Empirical Analysis of Bus Transit
On-Time Performance

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Abstract

This paper presents an empirical assessment of factors affecting on-time performance in Portland, Oregon's fixed route bus system. A multinomial logit model relating early, late and on time bus arrivals to route, schedule, driver and operating characteristics is developed and estimated. The model results show that the probability of on-time failures increases during PM peak periods, with longer headways and higher levels of passenger activity, and as buses progress further along their routes. Part time drivers are also more likely to fall behind schedule. With few exceptions, schedule changes and operations control actions can mitigate these effects.

1. INTRODUCTION

The 1980s may be characterized as the decade when transit operators shifted their attention from quantity to quality aspects of service. A survey of transit systems by Bates (1986), for example, identified on-time service as an important operating objective, for reasons that have become well known. Among them, a primary concern is that unreliable service adds to passengers' out-of-vehicle waiting times, which is one of the most onerous factors affecting the choice of mass transit modes.

The Bates survey also revealed a belief that more research was needed on the causes of poor on-time performance and on the development of scheduling and operating practices which would improve transit service reliability. As Abkowitz and Tozzi (1987) point out, however, empirical research has lagged analytical and simulation efforts, primarily as a result of logistical problems in assembling appropriate data.

In this paper we focus on the empirical question of determining the effects of various scheduling, route, driver and operating characteristics on schedule adherence. The
approach taken defines performance in terms of discrete events - being "early," "on time" or "late" - and a multinomial logit model is estimated to assess the contribution of potential determinants of these alternative outcomes. Our analysis uses data collected by the Tri-County Metropolitan Transportation District of Oregon (Tri-Met) in conjunction with its UMTA Section 15 reporting requirements for 1991.

Previous research has focused either on the shape of the frequency distribution of differences between actual and scheduled bus arrival times (Talley and Becker, 1987; Guenther and Hamat, 1988), or on key indicators of service reliability, such as running time and headway variation (Abkowitz and Engelstein, 1983, 1984). The former approach provides a clear descriptive picture of on-time performance, but does not systematically assess the effects of underlying causes. The latter approach considers various determinants of transit service reliability in detail, but does not directly address on-time performance. Thus, a basic purpose of this paper is to make an attempt at bridging these two areas of research.

In the next section we discuss various determinants of on-time performance. This is followed by a review of empirical research on the subject. We then present the model employed in the present analysis, along with a description of the data. The paper concludes with the presentation and discussion of empirical results.

2. FACTORS CONTRIBUTING TO POOR ON-TIME PERFORMANCE

A commonly employed convention is to distinguish contributors to poor on-time performance based on whether they are internal or external to the bus system. Associated with internal causes would be such factors as driver experience/behavior, the sensitivity of the schedule to route conditions (in regard to setting headways, run times, and layover times), and the complexity of the route (its length, number of stops, and spacing/variability of boardings and alightings). Factors which are external to the transit system include traffic
congestion and traffic incidents, signal timing, weather, and disruptions from on-street parking.

While one may be tempted to also classify factors affecting on-time performance as “controllable” and “uncontrollable,” Woodhull (1987) argues that this would be a mistake. He acknowledges that while “complete control is impossible, a bus service is like any other stochastic system; there are causes of variation, and there are actions that can result in partial correction.” (Woodhull, 1987; p. 3). Consequently, with information on the probability distributions of factors affecting on-time performance, Woodhull contends that one can accommodate the so-called uncontrollables in setting bus schedules or through real-time corrective actions. A greater understanding of the variation of key determinants of on-time service is being gained (e.g., see Levinson, 1983; and Abkowitz and Engelstein, 1984), and the result is that more realistic scheduling and service simulation models have been developed (Senevirante, 1990).

Depending on the causes of poor on-time performance, a number of actions can be taken to improve the quality of service. These actions can be characterized as either short term or longer term remedies. The objective of a short term remedy is to return service to the schedule in the event of an occasional “unanticipated” failure. For example, in the event of early arrivals, buses can be held at time points. For late arrivals, an additional bus can be inserted in the route to relay with the delayed bus, a following bus can be instructed to “leap-frog,” or a late bus can be instructed to turn around before it reaches the end of its route. An important consideration in holding or diverting strategies is the implicit time cost these actions impose on individuals who are either on board a bus that is held or diverted or who are waiting for a bus that is not on schedule.

Longer term remedies focus on systematic on-time failures and are concerned with either driver behavior or schedule and route design. If driver behavior is a root cause of poor on-time performance, monitoring is an essential first step, followed possibly by a program in which drivers who are consistently on schedule are rewarded and those who

3
consistently fail to maintain schedules are in some way penalized. Whatever the
programmatic response, monitoring on-time performance indicates to drivers that this
objective is important enough that resources and attention are being devoted to it.

Run times can be lengthened on routes experiencing consistent delays. On routes
where delays are frequent but not consistent, layover times may be increased so that drivers
who complete trips late can be assured of beginning their next trip on time. Also, high load
variation may call for a closer examination of headways. A complex route configuration
can produce poor on-time performance, and on-time failures are likely to be more frequent
if the peak load point occurs at the beginning of the run.

Clearly, one could maximize on-time performance by designing a system of short
routes containing few stops, and setting schedules with long run and layover times. But
such a system would neither adequately serve passenger demands nor represent an efficient
use of operator resources. The hypothetical optimal level of on-time performance thus
represents a trade-off involving marginal costs to the operator associated with providing
service of differing levels of on-time performance, and marginal user benefits, which
consist of the value of changes in waiting time, accounting for the effect of the timeliness of
service on ridership demand. As in the case of optimal road pricing, in which the outcome
contains some amount of congestion, optimal scheduling of transit service will result in
some percentage of arrivals which are not on time.

3. EMPIRICAL STUDIES

Studies of on-time performance are generally concerned with either establishing the
probability distribution of deviations of observed versus scheduled arrival times
(Turnquist, 1978; Talley and Becker, 1987; Gwenthner and Hamat, 1988), or with
assessing service reliability, as represented by running times, run time variation, and
Turnquist (1978) was the first to consider the frequency distribution of bus arrival times. He speculated that there was a limit to the time a bus could arrive early, as well as a number of mitigating actions that could be taken to avoid early arrivals, while various factors could collectively contribute to very late arrivals. Turnquist thus employed a log normal distribution of bus arrivals in evaluating the effect of service performance on passenger waiting times.

Talley and Becker (1987) sampled bus arrivals at selected stops on 41 routes served by the Tidewater Transportation District Commission and constructed probability distributions for both early and late arrivals. Route-specific probabilities of early arrival ranged from zero to 82 percent, while probabilities of late arrival ranged from zero to 54 percent. Talley and Becker were unable to reject the hypothesis that the sample distributions were drawn from an exponential probability distribution. They also analyzed the effect of alternative on-time standards on estimated failure probabilities, and suggested that transit managers consider adopting ranges of acceptable arrival times that are sensitive to route-specific conditions.

Guenthner and Hamat (1988) analyzed a sample of nearly 800 bus arrivals on four routes in Milwaukee. Tests of the sample probability distribution rejected the null hypothesis that the underlying distribution was log normal, but could not reject the null hypothesis for a gamma distribution. The authors also found that AM and PM peak arrivals were, on average, about a minute late, while arrivals during the mid-day period averaged more than a minute early, with the differences being statistically significant. Buses also tended to be late near their peak load points and early at end points.

If running times and headway variations can be statistically predicted with precision, this suggests that schedules can be written to account for a variety of conditions that buses encounter along routes. The contributions of Abkowitz and his associates on this topic have been important (Abkowitz and Engelstein, 1983, 1984; Abkowitz and Tozzi, 1987). Abkowitz and Engelstein (1983) regressed mean running times (from 56
space-time segments of two bus routes in Cincinnati) on segment length, the number of
boarding and alighting passengers, the proportion of the route in which peak period on-
street parking was permitted, the number of signalized intersections, and time-of-day and
direction dummies. All the parameter estimates were statistically significant, with the
independent variables accounting for over 90% of the variation in running times. Similar
results were also obtained from another bus system (Abkowitz and Tozzi, 1987).

Direct examination of run time and headway variation bring us a step closer to the
assessment of on-time performance. Abkowitz and Engelstein (1984) analyzed the former
by regressing running time standard deviations on mean running times (which the authors
defined to be an instrument for the variables identified in the paragraph above), using data
from Cincinnati and Los Angeles. Separate equations were estimated for AM peak, mid-
day, and PM peak periods. As with the case of their run time models, Abkowitz and
Engelstein (1984) found that the run time variation models provided a strong fit of the data.
However, the transferability of the latter model has not been clearly established (Abkowitz
and Tozzi, 1987).

Headway variation is an obvious consequence of run time variability, but the
relationship between these two service reliability indicators is neither direct nor easily
modeled. This is in part because a bus’s dwell time is influenced by its own headway
deviation which, in turn, may be influenced by headway deviation of the bus ahead of it
(the “bus bunching” problem). As Guenthner and Hamat (1988) have pointed out, this
inter-bus effect can result in relatively larger arrival time deviations for routes with either
short or long headways. Short headways, for example, reflect higher passenger demand
per stop. Failing to adhere to schedule in this case can quickly result in large changes in
dwell time. Alternatively, buses with long headways may be subject to greater passenger
demand variation over the route or over time. In either case, when headway variance
becomes large passengers are less able to plan their arrival at a stop to coincide with a bus’s
arrival. As a result, large headway variance contributes to a higher proportion of random
4. RATIONALE OF THE ON-TIME PERFORMANCE MODEL

The run time, run time variation and headway variation models are all very data intensive. The models use replicated observations of bus operations on selected route segments at designated times to establish unit values of the variables. As a result, the samples developed to estimate these models are fairly small, commonly with fewer than 100 observations, and are confined to a limited portion of the route network.

We adopt a more disaggregate approach in this paper. A bus arrival at a time point along a sampled route is defined as the unit of observation, and the factors determining whether bus arrivals are early, on time or late are similar to those used in previous studies to explain run times, and run time and headway variation. The larger sample size permitted with this approach will potentially result in greater estimating efficiency. Given that this study's sampling methodology also conforms with UMTA Section 15 reporting requirements (U.S. Department of Transportation, 1985), the findings can be clearly inferred to Tri-Met's route system.

A direct focus on the determinants of on-time performance also has more fundamental implications; essentially, it shifts attention from analyzing factors affecting bus operations for the basic purpose of designing efficient service to assessing whether bus services, as scheduled, are effectively delivered. In this context, our objective is to develop a model in which the observed on-time “failures” in a bus system can be predicted by the same factors which systematically affect running time and headway variation. Thus, a model assessing bus service characterized by minimal headway or running time variation would be unable to statistically predict on-time failures.
For factors which are identified as systematic contributors to poor on-time performance, conditions must be defined to determine whether controllability is achievable through basic scheduling adjustments. Regarding factors which are external to the bus system, this study posits that such controllability is subject to two conditions. First, it must be established that a given factor significantly reduces the likelihood of on-time arrival. This can be labeled the "existence condition." Second, one must also distinguish between early and late arrival as the direct consequence of the reduced likelihood of on-time arrival. This can be labeled the "directional condition."

As an example, peak period traffic congestion may be shown to reduce the probability of on-time arrival, satisfying the existence condition. The directional condition would be satisfied if an increase in the relative probability of arriving late rather than early was also found to be the consequence of greater congestion. In this case the on-time performance problem can be feasibly mitigated by increasing bus running times in peak periods. Alternatively, it may be found that peak traffic congestion significantly reduces the probability of on-time arrival, yet results in an indeterminate outcome in regard to its effects on the relative probability of late versus early arrival. In this instance one can conclude that congestion has an existence effect but not a directional one. As a result, a scheduling remedy cannot be reasonably implemented, and mitigation options are limited to the standard operations control actions reserved for random on-time failures.

Weaker controllability conditions can be defined for on-time performance-affecting factors which are internal to the bus system, given that these factors are subject to direct control through scheduling adjustments. Thus, we posit that satisfying the existence condition is sufficient for establishing controllability of internal factors. For example, it may be found that longer headways result in a lower probability of on-time arrival. Since headways can be shortened the on-time problem is controllable irrespective of whether it is possible to distinguish between consequent changes in the likelihood's of early and late arrivals.
It should be noted that the conditions defined above pertain to scheduling adjustments as the means of counteracting internal and external causes of poor on-time performance. While it may be determined that the effects of a given factor cannot be mitigated in this context, controllability may still be achieved through other more basic means. If traffic congestion is found to be a cause of poor on-time performance and not subject to control through scheduling, expanding the use of exclusive right-of-ways for transit vehicles would still be a possible option in the longer term. Here, the economic trade-offs discussed earlier would become especially relevant in assessing the merits of such action.

5. ON-TIME PERFORMANCE MODEL

Consistent with the Bates (1986) findings, a bus is defined to be on time if it arrives at a time point on a sampled bus trip no more than one minute early or no more than five minutes late. An arrival at a time point outside this range is defined to be either early or late.

The judgment of schedulers and drivers provides the basis for determining number and location of time points on a route. A general rule of thumb is to set time points at about five minute intervals along a route, but variation in traffic conditions, passenger activity and route features are also taken into account. Thus time points are usually added at route transfer points and major road intersections. The bus routes in Tri-Met's system contain as few as one and as many as fifteen time points, and average about eight per route.

A multinomial logit model is employed relating the three alternative arrival outcomes to the set of contributing underlying causes suggested in the literature. The model is specified on the left-hand side as the log of the relative probabilities of pairs of alternative outcomes. In the present application, with three alternative outcomes, three pair
combinations are addressed - on-time/early, on-time/late, and early/late - resulting in three equations. The general specification of the on-time performance model is as follows:

\[ \log \left( \frac{P_i}{P_j} \right) = f(\text{Ons, Offs, Stops, Count, Wkdy, AMP, PMP, PTD, Dist, Hdwy, New}), \]

where

\[ \log \left( \frac{P_i}{P_j} \right) = \text{the log of the relative probabilities of alternative outcomes } i \text{ and } j; \]

\[ \text{Ons} = \text{the number of boarding riders since the previous time point;} \]

\[ \text{Offs} = \text{the number of alighting riders since the previous time point;} \]

\[ \text{Stops} = \text{the number of service stops made since the previous time point;} \]

\[ \text{Count} = \text{the position of the sampled time point in the sequence of time points on the bus route;} \]

\[ \text{Wkdy} = \text{a dummy variable equaling 1 for weekdays, 0 otherwise;} \]

\[ \text{AMP} = \text{a dummy variable equaling 1 for AM peak inbound trips, 0 otherwise;} \]

\[ \text{PMP} = \text{a dummy variable equaling 1 for PM peak outbound trips, 0 otherwise;} \]

\[ \text{PTD} = \text{a dummy variable equaling 1 for part-time drivers, 0 otherwise;} \]

\[ \text{Dist} = \text{the distance (in miles) from the previous time point;} \]

\[ \text{Hdwy} = \text{the scheduled headway (in minutes);} \]

\[ \text{New} = \text{a dummy variable equaling 1 if the observation occurred in the first two weeks of a new sign up, 0 otherwise.} \]

Strictly speaking, boardings and alightings should not affect the relative probability of a bus arriving on time if passenger activity levels maintain a regular pattern and are properly accounted for in scheduling. Rather, it is the random variability of passenger activity that can contribute to poor performance, and we hypothesize that the variation of boarding and alighting activity is positively related to their nominal levels.

We also posit that the greater the number of stops a bus is required to make between time points, the greater the prospect that it will fall off schedule. With many stops one can expect larger variations in dwell times and time spent accelerating and decelerating.
The position of the time point on the route, represented by the variable "Count," may also be important. Delays or early arrivals in the initial part of the route can contribute to poor on-time performance later in the route, particularly if holding/control actions are not taken.

Given greater variation of internal and external performance-affecting conditions during the week, one would expect greater difficulty in maintaining on-time service on weekdays. This hypothesis is addressed by including a weekday dummy variable. Dummy variables for AM peak inbound and PM peak outbound trips are also included to assess on-time performance in the situations when ridership levels are highest and traffic and operating conditions pose the greatest challenge to maintaining scheduled service. These are also the periods where the negative economic consequences of poor on-time performance are greatest for bus users.

Bus operator behavior is addressed by a dummy variable identifying part-timers. One would expect these drivers to be on time less frequently, either as a result of their lack of general operating experience or their lack of familiarity with conditions on their assigned route.

All other things being equal, one would expect that buses traveling greater distances between time points would encounter more problems in adhering to schedule. Also, one would expect more difficulties in the first weeks of a new sign up, following changes in scheduled service.

As previously discussed, both short and long headways may negatively affect on-time performance. We thus include both the linear and quadratic forms of this variable in the model.

The sample observations are 1552 bus arrivals at time points encountered in 200 bus trips on 59 routes in the Portland metropolitan area served by the Tri-County Metropolitan Transit District of Oregon (Tri-Met). The bus trips were sampled according to procedures established for UMTA Section 15 reporting requirements (U.S. Department of
Transportation, 1985). In addition to recording Section 15 passenger activity, surveyors were instructed to record (in minutes) the deviation of actual versus scheduled arrival at time points. The surveyors were instructed to explain to drivers that they were gathering Section 15 passenger activity information (which does not include on-time performance data). Drivers have become accustomed to carrying surveyors for this purpose, and the prospect of the surveyors' presence having an effect on driver behavior is thus lessened. Data on the remaining variables were assembled from Tri-Met files.

6. EMPIRICAL RESULTS

The distribution of the 1552 sampled bus arrival times is presented in Figure 1. Of the total arrivals, 1360 (87.6%) fell within the on-time range of one minute early to five minutes late, while 106 observations (6.8%) arrived early and 86 (5.5%) arrived late. The distribution appears to be log normal, consistent with Turnquist (1978).

(Figure 1 about here)

The multinomial logit model parameter estimates are reported in Table 1. The first two columns of coefficients in the table pertain to the estimated equations for the probabilities of on-time arrival in relation to the alternatives of arriving early and late, respectively. The final column pertains to the equation estimating the relative probabilities of early and late arrivals. Put in another way, the first two columns' coefficients test for the previously defined condition establishing the existence of a controllable source of poor on-time performance, while the last column's coefficients test for the directional condition.

(Table 1 about here)

Regarding passenger activity, boardings are estimated to have a significant positive effect on the probability of on-time arrival relative to arriving early, and no effect on the on-time/late relative probabilities. As a consequence, on time failures are less likely to occur
with increases in boardings, but when they do they are more likely to occur in terms of late arrivals.

Greater numbers of passenger alightings result in increases in the likelihood of both early and late arrivals, with no discernible early/late directional effect. This represents an example of an external factor contributing to a decline in on-time performance which cannot be controlled by scheduling changes.

Generally, boarding activity requires a greater amount of time per passenger than does alighting (Abkowitz and Engelstein, 1984) and thus ought to represent a greater potential threat to on-time performance. But interference of alighting passengers with those attempting to board may be relevant in this instance. Although it is now discouraged, Tri-Met allowed alighting passengers to exit from both the front and rear doors in the recent past, and the practice was still very much evident at the time of this study. Although scheduling changes cannot remedy this problem, a public awareness campaign could.

The variable Count identifies the position of the observation among the sequence of time points on a route. The parameter estimates among the three equations indicate that the probability of late arrivals tends to increase as buses progress toward a route’s terminal point, which can be corrected by either increasing running times on routes with numerous time points or by designing shorter, less complex routes. Greater distances between time points tend to increase the estimated likelihood of early arrival, indicating a need to establish more time points.

The hypothesized disruptive effects of changes in scheduled service are not supported empirically. In fact, the estimates indicate that buses are relatively more likely to arrive on time rather than late in the first two weeks of a new sign-up. It may be that drivers give heightened attention to the schedule following a change in service and, once they become accustomed to the change, tend to be less diligent. Service changes implemented during the study period were fairly minor, however. More substantial changes could lead to different consequences. A similar result is observed in the estimate
of improved on-time performance on weekdays versus weekends, and a similar interpretation may pertain: the importance of maintaining the schedule during weekday high utilization periods is regularly emphasized to drivers and operations controllers, while limited attention is devoted to performance on weekends.

The estimates for the linear and quadratic headway variables indicate that late arrivals become more likely with greater headways, with maximum probability of late arrival occurring at headways of about an hour and ten minutes. Tri-Met schedules few runs with the short headways that Guenther and Hamat (1988) found to be problematic. Bus bunching is not very frequently encountered, and thus the headway effect estimated here is consistent with the deterioration that Guenther and Hamat observed for headways exceeding 11-15 minutes.

Driver experience appears to be an important consideration in maintaining on-time service. Part-time drivers are significantly more subject to late arrival. Moreover, since schedules are not written with different types of drivers in mind, the relative inability of part-time drivers to match the performance of more experienced drivers cannot be compensated. More basic control of this effect can be achieved by either upgrading training requirements or reducing the use of part-time drivers.

Peak period traffic conditions were also estimated to affect on-time performance. In the afternoon period the likelihood of both early and late arrivals increases, without a clear tendency toward either type of failure. This outcome is consistent with Abkowitz and Engelstein's (1984) finding that maximum running time deviations occur during the PM peak. Spyridakis et al's (1991) survey of commuters found that workers exhibited considerably more flexibility in their choice of afternoon departure times and routes, with the latter influenced by both traffic conditions and a greater tendency to satisfy shopping and recreational needs on the way home. The consequence for transit service planners is that the greater variation of traffic conditions afternoon peak period precludes schedule-based remedies.
Conditions in the AM peak, in contrast, can be more readily accommodated because travel is dominated then by work trips with regular and predictable work arrival times. What was not anticipated, however, is the model's estimate that on-time performance actually improves during the AM peak period and that when failures do occur, they are more likely to be in the form of early rather than late arrivals. The implication of this finding is that schedulers have added too much running time during this period.

Only one of the specified variables, the number of stops made between the observed and previous time point, was found to have no on-time performance effect. This variable is somewhat redundant with the passenger activity variables, as indicated by fairly strong correlation (r = .55 with boardings and .62 with alightings).

Regarding the overall performance of the on-time model, there is a substantial increase in the log likelihood function over its null value, and the corresponding value of likelihood ratio statistic (2194) easily exceeds the critical $\chi^2$ value of 54 (.001 level, 26 d.f.). The likelihood ratio index, a loosely interpretable indicator of goodness of fit (whose value ranges from 0 to 1), is .64.

7. DISCUSSION

The model developed and estimated in this paper reveals that factors which commonly affect variations in headways and running times also influence on-time performance. It was found that the probability of on-time arrival was negatively affected by the number of alighting passengers, the location of the observed time point on the route, headways, and for PM peak outbound runs. On-time performance was also found to deteriorate after the first two weeks of a new sign up and when buses were operated by part-time drivers.

One of the advantages of the sample used in this study is that it is representative of the network served by the transit agency. It thus provides a potentially generalizable
analysis of on-time performance and its determinants. There are also several drawbacks that should be considered. First, because it employs an \textit{ex post} approach, this study does not provide a usable framework for real time performance monitoring and control. Second, the inferences which can be drawn from this study relate to the overall bus route system. While one should be careful to not overly discount the importance of findings at this level, it should be acknowledged that it is at the trip segment level where service problems surface and adjustments are made. Third, the analysis undertaken here should be replicated in other operating environments to assess the robustness of the model. With respect to this issue we are guardedly optimistic in light of the evidence that running time models, which provided the basic framework for specifying the on-time performance model, are proving to be fairly robust (Abkowitz and Tozzi, 1987).

Logistical obstacles to on-time performance monitoring may shrink considerably for transit operators in coming years. A growing number of properties are acquiring automated vehicle monitoring (AVM) systems or automatic passenger counters (APC's). These systems are technically capable of generating massive amounts of data of the kind needed for implementing effective bus control procedures, as well as sufficient observations at the route level to systematically analyze underlying factors affecting on-time performance. Buneman (1984), for example, explains how the Bay Area Rapid Transit uses automatically recovered operational data to monitor passenger loads, estimate passenger delays, and allocate vehicles. Martín, Steane and Mauceri (1990) show how data collected by APC's can be used to monitor on-time performance. While ultimate adoption of AVM or APC technology may be confined to larger transit systems, this is also where the need for performance monitoring is likely to be greater.

Finally, it is important to recognize that corrections for poor on-time performance should ultimately be evaluated in the context of the costs and benefits of achieving an improvement. Without a corresponding economic analysis, for example, we cannot determine whether Tri-Met's 88 percent on-time record is too low, too high, or just right.
More research addressing inherent relevant trade-offs of this nature is clearly needed; it will likely provide reinforcement of Talley and Becker's (1987) contention that on-time performance standards should vary both within and between transit properties, depending on basic attributes of the transit system and its operating environment.
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Figure 1

Distribution of Recorded Bus Arrival Times at Time Points
(in minutes deviation from scheduled arrival)
Table 1
Multinomial Logit Estimates of On-Time Performance Model Coefficients
(Asymptotic t values in parentheses)

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<td>(-1.46)</td>
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<td>-.214</td>
<td>.175</td>
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<td>(-1.07)</td>
<td>(-4.97)**</td>
<td>(3.25)**</td>
</tr>
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<td>.003</td>
<td>-.009</td>
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<td>(1.45)</td>
<td>(4.53)**</td>
<td>(-2.50)**</td>
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<tr>
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<td>(2.01)**</td>
<td>(-2.04)**</td>
<td>(2.98)**</td>
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<td>(-.57)</td>
<td>(-1.73)</td>
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<td>(-3.48)**</td>
<td>(-5.95)**</td>
<td>(1.67)</td>
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Log-likelihood Function (0): -1705.0
Log-likelihood Function (β): -607.9
Likelihood Ratio Statistic: 2194.2
Likelihood Ratio Index: .64
n 1552

* Alternative 0 = early, alternative 1 = late, alternative 2 = on time.
** Significant at the .05 level.