	0.645	-1.901				0.548	14.329	131
Curve Fitting	-0.071	0.019	-3.785	0.293	0.189	1.551				0.548	14.329	131
Combined	-0.105	0.048	-2.180	-2.465	1.727	-1.428	0.726	0.935	0.776	0.529	7.180	131

Table 12. Distance Decay Functions for Transit Trips with Time Impedance

	Travel Time (β)			Constant (α)			Shape (μ)			Model Fit		
	Coeff.	S.E.	t	Coeff.	S.E.	t	Coeff.	S.E.	t	(adj.) R^2	F	N
Work Trips												
Excel	-0.010			0.032						0.041		176
Regression	-0.010	0.011	-0.908	-3.441	0.692	-4.974				0.008	0.825	176
Curve Fitting	-0.010	0.011	-0.908	0.032	0.022	1.445				0.008	0.825	176
Combined	-0.095	0.014	-6.702	-10.705	1.158	-9.244	3.210	0.482	6.659	0.682	23.475	176
Shopping Trips												
Excel	0.029			0.014						0.045		22
Regression	0.029	0.044	0.655	-4.252	1.402	-3.032				0.061	0.429	22
Curve Fitting	0.029	0.044	0.655	0.014	0.020	0.713				0.061	0.429	22
Combined	-0.215	0.076	-2.826	-12.011	2.419	-4.966	4.760	1.368	3.480	0.525	6.535	22