Paratransit Demand of Disabled People

Peter Bearse*, Shiferaw Gurmu‡, Carol Rapaport☐, and Steven Stern††

☐ University of North Carolina, Greensboro
‡ Georgia State University
† University of Virginia
☐ Federal Reserve Bank - New York

August 2003

Abstract

This paper estimates the demand for transportation systems that are used primarily by disabled individuals. These systems are known as paratransit systems, and have experienced large increases in number and average size over the past 15 years. We first use a national database and standard time series techniques to model aggregate demand. We then use a unique data set of administrative records from a paratransit system in central Virginia to estimate standard and nonstandard count models of individual demand. We conclude that most of the demand growth is from new passengers, but that predicting the growth of new passengers is very difficult. Our results also highlight the importance of incorporating autocorrelation and possible sample attrition into standard count models.

*We would like to thank the JAUNT Board of Directors for providing us with access to the data, Debbie Taylor from JAUNT for collecting it and helping us to understand it, Helen Poore, Betty Bollendorf, and Betty Saunders from CTS for collecting and helping us to understand the CTS data, and David Givens for excellent research assistance. Steven Stern was a member of the JAUNT Board of Directors at the time that much of the work for this paper was performed. The views expressed in this paper are the authors’ and not those of the JAUNT Board of Directors, the Federal Reserve Bank of New York, or the Federal Reserve System. All errors are the fault of the authors.

†Corresponding Author: Steven Stern, Department of Economics, Rouss Hall, University of Virginia, Charlottesville, VA 22903; Email: sns5r@virignia.edu; Phone: (804) 924-6754; FAX: (804) 982-2904.
1. Introduction

Transportation systems that provide services predominantly to disabled people are called paratransit systems. Since the middle 1980’s, there has been a large increase in the number of paratransit systems across the United States and the average size of those systems. For example, across 198 cities with less than 400,000 people in 1980, trips increased from 6.0 million in 1984 to 16.9 million in 1995 (Fitzgerald, Shaunesey, and Stern 2000). Unfortunately, very little is known about the demand for such paratransit systems, how demand depends upon characteristics of the local population, or how the systems change over time. While there are some case studies describing the ways that communities deal with paratransit demand (Everett 1985, Fix 1985), we have found no studies using available public national data or individual passenger data.

This paper uses National Transit Database (NTD) data on systems in moderately sized and small cities to measure demand growth over time. Our extract from the NTD is a panel data set over time and systems with information on aggregate annual trips per system. We merge Census population data to our extract. We use straightforward time series techniques to estimate a simple model of aggregate demand with panel data in the presence of missing observations.

Next we use a unique data set derived from the administrative records of a paratransit provider in central Virginia, JAUNT. JAUNT provides demand-response transportation services for disabled people in Charlottesville and Albemarle County. Eligible individuals make reservations for trips at least 24 hours in advance of the trip, and then a JAUNT vehicle transports them from any origin to any destination within the bounds of service delivery. JAUNT has been in existence since the middle 1970’s and began maintaining detailed passenger records in 1984. Over the period, 1984-1997, JAUNT has grown significantly and continues to grow. We derive a standard count model of trips per month per passenger. Then we add some reasonable structural features to the model. These features can not fit into the standard estimation models and require simulation methods. Our results show that incorporating autocorrelation and uncertainty over whether a previous user is still alive are important in explaining individual demand.

The goal of this paper is to use JAUNT’s administrative records to decompose the process generating JAUNT’s demand into demand growth per passenger and demand growth from the number of passengers. Anticipating the results, we find that most growth is due to new passengers, but that it is very difficult to

---

1 JAUNT used to stand for Jefferson Area United Transportation. Now, the acronym has no long form.
predict growth of new passengers. Furthermore, not all passengers are the same. In particular, a small proportion of passengers accounts for a large proportion of aggregate trips. Section 2 provides an empirical analysis for the magnitude of growth in moderately sized American cities. Section 3 describes the JAUNT data used in subsequent analysis. Section 4 provides the econometric methods used to assess the effects of observed characteristics, calendar time, and previous demand on the number of trips taken by a person during a month. Estimation results are discussed in sections 5 and 6. Section 7 provides a conclusion.

2. Analysis of Aggregate Trips Across Paratransit Providers

In this section, we provide some sense of the magnitude of growth of paratransit systems in moderately sized American cities. First, we present a model and estimation method to interpret the data, and then we describe the data and present our estimates.

2.1. Saturated Model

The saturated model of aggregate trips in levels is given by

\[ y_{it} = \mu_i + \gamma t + x_{it} \beta + \epsilon_{it} \]  \hspace{1cm} (2.1)

\[ \epsilon_{it} = \rho \epsilon_{it-1} + \epsilon_i, \quad \rho \in (-1, 1) \]

\[ \epsilon_i \sim iidN(0, \sigma^2) \]

\[ t = 0, 1, ..., T; \quad i = 1, 2, ..., N \]

where \( y_{it} \) is aggregate trips in transportation system \( i \) during year \( t \) and \( x_{it} = (\text{Pop}_{it}, \text{Pop}_{65it})' \) is a 2-vector of covariates for system \( i \) during year \( t \) where \( \text{Pop}_{it} \) denotes total population and \( \text{Pop}_{65it} \) denotes population aged 65 and over in the region serviced by system \( i \). The covariates are assumed to be strictly exogenous. The system specific unobserved heterogeneity term \( \mu_i \) is fixed across time within a system.

We eliminate fixed effects by putting the model in its differenced form,

\[ \Delta y_{it} = \gamma + \Delta x_{it} \beta + \Delta \epsilon_{it} \]  \hspace{1cm} (2.2)

\[ \Delta \epsilon_i \sim N[0, \Omega] \]

where \( \Delta \epsilon_{it} = \epsilon_{it} - \epsilon_{it-1} \), \( \Delta \epsilon_i = (\Delta \epsilon_{i1}, \Delta \epsilon_{i2}, ..., \Delta \epsilon_{iT})' \), \( \Delta y_{it}, \Delta y_i, \Delta x_{it}, \) and \( \Delta x_i \)
are defined analogously and

\[
\Omega = \frac{\sigma^2}{1 + \rho} \begin{pmatrix}
2 & -(1 - \rho) & -\rho(1 - \rho) & \cdots & -\rho^T (1 - \rho) \\
-(1 - \rho) & 2 & -(1 - \rho) & \cdots & -\rho^{T-1} (1 - \rho) \\
-\rho(1 - \rho) & -(1 - \rho) & 2 & \cdots & -\rho^{T-2} (1 - \rho) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
-\rho^T (1 - \rho) & -\rho^{T-1} (1 - \rho) & -\rho^{T-2} (1 - \rho) & \cdots & 2
\end{pmatrix}
\]

We need to handle missing observations. Let \( y_i^* \) be the trip observations for transportation system \( i \) which are not missing. Let \( A_i \) be a matrix such that \( y_i^* = A_i y_i \), let

\[
Z_i = \begin{pmatrix}
1 \\
2 \\
\vdots \\
T
\end{pmatrix},
X_i,
\]

and let \( Z_i^* = A_i Z_i \). Next define \( \Delta y_i^* \) as the differenced observed data, define \( \Delta Z_i^* \) and \( \Delta e_i^* \) analogously, and let \( T_i^* \) be the number of elements in \( \Delta y_i^* \). For example, if, for system \( i \), only observations 2 and 3 are missing, then \( \Delta y_i^* \)

\[
\Delta y_i^* = \begin{pmatrix}
y_{i1} - y_{i0} \\
y_{i4} - y_{i1} \\
y_{i5} - y_{i4} \\
\vdots \\
y_{iT} - y_{iT-1}
\end{pmatrix},
\]

i.e. any element of \( \Delta y_i^* \) corresponding to a difference with no missing observation corresponds to an element of \( \Delta y_i \), and any element corresponding to a difference with missing observations corresponds to a sum of elements of \( \Delta y_i \). Define \( \Psi_i \) such that \( \Delta y_i^* = \Psi_i \Delta y_i \), and note that \( \Delta Z_i^* = \Psi_i \Delta Z_i \).

Our model for system \( i \) can then be written as \( \Delta y_i^* = \Delta Z_i^* \delta + \Delta e_i^* \) where \( \delta = (\gamma, \beta)' \), \( \Delta e_i^* \sim N(0, \Omega_i^*) \),

\[
\Omega_i^* = E(\Delta e_i^*) (\Delta e_i^*)' = E(\Psi_i \Delta e_i) (\Psi_i \Delta e_i)' = \Psi_i \Omega \Psi_i',
\]

and \( \Omega \) is the covariance matrix defined in equation (2.2). The log likelihood for our observed data is then

\[
L^*(\theta) = \sum_{i=1}^N \left[ -\frac{T_i^*}{2} \ln(2\pi) - \frac{1}{2} \ln |\Omega_i^*| - \frac{1}{2} (\Delta y_i^* - \Delta Z_i^* \delta)' (\Omega_i^*)^{-1} (\Delta y_i^* - \Delta Z_i^* \delta) \right].
\]

(2.3)
2.2. Model Selection

We examine several models. In particular, we consider both differences of trips and differences of log trips. We consider all subsets of the regressors: a) a constant term, b) total population, and c) population over 65. Additionally, we consider the case of a stationary error term \( e_{it} \) (i.e., \( |\rho| < 1 \)) and the case of a random walk error term (i.e., \( \rho = 1 \)). In the former case, the differenced error term \( \Delta e_{it} \) is serially dependent, and, in the latter case, it is iid.

Our model portfolio then consists of 28 models which we rank using the Consistent Akaike Information Criterion with Fisher Information (CAICF) of Bozdogan (1987). The model with the smallest CAICF is ranked best. For models without the log transformation, the CAICF of model \( j \) is given by

\[
CAICF_j = -2L^*\left(\hat{\theta}_j\right) + 2m + \ln\left|F\left(\hat{\theta}_j\right)\right|
\]

where \( \hat{\theta}_j \) is the maximum likelihood estimator of the \( m \)-vector of free parameters under model \( j \) and \( F\left(\hat{\theta}_j\right) \) is the Fisher Information Matrix defined by

\[
F\left(\hat{\theta}_j\right) = E\left[\frac{-\partial^2 L^*\left(\hat{\theta}_j\right)}{\partial \theta_j \partial \theta_j^T}\right].
\]

For models where the log transformation has been applied, we adjust the log likelihood by the Jacobian term to ensure that all models are scored using the same likelihood points. The CAICF of model \( j \) for models involving the log transformation is then given by

\[
CAICF_j = -2L^*\left(\hat{\theta}_j\right) + 2m + \ln\left|F\left(\hat{\theta}_j\right)\right| + \sum_{i=1}^{N} \sum_{t=1}^{T_i} \ln y_{it}^*.
\]

Bozdogan’s CAICF is similar in form to the independently discovered Posterior Information Criterion (PIC) of Phillips and Ploberger (1996) and Phillips (1996). Both are consistent model selection criteria. Unlike PIC, however, CAICF is in the spirit of Akaike’s (1973) Information Criterion (AIC) in that it still uses minus twice the log likelihood and is not based on a Bayesian approach.

2.3. Data and Results

Our data consist of observations on aggregated trips, total population, and population aged 65 and over for 259 U.S. transportation systems observed annually.
over the 12 year period 1984-1995. The source of the data is the Federal Trans-
portation Administration’s National Transit Database (NTD). The data and its use are described in more detail in the appendix. Because we estimate our models using differenced data, the year 1984 is lost. Ideally, this would provide us with 2849 usable observations in differences.

Unfortunately, our original data set is incomplete in two respects. First, while our trip data span the years 1984-1995, we observe population data only during the Census years 1980 and 1990. We interpolate the population covariates according to the deterministic models

\[
\begin{align*}
\text{Pop}_{it} & = \alpha_i \exp \{\varsigma_i (t - 1980)\} , \\
\text{Pop}_{65it} & = \tilde{\alpha}_i \exp \{\tilde{\varsigma}_i (t - 1980)\} , \\
\end{align*}
\]

where \(\alpha_i = \text{Pop}_{i1980}, \quad \varsigma_i = \frac{1}{10} [\ln (\text{Pop}_{i1990}) - \ln (\text{Pop}_{i1980})],\)

and \(\tilde{\alpha}_i, \tilde{\varsigma}_i\) are defined analogously in terms of \(\text{Pop}_{65i1980}\) and \(\text{Pop}_{65i1990}\).

Second, some systems were not in operation over the entire period of observation, and, even when they were, trip data was not recorded for some systems in some years. In total, we have 913 such missing values. For models without the log transformation, we then have 1937 usable observations in differences.

Finally, for models in differences of logs, we treat observations where computation involves a zero as missing values. We have 32 such cases. This means that, for models with the log transformation, we have 1905 usable observations for differences of logs models. Table 1 provides summary statistics for the data used in our regressions. It is clear that there is significant growth in systems over time with an average annual growth rate of 10.9%. But it is also clear that there is even larger variation in growth across time.

Table 2 provides a summary of the regression results for differences in log aggregate trips. According to CAICF, models in differences of logs are always preferred to those with raw differences (and so no results are reported for raw differences). Its most preferred model has approximate growth in trips following a drifting random walk with 10.5% annual growth. Note that demand is growing 3.6 times as fast as the elderly population and 4.7 times as fast as the general population. The large variance observed in Table 1 manifests itself here as a value of \(\rho\) close to unity.

Cities across the United States have struggled with this growth, much of which must be paid for with local government funds. It is worth understanding what is causing the growth so that communities can determine if they are spending their resources wisely, and, if not, how to use them more efficiently. In the remainder
of this paper (excluding Section 2.4), we try to decompose this 10.5% growth into a “within passenger” effect and a “new passenger” effect. We do this using administrative records from a medium sized system in Central Virginia.

2.4. Other Alternatives

When the autoregressive coefficient, $\rho$, equals one, removal of the fixed effects via first differencing is the correct choice. If $\rho \in (-1,1)$, however, it is possible that the fixed effects estimator could be a more appropriate choice.\footnote{Assuming, of course, the number of time periods exceeds two. When there are just two time periods, the fixed effects and first difference approaches are identical.} Indeed, if the covariates are not strictly exogenous due to, say, measurement error, the first differences estimator will not be consistent. Even if the covariates are strictly exogenous, there is no practical method for determining \textit{a priori} which method is best.

In light of these considerations, we also examined the results based on a fixed effects estimator.\footnote{Detailed results are available at Bearse, Gurmu, Rapaport, and Stern (2003b).} The model is identical to before, with the exception that we now impose $\rho \in (-1,1)$, thereby ruling out the unit root case. Examining the case where all covariates are included in the model, our results for the coefficient estimates were similar to those presented in Table 2. In particular, the coefficient on the trend term remained statistically significant, whereas those on the log of total population and the log of population aged 65 years or over remained insignificant. Our point estimate of the trend coefficient was slightly smaller (0.071 instead of 0.079) under the alternative estimation strategy.

Another potential concern is heteroskedasticity in the error terms across systems. While this is certainly possible, it is likely mitigated by the estimation of the models in terms of log trips since trip volatility of trips appears to be, roughly, proportional to trip levels. Ideally, we would take a less casual perspective and incorporate heteroskedasticity directly into our model. This would not be a productive approach in our situation since we have few time observations relative to systems. On the other hand, it is straightforward to estimate the model via least squares with system dummies and then conduct inference using robust standard errors. We did this for the case where all covariates are included in the model and found that, while the standard errors increased, our previous conclusions regarding significance of the coefficient estimates were not altered.

One might worry that selection into the sample causes a standard selection bias. Consider a modification of the model in equation (2.1). We model log
trips for system $i$ at time $t$ as

$$y_{1it}^* = X_{it}\beta_1 + u_{1i} + \varepsilon_{1it}$$

and consider $u_{1i}$ a random effect rather than a fixed effect. In this application, the choice seems somewhat innocuous given the variables in $X_{it}$. We add to the model a participation equation,

$$y_{2it}^* = X_{it}\beta_2 + u_{2i} + \varepsilon_{2it}$$

where $y_{2it}^*$ is the value to $i$ of operating a system in year $t$. We assume $i$ operates a system iff $y_{2it}^*$ is positive,

$$y_{2it} = \begin{cases} 1 & (y_{2it}^* > 0), \\ 0 & (y_{2it}^* \leq 0). \end{cases}$$

$$y_{1it} = \begin{cases} y_{1it}^* & (y_{2it}^* > 0), \\ 0 & (y_{2it}^* \leq 0). \end{cases}$$

We assume that $u_i = (u_{1i}, u_{2i})'$ is a system specific random effect,$^4$

$$u_i \sim iidN(0, \Omega_u),$$

$$\varepsilon_{it} = \begin{cases} \Gamma\varepsilon_{it-1} + \eta_{it} & for t > 1, \\ \eta_{it} & for t = 1. \end{cases}$$

$$\eta_{it} \sim iidN(0, \Omega_\eta).$$

The likelihood is presented in the appendix.

Bearse, Gurmu, Rapaport, and Stern (2003a) report results for three specifications of the model. The first uses four explanatory variables and a rich covariance structure. The second limits explanatory variables to a constant and time, and the third limits the covariance structure so that the trips variable and participation variable are independent (i.e., no selection effect). The full model performs significantly better than the other two. However, the real issue is how the inclusion of the participation equation affects the trips equation estimates. In the model with selection with limited explanatory variables, the estimate of the growth coefficient is 0.07. In the linear model from equation (2.1), it is 0.102. The estimate of the first order serial correlation term is $\hat{\Gamma}_{11} = 0.821$ in the model with selection, and it is $\hat{\rho} = 0.951$ in the linear model. If we add the two population variables, the time estimate becomes 0.056 in the model with selection and

---

$^4$The alternative would be to assume it is a fixed effect. But differencing doesn’t work here, and methods such as in Honore and Kyriazidou (2000) do not work because they require no terms in $X_{it}$ that are growing with $t$.  

---

8
0.079 in the linear model, and the first order serial correlation estimate becomes 0.843 in the model with selection and 0.948 in the linear model.

The results suggest that the estimate of the growth rate is biased upwards when selection is ignored. The intuition for why this occurs must be linked to the covariance structure of the errors. However, intuition does not help here. First, the estimate of the correlation of the random effects, \( \Omega_{u12}/\sqrt{\Omega_{u11}\Omega_{u22}} \), is very unstable. When the population variables are included, the estimate is \(-0.053\), and when population variables are excluded, it is 1.000. This can occur if growth in the population variables dominates other sources of system specific unobserved heterogeneity. However, the estimates of the diagonal elements of \( \Omega_u \) are not very sensitive to the inclusion of the population variables. Thus, it is difficult to believe that exclusion of the population variables dominates other sources of system specific unobserved heterogeneity. The estimate of the correlation of the idiosyncratic error is positive and not sensitive to the inclusion of population variables. But a positive correlation should lead to a negative bias on the estimate of the growth rate as some of the effect of growth is hidden by lack of participation. Thus, the results are a bit perplexing. In any case, though, both the linear model and model with selection suggest large, similar growth rates strongly affected by growth in the elderly population.

3. JAUNT Data

There are four data sets used in this analysis. From the first two, we observe information on the number of trips taken per month and characteristics of the individuals taking trips in Charlottesville. Table 3 provides a list of names of variables used in the Charlottesville analysis.

The first data set, the administrative records of JAUNT, provides information on every trip reserved by a disabled person authorized by Charlottesville to use JAUNT between November 1, 1994 and October 31, 1996 (24 months). For each trip, we observe the origin, destination, date, and a card number of the individual taking the trip. These data are aggregated into a smaller data set providing the number of trips taken by each eligible user for each month in the observation period. Table 4 provides some information about the JAUNT data set.

The mean number of trips per person per month (conditional on having at least one trip) is 3.51, but there is a large standard deviation: 8.4. The first order serial correlation of monthly trips per person is 0.56, but it is not clear whether that is due to a large, constant person-specific effect or an autoregressive process. In fact, a random effects decomposition of the error suggests that there is both a large person-specific effect and a large person-time idiosyncratic effect.
Table 4 suggests a large amount of heterogeneity in demand. Figure 1 looks at heterogeneity in a different way. The curve labeled “People” is the distribution of trips where the unit of observation is a person. For example, 93% of eligible users take 20 trips or less per month. The curve labeled “Trips” is the distribution of trips where the unit of observation is a trip. For example, 53% of trips are taken by people who take 20 trips or less per month. This figure implies that 47% of JAUNT trips are taken by 7% of the users. These high demand users are using JAUNT mostly to go to work daily. Figure 1 suggests that measures taken to affect the demand of marginal users will have only marginal effects on total demand.

The second data set is the administrative records of the Charlottesville Transit System (CTS). CTS manages the eligibility process for Charlottesville users of JAUNT. A prospective JAUNT user completes a short application with CTS with a small amount of demographic information and disability information. Almost everyone who applies is granted eligibility. CTS keeps a data set with information on each eligible user, the information provided in their application, and a card number that can be used to merge the CTS information with the JAUNT information. We have the CTS records from 1984 until October 1996. Characteristics of the CTS data are available at Bearse, Gurmu, Rapaport, and Stern (2003a).

The distribution of issue dates, displayed in Figure 2, demonstrates the growth of JAUNT since 1984. The information is disaggregated by whether the user is an active user at any time between 11/94-10/96. Those not active will be referred to as “lapsed” users. Lapsed users are frequently dead, but they may also have just moved from the area or stopped using JAUNT for some other reason. The figure also suggests the short time span that most users remain active users. It suggests that an important part of predicting demand is to predict participation. But it is much harder to predict participation than to predict demand conditional on participation because we do not observe characteristics of non-users. Stern (1993) provides some information on participation. Also there is the potential to use recent local Census data to predict aggregate participation; this is attempted below.

---

5 Prospective applicants are given some eligibility information prior to application. To some degree, this serves as a prescreening device.

6 We attempted to match our records with state death records using name, self-reported birthdate, and county of residence. We were able to match only 2.5% of those who stopped using JAUNT. This is obviously not a good measure of true death. The problem occurs possibly because of misspelling of names or miscoding of birthdates.

7 Part of what is happening is that all local nursing homes file eligibility applications for all new nursing home residents. Many of those nursing home residents never use JAUNT.
The JAUNT trip data and CTS eligibility data can be merged on the basis of a common card number. There are a small number of trips in the JAUNT data that have no corresponding CTS information. These correspond to people who were given temporary permission to use JAUNT (thus the trips they take are in the JAUNT data) but never apply for permanent permission. The total number of trips corresponding to such an event is very small. There are 5067 people with 24 months of data per person in the merged sample. Characteristics of the merged sample are presented in Table 5.

The mean for TRIPS includes people who were lapsed by November 1994. The mean for trips for active people is 3.11. The mean for trips conditional on TRIPS > 0 is 10.64. Perhaps the best measure of the mean is the mean conditional on not having observationally lapsed; this is 3.76 trips per month.

The AGE variable is constructed by subtracting November 1994 minus the month and year of the person’s birthdate. In some cases the birthdate is missing, so AGE is missing. The average age of active people is 70.4, and the average age of lapsed people is 75.1. The YEARS variable is constructed by subtracting the month of a trip minus the issue date. It is surprisingly small given that it includes people who became eligible as early as 1984. The low means reflect the tremendous growth in the system over time.

MALE and FEMALE are constructed by observing the first name of the person. In those cases where it is unclear, we asked JAUNT staff to identify a person’s gender. If JAUNT staff could not identify the person, the person’s gender was coded as neither MALE nor FEMALE. The average number of medical conditions causing a need for JAUNT is 1.46, and the most common are mobility problems (NONAMBULATORY), problems with arthritis, amputation, or incoordination (ARTHRITIS, AMPUTATION, INCOORDINATION), and OTHER PROBLEM. Almost all users see their need as a permanent need.

Table 5 shows that 53% of JAUNT users live in nursing homes. However, on average, nursing home residents use JAUNT significantly less than other users. An OLS regression of logTRIPS on nine nursing home dummies and time dummies has 8 out of 9 nursing home dummies with very significant coefficients rang-

\[ \frac{1}{T} \sum_i \frac{1}{T_i} \sum_{t=1}^{T_i} y_{it}. \]

This occurs with some foreign names and names like Shirley, Marian, and Lee, which are common names for both men and women in central Virginia.

There are 9 nursing home dummies included in the analysis.
ing from −0.91 to −2.60.\footnote{A coefficient of −0.91 (for Eldercare) implies that a resident at that nursing home takes 40\% as many trips on average as a community resident, and a coefficient of −2.60 (for Westminster Canterbury) implies that a resident at that nursing home takes 7\% as many trips on average as a community resident.} This is also seen in the parameter estimates of the NURSING HOME coefficients.

Another important aspect of the data is the frequency of sequences of zero trip months of different lengths. Figure 3 presents the frequency for active person equivalents\footnote{A person equivalent is 24 months of trip data. This is different from a person because some people became eligible after November 1994.} both for right censored and uncensored sequences of zero trip months. The vertical axis is the number of sequences of a particular length per active person equivalent. Short sequences are very common: there are 1.48 sequences of length 4 months or less per active person equivalent.\footnote{0.116 of these sequences are of length 1 month and occur in the first month of eligibility. One may want to not include these.} Long sequences are not as common but still occur often enough to be of significance: there are 0.023 sequences of length 20 months or more per active person equivalent and 0.145 of length 12 months or more per active person equivalent. The uncensored long sequences of zeroes cause estimation problems.

The third data set is the Medicare Current Beneficiary Survey. It is used to estimate death rates, and it is described below. The fourth is Census data for Charlottesville. It is used to estimate the joint density of characteristics affecting paratransit usage, and it is also described below.

4. Econometric Methods

We want to model the number of trips taken by a person in a particular month as a Poisson process. We briefly consider some standard panel data count models (Hausman, Hall, and Griliches 1984, Liang and Zeger 1986). We then develop a general method that allows for dependence across months. The generalized model explicitly models the absorbing state for lapsed users.

Let \( y_{it} \) be the number of trips taken by person \( i \) in month \( t \) for \( i = 1, 2, \ldots, I \) and \( t = 1, 2, \ldots, T \).\footnote{Note that the notation in this section is independent of the notation used in Section 2.} Let \( X_{it} \) be the vector of observed covariates. Assume \( (y_{it} | \lambda_{it}) \sim \text{Poisson}(\lambda_{it}) \), where the mean parameter \( \lambda_{it} \) allows for both observed and unobserved characteristics. In particular, let

\[
\log \lambda_{it} = X_{it} \beta + u_i \tag{4.1}
\]

where \( u_i \sim iidF \). Assume that the random effect, \( \exp \{u_i\} \equiv \nu_i \), has a gamma

\[\begin{align*}
\text{where } u_i &\sim iidF. \\
\text{Assume that the random effect, } \exp \{u_i\} &\equiv \nu_i, \text{ has a gamma}
\end{align*}\]
distribution with mean unity and variance $1/\alpha$. The likelihood contribution of observation $i$ can be obtained by integrating out over the density of $\nu_i$. This gives the random effects Poisson (or negative multinomial) model. The Poisson random effects model has the restriction that the mean and the variance of the number of trips are equal. As shown in Table 4, the variance of the number of trips per month is substantially larger than the mean number of trips. We consider the negative binomial (Negbin) random effects model which allows the variance to be greater than the mean. Assume that $(y_{it} | \lambda_{it}) \sim \text{Negbin1}(\lambda_{it})$, and that $\nu_i^*$, a reparameterized version of the individual effects $\nu_i$, has a beta distribution with parameters $\alpha_1$ and $\alpha_2$. The ensuing log-likelihood function is given by Hausman, Hall, and Griliches (1984).

We also consider population-averaged panel data models using the generalized estimating equation (GEE) approach described in Liang and Zeger (1986). Apart from the specification of the marginal mean and variance of $(y_{it} | \lambda_{it})$, the approach accounts for serial correlation within the units. In implementation, we use the Poisson and negative binomial family with dispersion parameter $\phi$. In addition, we employ an exchangeable correlation as well as an autoregressive correlation structure, AR(1) with correlation parameter $\rho$.

The Negbin random effects specification allows for both overdispersion and for “individual” effects. Both the Poisson and Negbin random effects models do not allow for dependence over time through $\lambda_{it}$. The GEE approach accounts for within-units dependence and is useful only for analyzing population-averaged effects. Further, we need to address the problem of attrition due to death or other reasons. We consider generalizations along these lines.

We specify a Poisson process for the number trips taken by a person in a particular month by allowing for dependence across months. Let $e_{it} = 1$ if $i$ is active at $t$, and $e_{it} = 0$ if $i$ is lapsed at $t$. Assume $(y_{it} | \lambda_{it}) \sim \text{Poisson}(\lambda_{it})$ if $e_{it} = 1$ and $y_{it} = 0$ if $e_{it} = 0$. We allow for dependence through $\lambda_{it}$. In particular, let

$$\log \lambda_{it} = X_{it} \beta + u_i + \varepsilon_{it}$$ (4.2)

where $u_i \sim iid F$,$^{15}$

$$\varepsilon_{it} = \rho \varepsilon_{it-1} + \eta_{it},$$ (4.3)

$\varepsilon_{i0} \sim iid K$, and $\eta_{it} \sim iid G$ for some distributions $F$, $K$, and $G$. Now $\lambda_{it}$ allows for dependence through a person-specific effect $u_i$ and an AR(1) error $\varepsilon_{it}$. We allow $\varepsilon_{i0}$ to have a potentially different distribution than what would be implied by $G$ because of unobserved startup issues.

$^{15}$We now assume $u_i \sim iid N(0, \sigma^2_F)$.

$^{16}$We assume $\varepsilon_{i0} \sim iid N(0, \sigma^2_K)$ and $\eta_{it} \sim iid N(0, \sigma^2_G)$, and they are independent of each other.
We need to model lapsing to close the model. First, we assume that one cannot return from lapsing: \( e_{it} = 0 \) if \( e_{it-1} = 0 \). Next we assume that, for those active, lapsing occurs with probability \( p_{it} \) with

\[
p_{it} = \exp \{ X_{it} \gamma \} / [1 + \exp \{ X_{it} \gamma \}].
\]

This specification imposes \( 0 < p_{it} < 1 \) but still allows \( p_{it} \) to vary over people and depend upon observed characteristics of people.

The goal is to estimate \( \theta = (\beta, \gamma, F, G, K, \rho) \). There are two types of observations: a) those with \( y_{it} > 0 \) for some \( 1 \leq t \leq T \) and b) those with \( y_{it} = 0 \) for all \( 1 \leq t \leq T \). Let \( \tau_i \) be the last period where \( i \) takes a trip: \( y_{i\tau_i} > 0 \) and \( y_{is} = 0 \) for all \( s > \tau_i \). If \( y_{is} = 0 \) for all \( s \), then \( \tau_i = 0 \). Let \( S_i \) be the issue date, the date \( i \) became eligible to use JAUNT. Then

\[
q_{it} = \Pi_{s=S_i} (1 - p_{is})
\]

is the probability that \( e_{it} = 1 \) conditional on \( i \) being active at the issue date \( S_i \). We can now write

\[
H (y_{it}, \tau_i \mid u_i, \varepsilon_{it}, \theta) = \begin{cases} 
q_{it} \exp \{ -\lambda_{it} \} \lambda_{it}^{y_{it}} / y_{it}! & \text{if } t \leq \tau_i \\
[q_{it} \exp \{ -\lambda_{it} \}] + \left[ q_{i\tau_i} \left( 1 - \frac{q_{i\tau_i}}{q_{it}} \right) \right] & \text{if } t > \tau_i
\end{cases}
\]

as the likelihood of observing \( y_{it} \) and \( \tau_i \) conditional on \( u_i \) and \( \varepsilon_{it} \). The first term is the probability that \( i \) is still active at \( t \) times the Poisson probability of observing \( y_{it} \) trips. The second term is the probability of being active at \( t \) times the Poisson probability of observing 0 trips plus the probability of being lapsed given that \( i \) was active at \( \tau_i \). Since one can not observe \( u_i \) and \( \varepsilon_{it} \), one must integrate out over their joint density. Thus the likelihood contribution of observation \( i \) is

\[
L_i = \int_u \int_{\varepsilon_{i0}} \cdots \int_{\eta_{i1}} \cdots \int_{\eta_{iT}} \Pi_{i=1}^{T} [H (y_{it}, \tau_i \mid u_i, \varepsilon_{it}, \theta) dG (\eta_{it})] dK (\varepsilon_{i0}) dF (u_i),
\]

and the log likelihood function is

\[
\mathcal{L}_g(\theta) = \sum \log L_i. \quad (4.5)
\]

While \( L_i \) can not be evaluated analytically (or even numerically very easily), it can be simulated using the following procedure:

a) Simulate \( \varepsilon_{i0}^{r}, \eta_{i1}^{r}, \ldots, \eta_{iT}^{r} \), and \( u_i^{r} \) from their distributions for \( r = 1, 2, \ldots, R \).
b) Given simulated values, construct $\varepsilon_{it}^r$ and then $\lambda_{it}^r$, $t = 1, 2, \ldots, T$.

c) Evaluate $H_t^r = H(y_{it}, \tau_i \mid u_i^r, \varepsilon_{it}^r, \theta)$, $t = 1, 2, \ldots, T$.

d) Evaluate $L_t^r = \Pi_t H_t^r$.

e) Evaluate $L_t^* = \sum_{r=1}^R L_t^r / R$.

The variance of the simulator described above can be reduced by using antithetic acceleration (Geweke 1988 or Stern 1997).

Alternatively, we can assume that lapsing probabilities, $p_{it}$, should be at least as great as death probabilities. In fact, anticipating estimation results, we estimate very small, unrealistic lapsing probabilities. Thus, we estimate death probabilities using the 1992 Medicare Current Beneficiary Survey (MCBS) and then impose them on our transportation demand model as lapsing probabilities. There are 11660 observations in MCBS. Table 6 presents sample moments of the data, and Table 7 presents parameter estimates for the (probit) probability of dying in the year of the sample. These parameter estimates then can be used to predict $p_{it}^{12}$, and $\hat{p}_{it}$ (equals the twelfth root of the predicted $p_{it}^{12}$) can be substituted into equation (4.5).

5. Estimation Results

Preliminary results from the Poisson and Negbin random effects models show that the Negbin random effects model dominates the Poisson model in terms of both the log-likelihood and the Akaike information criterion. The estimates are not reliable because they do not incorporate demand by lapsed users and serial correlation. Nevertheless, they may still be suggestive. Since extra-Poisson variation usually leads to inflated $t$-ratios, the significance results from the Poisson regression should be treated with caution. We focus on the results from the Negbin model. The effect of age on the number of trips is insignificant. The coefficient on FEMALE indicates that, keeping other factors constant, women take about 30% more trips per month than men. The coefficient on NURSING HOME is negative, suggesting that nursing home residents take fewer trips than community residents. For most of the months, demand per user is constant over time. The unobserved heterogeneity parameters ($\alpha_1, \alpha_2$) are significant.

Results from the GEE approach (not reported here) show that the estimate of the correlation parameter is large: $\hat{\rho} = 0.83$. The effect of age on the number of trips is insignificant. The coefficient on FEMALE indicates that, keeping other factors constant, women take about 30% more trips per month than men. The coefficient on NURSING HOME is negative, suggesting that nursing home residents take fewer trips than community residents. For most of the months, demand per user is constant over time. The unobserved heterogeneity parameters ($\alpha_1, \alpha_2$) are significant.

---

17 Estimation results from the Poisson and Negbin random effects models and the GEE approach are available at Bearse, Gurmu, Rapaport, and Stern (2003a).
trips is negative: for each additional year of age, trips decrease by 1.627%, holding other observed factors constant. The FEMALE variable is not significant. The coefficient on NURSING HOME is negative and significant, suggesting that nursing home residents take fewer trips than community residents. As compared to the Hausman, Hall, and Griliches models, once we control for serial correlation using the GEE approach, most of the month-year dummies are insignificant. Results from the standard count models show that there is extra-Poisson variation in the trip data even after controlling for observed characteristics.

Next, we present results from the preferred model specified in Section 4. Table 8 presents parameter estimates conditioning on the death probability parameter estimates for $\gamma$ from Table 7.\textsuperscript{18} Except for the last four estimates ($\rho$, $\sigma_F$, $\sigma_G$, and $\sigma_K$), the parameter estimates are for the effects of observed characteristics on the log trip rate $\beta$. For example, the coefficient on AGE/100, $-1.547$, implies that, holding all other observed characteristics constant, each extra year of age decreases the log trip rate by 0.01547 (trips fall by 1.547%); this suggests that a relatively small number of younger users take most of the trips. Reported t-statistics are based on a parametric bootstrapping procedure.\textsuperscript{19} This was done because the usual BHHH (1974) standard errors are unreasonably small. We report median bias estimates in Bearse, Gurmu, Rapaport, and Stern (2003a) and show that almost all of the parameters are estimated with median biases smaller than their standard errors. In most cases, t-statistics are consistent with confidence intervals based on the median bias-adjusted 5% - 95% confidence intervals of the bootstrap order statistics. Table 8 stars those estimates whose median bias-adjusted 5% - 95% confidence intervals exclude zero.

The coefficient on NURSING HOME is $-0.558$, suggesting that, holding everything else constant, nursing home residents take 43% fewer trips than community residents. This is a significantly smaller effect than listed in the earlier section because there we were not holding everything else constant. In particular, we were not holding medical conditions constant. The calendar time dummies, NOV94 through OCT96, are graphed in Figure 4. They suggest large negative serial correlation and, once smoothed (over five months) a significant seasonal effect. However, they suggest for the most part that demand per user is constant over time.\textsuperscript{20} Thus, change in use per user will not explain aggregate growth of

\textsuperscript{18}We also estimated a model estimating $\gamma$. The estimates are qualitatively similar. The log likelihood function is significantly larger when $\gamma$ is estimated, but the resulting lapsing probabilities $p_{it}$ are unrealistically small. So we focus our discussion on the parameter estimates associated with setting $\gamma$ equal to the death probability parameters reported in Table 7.

\textsuperscript{19}The bootstrapping procedure estimates the model 50 times with independent draws of the data simulated using the estimated parameters.

\textsuperscript{20}The time trend has an OLS coefficient estimate of 0.003 with a t-statistic of 0.93.
the system.

The last four parameter estimates provide information about the sources of unobserved heterogeneity. The \( \rho \) coefficient is large and significant, suggesting an interesting autoregressive error process occurring in the log trip rates \( \lambda \). The estimate of \( \sigma_F \) is 1.478; this suggests a very large time-constant, person-specific effect. The estimate of \( \sigma_G \) is 1/7 the size of \( \sigma_F \) suggesting that innovations to \( \eta \) in equation (4.3) are significantly smaller than the standard deviation of the person specific effect \( u_i \) in equation (4.2). However the long run standard deviation of \( \varepsilon_{it} \) in equation (4.3) is \( \sigma_G/\sqrt{1 - \rho^2} = 0.752 \), only 1/2 the size of \( \sigma_F \). The estimate of \( \sigma_K \) is 3 times as large as \( \sigma_G \), and it is approximately equal to the long run standard deviation, suggesting that \( \varepsilon_{it} \) is generated by a stationary process. Together, \( u_i \) and \( \varepsilon_{it} \) add significantly more variance to the process generating trips than would be suggested by a Poisson model.

6. JAUNT Participation Estimates

As was shown in Figure 2, there has been significant growth in the number of people eligible to use JAUNT. One way to predict growth in eligible people would be to use 1980 and 1990 Charlottesville Census data to simulate the joint density of the population and then to compare the simulated joint density to the population of JAUNT users. We used 1990 Census data for Charlottesville and PUMS data for the PUMS region including Charlottesville to simulate the joint density of sex, race, age, education, and mobility disability. This exercise provided us with an estimate of the number of people in Charlottesville with a mobility disability by sex and age. The reported mobility disability rate in the Census data is 2.87\% for males and 4.63\% for females. We then compared these numbers to the number of JAUNT eligible riders by sex and age.

The ratio of JAUNT riders to size of population is presented in Table 9.\footnote{We performed the same exercise using 1980 Census data and got similar results.} For example, for every mobility disabled male between the ages of 30 to 34, there are 2.367 males in the same age range using JAUNT. Overall, the numbers in Table 9 suggest that either the Census grossly underreports disability rates or there is something very unique about JAUNT riders.\footnote{Part of the problem here is that nursing home residents are not included in the Census data. However, this can not explain the magnitude of the problem, especially for young and middle aged adults.} An alternative is to use the proportion of the total population, disaggregated by sex and age, reported in Table 9, as predictors of demand for JAUNT eligibility. These provide reasonable estimates in a cross-section sense. But they can not explain the phenomenal
growth in demand for JAUNT eligibility because the Charlottesville population did not significantly grow over the relevant period.

Figure 5 displays per capita trips for JAUNT relative to other paratransit providers across the United States in small and medium sized cities. In fact, JAUNT is in the 99th percentile of trips per capita, and its annual growth rate is more than twice as high as the average. It is clear that there is something unique about JAUNT, but it is not clear what it is. However, the qualitative results in JAUNT are similar to the rest of the country. In particular, there are three sources of growth in trips per capita: population growth, proportion of the population using paratransit, and trips per paratransit participant. The data for JAUNT shows that the proportion of the population using paratransit is growing robustly. Table 1 shows that the same phenomenon is occurring at a national level. The JAUNT results suggest that very little of the demand growth can be attributed to growth in trips per user. This strongly suggests that the significant source of growth is in the proportion of the population using paratransit. An area for further research is what is causing this growth.

7. Conclusions

Moderate sized American cities have shown phenomenal growth in demand for paratransit. Our results suggest that most of that growth is due to increased participation rather than increased demand per user. It is not clear what has caused large increases in participation. In fact, in Charlottesville, more than 100% of the estimated mobility disabled population is using paratransit.

Our results provide some insight on the variation in usage across users. They strongly suggest that a relatively small proportion of users represent a large fraction of total trips. This implies that programs aimed at marginal users such as nursing home residents will not be effective because they represent such a small proportion of total trips. An approach more likely to be fruitful is to organize heavy users more efficiently. For example, JAUNT tries to organize many heavy users into what are essentially fixed routes.

Further analysis will require better information on the population of potential paratransit users, their relevant characteristics, and their transportation choices. Stern (1993) was a small, specialized sample of that type.

---

23 The denominator is the local population, not just disabled people.
24 To the degree that marginal users require extra resources per trip, there may be some value in trying to help them use the paratransit system more efficiently (Fitzgerald, Shaunesey, and Stern 2000).
8. Appendix: Using Section 15 Data

The National Transit Database (NTD) provides information on many various aspects of public transportation systems across the United States. We have access to the years 1984 through 1995 and have stored it at 


We restrict our analysis to demand response systems in communities with no more than 400,000 people as measured by the 1980 PUMS Census Data (this is available at the same web site).

The key variable used in this analysis is the number of unlinked demand response passenger trips. Constructing this series involves some aggregation. In particular, sometimes the units in the NTD data do not correspond to geographic units. Thus, we aggregate systems from the same metropolitan area.

There are many missing observations in the NTD data. They generally are of two types. Consider a vector with 12 elements (the number of potential years in the data) where an “o” element signifies that the data for that year is observed and a “m” element signifies that the data for that year is missing. For example, \((m, m, m, m, m, m, o, o, o, o, o, o)\) signifies that there is no data for the first seven years and there is data for the last five years. One pattern of missing data is the example above where data is observed only for some year after 1984. We interpret this as a system that began in the first year of observed data. The second pattern of missing data can be characterized by the example \((o, o, o, m, o, o, o, m, o, o, o)\). We interpret such an example as truly missing data in years 4 (1987) and 9 (1992) and impute them by interpolation.

9. Appendix: Likelihood Function for Model with Selection

Given the model specification in equations (2.4) through (2.7), the likelihood contribution for system \(i\), conditional on \(u_i\), can be written as

\[
L_i(u_i) = \int_{D_{1i}}^{U_{1i}} \cdots \int_{D_{Ti}}^{U_{Ti}} \prod_{t=1}^{T} f_t(\eta_{it} \mid \tilde{\eta}_{it}) d\eta_{it} \tag{9.1}
\]

with

\[
D_{it} = \begin{cases} 
-\infty & \text{if } y_{2it} = 0 \\
-X_{it}\beta_2 - u_{2i} - \Gamma_{2e_{it}} & \text{if } y_{2it} = 1 
\end{cases}
\]

\(^{25}\)An appendix similar to this appears in Fitzgerald, Shaunesey, and Stern (2000).

\(^{26}\)An unlinked passenger trip is a trip from an origin to a destination with no intermediate stops. For example, one round trip would usually consist of two unlinked trips.
\[ U_{it} = \begin{cases} -X_{i1}\beta_2 - u_{2i} - \Gamma_2\varepsilon_{it} & \text{if } y_{2it} = 0 \\ \infty & \text{if } y_{2it} = 1 \end{cases} \]

\[ \tilde{\eta}_{it} = \begin{cases} \{ \eta_{i1}, \ldots, \eta_{it-1} \} & \text{for } t > 1 \\ \emptyset & \text{for } t = 1 \end{cases} \]

\[ f_t(\eta_{it} | \tilde{\eta}_{it}) = [1 (\eta_{1it} = y_{1it} - X_{i1}\beta_1 - u_{1i} - \Gamma_1\varepsilon_{it-1})]^{y_{2it}} \cdot \frac{1}{\sqrt{\Omega_{\eta_{11}}}} \phi \left( \frac{\eta_{1it}}{\sqrt{\Omega_{\eta_{11}}}} \right) \frac{1}{\sqrt{(1 - \rho^2)\Omega_{\eta_{22}}}} \phi \left( \frac{\eta_{2it} - \rho^* \eta_{1it}}{\sqrt{(1 - \rho^2)\Omega_{\eta_{22}}}} \right) \]

where

\[ \rho = \frac{\Omega_{\eta_{12}}}{\sqrt{\Omega_{\eta_{22}}\Omega_{\eta_{11}}}} \]

\[ \rho^* = \frac{\Omega_{\eta_{12}}}{\Omega_{\eta_{11}}} \]

The log likelihood function is

\[ \sum_i \log \int L_i(u_i) \, dF_u(u_i) \quad (9.2) \]

where \( F_u(\cdot) \) is the joint distribution function of \( u_i \). Equations (9.1) and (9.2) can be approximated with GHK (Hajivassiliou, McFadden, and Ruud 1994).

### 10. References

**References**


11. Tables and Figures

Table 1
Summary Statistics for NTD

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th># Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln$ (Trips)</td>
<td>0.105</td>
<td>0.506</td>
<td>1836</td>
</tr>
<tr>
<td>$\Delta \ln$ (Pop)</td>
<td>0.008</td>
<td>0.012</td>
<td>1836</td>
</tr>
<tr>
<td>$\Delta \ln$ (Pop65)</td>
<td>0.024</td>
<td>0.012</td>
<td>1836</td>
</tr>
</tbody>
</table>

Note: Descriptive statistics are based on only those observations where computing the first difference did not involve a missing value.
## Table 2
### NTD Regression Results

<table>
<thead>
<tr>
<th>Time</th>
<th>Total Population</th>
<th>Population Aged 65 and Over</th>
<th>$\rho$</th>
<th>CAICF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>14038.3</td>
</tr>
<tr>
<td>0.102**</td>
<td>0.951**</td>
<td>1.000**</td>
<td>4.688**</td>
<td>14080.8</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.028)</td>
<td>(0.025)</td>
<td>(0.775)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.646**</td>
<td>0.959**</td>
<td>1.017</td>
<td>14040.2</td>
</tr>
<tr>
<td></td>
<td>(0.391)</td>
<td>(0.027)</td>
<td>(0.827)</td>
<td></td>
</tr>
<tr>
<td>0.093**</td>
<td>0.949**</td>
<td>1.000**</td>
<td>-1.068</td>
<td>14038.9</td>
</tr>
<tr>
<td>(0.012)</td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(1.079)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.129</td>
<td>0.948**</td>
<td>0.466</td>
<td>14039.8</td>
</tr>
<tr>
<td></td>
<td>(0.843)</td>
<td>(0.028)</td>
<td>(1.165)</td>
<td></td>
</tr>
<tr>
<td>0.075**</td>
<td>1.139</td>
<td>0.948**</td>
<td>-1.058</td>
<td>14041.1</td>
</tr>
<tr>
<td>(0.023)</td>
<td>(0.916)</td>
<td>(0.027)</td>
<td>(1.189)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.062</td>
<td>1.000**</td>
<td>1.165</td>
<td>14040.4</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.028)</td>
<td>(1.295)</td>
<td></td>
</tr>
<tr>
<td>0.105**</td>
<td>1.000</td>
<td>1.000**</td>
<td>4.688**</td>
<td>14032.1</td>
</tr>
<tr>
<td>(0.013)</td>
<td>(0.843)</td>
<td>(0.028)</td>
<td>(0.771)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.720**</td>
<td>1.000**</td>
<td>1.062</td>
<td>14032.8</td>
</tr>
<tr>
<td></td>
<td>(0.422)</td>
<td>(0.028)</td>
<td>(0.916)</td>
<td></td>
</tr>
<tr>
<td>0.096**</td>
<td>1.000</td>
<td>1.000**</td>
<td>1.130</td>
<td>14034.1</td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.926)</td>
<td>(0.028)</td>
<td>(0.926)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.167**</td>
<td>1.000**</td>
<td>0.544</td>
<td>14034.1</td>
</tr>
<tr>
<td></td>
<td>(0.654)</td>
<td>(0.028)</td>
<td>(1.295)</td>
<td></td>
</tr>
</tbody>
</table>

Notes:

1. The dependent variable is difference in log aggregate trips.
2. Standard errors are in parentheses.
3. Double starred items are significant at the 1% level, and single starred items are significant at the 5% level.
4. The CAICF for all log regressions are significantly smaller than the corresponding numbers for levels regressions.

5. The sample size is 1905.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>constant</td>
</tr>
<tr>
<td>TRIPS</td>
<td># trips taken per month</td>
</tr>
<tr>
<td>TTRIPS</td>
<td># total trips taken between 11/94-10/96</td>
</tr>
<tr>
<td>CVILLE</td>
<td>client is a Charlottesville resident</td>
</tr>
<tr>
<td>AGE</td>
<td>age at 11/94</td>
</tr>
<tr>
<td>YEARS</td>
<td># years using JAUNT as of time of the trip</td>
</tr>
<tr>
<td>FEMALE</td>
<td>client is female</td>
</tr>
<tr>
<td>MALE</td>
<td>client is male</td>
</tr>
<tr>
<td>NONAMBULATORY</td>
<td>client is nonambulatory</td>
</tr>
<tr>
<td>MOBILITY AID</td>
<td>client needs a mobility aid</td>
</tr>
<tr>
<td>ARTHRITIS,</td>
<td>client has problem with arthritis, amputation, or incoordination</td>
</tr>
<tr>
<td>AMPUTATION,</td>
<td></td>
</tr>
<tr>
<td>INCOORDINATION</td>
<td></td>
</tr>
<tr>
<td>CEREBRO-</td>
<td>client has cerebrovascular problem</td>
</tr>
<tr>
<td>VASCULAR</td>
<td></td>
</tr>
<tr>
<td>PULMONARY</td>
<td>client has pulmonary problem</td>
</tr>
<tr>
<td>KIDNEY</td>
<td>client has kidney problem</td>
</tr>
<tr>
<td>SIGHT</td>
<td>client has sight problem</td>
</tr>
<tr>
<td>MENTAL</td>
<td>client is mentally retarded or autistic</td>
</tr>
<tr>
<td>RETARDATION</td>
<td></td>
</tr>
<tr>
<td>NEUROLOGICAL</td>
<td>client has neurological problem</td>
</tr>
<tr>
<td>PROBLEM</td>
<td></td>
</tr>
<tr>
<td>OTHER PROBLEM</td>
<td>client has “other” problem</td>
</tr>
<tr>
<td>PERMANENT</td>
<td>client’s problem is permanent</td>
</tr>
<tr>
<td>PROBLEM</td>
<td></td>
</tr>
<tr>
<td>NEEDS</td>
<td>client needs an attendant</td>
</tr>
<tr>
<td>ATTENDENT</td>
<td></td>
</tr>
<tr>
<td>NURSING HOME</td>
<td>client lives in a nursing home</td>
</tr>
</tbody>
</table>
Table 4
Moments of JAUNT Data

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean # Trips/Month</td>
<td>3.51</td>
</tr>
<tr>
<td>Std. Dev. # Trips/Month</td>
<td>8.40</td>
</tr>
<tr>
<td>First Order Autocorrelation</td>
<td>0.564</td>
</tr>
<tr>
<td>Individual Specific Std. Dev.</td>
<td>8.686</td>
</tr>
<tr>
<td>Idiosyncratic Std. Dev.</td>
<td>5.084</td>
</tr>
</tbody>
</table>
Table 5
Merged Data Moments

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRIPS</td>
<td>1.16</td>
<td>5.10</td>
<td>MENTAL RETARDATION</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>AGE</td>
<td>73.16</td>
<td>19.22</td>
<td>NEUROLOGICAL PROBLEM</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>NONAMBULATORY</td>
<td>0.27</td>
<td>0.44</td>
<td>OTHER PROBLEM</td>
<td>0.27</td>
<td>0.45</td>
</tr>
<tr>
<td>ARTHRITIS, AMPUTATION, INCOORDINATION</td>
<td>0.27</td>
<td>0.44</td>
<td>NEEDS ATTENDENT</td>
<td>0.16</td>
<td>0.37</td>
</tr>
<tr>
<td>CEREBRO-VASCULAR</td>
<td>0.24</td>
<td>0.43</td>
<td>FEMALE</td>
<td>0.65</td>
<td>0.48</td>
</tr>
<tr>
<td>PULMONARY</td>
<td>0.11</td>
<td>0.31</td>
<td>MALE</td>
<td>0.35</td>
<td>0.48</td>
</tr>
<tr>
<td>KIDNEY</td>
<td>0.04</td>
<td>0.19</td>
<td>NURSING HOME</td>
<td>0.53</td>
<td>0.50</td>
</tr>
<tr>
<td>SIGHT</td>
<td>0.13</td>
<td>0.34</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 6
Sample Moments for the MCBS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGE/100</td>
<td>0.706</td>
<td>0.146</td>
<td>SIGHT(little)</td>
<td>0.326</td>
<td>0.469</td>
</tr>
<tr>
<td>FEMALE</td>
<td>0.564</td>
<td>0.496</td>
<td>SIGHT(lot)</td>
<td>0.117</td>
<td>0.321</td>
</tr>
<tr>
<td>NONAMBULATORY</td>
<td>0.225</td>
<td>0.418</td>
<td>MENTAL RETARDATION</td>
<td>0.041</td>
<td>0.199</td>
</tr>
<tr>
<td>MOBILITY AID</td>
<td>0.185</td>
<td>0.388</td>
<td>NEUROLOGICAL PROBLEM</td>
<td>0.020</td>
<td>0.139</td>
</tr>
<tr>
<td>ARTHRITIS, AMPUTATION, INCOORDINATION</td>
<td>0.586</td>
<td>0.493</td>
<td>OTHER PROBLEM</td>
<td>0.435</td>
<td>0.496</td>
</tr>
<tr>
<td>CEREBRO-VASCULAR</td>
<td>0.683</td>
<td>0.465</td>
<td>NURSING HOME</td>
<td>0.090</td>
<td>0.286</td>
</tr>
<tr>
<td>PULMONARY</td>
<td>0.141</td>
<td>0.348</td>
<td>DIED</td>
<td>0.050</td>
<td>0.218</td>
</tr>
<tr>
<td>KIDNEY</td>
<td>0.156</td>
<td>0.363</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The variables are defined in Table 3.
Table 7
Parameter Estimates for Death Probabilities

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-5.189</td>
<td>(-5.36)</td>
</tr>
<tr>
<td>MOBILITY AID</td>
<td>0.416**</td>
<td>(0.110)</td>
</tr>
<tr>
<td>SIGHT (little)</td>
<td>0.228</td>
<td>(2.21)</td>
</tr>
<tr>
<td>MOBILITY AID</td>
<td>0.416**</td>
<td>(0.110)</td>
</tr>
<tr>
<td>SIGHT (lot)</td>
<td>0.565</td>
<td>(4.52)</td>
</tr>
<tr>
<td>AGE/100</td>
<td>-1.054</td>
<td>(-0.40)</td>
</tr>
<tr>
<td>SIGHT (little)</td>
<td>0.228</td>
<td>(2.21)</td>
</tr>
<tr>
<td>SIGHT (lot)</td>
<td>0.565</td>
<td>(4.52)</td>
</tr>
<tr>
<td>(AGE/100)^2</td>
<td>3.937</td>
<td>(2.13)</td>
</tr>
<tr>
<td>PULMONARY</td>
<td>0.326</td>
<td>(2.79)</td>
</tr>
<tr>
<td>OTHER PROBLEM</td>
<td>0.268</td>
<td>(2.91)</td>
</tr>
<tr>
<td>FEMALE</td>
<td>-0.713</td>
<td>(-7.59)</td>
</tr>
<tr>
<td>KIDNEY</td>
<td>0.314</td>
<td>(2.78)</td>
</tr>
<tr>
<td>NURSING HOME</td>
<td>0.715</td>
<td>(5.91)</td>
</tr>
<tr>
<td>NONAMBULATORY</td>
<td>0.745</td>
<td>(6.54)</td>
</tr>
</tbody>
</table>

Notes:

1. Only statistically significant estimates excluding regional dummies are reported. A full table of estimates is available at Bearse, Gurmu, Rapaport, and Stern (2003a).

2. Numbers in parentheses are t-statistics.
Table 8
Parameter Estimates for Trip Demand
Generalized Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Variable</th>
<th>Estimate</th>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>2.293*</td>
<td>KIDNEY</td>
<td>-0.917*</td>
<td>$\rho$</td>
<td>0.961*</td>
</tr>
<tr>
<td></td>
<td>(7.89)</td>
<td></td>
<td>(-2.44)</td>
<td></td>
<td>(73.92)</td>
</tr>
<tr>
<td>CVILLE</td>
<td>-0.371*</td>
<td>SIGHT</td>
<td>0.505*</td>
<td>$\sigma_F$</td>
<td>1.478*</td>
</tr>
<tr>
<td></td>
<td>(-2.43)</td>
<td></td>
<td>(2.46)</td>
<td></td>
<td>(43.49)</td>
</tr>
<tr>
<td>AGE/100</td>
<td>-1.547*</td>
<td>MENTAL RETARDATION</td>
<td>0.511*</td>
<td>$\sigma_G$</td>
<td>0.208*</td>
</tr>
<tr>
<td></td>
<td>(-5.00)</td>
<td></td>
<td>(2.00)</td>
<td></td>
<td>(5.49)</td>
</tr>
<tr>
<td>NONAM BULATORY</td>
<td>-0.427</td>
<td>OTHER PROBLEM</td>
<td>-0.327*</td>
<td>$\sigma_K$</td>
<td>0.776*</td>
</tr>
<tr>
<td></td>
<td>(-1.88)</td>
<td></td>
<td>(-1.82)</td>
<td></td>
<td>(5.95)</td>
</tr>
<tr>
<td>MOBILITY AID</td>
<td>0.340</td>
<td>PERMANENT PROBLEM</td>
<td>-0.356</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
<td></td>
<td>(-1.59)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PULMONARY</td>
<td>-0.272*</td>
<td>NURSING HOME</td>
<td>-0.558*</td>
<td>LogLik</td>
<td>-144860.8</td>
</tr>
<tr>
<td></td>
<td>(-1.27)</td>
<td></td>
<td>(-3.33)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:

1. Only statistically significant estimates excluding time dummies are reported. A complete set of estimates is available at Bearse, Gurmu, Rapaport, and Stern (2003a).

2. Numbers in parentheses are t-statistics from the parametric bootstrapping method. Starred items have a median-bias adjusted 90% confidence interval excluding zero.
Table 9
Estimated Proportion of Population Using JAUNT Based on Census Data

<table>
<thead>
<tr>
<th>Age Range</th>
<th>Disabled Males</th>
<th>All Males</th>
<th>Disabled Females</th>
<th>All Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-29</td>
<td>2.34</td>
<td>0.007</td>
<td>0.58</td>
<td>0.004</td>
</tr>
<tr>
<td>30-34</td>
<td>2.37</td>
<td>0.006</td>
<td>1.04</td>
<td>0.005</td>
</tr>
<tr>
<td>35-39</td>
<td>1.30</td>
<td>0.005</td>
<td>0.83</td>
<td>0.005</td>
</tr>
<tr>
<td>40-44</td>
<td>1.16</td>
<td>0.005</td>
<td>1.61</td>
<td>0.011</td>
</tr>
<tr>
<td>45-49</td>
<td>2.37</td>
<td>0.015</td>
<td>1.75</td>
<td>0.014</td>
</tr>
<tr>
<td>50-54</td>
<td>2.73</td>
<td>0.021</td>
<td>1.45</td>
<td>0.017</td>
</tr>
<tr>
<td>55-59</td>
<td>0.95</td>
<td>0.015</td>
<td>1.01</td>
<td>0.026</td>
</tr>
<tr>
<td>60-61</td>
<td>0.80</td>
<td>0.019</td>
<td>1.06</td>
<td>0.026</td>
</tr>
<tr>
<td>62-64</td>
<td>0.52</td>
<td>0.012</td>
<td>0.87</td>
<td>0.031</td>
</tr>
<tr>
<td>65-69</td>
<td>0.28</td>
<td>0.011</td>
<td>0.64</td>
<td>0.039</td>
</tr>
<tr>
<td>70-74</td>
<td>0.46</td>
<td>0.038</td>
<td>0.66</td>
<td>0.066</td>
</tr>
<tr>
<td>75-79</td>
<td>0.36</td>
<td>0.053</td>
<td>0.77</td>
<td>0.134</td>
</tr>
<tr>
<td>80-84</td>
<td>0.29</td>
<td>0.070</td>
<td>0.57</td>
<td>0.165</td>
</tr>
<tr>
<td>85+</td>
<td>0.48</td>
<td>0.188</td>
<td>0.76</td>
<td>0.346</td>
</tr>
</tbody>
</table>
Figure 11.2:

Figure 2
Figure 11.3:

Figure 3
Figure 11.4:

Figure 4
Figure 11.5:

Figure 5