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Modeling the Role of Operational Characteristics in Safety Performance of PublicTransportation Systems: The Case of TriMet Bus Collision and Non-collision Incidents.

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Modeling the Role of Operational Characteristics in Safety Performance of

PublicTransportation Systems:

The Case of TriMet Bus Collision and Non-collision Incidents.

by

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Abstract

The incidence of bus crashes in the US have been trending upwards, with accident, injury and fatality rates increasing 171%, 37.8%, and 5.1% respectively, between 2003 and 2007. Reversing the upward trend is an important objective of both transit providers and the society in general. This study introduces an operator-based safety methodology that utilizes data recovered from transit Intelligent Transportation Systems (ITS) technologies and related systems to identify and assess factors contributing to bus operations safety incidents at TriMet, the transit provider for the Portland, Oregon metropolitan region. The analysis specifically focuses on collision, non-collision and total incidents, as well as on preventability of incidents that occurred between 2006 and 2009.

Regression analysis established that bus operator age, experience, short duration absenteeism from work, operator's work span and variability in daily work span/assignments are empirically correlated with bus safety incidents. In addition, schedule adherence pressures and bus lift operations are also related to safety incidents. The other factors that influence safety performance are operators' responsive action events and customer complaints about unsafe bus operation. These findings make some contributions to the understanding of the factors that are empirically related to the frequency of safety incidents as well as offer insights into operation practices and policies that hold promise for reducing bus safety incidents.

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Finally to my family — I am very fortunate to have you on my side.

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Glossary

TriMet	Tri- County Metropolitan Transportation District of Oregon
NTD	National Transit Database
BDS	Bus dispatch system
APC	Automatic passenger counter
AVL	Automatic vehicle location
FTA	Federal Transit Administration
ITS	Intelligent Transportation Systems
APTA	American Public Transit Association
NB	Negative Binomial Model
ZIP	Zero-Inflated Poisson Model
ZINB	Zero-Inflated Negative Binomial Model
FENB	Fixed Effects Negative Binomial
RENB	Random Effects Negative Binomial
RF	Risk Framework
IRF	Operator Signup-Based Risk Framework
MLE	Maximum Likelihood Estimation
TTI	Texas Transportation Institute
MDT	Mobile Data Terminal
LRT	Likelihood Ratio Test
NHTSA	National Highway Traffic Safety Administration
LDV	Limited Dependent Variable
MNL	Multinomial Logit Model
GEV	Generalized Extreme Value
PA	Preventable Accidents
NPA	Non-Preventable Accidents
IIA	Independence of Irrelevant Alternatives
RRR	Relative Risk Ratios
USDOT	U.S. Department of Transportation

CHAPTER 1.0: STUDY OUTLINE

1.1. Introduction

This study examines the relationship between transit bus safety incidents and operational characteristics using an operator-level, risk based approach. Increases in traffic volumes and land use intensification policies have made the operating environment for bus transit more difficult in recent years, leading to increased safety concerns and heightened levels of risk. Examples of the types of transportation and land use factors influencing transit safety include higher levels of pedestrian and bicycle traffic, increases in population and employment density, and various “smart growth” design elements (i.e., narrow streets, on-street parking, retrofitting streets with pedestrian and bike facilities).

Previous transit industry safety research, as well as research focused more generally on commercial motor vehicles, has provided considerable insights into the effects of human, physical and environmental conditions on safety. Recent efforts to examine the influence of operating environment on bus accident likelihood have been limited. As a result, the relationship between operational characteristics and safety performance of bus transit systems is not well understood.

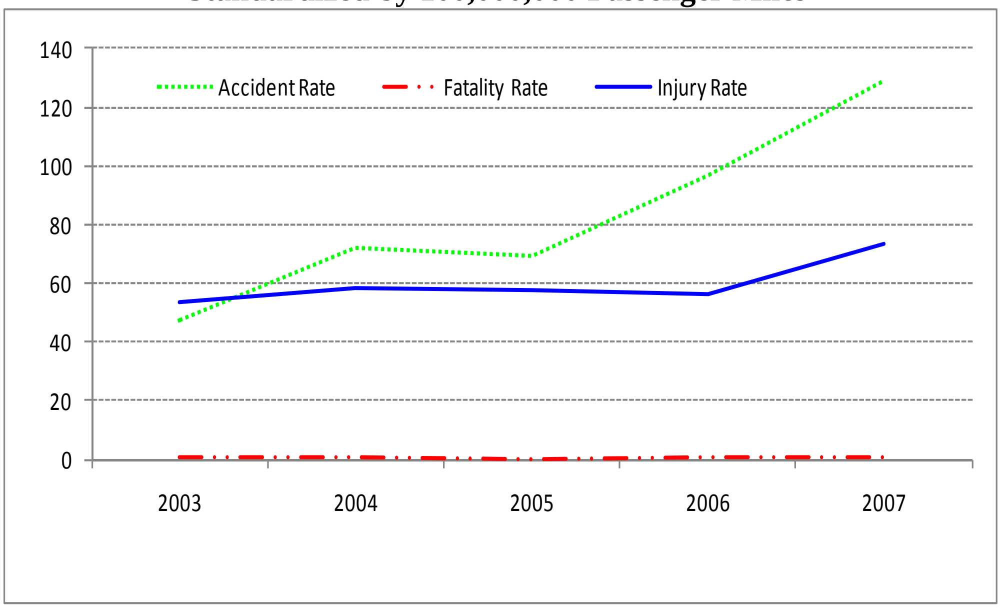
The goal of this research is to better understand the relationship between operational characteristics and bus accident occurrences, in order to identify and assess contributing factors to bus operations safety incidents. This research is made possible by the emergence of data from Intelligent Transportation Systems (ITS) technologies and related systems. These data have created an opportunity to explore a new dimension of safety— the transit operating environment. Previous research could not systematically and comprehensively address this dimension due to data limitations and research design complications.

1.2. Problem Setting

Concerns about safety are central to transit system planning and delivery of service. The incidence of bus transit crashes in the US has continued to rise steadily since 2003 and the trend does not seem to show any signs of slowing down (FTA, 2009). The consequences of injuries, fatalities and property damage resulting from bus crashes are serious problems that continue to affect both the general public and transit agencies in the United States. For example, in 2002, the Federal Transit Administration (FTA) reported that there were approximately 12,750 collisions involving fixed-route buses accompanied by 12,000 injuries and 80 fatalities (FTA, 2002).

The most recent FTA report indicates that while ridership has grown annually at a relatively steady pace, the bus industry's accident rate has risen at a greater rate (FTA, 2009). In particular, FTA analysis of the National Transit Database (NTD), visualized in Figure 1, reveals that bus incident rates have been trending upward, with accident, injury and fatality rates increasing 171%, 37.8%, and 5.1%, respectively, between 2003 and 2007 (FTA, 2009) . Similarly, the total value of property damaged in bus collisions has also continued to rise steadily. For example, in 2003 the total inflation adjusted value of property damaged in the U.S. rose to $28.7M from $25.7M in 2002 (FTA, 2004).

Figure 1. Bus Accident, Injury and Fatality Rates: 2003- 2007, Standardized by 100,000,000 Passenger Miles



Source: Authors compilation using data from FTA Winter, 2009

An analysis of risk management and risk financing practices for a select number of transit properties by Chaney and Derr (1996) found that bus accident losses characterized as property damage or bodily injury to passengers, pedestrians or other motorists were responsible for about 50% of the total risk cost. Similarly, Abacus Technology Corporation (1996) also found that losses related to traffic accidents involving collisions and passenger accidents accounted for about 51 percent of the total risk cost and, on average, the total risk cost was 4.85 percent of a bus transit agency's operating expenses. An indication that for every one hundred dollars spent on operating expenses, $ 4.85 actually goes towards covering the cost of risk. Other components of total cost of risk include safety and loss control program cost, risk management program cost, claims handling, and insurance premiums.

A careful review of data on safety performance of major surface transportation modes reveal that US transit systems are relatively safe when compared to automobile travel. For example, the American Public Transit Association reports that the bus passenger fatality rate (standardized by passenger miles) in 2003-2005 was only 2.8% of the fatality rate for automobile travelers (APTA, 2009). Nevertheless, the safety risks faced by bus riders are relatively greater than the risks associated with travel by other transit modes. For example, the Federal Transit Administration reports that across the transit industry, bus accidents account for more than 80 percent of all public transportation accidents while providing roughly 45 percent of all passenger trips (FTA, 2003). Similarly, the most recent information reported to the Federal Transit Administration's National Transit Database (NTD) reveals that while buses accounted for 40% of transit passenger miles in 2006, they were associated with 58% of the industry's safety incidents, 61% of injuries, and 41% of fatalities (FTA, 2009).

Given the increasing trend of accident rates, prevalence of bus accidents and their associated costs, there is a need for transit providers and other agencies such as the FTA to take a more concerted and unified approach toward slowing down and possibly reversing this upward trend. The common approach would be to undertake safety investment programs, but the challenge is ascertaining where the focus should be and what level of safety resources to allocate. One way to meet this challenge is to conduct a systematic and thorough safety analysis to identify and assess contributing factors that are within the control of transit providers, so that changes in operating policies and practices can be introduced to improve safety. As the FTA (2009: 5) has observed, "… a transit bus system does have influence over how its bus operators perform their duties and can implement training and supervisory monitoring programs to improve operator safety related performance." Beyond the operator, a variety of factors related to the planning and delivery of bus service affect safety performance and are also subject to managerial control (Technology and Management Systems, 2001).

1.3. Purpose of the Study

While previous transit industry safety research and research focused more generally on commercial motor vehicles have provided insight into the effects of human, physical and environmental conditions on safety, there has been little empirical examination of how operational factors impact bus accident likelihood. The purpose of this study is to empirically examine the relationship between the operational characteristics and accident occurrences in a transit system, in order to identify and assess factors contributing to bus operations safety incidents. The analyzes is designed to offer insights into potential operations policies and practices that may be used or changed to improve bus operator safety performance.

Previous studies on this topic have specifically addressed the effects of operator demographics, factors contributing to operator stress and fatigue, various measures of safety risk exposure (e.g., related to time and/or distance, passenger volumes served), and route or vehicle characteristics representing potential safety hazards. While the collective scope of prior transit safety research has been broadly established, it is also important to acknowledge that the various human, physical and environmental dimensions of safety risk corresponding to a transit bus operating environment, particularly in a medium to large scale urban setting, are dynamic and highly complex.

Prior empirical studies that have investigated factors contributing to bus transit crash and/or passenger injury incidence have generally fallen well short of sufficiently representing this complexity, particularly with respect to those risk determinants that are within the control of the transit provider. Data resource limitations have often compromised safety analysis in the transit industry as reflected in overly-aggregated research designs and model specifications lacking either relevant variables or relying on measures that only roughly approximate safety risk determinants. The widespread deployment of intelligent transportation system (ITS) technologies in the transit industry over the past decade carries the potential to mitigate many of the data resource limitations that have constrained prior safety research. Unlike other conventional ways of data collection, ITS and related systems collectively generate information which is comprehensive and provides a detailed portrayal of operators' work qualifications, work environment, and work performance.

From a methodological perspective, attempts to model accident rates and frequencies have varied from the use of the mean-variance approach to least squares regression techniques to count data methodological approaches, such as, Poisson models (P), Negative Binomial models (NB), Zero- Inflated Poisson (ZIP) or Negative Binomial models (ZINB). The mean-variance approach entails use of the mean and variance of accident involvement rates. It is often undertaken to test the equality of accident risk between different exposure groups (Jovanis and Delleur, 1981; 1983). This approach models well the nonnegativity and heteroskedasticity but does not address the discreteness of the count data (Cameron and Trivedi, 2005).

A number of studies have discussed the advantages and disadvantages of using the Poisson regression approach as an alternative to least squares methods. For example, in research that examined the appropriateness of Poisson and least squares methods to modeling of accident frequencies, Jovanis and Chang (1986) found that Poisson distribution is superior to least squares techniques in modeling crash data because it requires a smaller sample size and, unlike the least squares models, Poisson models neither predict non-integer nor negative values. Consequently, Jovanis and Chang (1986) recommend use of Poisson estimation in modeling crash data.

One requirement, which is also the major limitation of Poisson estimation, is that the mean of the count process equals its variance. When the variance of an accident event is greater than the mean of accident event, data violates the equality constraint and using a Poisson model leads to biased standard errors. Negative binomial distribution has been used as an alternative approach to address this problem (Shankar et al. 1995; Washington et al., 2003). The NB model is more flexible and easily overcomes over-dispersion problems (Cameron and Trivedi, 2005; Washington et al., 2003).

This research primarily uses a count data modeling framework to assess the role of operational characteristics in bus transit accidents. In addition, a discrete outcome modeling structure is employed in exploring incident preventability. The ITS generated incident data and other data archived by TriMet, the transit provider for the Portland, Oregon metropolitan area, is used to assess in-service collision, non-collision and total incidents, as well as the likelihood of involvement in preventable and non-preventable incidents that occurred on the agency's bus system over a three year period, from September, 2006 through February, 2009.

The remainder of this thesis is structured as follows. Chapter 2.0 presents a review of safety research literature. This is followed by data description and research methodology discussion in chapter 3.0. In chapter 4.0 the safety incident frequency analysis results are discussed. This is followed with the description and development of the preventability analysis model in chapter 5.0. In addition, this chapter also presents and discusses factors that influence the likelihood of preventable incident involvement. Finally, chapter 6.0 provides the concluding remarks, highlighting the policy or management implications, study contributions and potential future research directions.

CHAPTER 2.0: LITERATURE REVIEW

2.1. Introduction.

This chapter is divided into four parts. Part 2.2 covers theoretical perspectives and the related conceptual structures. Part 2.3 presents various modeling frameworks or econometric approaches that have been used in similar safety research efforts. In part 2.4, empirical findings from a sample of selected safety studies that focus specifically on operator safety performance are presented. In addition, this part will also cover general research that examines the influence of non-driver level factors on safety. Finally, section 2.5 presents the summary of what is known and not known, including what is addressed in the present study.

2.2. The Conceptual / Theoretical Frameworks

The human capital theory formulated by Becker (1964; 1962) suggests that variations in human capital across individuals and companies can explain the differences in labor force outcomes, such as safety and productivity. More job experience, higher level of education or skills set, and perhaps, higher employee compensation, for example, are expected to lead to fewer crashes and/or better employee outcomes. Human capital theory has empirically been tested and supported by a number of truck industry safety studies (Rodriguez et al. 2006; Rodriguez et al. 2003; Krass, 1993; Monaco and Williams, 2000). For example, Rodriguez et al. (2003) found that human capital, occupational and compensation factors were important predictors of crash frequencies.

A careful review of empirical studies in the large area of safety reveals that application of human capital theory has been used in truck industry safety analysis only to a limited scale. In general, there seems to be *no consensus on one unified theory* of accident occurrences. However, it is also evident that the traditional highway–based empirical framework has most often been adapted and applied to bus transit safety research at both industry and firm levels.

The conventional highway-based empirical approach treats occurrences of highway or commercial vehicle accidents as being the result of the interaction between the driver, vehicle, roadway and environmental conditions (Jovanis, 1989; Jovanis, 1986). Evidence suggests that empirical studies that have used this approach have had a driver focus, in part because human error is recognized as the key determinant of commercial vehicle accidents (Jovanis, 1989). Whereas this empirical framework is useful, still it cannot directly be applied to bus transit accident analysis because of the complications that are inherent and specific in the transit industry.

There are features which are unique to bus transit and have no parallel structure in the traditional highway safety field. First, there is the risk of an accident in bus transit which is affected in part by transit service characteristics and by agency policy environment in addition to the traditional factors of human, vehicle, roadway and environmental conditions, such as, weather and lighting factors. Second, passenger injuries resulting from non-collision incidents are also a major concern in the transit industry. In particular, injuries to transit passengers occur in non-collision incidents, especially while the vehicle is accelerating or decelerating (Wahlberg, 2007), and during boarding and alighting processes (Morlok et al., 2004; Hudenski, 1992).

At an industry or aggregate level, the organizational-based conceptual framework proposed by Reason (1997) has been used as a tool to investigate factors that are important in bus accident occurrences (Chang and Yeh, 2005; Arnold and Hartley, 2001). In this structure, organizational factors influence work place factors, which in turn result in unsafe acts and these unsafe acts might eventually lead to an accident. In other words, the accident risk at an industry level is determined by organizational factors, workplace factors and unsafe acts. This framework considers the organizational and work place factors and has potential to provide more insight into the safety performance of transportation companies than does the highway-based structure (Chang and Yeh, 2005). The major shortcoming of this framework is that it cannot be used to identify safety problem areas within a specific transit agency.

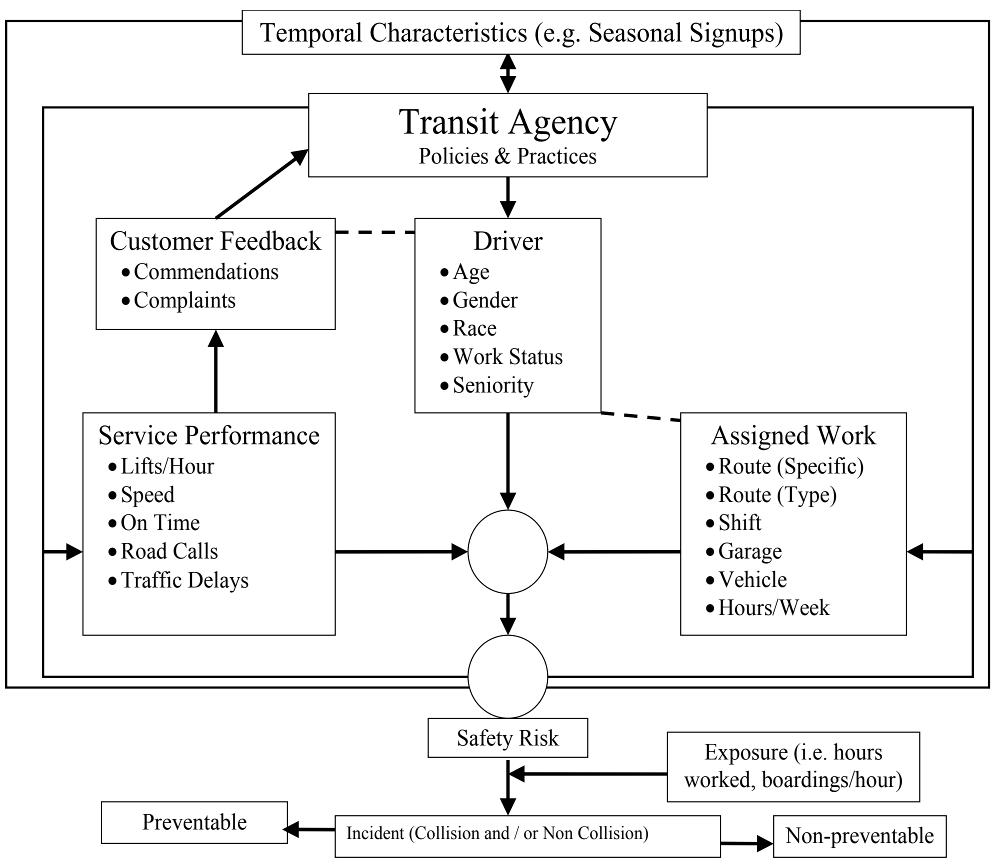
At the level of an individual bus transit agency or firm, perhaps the most important and relevant empirical structure is the risk-based conceptual framework (RF) proposed by Jovanis et al. (1991). This conceptual approach is broader in scope than the highway-based approach but as with other structures, RF is spatially-based and therefore it is not appropriate for the present study. However, RF is attractive because it can be used to provide insight into safety performance for a specific transit company at multiple-levels (i.e. system-wide, route or even at trip level).

On the other hand, RF has obvious limitations because accident data and associated attributes are organized around the individual routes or roadway segments. When accident data is organized around the routes, as was the case in the study of Jovanis et al. (1991), it becomes almost impossible to consider both the behavioral and non-behavioral factors in the same estimation model. This may in part explain why Jovanis et al., did not account for factors related to the operator and to operator assigned work in their estimation model.

For this study, the conceptual structure formulated by Jovanis et al. (1991) was modified into an integrated empirical framework or model that is consistent with the human capital theoretical perspective. The Integrated Operator Signup-Based Risk Framework (IRF) shown in Figure 2 was applied in the present study. In this framework a particular level of safety risk is treated as resulting from the interaction between the bus operations related factors (i.e. operator factors, assigned-work characteristics, customer feedback, temporal factors, and transit service characteristics and agency policies). The resulting risk level may lead to a collision or non-collision incident, which may be classified as either a preventable or non-preventable incident.

The empirical analysis showed that IRF is a promising tool for determining operational factors that are related to bus transit incidents. The key strength of IRF is that it considers and performs well at capturing a wide array of operator-level information sources that are important in explaining bus collision and non-collision incidents. The specific information captured ranges from operator demographics, employment status, work assignment factors, service delivery to the customer/passenger feedback and temporal factors. IRF also captures information

Figure 2. Integrated Operator Signup-Based Risk Framework



(*Source: Authors compilation*, 2010)

on preventable and non-preventable incidents which is used to provide more insight about policies and practices that are important in minimizing occurrences of preventable incidents and thus improving bus, as well as passenger/customer safety.

Notable omissions from the IRF framework include lack of consideration of factors that capture workplace and organizational or agency-wide culture. In addition, information on time of the day variations in traffic volume and changing conditions or passenger demand patterns are not well captured. These omissions and use of coarse or rough proxies to represent risk exposures limit the ability of IRF to better identify and assess factors that influence bus operations safety.

The estimated empirical model (see chapter 4) indicates that the variable "total hours worked' performs well at capturing risk exposure. Similarly, incorporation of the number of passenger complaints in the previous signup period as well as inclusion of an interaction term between absence hours and fit for duty commendation improves model performance and accounts for historical effects of customer complaints. Conversely, the "passenger boardings" variable, which ideally should represent the risk exposure for non-collisions events, did not perform as well as expected.

The safety literature suggests that IRF structure may be improved by stratifying total hours worked and number of passenger boarding in order to capture non-linear effects. Potential factors that future research can add to the structure include the average hours worked and number of passenger boardings during the peak and off-peak periods respectively. Also, as shown in Chimba et al. (2010) stratification of the speeding variable better captures the changing driving or traffic conditions and thus may improve IRF performance.

Prior research on bus safety performance has mainly been examined at two-levels of analysis; system and route–levels. The system level approach is used where the goal of the analysis is to investigate factors that are important in safety and to provide broad level indicators of safety performance (Chang and Yeh, 2005; Jovanis et al. 1991). Beyond the big picture or safety performance indicators, route level designs are used in determining geometric and other non-behavioral factors that contribute to crash incidents (Jovanis et al. 1991; Chimba et al. 2010). Data in route-level design are organized around the individual routes or network facility segments. As observed in the studies by Jovanis et al. and Chimba et al. the route-based design approach is limited to the sample of operators who are involved in incidents and consequently, information on those without incidents is not recovered. In addition, behavioral factors are not captured in the route based designs.

In contrast to earlier safety research, the present study examines the contributing factors to bus safety using the operator signup based approach. This approach is consistent with Evans (2004) perspective that efforts to improve safety should focus on human behavior. Similarly, FTA (2009) policy paper on bus safety improvement strategies recommends that the focus should be to identify and assess effects of factors that are within transit agency control. In the next section, various analytical frameworks that have been used in examining the factors that influence safety are discussed.

2.3. Modeling Approaches and Estimation Methods

This section specifically reviews issues associated with various analytical frameworks that are used in modeling crash data, and is structured into four sections. Section 2.3.1 discusses the strengths and weaknesses of modeling crash data by least square regression models. Section 2.3.2 presents the Poisson distribution modeling approach, how it has been implemented in practice and the issues that limit its widespread application. Section 2.3.3 presents the negative binomial modeling approach and the associated issues. In section 2.3.4, the negative multinomial modeling method and related issues are provided. This is followed in section 2.3.5 with the discussion of issues associated with application of fixed and random effects negative binomial methods. Finally, section 2.3.6 covers Zero-inflated Poisson /negative binomial methods and other count data modeling approaches.

2.3.1. The Least Squares Regression Models

Least squares and linear regression modeling approaches have been used in a number of safety studies (Ceder, 1982; Ceder and Livneh, 1982). The dependent variable is either accident frequency (defined as the number of accidents) or accident rate (defined as number of accidents per mile or million miles). The risk components are assigned as independent variables, and may include various factors (.i.e. vehicle type, human factors, etc.). A linear regression models is specified as;

$Y_i = \beta_o + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_{k-1,} X_{k-1,i} + \varepsilon_i$ 1.0

Where,

β_o is a constant term, β_i are parameters to be estimated, X_i are independent variables, and ε_i is the random or error term which captures the unobserved effects.

In practice this model is used to model a continuous variable as a function of covariates for explanation or prediction purposes. It has fairly robust assumptions and is used to model a variety of multivariate, linear and non-linear relationships, and also has the advantage of being flexible and easy to learn to use. Linear regression modeling is limited in model forms however. For example, it cannot handle both additive and multiplicative effects. In addition, least squares regression analysis is only suitable and appropriate for continuous variables. When used in crash data analysis, linear regression can yield predicted values that are either non-integer or negative. These are not appealing statistical properties, and also, they are inconsistent with count data distributions (Washington et al., 2003).

Poisson distribution has been recommended as an alternative to least squares regression in modeling crash incident data (Jovanis and Chang, 1986). In the next section, Poisson regression modeling is examined.

2.3.2. The Poisson Modeling approach

Count data are usually modeled by assuming a Poisson distribution (Cameron and Trivedi, 2005; Washington et al., 2003). The Poisson distribution is appropriate for a dependent variable that takes only nonnegative integer values and can be used to model the number of occurrences of an event, such as the number of accidents. Poisson regression is also appropriate for rate data, where the rate is a count of events occurring to a particular unit of observation, divided by some measure of that unit's *exposure* to crash risk. For example, number of accidents per given time period.

More generally, event rates can be calculated as events per unit time, which allows the observation window to vary for each unit. Shankar et al. (1995) provides a number of reasons why Poisson distribution should be the starting point for modeling safety incidents. First, it lends itself well to the modeling of count data by virtue of its discreteness, and nonnegative integer distribution characteristics. Second, it can be generalized to more flexible distribution forms.

In a Poisson regression model, the probability of operator j being involved in y accidents per time period, t, where y is a non-negative integer, is expressed as;

$P\ (Y_{jt}= y_{\ jt}) = \exp(-\lambda_{jt})\ \lambda_{j\ t}^{\ yj\ t} / y_{j\ t}!$ ……………………………….............1.1

Where,

$P(y_{jt})$ is the probability of operator j being involved in y accidents per time period t, and Yjt is the observed frequency of accidents in time period t involving operator j.

While λ_{jt} is the Poisson parameter for operator j, which is equal to the expected number of accidents involving operator j in time period t, $E[y_{jt}]$.

The Poisson regression models are estimated by specifying the Poisson parameter: the expected number of events or accidents per period as a function of explanatory variables. The most common relationship between independent variables and the Poisson parameter is the log-linear model and is expressed as;

$\ln \lambda_{jt} = \beta X_{jt}$ or, equivalently.. 1.2a.

$\lambda_{jt} = \exp(\beta X_{jt})$ .... 1.2b.

Where,

X_{jt} is a vector of operator- and time-specific explanatory variables, and β is a vector of coefficients to be estimated.

In this formulation the expected number of accidents per time period is given by;

$E[y_j] = \lambda_j = \exp(\beta X_j)$..1.3

In practice, the exposure variable enters on the right-hand side of the equation, but with a parameter estimate constrained to one (Greene, 2003). The model is specified as

$\log(\lambda_{jt}) = \log(\text{exposure}) + \beta_o + \beta_i X_{jt}$ 1.4

Where,

β_o is the constant term and exposure, for example in the case of the present study is the total hours of service per operator signup. The above model can be expressed as;

$$\log(\lambda_{jt}) - \log(\text{exposure}) = a + \beta X_{jt} = \log\left(\frac{\lambda_{jt}}{Exposure}\right) = \beta_o + \beta_i X_{jt} \ldots\ldots\ldots\ldots 1.5$$

This model is often estimated by using standard maximum likelihood methods, with the likelihood function given as;

$$L(\beta) = \prod_{j} \left(\exp[-\exp(\beta X_j)][\exp(\beta X_j)]^{y_j} \right) / y_j! \ldots\ldots\ldots\ldots 1.6$$

The log of the likelihood function provided below is simpler, convenient and more appropriate to estimate using standard econometric softwares.

$$LL(\beta) = \sum_{j=1,}^{n} [-\exp(\beta X_j) + y_j \beta X_j - \ln(y_j!)] \ldots\ldots\ldots\ldots 1.7$$

Poisson regression is a powerful analysis tool. It easily overcomes the constraints that limit use of linear regression models. In particular, the Poisson distribution approach has successfully been used for modeling crash data because it fits count data well. But as with other methods, this tool has to be used appropriately.

Failure to recognize that count data is truncated or contains a preponderance of zeros often limits the application of Poisson regression. For excess zeros, if there are two processes at work, one determining whether there are zero events or any events, and a

Poisson process determining how many events there are, there will be more zeros than a Poisson regression would ideally predict.

The Poisson distribution requires that the mean of accident outcomes be equal to the variance, that is, $E[y_i]= Var[y_{jt}]$. When crash data is over-dispersed, the estimated variance term is larger than in a true Poisson process. As overdispersion becomes larger, so does the estimated variance. As a result all of the standard errors of parameter estimates become inflated. Shankar et al. (1995) observed that when data is over-dispersed or under-dispersed and Poisson distribution is used in estimation, then the equality assumption will be violated resulting in biased estimates of β, which consequently can lead to making erroneous inferences.

Over-dispersion arises when variables influencing the Poisson rate across observations are omitted from the regression (Washington et al., 2003). Over-dispersion was an issue that confronted the present study since some variables, particularly those related to bus operator habits, were not considered. The conditional mean and variance equality assumption is typically taken to be the major shortcoming of the Poisson regression modeling approach.

Many alternative formulations that can overcome this limitation have been suggested in modeling literature. For example, Greene (2003) observes that a negative binomial model, which arises from a natural formulation of cross-section heterogeneity is the common approach used in practice as an alternative to Poisson regression. To overcome over-dispersion or under-dispersion complications, the negative binomial distribution is often used. This alternative specification and associated issues are examined in the next section.

2.3.3. The Negative Binomial Modeling Approach

The negative binomial distribution model relaxes the Poisson's mean-variance equality constraint. It is especially useful for discrete data over an unbounded positive range whose sample variance exceeds the sample mean. A negative binomial distribution or modeling (NB) approach is considered the current state of practice for modeling the over-dispersed crash data. It is derived by generalizing or rewriting the Poisson model (equation 1.2a or 1.2b) by introducing an individual, unobserved effect into the conditional mean.

In NB approach, each observation j can be specified as;

$\lambda_{j\,t} = \exp(\beta X_{jt} + \varepsilon_{jt})$ or alternatively………..…………………………....1.8a.

$\ln \lambda_{j\,t} = \beta X_{jt} + \varepsilon_{jt}$ ……………………………….……………....……….... .1.8b.

Where ,

$\exp(\varepsilon_{jt})$ is a gamma-distribution error term with mean 1 and variance α^2.

The addition of the error term allows the variance to differ from the mean, resulting in a mean-variance relationship provided in equation1.9 below;

$\mathrm{Var}[y_{jt}] = E[y_{jt}][1 + \alpha E[y_{jt}]] = E[y_{jt}] + \alpha E[y_{jt}]^2$………………………………….…. 1.9.

The α is often referred to as an over-dispersion or under-dispersion parameter and the decision to use either Poisson or negative binomial is dependent on the value of α. When α approaches zero, Poisson specification is used and vice versa. Washington et al. (2003) notes that the test for over-dispersion is provided by Cameron and Trivedi (1990) and is based on the assumption that under Poisson model, $(y_{jt} - E[y_{jt}])^2 - E[y_{jt}]$ has mean zero, where $E[y_{jt}]$ is the predicted count λ_{jt}.

Therefore the competing hypotheses are given as;

H_O: $\mathrm{Var}[y_{jt}] = E[y_{jt}]$ .... 2.0a.

H_A: $\mathrm{Var}[y_{jt}] = E[y_{jt}] + \alpha g(E[y_{jt}])$ ....2.0b.

Where,

$g(E[y_{jt}])$ is a function of the predicted counts that is usually given the values of $g(E[y_{jt}]) = E[y_{jt}]$ or $E[y_{jt}]^2$.

In performing overdispersion test, a simple linear regression is estimated as shown in equation 2.1 below;

$Z_{jt} = bW_{jt.}$ ……………………………………………………….…….………...…...2.1

Where,

$Z_{jt} = (y_{jt} - E(y_{jt}))^2 - y_{jt} / E(y_{jt})\sqrt{2}$ …………………………...………..……................2.2

$W_{jt} = g(E(y_{jt})) / \sqrt{2}$ ………………………………..…………………....………..2.3

The regression in equation 2.1 is run for both $g(E[y_{jt}])$ equal to $E[y_{jt}]$ and $E[y_{jt}]^2$, if b is statistically different from zero in either case, then H_o is rejected and therefore the negative binomial regression model is used for data analysis.

According to Washington et al. (2003) and Cameron & Trivedi (2005) the negative binomial distribution form can be specified as provided below;

$$P(y_{jt}) = (\Gamma((1/\alpha) + y_{jt}) \,/\, \Gamma(1/\alpha)\, y_{jt}!)\, (1/\alpha \,/\, 1/\alpha + \lambda_{jt})^{1/\alpha}\, (\lambda_{jt} \,/\, 1/\alpha + \lambda_{jt})^{yjt}, \quad \ldots 2.4$$

Where $\Gamma(.)$ is a gamma function. The equation 2.4 , results in the likelihood function (the product of probabilities) expressed below;

$$L(\lambda_{jt}) = \prod_{j} (\Gamma((1/\alpha) + y_{jt}) \,/\, \Gamma(1/\alpha)\, y_{jt}!)\, (1/\alpha \,/\, 1/\alpha + \lambda_{jt})^{1/\alpha}\, (\lambda_{jt} \,/\, 1/\alpha + \lambda_{jt})^{yjt}, \ldots 2.5$$

This function is maximized to obtain α and β coefficients.

According to Green (1998), estimation of equation 2.5 can be done through the standard maximum likelihood procedures (MLE). Lord and Mannering et al. (2010) as well as Shankar et al. (1995) and Lin(2001) review some of the estimation methods that can be used in an estimation process besides the MLE procedures. These include quasilikelihood, weighted least squares, regression-based estimation and moment estimation techniques. However, Shankar et al. (1995) cite evidence from the study by (Piegorsch, 1990) which indicates that for large samples (J > 20) the quasilikelihood and MLE methods are efficient and perform better in estimating the parameters.

Just like the Poisson approach, the NB approach easily overcomes the constraints that limit linear regression applications. The NB distribution approach has successfully been used for modeling crash data. Unlike the Poisson model, the NB approach is not limited by over-dispersion complications. However, the NB approach is also limited. First, the NB model leads to inefficient coefficient estimates and biased estimated standard errors when used to estimate pooled count data with serial correlation in error structures. Second, NB specification is not easy to implement as "in-depth" knowledge is required to estimate and interpret the results. In the next sections, more advanced specifications which can overcome some of these issues are discussed.

2.3.4. The Negative Multinomial Modeling Approach

The negative multinomial modeling method (NMM) is basically an extension of the negative binomial model. While NMM is suitable for estimating count data with correlated error terms, it has not been used widely because the specification is fairly complex and interpretation of results is difficult. Serial correlation has been observed to be an issue in count data (Ulfarsson and Shankar, 2003; Washington et al., 2003). However, only a few safety studies have bothered to correct or even test its presence. Ulfarsson and Shankar (2003) observe that most researchers that estimate Poisson or negative binomial assume that serial correlation does not exist.

Serial correlation has been attributed to a number of factors. For example, Lin (2001) reports that in most cases autocorrelation problems are due to omitted variables. On the other hand, Washington et al. (2003) attributes it to the time series nature of count data especially from panel. When errors are correlated for different time periods for given observations, then the independence assumption of unobserved error terms is violated and, if not corrected, autocorrelation leads to inefficient coefficient estimates and biased estimated standard errors. Therefore, negative multinomial distribution has been a preferred statistical approach in modeling data with auto-correlated error structures.

The fixed-effects and random effects count data modeling approaches are other methods that easily overcome serial correlation related issues (Ulfarsson and Shankar, 2003; Washington et al., 2003) and they are examined in the next section.

2.3.5. Fixed /Random Effects Negative Binomial Modeling Approaches

The fixed- and random effects negative binomial models are simple extensions of negative binomial models. These models are different from each other. The random effects modeling approach accounts for possible autocorrelation and over dispersion, which is often attributed to the unobservable heterogeneity. In contrast, the fixed-effects approach is limited as it does not account for heterogeneity in observations (Washington et al. 2003).

Specifically, group-specific variations (in this case, individual bus operator– specific effects) would be unaccounted for in the fixed effects negative binomial (FENB) models. While the regular NB models can overcome over dispersion, they fail to account for individual-specific effects and serial correlation that may occur over time in crash count data.

Empirically, over dispersion and serial correlation can be overcome by incorporating in the model structures the indicator and trend variables that capture individual and temporal effects respectively. This approach however is limited as all unobserved heterogeneity will not be fully captured. Shankar et al. (1998) has suggested addressing these issues through use of an appropriate modeling framework that can produce efficient parameter estimates. Chin and Quddus (2003) indicate that one way to overcome over dispersion and serial correlation is by analyzing count data in panels and considering separate persistent individual effects in the negative binomial model.

In the context of count data, Hausman et al. (1984) first examined random effects negative binomial (RENB) and fixed effects negative binomial models for panel data in their study of research and development patents. Other studies that have used random effects in crash frequency analysis include: Johansson (1996) who examined the effect of a lowered speed limit on the number of crashes on roadways in Sweden; Miaou et al. (2003) used random effects in the development of crash risk maps in Texas. The findings of the study by Shakar et al. (1998) that compared standard/ regular NB and RENB models in analyzing the crashes caused by median crossovers in Washington State indicates that RENB specifications are more appropriate in modeling crash data because they account for group-specific effects. In addition, their study indicates that RENB models can significantly improve the explanatory power of the accident models.

The RENB specification basically layers a random “individual and time” effect on the regular NB by assuming that the over dispersion parameter is randomly distributed across groups (Hausman et al . 1984; Shankar et al. 1998). This formulation is better able to account for the unobserved heterogeneity across observation units and time. Ultimately the variance- to- mean ratio is not constrained to be constant across individual operators, as is often the case in the cross-sectional or regular NB.

The RENB model structure is derived by introducing a random individual –specific effects term into the relationship between the expected number of crash incidents λ_{jt} and the covariates, X_{jt}, of an observation unit j for a given time period (Shankar et al. 1998; Chin and Quddus, 2003). Mathematically, this specification is expressed as

$\ln \lambda_{jt} = X_{jt}\beta + u_j$ ………………………..……………………………………..2.6

Where,

X_{jt} is a vector of operator- and time-specific explanatory variables, β is a vector of coefficients to be estimated, u_j is a random effect for the j^{th} individual operator or observation group such that $\exp(u_j)$ is a gamma-distribution with mean one and variance α, where α is also an overdispersion parameter in the regular NB model .

As indicated by Shankar et al. (1998), variations of individual group effects over time are accounted by using $\theta_j / (1 + \theta_j)$ to be B(a, b), where θ_j is 1/ α and B(.) is the beta-distribution.

Using the results derived by Hausman et al. (1984), the probability density function for the RENB specification for the j[th] individual group can be written as

P(n_{j1}, …. .,n_{jT} | X_{j1}, ……, X_{iT})

$$= \frac{\Gamma(a+b)\Gamma(a+\sum_T \lambda_{jt})\Gamma(b+\sum_T n_{jt})}{\Gamma(a)\Gamma(b)\Gamma(a+b+\sum_T \lambda_{jt}+\sum_T n_{jt})} \prod_T \frac{\Gamma(\lambda_{jt}+n_{jt})}{(\lambda_{jt})n_{jt}!} \qquad \text{…………………2.7}$$

Where Γ (.) is a gamma function and n_{jt} is the number of crash incidents involving operator j during time period t. The parameters a, b and the coefficient vectors β are estimated using standard maximum likelihood procedures (Shankar et al . 1998; Chin and Quddus, 2003).

Generally, simple Poisson and negative binomial models and their extensions have made valuable contributions in uncovering crash risk factors. However, work by Shankar et al. (1997) suggest that these modeling efforts do not address the possibility that some observed units have zero accidents during a specified time period that may be qualitatively different from Poisson or negative binomial distributed accident frequency counts. They suggest that two processes may be simultaneously at work in such situations. The consequences of estimating a dual –state system as a single –state system can lead to erroneous inferences regarding over dispersion in the data and underlying causality. These issues are overcome by using the zero inflated models for analyzing the dual-state systems (Carson and Mannering, 2001; Washington et al. 2003; Shankar et al.1997). The zero-inflated models and associated issues are discussed next.

2.3.6. Zero- Inflated and other Modeling Approaches

The Zero Inflated Poisson (ZIP) and Zero Inflated Negative Binomial (ZINB) models are simple extensions of Poisson and negative binomial models respectively. These specifications often model count process as a dual state process (Washington et al. 2003; Greene, 2003). Where in state one, the count of zero is taken as an inherently a safe state. Whereas in the other count state, state two, is taken as a Poisson or negative binomial process. The strength of the zero inflated modeling approach is that the ZIP and ZINB regressions often fit crash data well and they better account for the excess zeros often found in count data. In particular, these models account for zeros that are often not explained by the simple Poisson and negative binomial process.

The major shortcoming confronting the zero-inflated modeling approach is that it is very hard to justify or support the notion of inherently safe situations; there is practically no theoretical appeal, as a safe state or situation in transportation is only possible if there is no movement. The other weakness for these models is that they are very difficult to interpret or explain differences in dual states.

Apart from the incident frequency analysis models discussed above, some safety studies have employed other analytical frameworks; such as system equations modeling, neural network (AI models) and meta- analysis. These models and related issues are equally important but they are beyond the scope of the present study and consequently they are not discussed.

2.3.7. Summary and Lessons Learned

In summary, modeling literature in this area reveals that all safety models have some strengths and weaknesses. The choice or selection of a given analytical model depends on the research problem at hand, data and individual judgment.

There is evidence which reveals that a least squares or multiple linear regression approach is not a suitable method for modeling crash data. Poisson regression is appropriate for modeling accident or count data. However, if there is over-dispersion in data, an alternative framework, the negative binomial modeling is preferred. In contrast, if over dispersion and/or serial correlation is present, then the negative multinomial specification, as well as fixed and random effects negative binomial modeling methods are preferred.

The next section presents the results from a sample of safety studies that use log-linear or count data models as their analytical frameworks.

2.4. The Empirical Findings

Turning to the specific factors and how they are related to accident rates and frequencies, evidence is clear that numerous factors play roles in accident occurrences. These factors have been well identified in the empirical framework conceptualized by Jovanis et al. (1991) and they are consistent with the human capital theoretical framework (Rodriguez et al. 2003; Monaco and Williams, 2000).

In general, traffic safety literature has found negligent driver behavior to be the principal cause of crashes. Evans (2004), for example, summarizes the findings of two large independent studies undertaken in the U.S. and U.K. Analyzing the details of thousands of crash records, both studies found driver behavior to be either the sole or contributing cause of over 90% of crashes. The principal causes of the remaining crashes were identified as vehicle failures (e.g., brakes and tires), environmental factors (e.g, weather and lighting), and roadway factors (e.g., design and condition).

The following sections present findings from a sample of previous empirical studies that have examined the relationships between accident occurrences and the identified factors, starting with operator specific factors in section 2.4.1, followed by factors beyond the operator, that can still be influenced and controlled by transit system management in section 2.4.2. In section 2.4.3, a brief acknowledgment and discussion of the general safety effects of other factors (e.g., factors related to design of facilities, land use and system operations related conditions respectively), mainly those beyond the control of transit agencies are provided. Section 2.4.4 cover findings from bus transit practice literature. Finally, section 2.5, provides summary of what is known and not known, including the specific research questions that are addressed and the hypotheses for the present study.

2.4.1. Operator-level Factors & Safety Performance

There has long been a concern in the transit industry about the safety consequences of fatigue (Gertler et al., 2002). Fatigue among operators can be linked to selected work assignment practices in the industry. For example, rapid increases in fringe benefit costs have led to wider use of scheduled overtime assignments rather than additional hires in an effort to control costs. Similarly, splitting a full time operator's shift (to cover both the AM and PM peak service periods) is less costly than covering each peak with a part time operator, but it also extends the span of the workday. Variability in shift time assignments also contributes to fatigue. Such variability is most prevalent among operators who work the extraboard, which fills assignments that are vacant due mainly to absences.

The safety risks to operators from occupational stress are also a longstanding concern in the industry. The transit operator's job has been characterized as being typical of a high-stress occupation, with heavy work demands, low control, low support and elevated risk of chronic health problems (Kompier and Martino, 1995; Long and Perry, 1985; Winkleby et al., 1988). The job entails three general responsibilities that often come into conflict: provide positive customer service; adhere to a schedule; and drive safely. Operator surveys reveal stressors that act to undermine each of these responsibilities: heavy passenger loads with a risk of assault; unpredictable delays related to congestion and variable passenger loads; and the risks of navigating a large vehicle in and out of traffic to serve stops that are typically located at busy intersections (Long and Perry, 1985).

Research on occupational stress in the transit industry has focused on its effects on absence and health rather than on accident consequences. A study by Wahlberg and Dorn (2009) is an exception. They found a positive association between absence and accident frequencies among three independent samples of bus operators from the UK and Sweden, and thus posited that absence frequency signals health conditions that impair driving performance. An alternative interpretation may be drawn from the work of Strathman et al. (2009). Their study of US bus operators found that absences spiked on the days before and after scheduled days off, which suggests that an association between accident and absence frequencies may also reflect diminished driving performance related to low levels of job satisfaction and commitment.

With respect to demographic and employment status attributes, crash incidence has been found to decline with operators' age (Dorn and Wahlberg, 2008; Jovanis et al., 1991; Zegeer et al., 1993a). The effect of seniority was found to be non-linear by Jovanis et al. (1991), who determined that PACE operators with 3-6 years service were overrepresented in crash incidents relative to operators with greater or less seniority. Rodriguez et al. (2003) found that married, non-Caucasian, and female truck operators had fewer crashes. Distinctions between full and part time operators have not been explored to date.

Research on crash risk related to operators' work schedules indicates that crash likelihoods are greater for morning than afternoon and evening shifts, as well as for split shifts (Pokorny et al., 1987a; Pokorny et al., 1987b). Gertler et al. (2002) state that crash risk tends to increase over the course of the workday. Hamed et al. (1998) found crash incidence to be inversely related to operators' break time. Other factors that are known to influence operator safety performance include; bus routes (.e.g., bus stop location) and vehicle characteristics. These factors are beyond the control of bus operator, but they are subject to the control of transit agency management. The role of these factors in safety performance is discussed next.

2.4.2. Planning & Service Delivery Related Factors

The location and design of bus stops have been found to influence safety and crash risk. Stops located at the far side of intersections experience lower crash incidence than near side or mid-block stops (Cheung et al., 2008; Texas Transportation Institute, 1996; Zegeer et al., 1993a). Bus turn-out lanes have been recommended in moderate traffic volume situations, as have lighting upgrades and pedestrian facility improvements (Texas Transportation Institute, 1996).

The vehicle-specific attributes that are known to influence bus accident risk include; vehicle age, model year, vehicle door steps and configuration. Older vehicles and old bus models have been reported to be over- represented in crashes relative to the newer bus models (Zeeger et al. 1994; Chang and Yeh, 2005). These findings can be attributed to a number of reasons. First, new vehicles incorporate new technologies which are often geared at improving safety. Second, new vehicles tend to have fewer failures while in operation and therefore they are less likely to be involved in preventable collisions. Third, vehicle age may affect handling characteristics and these may also vary for different types of buses.

Vehicle door type and designs are known to have negligible impact on bus transit collisions. In contrast, these attributes have been found to be important in non-collision passenger accidents. More specifically, evidence suggests that door-related passenger accidents in part depend on the number of door steps and also on the direction in which the door opens. For example, Hudenski (1992) showed that vehicles with three door steps had higher rates of falling and boarding accidents than vehicles with two door steps. He also found that vehicles with inwardly opening doors were more likely to strike passengers while they were alighting or standing on board than outward or sideward opening doors.

A number of measures have been employed or suggested in order to control for safety risk exposure. Such measures include the number of vehicle hours and miles;

passenger movements and stops served; route length, traffic volume, and number of intersections per route; and the extent of on-street parking (Cheung et al., 2008; Jovanis et al., 1991; Ragland et al., 1992).

Lastly, factors related to road facility design, system operations and land use adjacent to roadways have been found to influence safety of commercial vehicles, as well as automobiles. These factors are generally beyond the transit management control, but they are important to the present study because they provide valuable insight into how these factors are related to accident rates and frequencies. The role of these factors in traffic safety performance is discussed next.

2.4.3. Factors Beyond Transit Management Control

Turning to factors specifically related to design and other related conditions, there is clear evidence indicating that the effect of these factors on crash activity depends in part on the type of the variable and how the given variable is entered in the estimation model. Roadway segments or zones with higher average posted speed limits are consistently associated with fewer accident occurrences (Cheung et al. 2008; Carson & Mannering, 2001; Hadayeghi et al. 2003; Milton & Mannering, 1998; Shankar et al. 1997; Jovanis et al. 1991 and Strathman et al. 2003).

This relationship is, however, counter-intuitive and has been explained in various ways. Some authors have argued that high speed roads are likely to be well designed, carry small traffic volumes and have fewer stops and are therefore relatively safer (Cheung et al. 2008; Jovanis et al. 1991). The challenge is that such routes allowing faster travel may be safer but might not be preferred for transit operations if fewer patrons exist. Alternatively, higher speed limit may mean lower spacing between intersections and thus less opportunity for conflicts.

Another explanation is that there are simultaneity issues associated with the speed limit variable (Hadayeghi et al. 2003; Carson & Mannering, 2001). The latter argument is based on the fact that speed limit is often instituted in response to occurrence of crashes and therefore speed sign placement need to be treated as an endogenous variable in crash frequency analysis.

Shoulder width and travel lane width have mixed effects on accident occurrence. The effect and magnitude of each of these variables depend on whether the factor is entered in the estimation model as a continuous or as a dummy variable. For example, Shankar et al. (1997) showed that when defined as categorical or dummy variables, travel lane and shoulder width have positive and significant effects on crash frequency. On the other hand, when treated as a continuous variable, lane width has a negative effect (Hadi et al., 1995) and in another study, lane width had a negligible effect on crash frequency (Hauer et al., 2004).

The numbers of lanes on a roadway are positively and significantly related to the frequency of accidents (Carson & Mannering, 1998; Milton and Mannering; 1998; Shankar et al. 1997). This relationship has been interpreted by Strathman et al. (2003) as highlighting the increased hazard associated with lane changes. The latter study uses incident frequency data from Oregon to show that right turn lanes increase crash frequency, whereas the left turn lanes have a negative effect.

Crash frequencies are generally estimated to be positively correlated with the number of intersections and access points on a roadway. This relationship has, however, been shown to be sensitive to the type of intersections along the roadway. The number of unsignalized intersections and access points on a roadway are positively correlated to crashes (Sawalha et al., 2000; Brown & Tarko, 1999). In contrast, the number of signalized intersections has been shown to have a negative impact on crash activity.

Evidence also suggests that the effect of signalized intersections on crash frequency partly depends on the spatial and operational features of the given intersections. For example, Abdel-Aty and Wang (2006) showed that signalized intersections with a relatively high number of lanes had higher crash frequencies than small-sized signalized intersections located in primarily residential areas.

Research on crash risk related to land use factors has found that the likelihood of crash activity partly depends on the type of land use. Commercial and related (.i.e retail, visitor lodging, manufacturing, auto sales, etc.) uses have been shown to exhibit a stronger positive effect on crash activity than the non-commercial land uses, such as, residential, vacant or open lands (Hadayeghi et al., 2003; Hadayeghi et al., 2007; Kim and Yamashita, 2002; Ronkin, 2004). Land used for hospital activity has been shown to have a negative influence on crash frequency (Kim et al., 2006). This finding can be interpreted in various ways. The most common explanation is that the true determinants of the hospital activity's influence on safety were not controlled in the estimation model.

The conventional environment conditions, such as, weather related factors, road surface conditions, and lighting conditions are, by definition, beyond the control of transit agencies. The role these factors play in accident occurrences has been shown to be significant. For example, Zeeger et al. (1993a) showed that while bus crashes were more prevalent on dry pavement, crashes occurring on wet pavement were significantly more likely to result in injury. They revealed that bus crashes that occur on snowy or icy roadways were less likely to result in injury.

In general, Jovanis et al. (1991) cites a study by (Jovanis and Delleur, 1983) which provides evidence from truck safety studies that tend to support the contention that weather conditions are likely to have only modest effects on bus transit accidents compared to automobile accidents because the bus operator is a professional who better cope with adverse driving weather conditions. This argument however, fails to recognize that other road users are non-professionals.

It is true that these highway safety studies have contributed to a better understanding of the influence of factors related to design of facilities, land use, and system operations in accident occurrence and resulting injuries. The findings cannot be assumed to be directly transferable to design of safety countermeasures in the bus transit industry. More specifically, bus transit safety practices literature suggests that a number of countermeasures can be implemented to reduce bus transit crashes (Technology and Management Systems, 2001). But the key challenges are determining where the focus should be and what level of resources or which strategy to use.

The next section presents findings from a sample of transit safety practices literature, highlighting some of the issues associated with the safety countermeasures that are often used in response to safety problems.

2.4.4. Bus Transit Safety Countermeasures

The most common safety practices across transit systems include operator training programs, retrofitting vehicles with advanced safety technologies such as LED brake lights at the rear of the bus, providing customer safety information and routine vehicle inspection and maintenance. The Texas Transportation Institute (TTI) report (1996) presents findings and recommendations from research on bus stop location and design that can be used by agencies to improve the safety of bus stops for passengers, buses, pedestrians and other vehicles.

The TTI report particularly indicates that efforts to improve safety should include placement of bus stops at the far side of an intersection. The document provides information about the factors that need to be considered in bus stop zone designs. For example, the document recommends that bus bays should be considered where curb lane traffic exceeds 250 but has less than 1000 vehicles during the peak hour. Otherwise merging back into traffic would be unsafe. Further, the document calls for coordination and cooperation of public and private interests, especially in providing sidewalks, lighting, access to streets, curbs and in minimizing potential conflicts or interactions of the stopping bus with pedestrian and the general traffic stream.

The earlier reported empirical findings on bus stop location or placement are clearly consistent to what is being done in practice. Findings from a number of practice studies indicate that locating the stop just after the intersection (far-side) is safer than either placing the stop at just before the cross street at the intersections (near–side), or on the block face between two intersections (Texas Transportation Institute,1996; Zeeger et al., 1993a). These authors have argued that far-side stop location minimizes conflicts between right turning vehicles and the buses. But they also fail to highlight the fact that far-side location might increase the number of rear end accidents. For instance, a driver in the vehicle immediately behind the bus may not expect the bus that just stopped, say, at the light before the intersection, to again stop at the far–side stop location, and consequently the vehicle immediately behind might run into such a bus.

Bus stops are sometimes placed between the driveways of gasoline service stations and convenience stores. While this location has several appealing features, some disadvantages exist as well. For example, Texas Transportation Institute (1996) reported that because these facilities are usually on corners, vehicle turning movements abound and pedestrian access is seldom clearly marked. Consequently, placement of a bus stop in such a location increases the potential for conflicts and crashes.

Although these practices and programs have contributed to safety improvement, the absence of references to safety-oriented practices in the areas of work organization (.e.g., scheduling, compensation, service and operations planning) is notable. A more systematic approach is needed in order to gain insight into the relative importance of the operator-based factors in explaining bus crashes and in identifying safety countermeasures that can be applied to reduce the occurrence of preventable incidents, as well as the frequency of collision and non-collision incidents.

2.5. Summary and Lessons Learned

The findings from the empirical literature review reveal that prior empirical studies specifically examining bus crashes primarily addressed the effects of operator demographics, factors contributing to operator stress and fatigue, various measures of safety risk exposure and route or vehicle characteristics representing potential safety hazards. The importance of operational characteristics has also been recognized by researchers (Jovanis et al., 1991; Zegeer et al., 1993a; Zegeer et al., 1993b). Due to data limitations and research design issues these studies could not directly model the likelihood of preventable incident involvement and crash frequencies at the operator level.

The literature review also reveals a number of limitations to prior studies on bus transit accident analysis. First, there are no studies that have comprehensively examined the operational determinants of bus transit accidents at the operator signup level. Second, the influence of employment status, assigned work, work performance abilities and customer feedback on the expected frequencies of bus collision and non-collision has not been quantitatively determined. Third, there is no study that has used data recovered from Transit ITS technologies and related systems to develop an operator-based safety incident model that can help in identifying and assessing the effect of factors that contribute to the likelihood of preventable incident involvement and occurrence of transit bus safety incidents.

This research strives to fill these knowledge gaps and builds on earlier studies to broaden bus transit accident literature by developing a more comprehensive operator signup- based approach to exploring the role of operator specific factors and how they affect the frequency and preventability of crash incidents.

2.5.1. Research Questions

The purpose of this research is to better understand the relationship between operational characteristics and transit bus accident occurrences, and, consequently, identify and assess factors contributing to bus operations safety incidents, so that changes in operating policies and practices can appropriately be considered to improve operator safety performance. This goal is accomplished by developing an operator signup-based safety model that is used to address the following research questions:

1. How do bus operator's employment status, demographic factors and assigned-work characteristics affect the frequency of bus safety incident occurrences?
2. How do operator's ability to perform work and attitudes toward service and safety issues influence the frequency of bus operations safety incidents?

2.5.2. Study Hypotheses

1. It is expected or hypothesized that the bus operator's age, experience and variations in short duration absenteeism from work , as well as the operator's assigned work characteristics, such as work span and variability in daily work

are empirically related to the likelihood of preventable incident involvement and frequency of collision and non-collision incidents.

2. It is hypothesized that schedule adherence pressures associated with running late and lift operations, as well as responsive action events and customer complaints about unsafe bus operations are expected to be correlated with the likelihood of preventable incident involvement and frequency of bus safety incidents.

This study uses safety incident data from TriMet's Accident and Incident Tracking System to construct a model to answer the above stated questions. While data recovered by transit ITS technologies and related systems have made important contributions to operations management and service planning (Furth, et al., 2006), as well as to market research (Strathman, et al., 2008), there is no prior study that has comprehensively investigated the potential of using these databases for transit safety analysis and planning.

In contrast to earlier safety research, the present study uses incident data recovered by these technologies in combination with information from Human Resources, scheduling, and customer relation databases to provide a comprehensive and detailed representation of the transit operating environment. This approach has the advantage of relying on operator-level data to investigate the effects and role of operational characteristics on safety incident occurrences. This is obviously different from aggregated approaches used in the previous studies, which heavily relied on databases that were largely constructed from police reports or operator-self reported safety data.

CHAPTER 3.0: DATA AND METHODOLOGY

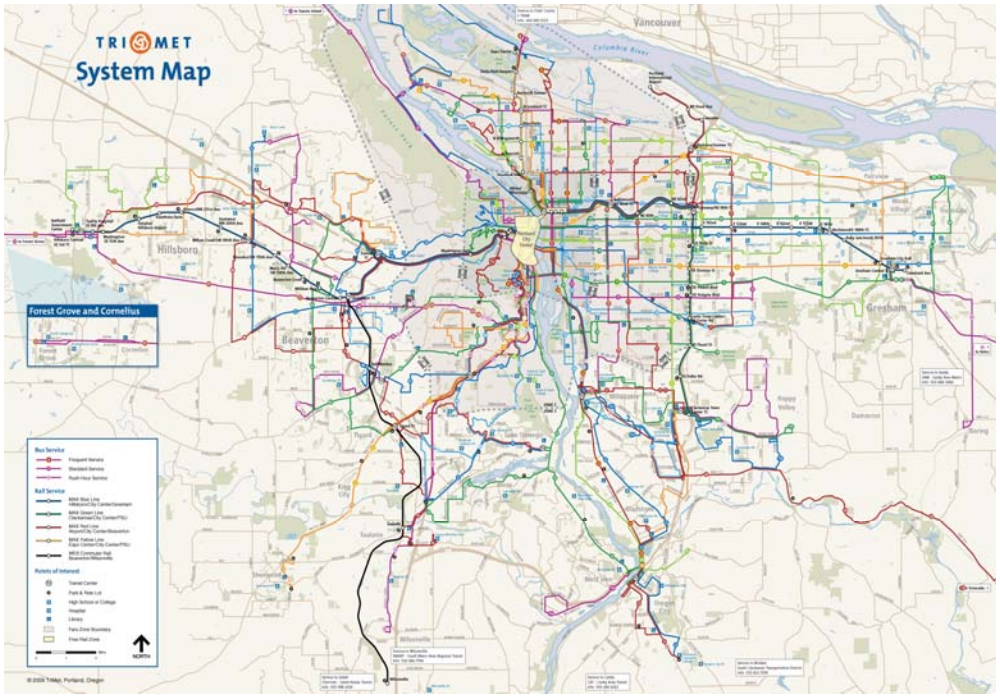
3.1. Introduction

This research design section is divided into five parts; part 3.2 describes the study area and provides a detailed description of type and sources of data. Part 3.3 presents the research methodology. Part 3.4 presents the safety incident patterns observed in the study data. While part 3.5 provides the basic structure of the safety model that is used to empirically analyze the effects of operational factors on transit bus safety incidents. This part also provides the description of safety model variables. Part 3.6 covers model selection process and criteria, as well as the model specification issues encountered and how they are addressed.

3.2. The Study Area, Type and Sources of Data

TriMet can be characterized as a mid-sized urban transit system, providing fixed route bus, light rail and streetcar service to the Portland, Oregon, metropolitan area, shown in Figure 3. TriMet's system was selected as a case study for this safety research for a number of reasons. It was an early adopter of automatic passenger counter (APC) techonology and leveraged its APC experience in the design of its automatic vehicle location (AVL) system. TriMet's experience with APC techonology dates back to a demonstration project in the early 1980s, while AVL was deployed in 1998. Second, the agency has a strong reputation in the industry for its innovative uses of archived AVL and APC data for internal decision making in areas such as performance monitoring, scheduling, service planning and market research.

Figure 3. Map of TriMet Bus Service District



Source (TriMet website, 2010)

Third, TriMet's ITS and related systems recovered databases on bus accidents/incidents and potential risk determinants provide a rare and unique opportunity to use data from a single source to analyze safety performance. This database is unique because data are recovered and recorded by the agency. This is obviously different from survey generated databases which often rely on driver recall. On the other hand, using an agency-specific database has shortcomings, the major one being that the results will apply exclusively to the population of TriMet operators.

To date, data sources for safety analysis are generally limited. While data recovered by transit ITS technologies and related systems have made important contributions to operations management and service planning, they have not been widely used for transit safety analysis and planning. Until recently, TriMet relied on manual data collection methods (e.g., ride checking staff, driver recall and operator self-reported data) for safety analysis and for National Transit Database reporting. The deployment of ITS and related systems have made the data collection process relatively simpler, more comprehensive and less expensive. The TriMet Bus Dispatch System (BDS) includes a variety of technologies, such as APC and AVL. This system has proven to be more reliable and accurate compared to manual methods of data collection.

The ITS generated accident/incident data and data on incident determinants archived by TriMet, were used to assess in-service collision, non-collision and total safety incidents that occurred on the agency's bus system over the three year study period: September, 2006 through February, 2009. The AVL system serve as the backbone technology, providing time and location referencing for monitoring passenger activity, as recorded by APCs, as well as for a wide range of in-service incidents recorded by operators on mobile data terminals (MDTs). AVL data are also useful in their own right for monitoring schedule and headway adherence, on-time performance, vehicle speeds, dwell times, running times, departure times and layover times.

The highly detailed data records recovered by ITS technologies are archived in an enterprise data warehouse. The warehouse also maintains other databases that are relevant to transit safety analysis and these data were merged with ITS data through operator references. The human resource database provides information about operator demographics, employment status, experience, and work attendance. In addition, an automated scheduling and run cutting database provides detailed information about operators' assigned work, covering: vehicles, routes, days, time of day and scheduled overtime.

Lastly, a customer relations database provides information about customer reactions to their riding experience, including commendations of operators' performance on the job and concerns about operators' treatment of passengers, handling of vehicles or fitness for duty. Collectively, the information from these archived databases provides a comprehensive and detailed portrayal of operators' work qualifications, work environment and work performance.

3.3. Research Methodology

This study addressed the research questions and hypotheses stated in section 2.5.1 and 2.5.2 respectively through analysis of archived ITS and related systems data described above using an operator-based design approach (discussed in section 2.2). This database is rich because it contains information on operators' work qualification, work environment and safety/work performance for both crash involved and crash-uninvolved bus operators- characteristics usually unavailable in other safety databases.

The operator-based design makes it possible to organize safety incidents data and information on corresponding operational factors around each bus operator –signup period. This design enables both behavioral and non-behavioral factors to be incorporated in the same estimation model. In addition, both operators with and without safety incidents are included in the sample and thus all information is recovered.

The most apparent shortcoming of operator signup design is the challenge of ensuring control or representation of risk exposure. While in route-based designs the variable total miles traveled is often used to account for the risk exposure. In contrast, the variable total hours worked (by the operator during each signup period) is used as a proxy measure to account for risk exposure in the present. However, it does not account for differences in risk exposure by route or time of the day. Some routes have high incidents of crashes due to factors mentioned earlier that are not controlled in this study (discussions on performance of exposure proxies and how they might limit research findings is provided in section 5.7).

The overall methodology process consists of three main steps. In the first part, the research identifies a list of 1,502 bus operators that operated TriMet buses between

September, 2006 and February, 2009. The second part involves identifying the number of incidents and the attributes associated with each operator for every operator sign-up period. The third step involves aggregating the number of incidents and specifying the associated operator attributes at the operator sign-up level. The analysis is done at the operator sign-up level in order to reflect the operational conditions at the agency.
The unit of observation of the safety model is defined as an operator signup, a three-month period for which regular duty operators select (on the basis of seniority) work assignments developed by the agency's scheduling and run cutting software. Given the three-year time frame of this study, the analysis as such spans 12 signups and includes 1,502 bus operators. The number of operator-signup observations totals 13,796. This results in an unbalanced panel, as some bus operators were not observed in every signup because of retirements, quits, new hires, and transfers to or from other transit mode assignments.

The organization of sample observations into 3-month signups involves reconciling trade-offs between the need to address "zero-inflation" issues related to the incidence of collision and non-collision events, and the need to minimize measurement error and heterogeneity in the variables representing operators' work and risk exposure (Lord et al., 2005; 2007). Regarding zero-inflation, it can be argued that a signup is too short a time span for modeling collision and non-collision events. Also, there are more than sufficient degrees of freedom to allow the analysis to be cast at the annual (or longer) scale.

Although a longer time span would reduce the share of zero-event observations, it would exacerbate other problems. First, except for extraboards, operators' work is defined by signups. This work remains relatively fixed with respect to the variables that proxy its characteristics. Over a longer time frame, the correspondence of these variables with the work attributes they represent erode, with the consequences reflected as measurement error or risk heterogeneity. Second, the seasonality of collision and non-collision events, an important feature of these phenomena, would not be captured in an annual model.

In general, previous empirical studies reveal that the design of studies examining the factors that are important in safety has clearly been problematic. Strathman et al. (2003) observed that while the before and after approach is often relevant when safety countermeasures or interventions are being evaluated, its' validity is subject to two problematic phenomena. First, regression to the mean problem. Second, crash migration problems. The crash migration problem occurs when countermeasure implementation shifts the crash location from one place to another rather than reducing crash frequency. On the other hand, regression to the mean results when countermeasures are applied where high incidences of crashes occur. Ascertaining whether reduction in crashes is due to countermeasures implemented rather than other forces is a challenge. Use of comparable locations or sites has been proposed in literature as a potential remedy to address this problem. Finding a truly comparable site is not an easy task (Strathman et al., 2003). The cross-sectional approach is perhaps the most popular method used in systematic safety studies. The major advantage of this approach is that it provides information that can have long run perspectives or implications. The disadvantages are that this approach cannot be used in examining effectiveness of program interventions or for safety policy evaluations. Omitted variable bias has been a common challenging issue, especially in cross-sectional safety studies. Factors that are omitted in the model specification are expected to be represented in the error structures of the specified model. If the omitted variables are correlated with the variables included in the model, the estimates may be spurious.

Use of the panel data approach in transportation applications exists, but it is not widely used in safety evaluation studies (Washington et al., 2003). The advantage of the panel data approach is that a large sample size or more data points can be readily available on the variables of interest. The key misspecification issues that have to be confronted when this approach is employed include serial correlation and heteroscedasticity (Washington et al. 2003). The present study employs the latter approach, and specification related issues are addressed as discussed in Section 3.6.2.

3.4. The Observed Pattern of Safety Incidents

The safety incident data for this study were retrieved from TriMet's Accident and Incident Tracking System. The records of all bus-involved safety incidents from September 2006 through February 2009 were retrieved and reviewed. Records of incidents that did not occur within the platform service time window (e.g., between pull-out and pull-in times) were deleted. Such incidents were typically associated with bus maintenance, refueling, and “yardspotting” activities. Also, records of safety incidents or injuries witnessed by an operator but not directly involving bus operations were deleted. Two records were produced each time collisions involving a bus and another transit vehicle occurred. In these infrequent cases, the record that had previously been coded as “preventable” was retained and the other record was deleted. Lastly, duplicate records were deleted.

A breakdown of the safety incidents is presented in Table 1. Nearly 57% of the incidents were collisions. About half of the collisions involved other motor vehicles, and about two-thirds of these collisions were result of another motor vehicle running into a bus. The second most frequent collision type involved mirror strikes with other vehicles or fixed objects. Least frequent among collisions were those involving pedestrians and cyclists. Non-collision incidents consisted mainly of passenger slips, trips and falls. About 44% of these incidents occurred during the boarding or alighting process. Other slip, trip and fall incidents occurred on board, usually in connection with hard stops or during the stop-servicing phases of acceleration and deceleration. The remaining non-collision incidents involved a variety of circumstances, the most common being struck by a door movement or by a falling object in the vehicle. TriMet risk managers review reports prepared after each incident to determine whether the incident could have been prevented by following the agency’s established operating policies and practices. As shown in the crash summary statistics provided in Table 1, about one in five incidents were subsequently judged to have been preventable. However, the extent of preventability varies considerably across the incident typology. At the upper end, a majority of incidents involving a bus running into another vehicle or a fixed object was judged to have been preventable. Alternatively, only one in twenty-five non-collision incidents was judged to have been preventable, with slips, trips and falls during boarding or alighting being the least preventable.

Table 1. Breakdown of TriMet Bus Safety Incidents, Sept, 2006 -Feb, 2009.

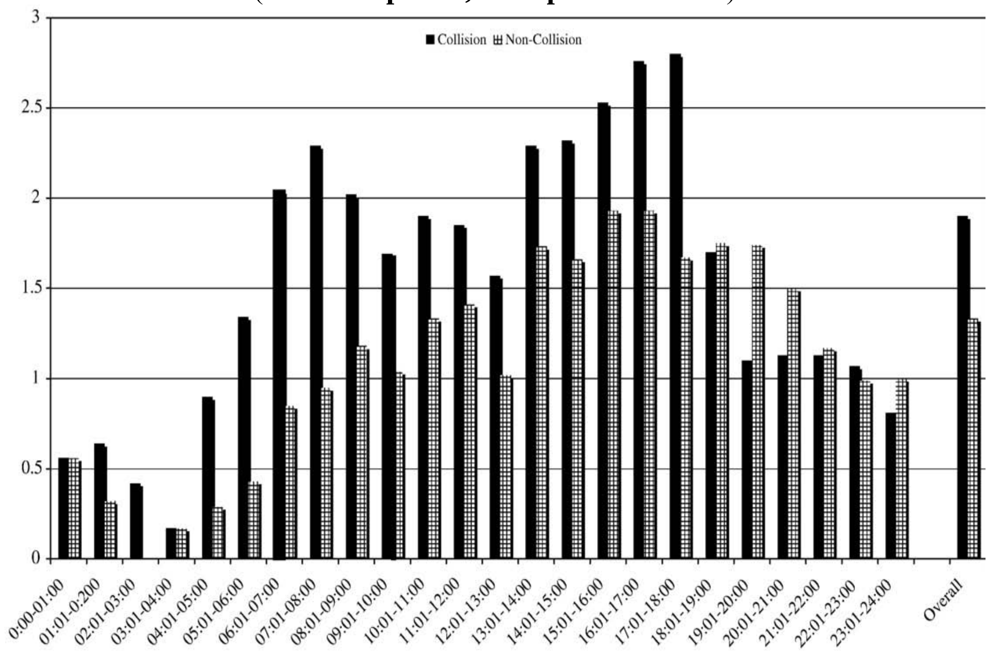
Incident Type	Percent of Total	Preventable (%)
Collisions	56.80%	30.70%
- With Motor Vehicles	27.3	29.6
- Vehicle into Bus	17.4	9.5
- Bus into Vehicle	9.9	66.2
- With Fixed Objects	5.5	58.6
- Mirror Strikes	21.9	25.6
- With Pedestrians	1.1	32.7
- With Bicyclists	1	19.6
Non-Collisions	43.2	4.1
- Slips, Trips & Falls	35.2	4
- Related to Boarding & Alighting	15.4	2.4
- Other Slips, Trips & Falls	19.9	5.2
- Other Non-Collision	8	4.7
Overall	100	19.2

(n= 4,631)

The other safety incident patterns observed are related to the course of operators' shifts and daily operations. These patterns were developed for both collision and non-collision incidents. In each case, exposure is controlled by operator hours of service.

As shown in Figure 4, the rate of collisions over daily operations is elevated during the morning and more intensity is observed in the evening peak periods.

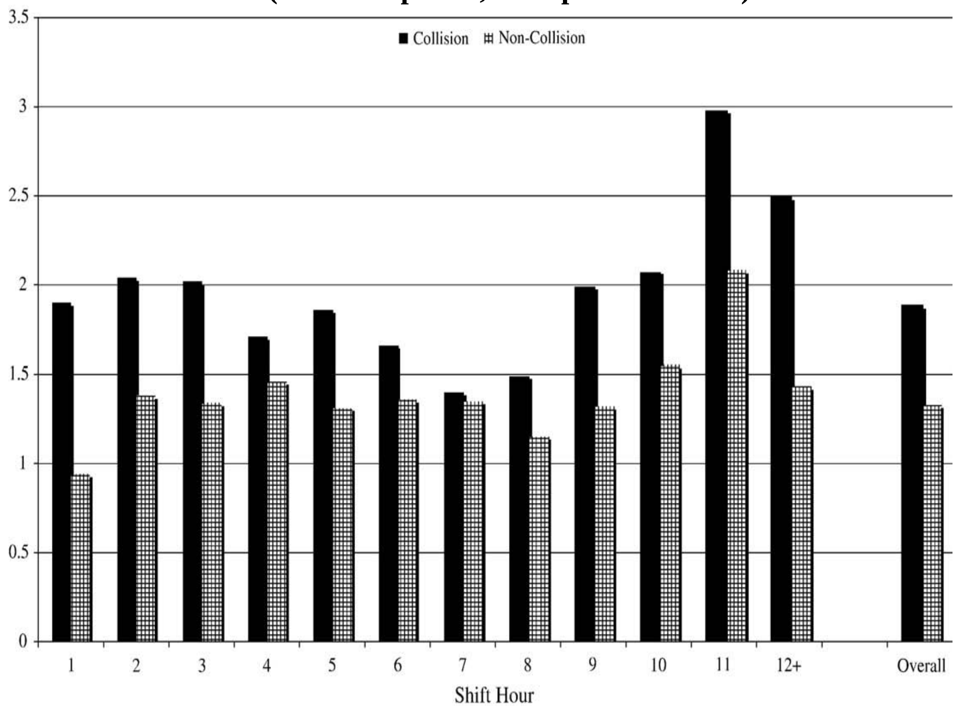
Figure 4. Collision and Non-Collision Rates By Time of Day
(Incidents per 10,000 Operator Hours)



This pattern can be attributed to the higher collision risk related to the greater traffic volumes that occurs during the same periods. In contrast, the non-collision rate gradually increases from a low at 3:00 AM to a peak at 5:00 PM, possibly reflecting growing fatigue among work commuting passengers.

Turning to the shift related safety incidents pattern visualized in Figure 5, it can be observed that the collision rate generally declines over the first 8 shift hours.

Figure 5. Collision and Non-Collision Rates By Shift Hour (Incidents per 10,000 Operator Hours)



The collision rate then turns upward for those operators transitioning into overtime work, with the peak occurring in the 11th work hour. The relatively few operators working beyond 11 hours are typically providing a voluntary fill of open work.

Overall, the collision rate pattern over shift hours is consistent with concerns expressed in the literature on operator fatigue. The rate of non-collision incidents is fairly stable over the first 8 shift hours, but also turns upward with overtime. It thus appears that overtime-related operator fatigue is contributing to greater collision than non-collision risk.

Another related pattern to consider in evaluating the resulting sample is the distribution of the number of safety incidents with respect to operator signup. Table 2 shows the frequency distribution of the safety incidents at TriMet during the three year study period. Overall, the number of the operator signups totals 13,960, of which 10,316 operator signups (74.78%) contain no safety incident for the three year period. The implications of these distributions are twofold. First, the distribution is skewed towards zero. This implies that linear regression methods are not appropriate. A count data modeling framework is a better option. Second, the large number of operator signups with zero safety incidents implies or represents something other than a censoring outcome (Greene, 2003).

An operator-based risk model described below relates the safety incidents to demographic characteristics and employment status of operators, their actual assigned work, their actual service delivery performance and customer feedback on their performance. Neither in transit safety research nor in the perspectives of transit operations and risk managers there is a basis for positing that a "virtually safe" state exists among bus operators and their assigned work. Evidence of such is necessary to justify the application of zero-inflation estimators. Zero-inflation estimators were thus not considered. As designed, the operator signup level model used in the present incident frequency analysis corresponds most closely to Lord et al.'s (2005) designation of low risk/low heterogeneity conditions.

Table 2. Frequency Distribution of Safety Incidents at TriMet, Sept, 2006- Feb, 2009

Number of Safety Incidents	Collision Incidents Frequency	Non-collision Incidents Frequency	Total or Overall Incidents Frequency
0	11544	12214	10316
1	1990	1398	2769
2	237	146	577
3	23	29	109
4	2	6	18
5	–	2	6
6	–	1	1

(Source, Authors compilation, 2010)

3.5. The Safety Model Structure

A count data estimation framework is employed in the bus incident frequency analysis. This framework reflects both the relative rarity of events and the fact that the frequency distribution of incidents across operator signups is highly skewed toward zero. In the simplest context, one model is possible. However, to distinguish between models with and without lag variables for collision, non-collision and total crash events required an estimation of six safety models, a more detailed breakdown of incident types would provide greater specificity, but this would also likely lead to an increasing share of zero event observations per operator-signup a situation that needs to be avoided.

The basic structure of the bus transit safety incidence model takes the following general form:

$Incdts._{ijt}$ = f($Dem._{jt}$, $Empl._{jt}$, $Work._{jt}$, $Perf._{jt}$, $Cust._{jt}$, $Temp._{jt}$),

Where,

$Incdts._{ijt}$ = the total number of safety incidents (or of type i) involving operator j's bus that occurred during signup t;

$Dem._{jt}$ = a vector of operator j's demographic characteristics on the first day of signup t;

$Empl._{jt}$ = a vector of operator j's employment status characteristics on the first day of signup t;

$Work._{jt}$ = a vector of operator j's assigned work characteristics during signup t;

$Perf._{jt}$ = a vector of operator j's service delivery and performance characteristics during signup t;

$Cust._{jt}$ = a vector of customer commendations and complaints referencing operator j received during signup t.

$Temp._{jt}$ = a vector of temporal characteristics capturing effects of seasonal and annual variations.

3.5.1. Independent Variables

The explanatory variables incorporated in the safety model are organized into six categories. Categories one through five are of interest to the present study. The other remaining category, temporal characteristics, is mainly used as a control and also serves to capture seasonality in the model. General information about variables included in each category is provided next. More specific details; such as how each variable in a given category is defined, measured and corresponding measurement units are provided in Appendix A.

i. Demographic Characteristics

Variables covering demographic characteristics include operator's age, sex, race and ethnicity.

ii. Employment Status Characteristics

Employment variables cover seniority (years) and full time, part time or probationary (initial six months) status.

iii. Assigned Work Characteristics

The assigned work of regular duty operators is fixed throughout a signup with respect to shift time, total hours of work, span of work, route, and bus type. The assigned work of other types of operators varies, in some instances across all of these characteristics. For example, the assigned work of extraboard operators can vary daily in filling work that opens as a result of regular duty operator absences. A less extreme example is the work of regular relief operators, who fill open work blocks of operators on leave (e.g., vacations, jury duty). Least variable, but still an issue, is the work of regular duty operators with assignments covering multiple (e.g., interlined) routes. Overall, about 25% of a mid-sized transit agency's actual delivered work varies in the ways described above.

To account for such variations, an operator's assigned work is defined by the allocation of one's actual hours in service across risk-differentiated operational characteristics. With respect to work shift, each operator's hours are ideally allocated over the following service periods: Early AM (before 06:00); AM Peak (06:01-09:00); Midday (09:01-15:00); PM Peak (15:01-18:00); and Evening (after 18:00). Hours spent in providing weekday service are distinguished from weekend service hours.

Hours are also allocated over a route typology covering radial, crosstown, feeder and peak express service. Hours by vehicle type distinguish between low floor and standard buses. Lastly, actual overtime hours are represented. In addition to the breakdown of hours across the characteristics of assigned work, dummy variables are defined for the following operator designations: extraboard service; full and part time splits; and regular relief service.

iv. Service Delivery and Performance Characteristics

Operators' service delivery and performance are represented by a variety of variables that employ archived ITS data. For each operator, the percentage of early, ontime and late departures from route time points is measured in relation to the average performance of all other operators serving the same route(s) at the same time(s). The operator's average speed between time points is similarly measured in relation to peer operators. Boardings and lift usage activity are measured per revenue hour. The lift usage variable is included to proxy service to passengers with mobility impairments. Overloads are measured as the percentage of trips whose peak passenger loads exceed the agency's capacity standard. Actual average layover time is measured in relation to actual average revenue service time per trip.

Archived mobile data terminal (MDT) data provide counts of the following events having potential direct or indirect safety implications: security response requests; vehicle replacement requests; road call (e.g., bus non-operable and out of service) requests; and traffic-related delays.

v. Customer Commendations and Complaints

Customer information variables include the number of recorded (i.e., received by Customer Relations via phone or email) complaints related to an operator's unprofessional conduct, unsafe operation of the bus or problems related to timely service delivery (e.g., missed stops, pass-ups, early departures). Customer commendations of operators distinguish between those related to stop announcements and those for all other reasons. Lastly, the number of incidents involving questions related to an operator's "fitness for duty" is measured. The sources of this information include customers, field supervisors and others.

vi. Temporal Characteristics

Seasonality and temporal effects are represented by signup and year-specific dummy variables.

3.5.2. Dependent Variables

The number of bus collisions and non-collision incidents, as well as the total number of incidents during each operator signup period were used as the dependent variables for the models with and without lags respectively. Summary statistics for considered variables are provided along with the other model estimation results in Table 3 in chapter 4 and also in Appendix B.

3.6. Model Selection Process and Criteria

The effects of operational factors on incident frequency were examined using a set of three separate but statistically validated operator –based models. These included the overall or total incidents model, as well as the collision and non-collision incident models. Independent of statistical validation, specific incident type models were estimated because of their potential for providing greater explanatory power relative to a single, total or overall incident frequency model as separate models allow parameters to vary across crash types (Shankar et al.,1995). From a practical perspective, this variation is fairly reasonable, as the effects of some variables, such as lift operation or usage, are expected to have different effects on expected frequency of collision and non-collision incidents.

Previous research has shown that conventional linear regression models are not appropriate for analyzing crash data. A Poisson model is often the starting model but if there is overdispersion a negative binomial model becomes the preferred specification over Poisson. The decision approach or rule adopted in selecting the appropriate econometric models for analyzing the frequency of total or overall, collision and non-collision incidents mirrored the standard practice in econometrics analysis. An overall or total incident frequency model was selected as the base model. Using an overall model as the base case is consistent with the observed practice in the traffic safety analysis (Lee and Mannering, 2002).

The process of selecting an appropriate model specification for analyzing total incident frequency data involved the following five steps: First, the total incidents data was estimated using Poisson regression in the Stata software. The estimated value for Poisson goodness-of-fit was significantly large at α =0.05 level. This finding suggests that the Poisson distribution is not a good choice.

In the second step, total incidents data were estimated using negative binomial regression. The test for overdispersion (Washington et al., 2003) parameter α_{nb} was found to be significantly different from zero (α_{nb} =0.278, LR test $\chi 2$ value = 56.15, P = 0.000). This finding confirms that incident data are over-dispersed and therefore Poisson regression is not the appropriate specification. In addition, the null hypothesis provided in equation 2.3.3 (see equation 2.0a & 2.0b) that the variance of total incidents is not different from the mean was rejected at α =0.05 level. These findings indicate that negative binomial structure is preferred to the Poisson specification.

In the third step, the likelihood ratio test was performed to determine whether a pooled negative binomial model (with constant overdisperson parameter for a given observation unit) is preferred to the panel or unrestricted models (with a varying overdispersion parameter). Washington et al., (2003) has specified the formula for the likelihood ratio test as;

$X^2 = -2(LL(\beta_R) - LL(\beta_{UR}))$ ……………………………………………………2.8

Where .

X^2 statistic is $\chi 2$ distributed with the degrees of freedom equal to the difference in the numbers of parameters in the restricted model β_R and unrestricted model β_{UR}. The LR test of panel versus pooled specification, yields $\chi 2$ value of 75.68 and P= 0.000. This finding indicates that a panel specification or structure is preferred to the pooled model.

Fourth, fixed and random effects negative binomial models were estimated. The specification test devised by Hausman (1978) was then used to assess whether individual effects were fixed or random. The LR test $\chi 2$ value was equal to 178.59, with 47 degrees of freedom and P= 0.000, an indication that the difference in coefficients of fixed and random effect models was systematic. This test finding showed that individual effects are random and therefore, random effects negative binomial model is preferred to the fixed effects negative binomial specification in analyzing frequency of total incidents.

Fifth, steps one through fourth were repeated for collision and non-collision incidents. As in total incidents frequency, the tests also indicated that the random effects negative binomial models were the preferred model specifications rather than the fixed effects negative binomial models.

Apart from the above stated tests, the Bayesian information criterion (BIC) and Alkaike Information Criterion (AIC) were also considered in selecting the appropriate random effect negative binomial model. The model specification with a lower value is preferred to those with higher values (Greene, 2003; Abdel- Aty and Radwan, 2000). The choice of variables for inclusion into the model was achieved through an extensive search of the operations safety incidents and related operator database. The variables that were chosen were those that provided significant improvements in the log-likelihood function (LL-value) of the model at convergence.

In summary, the above tests indicated that the random effects negative binomial specifications (discussed in section 2.3.5) were preferred over other count data models for analyzing the relationship between operational characteristics and the frequency of total incidents, as well as with the collision and non-collision frequencies.

3.6.1. Model Evaluation

The ratio of log-likelihood index (ρ^2) is a measure used to determine the additional variation in accident frequency explained by the obtained model to the constant term

(Abdel-Aty and Radwan, 2000). This measure is similar to the coefficient of multiple determination in multiple linear regressions and has been applied in evaluation of negative binomial models by Chin and Quddus (2003), as well as by Abdel and Radwan (2000) .

Similarly, this measure is adopted to evaluate if the selected RENB models have sufficient explanatory and predictive powers. Mathematically, the log –likelihood index is expressed as:

$\rho^2 = 1 - L(\beta)/L(0)$ ……………………………………..……..………2.9a

Where,

$L(\beta)$ is the log-likelihood value of the fitted model, and $L(0)$ is the log-likelihood value of the zero model. The disadvantage of this specification is that the index will increase whenever new variables are added to the model. This weakness is addressed by incorporating a correction for the number of independent variables, k.

According to Chin and Quddus (2003) the adjusted log-likelihood ratio index is derived from equation 2.9a and, is expressed as:

$\rho^{-2} = 1 - (L(\beta) - k)/L(0)$ ……………………………………………………...2.9b

Where, all parameters are as previously defined.

The estimated log-likelihood index and associated adjusted values for collision, non-collision and total incidents of estimated RENB models are provided in Table 3 (section 4.2) and Appendix B. The derived log-likelihood ratio indices for all estimated models were in the range of about 0.3 to 0.5. In addition all the distribution parameter values (a & b) were significant at $\alpha = 0.05$ level. These findings indicate that the RENB specifications perform well at predicting the expected frequencies of collisions, non-collisions and total incidents and have sufficient explanatory as well as predictive powers and distributional advantages.

3.6.2. Justification for Separate Incident Type Models

The likelihood ratio (LR) test was also performed to determine whether or not there is statistical justification for independent or separate analysis of collision and non-collision incidents. The procedure used here broadly resembles what has been documented in traffic safety analysis. However, a careful look reveals some variations. Lee and Mannering (1999) employed an LR test in assessing whether to analyze crash frequencies occurring in urban and rural road arterials as pooled or as separate models. They found that beyond an overall crash model, it was statistically valid to analyze separate types of crash models.

In the present case, the statistical justification process for estimating separate incident type models followed the approach that has been developed for econometric analysis (Greene, 1999: 2003; Judge et al., 1980) and has been applied in safety model selection by Ulfarson and Shankar (2003). Overall the process has three steps. First, the total incidents model without constraints (unrestricted β_{UR}) is estimated. In the Second step, total incidents model with coefficients constrained to be equal to the coefficient values of collision model (restricted - $\beta_R c$) is estimated. Similarly, another total incident models with coefficient constrained to be equal to the coefficient values of non-collision model (restricted - $\beta_R nc$) is also estimated. In the third step, the likelihood ratio tests comparing the unrestricted to restricted total incident models are then performed using the formula specified in equation 2.8.

The results of the likelihood ratio test between unrestricted total incident model β_{UR} and restricted total incident model-c were statistically different at α =0.05 level. Similarly, the unrestricted β_{UR} and restricted total incident model-nc were also significantly different (α =0.05). The model comparison indicates a difference between these models and suggests a need for separate analyses of the incident types.

3.6.3. Model Specification Issues

Given the comprehensive nature of the safety estimation model, multicollinearity related issues were expected because some of the explanatory variables are likely to be correlated. While multicollinearity cannot cause estimators to be biased, inefficient or inconsistent, its presence in data can increase standard errors of the coefficients. This consequently might lead to estimated coefficient parameters that are less significant and in turn can lead to erroneous inferences.

The presence of multicollinearity can be identified by low values of t-statistic, high value for correlation coefficients between variables and the sensitivity of estimated coefficients parameters (Lin, 2001; Ramanathan, 1995; Abdel-Aty and Radwan, 2000). Other approaches of detecting multicollinearity include running pair wise correlations between independent variables and checking if estimated coefficients are drastically altered when variables are dropped or added to the model (Abdel-Aty and Radwan, 2000). The pairwise correlations between the independent variables were found to be relatively small. The parameter estimates were not very sensitive to the addition or removal of variables, an indication that multicollinearity was not an issue of concern. Furthermore, the coefficients in estimated models had meaningful signs and magnitudes. Hence, there is no basis for concern about multicollinearity.

There were concerns about presence of endogeneity. This was a concern in that senior drivers might choose a safer or easy routes or vehicles. When independent variables in the model are endogenous, their parameter values may depend on the frequency of crashes. For example, Carson and Mannering (2001) studied an endogeneity problem when they examined the effectiveness of ice-warning signs in reducing frequency of ice-related accidents and their severity. Ignoring the endogeniety may lead one to erroneously conclude that ice-warning signs increase the frequency of ice-related crashes because the signs are associated with locations of high ice-crash frequencies. Truly, this was an endogeneity problem because ice-warning signs were more likely to be placed at locations of high ice-crash frequencies.

In a recent paper focusing on statistical analyses of crash frequency data, Lord and Mannering(2010) observe that while accounting for endogenous variables in traditional least squares regression models is relatively straight forward, the same is not true for count data models. They observe that for count data models, the modeling processes typically applied do not lend themselves to standard endogenous-variable correction techniques, such as instrumental variables. In addition, they point out that accounting for endogenous variables adds considerable complexity to the count data modeling process.

In the present study, concerns that there might be endogeneity problems related to operator seniority or experience could not be supported by TriMet data. As the experience variable (measured in years) for a subsample of bus operators who run same assignments was not significantly correlated to the frequency of incidents in all models. An indication that endogenous concerns related to bus operator seniority can safely be ignored. This observation in part can be attributed to the overtime incentives or trade in shifts and therefore in practice drivers work on a wide variety of routes in the service district. However, omitted variable bias is a concern as some variables such as operator habits are not controlled in this study.

CHAPTER 4.0: INCIDENT FREQUENCY ANALYSIS RESULTS

4.1. Introduction

The presentation in this section mainly focuses on the model interpretation and discussion of the estimated results. In general, the findings indicate that there are many differences and similarities among bus transit operational characteristics, especially as it relates to their effects and influence on the expected incident frequencies. The effects for each of the variables incorporated in the safety models are discussed in the next section.

4.2. Estimation Results, Interpretation and Discussion

The count data modeling approach was used to examine the empirical relationship between operational characteristics and bus transit incident frequency. Overall, a total of six operator – based Random Effects Negative Binomial (RENB) models were estimated using maximum likelihood methods in STATA software. To better account for the role of operational factors in bus transit safety, both standard and modified RENB specifications were estimated for collision, non-collision and total incident events.

The distinction between these models is that while modified specifications had variables accounting for main, interaction and lagged effects. In contrast, the standard specifications accounted for main and interaction effects, but not lagged or historical effects.

Elasticities were computed to provide some insight into the impact and role of parameter estimation results. In particular, elasticities were computed to ascertain the marginal effects of the independent variables. Washington et al. (2003) provide formulas for the elasticities for continuous and indicator variables.

The elasticity for continuous variables represents a proportionate change in the expected incident frequency with respect to a proportionate change in a given variable. This is expressed as:

$$E^{\lambda jt}_{Xjtk} = \frac{\partial \lambda_{jt}}{\lambda_{jt}} \text{ x } \frac{X_{jtk}}{\partial X_{jtk}} = \beta X_{jtk}\text{ , } \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.0$$

Where E reprsesents the elasticity , X_{jtk} is the value of the k^{th} independent variable for observation j , β_k is the estimated parameter for the k^{th} independent variable and λ is the expected frequency for observation j.

The pseudo-elasticity for indicator variables represents the proportionate change in expected frequencies relative to the reference group or base category excluded from the model. This is computed as,

$$E^{\lambda jt}_{Xjtk} = \exp (\beta X_{jtk})\text{-}1 \,/\, \exp (\beta X_{jtk}) \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.1$$

Elasticities are computed for each observation j. However, in practice, only the average elasticity over all observations is reported. The coefficient estimates, elasticities for continuous variables and pseudo-elasticities for categorical variables are summarized in Table 3. The elasticities and pseudo-elasticities were computed for significant variables at $\alpha = 0.05$ level.

In addition, the joint elasticities for age and experience variables were also computed to determine the operator's age-experience combinations (e.g., age 25/0 years experience………...age 60/35 years experience) at which the collision and total incidents risk is minimized (i.e., where the joint elasticity equals zero). The joint elasticities were not derived in non-collisions case because the estimated parameters for the experience variable are based on linear estimates.

The presentation in this section largely focuses on the estimated results from the modified RENB models. However, the standard model results provided in the appendix B will occasionally be referenced. The effects for variables considered in the safety models are examined next — starting from the operator demographics to work-assigned characteristics: service performance, customer feedback and temporal factors.

Operator Demographics

The estimated parameters are clearly consistent with the human capital perspective. For example, among the operator factors, age, experience and female gender were found to be significantly related to incidents frequencies. Specifically, age has a negative and diminishing effect on the incident of crash frequency. This means that at

Table 3. Modified RENB Estimates and Elasticities

VARIABLES & PARAMETERS	Mean (Std. Dev)	TOT β (S.E)	COL β (S.E)	NCOL β (S.E)	TOT E	COL E	NCOL E
Dependent Variables							
Total Incident Events (T0T)	0.312 (0.609)	—	—	—	—	—	—
Collision Events (COL)	0.183 (0.449)	—	—	—	—	—	—
Non-collision Events (NCOL)	0.129 (0.400)	—	—	—	—	—	—
Independent Variables							
OPERATOR DEMOGRAPHICS							
Age	50.32 (9.311)	−.0526* (.0170)	−.0433* (.0204)	−.0589* (.0270)			
Age^2	2619.1 (906.4)	.0006* (.0002)	.0006* (.0002)	.0005* (.0003)	0.778	1.708	-0.858
Female	0.308 (0.462)	.1158* (.0465)	.0606 (.0557)	.1945* (.0738)	0.109	—	0.177
African American	0.142 (0.349)	−.1187* (.0600)	−.1132 (.0719)	−.1330 (.0947)	-0.130	—	—
Asian/Pacific Islander	0.0360 (0.186)	−.1109 (.1130)	−.1778 (.1364)	−.0225 (.1784)	—	—	—
Hispanic	0.037 (0.189)	.0505 (.1009)	.0155 (.1225)	.0907 (.1582)	—	—	—
EMPLOYMENT STATUS CHARACTERISTICS							
Years of Experience	10.74 (8.31)	−.0400* (.0101)	−.0494* (.0118)	−.0307* (.0161)			-0.330
Years of $Experience^2$	184.22 (257.3)	.0006* (.0003)	.0008* (.0003)	.0005 (.0005)	-2.711	-3.222	—
Probationary Status	0.045 (0.207)	.2374* (.0912)	.1052 (.1174)	.4778* (.1401)	0.211	—	0.380
ASSIGNED-WORK CHARACTERISTICS							
Unique Assignments	11.85 (17.904)	−.0006 (.0016)	−.0039 (.0022)	.0034 (.0028)	—	—	—
Split Shift	0.270 (0.444)	—	−.0668 (.0912)	.0651 (.1129)	—	—	—
Lag Split Shift	.2843 (.4511)	.1034* (.0459)	—	—	0.098	—	—
Total Hours Worked	396.90 (123.57)	.0022* (.0002)	.0020* (.0003)	.0023* (.0004)	0.873	0.794	0.913
Weekend Hours	78.59 (81.53)	−.0010* (.0003)	−.0014* (.0004)	−.0004 (.0005)	-0.079	−.110	—
Average Daily Span	9.353 (1.629)	−.0040 (.0144)	.0565* (.0231)	−.0811* (.0284)	—	0.528	-0.759
Daily Span CV	0.140 (0.116)	.5022 (.2604)	1.038* (.3352)	−.1729 (.4265)	—	0.145	—
Three Day/ 30 Hour Week	0.023 (0.149)	.3458* (.1333)	.1920 (.1753)	.5582* (.1976)	0.292	—	0.428
Four Day/ 40 Hour Week	0.004 (0.059)	−.5056 (.3562)	−2.194* (1.004)	.3143 (.3910)	—	-7.971	—

Table 3 -continues		TOT	COL	NCOL	TOT	COL	NCOL
ASSIGNED-WORK CHARACTERISTICS - continue	Mean (Std. Dev)	β (S.E)	β (S.E)	β (S.E)	E	E	E
Short Term Absence Hours	14.74 (22.30)	—	.0038* (.0010)	—	—	0.400	—
Interaction of Fit for Duty & Short Term Absence Hours	.123 (2.200)	—	.0228* (.0100)	—	—	—	—
Lag Short Term Absence Hours	14.19 (21.80)	.0022* (.0009)	—	.0013 (.0015)	0.031	—	—
Merlo Garage	0.225 (0.418)	−.1383* (.0696)	−.2012* (.0857)	−.0564 (.1106)	-0.150	−.223	—
Powell Garage	0.346 (0.476)	.0057 (.0468)	.0484 (.0577)	−.0335 (.0739)	—	—	—
Secondary Radial Route	0.152 (0.359)	−.0254 (.0664)	.0227 (.0810)	−.1303 (.1100)	—	—	—
Crosstown Route	0.244 (0.430)	−.1158* (.0485)	−.0996 (.0614)	−.1278 (.0754)	-0.120	—	—
Feeder Route	0.060 (0.237)	−.0847 (.1354)	−.1730 (.1634)	.1485 (.2213)	—	—	—
Peak Express Hours	0.023 (0.150)	−.0684 (.1604)	−.0794 (.1771)	−.5462 (.3551)	—	—	—
Shift Ends 4:00-7:00 pm	0.479 (0.500)	−.0741 (.0502)	−.1075 (.0641)	.0100 (.0830)	—	—	—
Shift Ends After 7:00 pm	0.197 (0.398)	−.0421 (.0623)	−.1601* (.0788)	.1062 (.0975)	—	−.174	—
Low -Floor Bus	0.666 (0.472)	.0557 (.0682)	.0461 (.0851)	.0667 (.1085)	—	—	—
Old Bus	0.229 (0.420)	−.1020 (.0908)	.0223 (.1112)	−.3266* (.1511)	—	—	-0.386
Small Bus	0.047 (0.211)	−.1643 (.1545)	−.1391 (.1782)	−.3442 (.2840)	—	—	—
SERVICE PERFORMANCE CHARACTERISTICS							
Boardings Per Revenue Hour	43.16 (10.25)	.0034 (.0027)	.0008 (.0033)	.0061 (.0043)	—	—	—
Lifts Per Hour	0.286 (0.148)	.6061* (.1590)	.4824* (.2016)	.8460* (.2466)	0.173	0.138	0.242
Ave.Max. Speed - Peer Speed	0.068 (1.500)	.0145 (.0140)	−.0013 (.0167)	.0354 (.0231)	—	—	—
Proportion Late Departs	0.1402 (0.098)	.8926* (.2218)	.5932* (.2735)	1.118* (.3504)	0.125	0.083	0.157
Proportion Early Departs	0.057 (0.060)	.4908 (.3476)	1.033* (.4111)	−.3959 (.5793)	—	0.059	—
Layover Proportion	0.256 (0.198)	−.1403 (.1530)	−.0393 (.1165)	−.5359 (.3358)	—	—	—
Security Requests	0.526 (1.015)	.0551* (.0160)	.0174 (.0220)	.0806* (.0227)	0.029	—	0.042
Evasive Action Events	0.023 (0.160)	.5755* (.0680)	.0095 (.1281)	.8881* (.0838)	0.013	—	0.020

Table 3 -continues	Mean (Std. Dev)	TOT β (S.E)	COL β (S.E)	NCOL β (S.E)	TOT E	COL E	NCOL E
CUSTOMER SERVICE INFORMATION							
Unsafe Operation	0.214 (0.528)	—	—	.1081* (.0479)	—	—	0.023
Lag Unsafe Operation	.2135 (.5276)	.0796* (.0315)	.1086* (.0382)	—	0.017	0.023	—
Unprofessional Treatment	0.410 (0.836)	—	.0516* (.0254)	—	—	0.021	—
Lag Unprofessional Treatment	.4022 (.8203)	.0674* (.0203)	—	.0742* (.0303)	0.027	—	0.030
Fit for Duty	0.007 (0.086)	.2994 (.1717)	−.2762 (.3534)	.4397** (.2594)	—	5.987	0.003
Service Delivery Problem	0.112 (0.412)	.0107 (.0426)	−.0005 (.0520)	.0330 (.0682)	—	—	—
Commendation: Calls Stops	0.747 (1.426)	.0064 (.0112)	.0018 (.0155)	.0118 (.0188)	—	—	—
Commendation : Other	0.302 (0.685)	—	—	.0458 (.0392)	—	—	—
Lag Commendation : Other	.3014 (.6919)	.0022 (.0250)	.0440 (.0296)	—	—	—	—
TEMPORAL CHARACTERISTICS							
Fall Signup	0.163 (0.369)	−.0555 (.0576)	−.1417 (.0732)	.0670 (.0887)	—	—	—
Spring Signup	0.289 (0.453)	.0141 (.0536)	.0204 (.0667)	−.0207 (.0866)	—	—	—
Summer Signup	0.190 (0.392)	−.0100 (.0538)	−.0391 (.0680)	.0455 (.0847)	—	—	—
2007	0.442 (0.497)	.1849* (.0821)	.2233* (.1041)	.0888 (.1291)	0.169	0.200	—
2008	0.374 (0.484)	.0416 (.0864)	.0992 (.1093)	−.1054 (.1363)	—	—	—
2009	0.100 (0.300)	−.0326 (.1076)	−.0501 (.1356)	−.0174 (.1689)	—	—	—
Intercept	—	1.638* (.5356)	2.2099 (1.5560)	1.830 (.7919)	—	—	—
Parameter, a	—	145.842 (39.476)	1000.59 (1379.7)	62.67 (19.585)	—	—	—
Parameter, b	—	7.898 (1.317)	9.452 (2.795)	2.828 (.430)	—	—	—
Sample Size	11,585	11,585	11,585	11,585	—	—	—
Number of Groups	—	1,425	1425	1,425	—	—	—
Walds chi-value	—	621.9	298.4	529.4	—	—	—
LR Test Vs. Pooled chi-value	—	62.2	15.21	96.5	—	—	—
Ratio of log-likelihood index(ρ^2)	—	0.297	0.281	0.513	—	—	—
Adjusted ratio log-likelihood (ρ^{-2})	—	0.281	0.273	0.507	—	—	—

* Variable is significant at $\alpha = 0.05$ level and E represents Elasticity

lower age levels, an increase in age has a negative effect on expected crash frequency, reaching zero when the operators age is 36.08 years and turning positive at higher age levels. While age elasticity is positive, collision incidents are more sensitive (elastic) to age changes than to total incidents. The positive elasticity is attributable to the fact that the negative–to- positive transition is reached at the age 36.08, which is well below that of the sample average of 50.32 years. In contrast, age elasticity for non-collision is negative and is based on a non-linear parameter estimate.

The parameter estimates indicate that the expected total incidents frequency for African Americans is 13% lower than their white counterparts. The relevance of race disappears when associated incident type data are estimated. For example, collision and non-collision data estimates indicate that there are no significant distinctions in the expected frequency that can be related to the operator's race or ethnicity. In contrast, the expected frequency of non-collision and total incidents for female operators is about 17% and 10% greater respectively than for their male counterparts.

There is no clear interpretation of this finding, although it should be noted that incidents are self-reported by operators. Collisions where no gender distinctions are established leave tangible evidence that non-reporting is not a plausible explanation. Arguably, it may be either reflecting cultural bias such that female operators are more likely to report truth as others see it or that passengers who experience non-collision incidents are more likely to acknowledge them when a female rather than a male operator is involved or both arguments may be true.

Operator Employment Status Characteristics

Turning to operator employment status characteristics, the parameter estimates indicate that the operator's incident frequencies are clearly related to operator's length of service. In particular, those operators who are new to the job and still are on probation status have expected frequencies of non-collision and total incidents about 38% and 21 % greater respectively than the corresponding frequencies for seasoned or regular operators. In contrast, there is no difference in the collision incident occurrences between regular operators and operators who are still new on the job.

Holding probation status variable fixed, the estimated effect of experience on collisions is negative and diminishing, reaching minimum at 30.8 years of service and turning positive beyond that point. The negative experience elasticities of -3.222 and -2.711- for collision and total incidents respectively are fairly elastic, and their negative signs reflect the fact that average operator experience (10.74 years) is well short of the 30.8-year transition point. The effect of experience on non-collision frequency is estimated to be linear and negatively inelastic (E = -0.33), with the expected non-collision incident frequency of an operator, for instance, with 10 years of service being 33% higher than that of an operator with 20 years of service.

Beyond the estimated independent elasticities for age and experience variables, the computed joint elasticities for age-experience combinations indicate that the collision incidents risk is minimized for an operator who is 47 years and has operated the bus for about 22 years. This finding suggests that there is an operator age-experience combination at which the safety gains of experience exceeds the safety effects of aging. For the overall incidents model, the risk is minimized when the age-experience combination is 51 and 26 years respectively.

The derived age-experience combinations should be seen as representing the hypothetical or stereo-typical bus operator. This is because while some people work as bus operators for a longtime, say from 25 to 60 years, in contrast, others especially the young operators often quit after a short-time in search of better opportunities. Similarly, some older persons, without prior bus operating experience become bus operators. As a result of these dynamics or turnovers, only a small number of bus operators may fit the age-experience description of a stereo-typical bus operator. In the case of the non-collision incidents, the age-experience combination with minimum risk could not be established because the estimated parameters for the "experience" variable are based on linear estimates.

Assigned Work Characteristics

Overall, the parameter estimates indicate that among the 22 variables that were used to explore how expected incident frequencies are influenced by the assigned work characteristics, fourteen variables were found to have a clear significant effect at, $\alpha = 0.05$ level. Seven of these variables are positively related to the expected incident frequencies, on the other hand, six have a negative relationship. The other factor, span variability, has a mixed effect on safety.

An operator's total hours of work during a signup represents an indicator of crash risk exposure and had a significant positive relationship with the expected collision, non-collision and total incident frequencies. A test of the null hypothesis that total hours of work have a unitary elasticity (E= 1) was rejected for the collision and total incidents models but not for the non-collision incidents. The negative weekend hours elasticity suggests that collision and total incidents risk diminishes on days when regional traffic volumes are lower and congestion is less pronounced. Reductions in weekend risk do extend to non-collision incidents. However, the effect is relatively small.

Apart from the total hours of work variable, the parameter estimate for the dummy variable identifying operators with split shifts is not significant across all the estimated models. This can partly be explained by the fact that experience effects have already been accounted for in the estimated models, and therefore the direct effect of split shift dummy is negligible. Surprisingly, the split shift variable in the prior signup was found to have a significant positive effect on the expected total frequency incidents. Given that split shift dummy is a proxy measure for fatigue, the positive and significant effect associated with this variable when lagged for one period may signal that fatigue in the last period has safety effects in the current period. The effects for lag of split shift, however, could not be established in collision and non-collision models.

Two dummy variables were also specified to identify bus operators who worked compressed workweeks. The findings are mixed, with part time operators on 3-day, 30-hour weeks estimated to experience higher non-collision and total incident frequencies. In contrast, operators on 4-day, 40-hour weeks were estimated to experience significantly lower collision frequencies than operators on standard workweeks.

The expected frequencies of collision and non-collision incidents are influenced by the average daily span of hours as well as the span variability. The collision incidents model indicates that an increase in work span for one more hour is estimated to result in about 5.3 % increase in expected collision frequency. For span variability, a 10% increase in the span's coefficient of variation is estimated to result in about 1.5 % increase in expected collision frequency.

The work span finding is most relevant to bus operators on split shifts, and it suggests that an increase in the amount of time separating shifts would contribute to greater collision frequency. It also suggests that compressed workweeks, with their approximate 25% increase in daily span for full time operators, would also result in greater collision frequency. The span variability finding is most relevant to operators who work the extra-board and those operators who engage in frequent trades of their assigned work. Both circumstances are associated with greater span variation. For non-collisions, while the effect of span variability is negligible, on the other hand, the negative sign associated with an increase in average work span was not anticipated.

Beyond operator work hours and related safety effects, the collision model estimates reveal that variations in short duration absence hours are positively related to the expected collision frequency. Short duration absences account for about half of total time loss among operators at TriMet. Focusing on the short duration component of operator time loss lessens the prospect of simultaneity, wherein it would be necessary to consider operator absences as a contributor to safety incidents as well as a consequence. The estimated short duration absence elasticity can be interpreted as a contributor to collision frequency.

Alternatively, the elasticity for the lag of short duration absence hours may be interpreted as an indicator that job dissatisfaction is the basis of the crash contributions, not operator's health. This interpretation is contrary to the argument that accident/health related absenteeism could be at play in estimated safety incidents (Wahlberg & Dorn, 2009). In other words, absenteeism is not necessarily a consequence of crashes. As documented in absenteeism literature (Strathman, et al., 2009), it may be a signal of worsening job attitudes, which in turn could compromise safety. The positive and significant coefficient on interaction term, between the fit for duty variable and short duration absence hours, suggest that the safety risk of a unit increase in fit for duty complaints is more pronounced for operators with diminishing job satisfaction.

Shift period is represented by two categories of variables which identify the time of day when an operator's run concludes. The expected collision frequencies of operators whose runs conclude after 7:00 pm, which accounts for about 20 % of all runs, are estimated to be 17.4 % lower than the expected frequencies of operators whose runs conclude before 4:00 pm. On the other hand, operators whose runs conclude between 4:00- 7:00pm, which account for about 50 % of all the runs, are estimated to have safety performance that is not significantly different from those whose shift ends before 4:00 pm. This finding should be interpreted cautiously as split shifts are highly correlated with peak periods.

Among the three garages, the expected collision and total incidents frequency of buses dispatched from Merlo is estimated to be 22.3 % and 15 % below Central garage respectively. In contrast, there is no significant difference in safety performance of buses dispatched from Powell and those dispatched from Central garage.

Bus route operating conditions are represented by four route typology dummy variables. It was expected that collision frequencies would be higher on frequent service radials than any other route type given that traffic volumes are generally higher along these routes and on-street parking is more prevalent. However, with the exception of crosstown route, on which expected total incidents frequency is estimated to be 12% lower than the frequent service radials, the incident elasticities of other alternative route types, namely, secondary radial, peak express hours and feeder routes, are not statistically different from frequent service radials.

The effects of type and size of bus on the expected incident frequency was also explored. The null hypothesis that the expected non-collision frequency among low floor buses is not significantly different from other bus types could not be rejected. This finding is contrary to what has been reported elsewhere (Hudneski, 1992) and can partly be attributed to the practice at TriMet of assigning its low-floor vehicles to the most heavily patronized routes, which would contribute to a confounding of the bus type and passenger boarding variables in the model. In the case of vehicle size, parameter estimates indicate that safety performance of small vehicles is not significantly different from the standard vehicles.

Another unanticipated result is that the expected non-collision frequency among buses older than 15 years is estimated to be 38.6% below that of newer buses. This finding is not consistent with what has been documented in transit safety literature (Zeeger et al., 1994; Chang and Yeh, 2005) and can be interpreted in two ways. First, older buses at TriMet are mainly used during morning and evening peak periods to help deal with the increased demand for the service. Therefore, like most urban areas the profile of passengers during peak periods tends to consist of more young people and customer cohorts that are not physically challenged.

Another possible explanation is based on the risk compensation or offsetting behavior hypothesis (Peltzman, 1975). That is, because these vehicles are older, it is possible that operators and users of these bus types respond by being more careful and more alert to the bus operating conditions. Evans (2004) has argued that the risk compensation theory is weak and is not supported by empirical evidence.

Service Performance Characteristics

Among the eight service performance related variables that were examined, five were found to have a significant positive relationship with expected incident frequencies, while the rest had an insignificant effect. The passenger boardings per revenue hour was expected to have a positive influence on expected incident frequency but for unknown reasons, it turned out to have an insignificant effect on safety.

The estimated elasticity for lift movements per hour is positive for collision and non-collision, as well as in the total incidents model. This suggests that passengers with mobility impairments face unique safety risks associated with lift functioning and on-board securement. This finding is consistent with what has been documented in the safety literature (NHTSA, 1997). While it is straightforward to interpret the positive elasticity associated with lifts movement and what it means in non-collisions, the same is not true for the collision and total incident models.

One possible explanation for positive elasticity found in the latter models is that the time and attention that operators devote to serving passengers with disabilities conflicts with the time and attention needed to operate the bus safely. For example, Dueker et al. (2004) estimate that a bus lift operation requires about 60 seconds of additional dwell time. This implies that bus lift operation contributes to the likelihood of a bus running late and, as such, it may serve as an incentive to the bus operator to pay less attention and to rush in an effort to adhere to the schedule, which may compromise safety.

Variation in operator average maximum speed relative to the peers was expected to be positively related to the expected frequency of collision and non-collision incidents. But the test for the null hypothesis that the safety effect of operator average maximum speed relative to the peers is significantly different from zero was rejected.

Independent of speed and the bus lift operation effects examined above, two variables, namely, proportionate late and proportionate early departures, were included in the models to capture the safety effects of operators' inability to adhere to a schedule. The estimated results indicate that the expected frequency of collision, non-collision and total incidents is estimated to increase with the proportion of late (by more than 5 minutes) departures from time points. One may be tempted to attribute this finding to operator speeding, but a careful eye can see that this variable is already accounted for in the models and its effect is found to be small. Other alternatives for schedule recovery would be to cut deceleration, dwell, or acceleration times, each of which is known to contribute to elevated safety risk.

Operator early departure, by more than one minute from time points, was entered in the models as a proportionate early departure variable. The parameter estimates are significant and positively related to the expected collision frequency, but in the case of non-collision and total incidents models, the effect is not large. While the estimated coefficients for running late and early are both positive and significant in the collision model, the elasticity for running late is almost double that of running early.

One motivation for running early is that it adds to the amount of layover time. While previous literature has identified insufficient layover time as a contributor to operator fatigue and safety risk, the collision, non-collision and total incident's parameter estimates for the share of platform time devoted to layover was not significantly different from zero at $\alpha = 0.05$ level. Following an agreement between the union and the management, TriMet run cuts must assure a minimum of 80 minutes of layover and break time in an 8-hour shift, which represents about 17% of platform time. More specifically, the study period data indicates that the estimated actual run cuts implemented yielded a layover share of 8.5 % more than the agreed minimum.

Therefore, in practice, it appears that the layovers built into the run schedules are reasonably sufficient to ensure that safety is not compromised.

An operator's responsive actions to security and safety concerns are examined by incorporating in the model variables that account for the effects of the number of messages sent to dispatchers requesting security personnel and for evasive action events, such as taking hard stops to avoid a crash. While the estimated effect of these two types of events on expected non-collision and total incidents frequencies is positive, the relative significance of evasive action events is roughly half the magnitude associated to security request incidents. Taking evasive action itself may be a contributor to an on-board safety incident.

In contrast, a security request may occur as an outcome of an on-board safety incident, particularly when the consumption of alcohol or other substances is involved. In the case of collisions, the test for the hypothesis that the estimated coefficient of operator responsive action is not different from zero was rejected.

Customer Service Information

Turning to customer feedback factors, it was expected that the effect of customer complaint variables on expected incident frequency would be positive, and on the other hand, commendations related variables were expected to have a negative relationship. But contrary to prior expectations, it turns out that the direction of the relationship and the relative significance of these factors depends not only on the specific variables but also on the incident type considered.

The expected frequency of non-collision incidents is estimated to be positively related to passenger complaints addressing operator unsafe operation of the bus. It may be reasoned that positive association between customer complaints variables and safety incidents may be because of previous customer experience of safety incidents which may serve as a motivation for lodging a complaint. This simultaneity issue is addressed in the present study by lagging any complaint related variable reported in standard RENB models (See Appendix B) with a positive and significant effect on expected crash frequencies.

The estimated elasticity for lag of unsafe operation variable is positive in the collision and total incidents models. Although inelastic, this finding suggests that passenger complaints about an operator's unsafe bus operation is not motivated by their prior experience with bus crash incidents, but may be signaling elevated safety risk and associated consequences. In other words, this finding can be interpreted as indicating that chronic complaints regarding an operator unsafe bus operation elevates the risk of being involved in a collision, which may be in the present or future signups. The model estimates also reveal that customer complaints of unprofessional treatment by operators are estimated to be positively related to the expected frequency of collision incidents. On the other hand, their effects are negligible in non-collisions.

In contrast, the estimated elasticity of the lag of unprofessional treatment variable is positive in non-collision and total incidents frequency models but not in collisions. This finding can similarly be interpreted as indicating that a pattern of complaints about an operator's unprofessional treatment of passengers or customers may be a signal for an elevated risk for a non-collision incident. The variable capturing a service delivery problem is insignificant in all estimated models. The fit for duty variable is positively related to both the expected collisions and non-collision frequencies. In the case of non-collisions, the fit for duty variable is estimated to have an inelastic elasticity. In contrast, it has an interaction effect with short duration absence hours on expected collision frequency, with an elasticity value more than one (elastic).

The positive effect of fit for bus operation variable can be interpreted as capturing the safety effect of an operator, who may be taking prescription medication or who may be using alcohol. Whether on medication or alcohol, any operator deemed unfit to operate the bus by either customers or supervisors is a great collision risk and should not sit behind the wheel. The interaction term, between fit for duty variable and short duration absence hours, suggests that the effect of a unit increase in the fit for duty complaints about an operator on expected collisions frequency is more pronounced in the presence of short duration absence hours.

Among the variables related to customer commendations of operators, the coefficient estimate of the variable commendation other, not for stop announcements, in the standard RENB was found to be positively related to expected collision and total incidents frequency. However, on lagging this variable, the estimated coefficient for the lag of commendation other turns out not to be significantly different from zero at $\alpha = 0.05$ level. A test for the hypothesis that the coefficient of the variable commendation of the operator, related to stop announcements, is significantly different from zero was rejected. This finding may be interpreted in a number of ways. First, it may suggest that safety performance is not influenced by operator personality characteristics. Another possible explanation is that the conflicts between safe bus operation and customer service responsibilities have been well reconciled at TriMet.

Temporal Characteristics

The effect of annual and seasonal variations on bus safety performance was examined by incorporating year and signup-specific dummy variables in the estimation models. The parameter estimates for the signup indicators were found not to be significantly different from zero. About a week of snow and ice conditions were experienced in two winter signups during the study period. Also, unlike the summer and fall, the winter and spring signups consistently experienced variable rainfall. However, none of the signup indicators were found to be significant, suggesting that seasonal variations in the Portland region's weather have no discernable consequences for bus safety.

In contrast, of the three indicators, only the one year-specific dummy variable was found to be significantly different from zero. The indicator for the year 2007 was estimated to have about 20% and 17% more expected collision and total incidents frequencies respectively than the base year, 2006.

This finding can be attributed to a number of factors. First, the economic downturn in the Portland region after 2007 may have had an effect on safety. Between January 2008 peak and August 2009, regional employment fell 6.3% and total regional employment returned to early 2001 levels (Vander, 2009). Therefore, some easing of traffic-related risk exposure was likely to have occurred during that period. Secondly, unobserved effects of agency operational procedures might have been at play. For example, the aggressive practice of operator recruitment that was enforced around and during the same period might have had unintended safety effects. The strategy was to recruit/hire and create a large pool of operators, so that over time the agency would have a more reliable base of experienced operators. While this strategy had good intentions, limited agency personnel and resources might have compromised the supervision, monitoring and training of the recruited crew resulting in unintended safety outcomes.

In summary, there are notable differences obtained for collision and non-collision safety incidents. In particular, age and experience have negative and diminishing effect on expected frequencies of collision incidents. In the case of non-collisions, the expected incidents frequencies are inversely related to operator's age and experience.

Beyond the operator characteristics, an increase in work span by one more hour is estimated to result in 5.3% increase in expected collision frequency. A similar increase is estimated to result in about 7.6 % decrease in expected non-collision incidents. Work span variability is another factor that affected collision and non-collisions incidents differently. Specifically, a 10 % increase in the span's coefficient of variation is estimated to result in 1.5% increase in expected frequency of collision incidents. In non-collisions this variable is not significant.

Regarding operator absenteeism, variations in short-duration absence hours are estimated to have positive influence on expected collision frequency, but are insignificant in the case of non-collision incidents data. With respect to schedule adherence ability, the analysis found that while running late is positively related to collision and non-collision incidents, the magnitude of the elasticity estimate in non-collision is about twice as much that obtained in collision incidents model. In addition, the early depart variable is positively related to frequency of collisions incidents. In non-collisions the effect is insignificant.

Turning to operator's responsive actions to security and risk situations, the number of security requests and evasive action events are positively related to occurrences of non-collision incidents, but their effect in collision is insignificant. Customer complaints had an opposite effect. Non-collision incidents are positively related to passenger complaints about unsafe bus operation, but in collision incidents the variable unsafe complaint is insignificant.

Given what these models have so far established, the next logical question or challenge is: how can TriMet reduce occurrences of collision and non-collision bus incidents? One possible approach is to ensure that preventable bus incidents are avoided or minimized in the service district. This, however, requires identification and assessment of the factors that influence occurrences of preventable bus incidents. This task is the focus of the next chapter.

CHAPTER 5.0: PREVENTABILITY ANALYSIS AND RESULTS

5.1. Introduction

Beyond safety incident frequency analysis, the effect of operational characteristics on the likelihood of preventable incident involvement was also examined. The distinction between incident frequency and preventability analysis is that while count data methods were used in modeling the former, the latter was modeled as discrete safety outcomes. This approach is consistent with what has been done in the traffic safety literature. Specifically, McCarthy and Madanat (1994) have indicated that binary logit models can appropriately be used to analyze crash occurrence, especially when the dependent variable takes on very small integer values.

In the case of this study, only a few TriMet bus operators were involved in preventable incidents and a large number were not involved in any incidents at all. Given the large number of operators that were either involved in a few or no preventable incidents, a set of binary logit specifications was developed to estimate how preventable incident involvement is influenced by bus operations.

The reminder of this chapter is organized as follows: In the next section the limited dependent variable (LDV) modeling approaches and related issues are discussed. Data description and discussion of model estimation is provided in section 5.3. In section 5.4, model specification issues are presented. In section 5.5, the discussion of alternative model interpretations is provided. This is followed in section 5.6 with the estimated model results. Finally, section 5.7 presents a discussion of methodological considerations and result limitations.

5.2. Discrete Outcome Modeling Methods

There is a well-developed record of safety literature which has established that accident data can appropriately be analyzed through LDV modeling methods. In particular, multinomial (MNL) and nested logit modeling structures have largely been used in accident severity analysis (Shankar and Mannering, 1996; Carson and Mannering, 2001; Lee and Mannering, 2002). According to Carson and Mannering (2001), these methods are applied in estimating the likelihood of various severity outcomes given that an accident has occurred.

As in the earlier studies (Shankar and Mannering, 1996; Carson and Mannering, 2001) an appropriate binary logit model was developed and then used to estimate the probability of observing a safety outcome i given that the bus was in the revenue service operation. In the simplest case, a standard logit model that defines the dependent variable y_{jt} to be one if bus operator j is involved in a preventable incident outcome during time period t and zero otherwise was appropriate.

In particular, the logit structure proposed by McCarthy and Madanat (1994), for analyzing the likelihood of fatal accidents was adapted and applied in indentifying the operational factors that are correlated with the likelihood of preventable incident involvement. The general expression for the probability of preventable incident involvement is expressed as:

P(preventable incident involvement)

$$= P\ (y_{jt} = 1) = \frac{\exp(\beta' x_{jt})}{1+\exp(\beta' x_{jt})} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

$$j = 1, , , , , J; \;\; t = 1, , , , , , , T \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

Where,

X_{jt} is a vector of operator- and time-specific explanatory variables, β is a vector of coefficients to be estimated and y_{jt} is assigned one if an operator j is involved in a preventable incident and zero otherwise.

The parameter vector β is estimated using the maximum likelihood methods. The likelihood function according to Washington et al. (2003) is expressed as:

$$L = \prod_{j=1}^{J}\prod_{i=1}^{I} P(i)^{\delta_{ij}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

Where,

J is the total number of observations and δ is defined as being equal to one if the observed discrete outcome for observation j is one and zero otherwise. This model is easy to estimate using standard econometrics software. In addition, interpretation of the parameter estimates is straight forward. However, this model can only be used if the dependent variable has two discrete outcomes.

Beyond the two safety outcomes, factors influencing the likelihood of the other safety outcomes; namely non-incident involved, preventable incident involved, non-preventable incident involved and other unclassified incident category were also considered. This required either developing a simple multinomial or a more advanced but flexible nested logit model. Following established practices in LDV modeling, multinomial logit was selected first because it is the simpler specification. In addition, the multinomial logit model has previously been derived and applied to severity analysis (Shankar and Mannering, 1996), and can intuitively be extended to incident preventability analysis.

Specifically the multinomial logit model can estimate the likelihood of bus operator j being involved in safety outcome i during signup t. Mathematically, $P_j(i)$ represents the probability of operator j being involved in safety outcome i and S_{ijt} being a linear function that determines the safety outcome of bus operation such that

$S_{ijt}= \beta i X_{jt}, + \varepsilon_{ijt}$ …………………………………………………..……….3.5

Where,

X_{jt} is a vector of observable operator and time-specific explanatory variables that determines safety outcome, β is a vector of coefficients to be estimated and ε_{ijt} is unobservable random error.

According to Carson and Mannering (2001), the probability that an operator j is involved in safety outcome i can be rewritten as the probability that S_{ijt} is greater than all other $S_{Ijt.}$ Therefore, the general probability statement can be expressed as

$P_j(i) = P(S_{ijt} > S_{Ijt})$, for all $I \neq i$ ……………………………………………………3.6

Where,

I is the set of possible safety outcomes. Substituting equation 3.5 into equation 3.6, the latter equation can be expressed as

$P_j(i) = P(\beta i\ X_{jt}, + \varepsilon_{ijt} > \beta_I X_{jt}, + \varepsilon_{Ijt})$, for all $I \neq i$ 3.7a

$= P(\beta i\ X_{jt}, - \beta_I X_{jt}, > \varepsilon_{Ijt-} \varepsilon_{ijt})$, for all $I \neq i$ ………………..…………...3.7b

With equation 3.7b, an estimable safety outcome model is developed by assuming a distribution form of the random error term. A natural choice would be to assume that the random error is normally distributed. The resulting specification structure would then be a probit model. However, models of this type are computationally impractical in a situation with more than two discrete outcomes, and they are not easy to estimate (Carson and Mannering, 2001; Shankar et al., 1996).

A more common and widely used approach is to assume that the random error terms are generalized extreme value (GEV) distributed, sometimes also called the Gumbel, Weibull, or double exponential distribution (Small and Verhoef, 2007). The GEV assumption produces a closed form model which is computationally easy to estimate (Shankar et al., 1996). In addition, based on GEV assumption, it can readily be shown (McFadden, 1981; Washington et al., 2003) that a multinomial logit is produced.

The general expression for the probability of operator j being involved in safety outcome i given a possible set of I outcomes is mathematically expressed as:

$$P_j(i) = \frac{\exp[\beta_i X_{jt}]}{\sum_I \exp[\beta_I X_{jt}]} \qquad \text{.......................................3.8}$$

Where all variables are as previously defined and to estimate the coefficient parameter vectors (β) by the standard maximum likelihood methods, and the log likelihood function formulated by Washington et al., (2003) was adapted. This is expressed as:

$$LL = \sum_{j=1}^{J} \left(\sum_{i=1}^{I} \delta_{ij} \left[\beta_i X_{ij} - LJ \sum_{\forall I \neq i} \exp(\beta_I X_{Ij}) \right] \right) \qquad \text{.......................................3.9}$$

Where,

I is the total number of safety outcomes, J is the total number of observations, δ is defined as being equal to one if the observed discrete outcome for observation j is one and zero otherwise. The concerns relating to the suitability of this model for analyzing the effect of operational factors on the likelihood of incident preventability are addressed in section.5.4.

5.3. Model Development

The effect of operational characteristics on the likelihood of incident preventability was also estimated through analysis of TriMet‘s archived ITS and related systems data. As with incident frequency analysis, in the first step a list of 1,502 bus operators that had operated TriMet buses, between September, 2006 and February, 2009 was developed. In the second step, all the 10,316 operator signup observations without incidents were identified and coded as one. Since incidents at TriMet are classified as either Preventable (PA) or non-preventable (NPA), the third step involved coding all 817 operator signup observations with a PA entry as 2 while coding 873 operator signup observations that had an NPA entry as 3. There were 1,790 operator signup observations that were not classified or categorized and were coded as 4. In the fourth and final step, the multinomial logit model was then estimated. In total there were 13,796 operator signup observations, 12 signups during the three year study period.

In the case of binary logit specifications, the model development process had three distinct but well connected steps. First, the 1,790 unclassified operator signup observations were deleted from the sample. Second, the 817 operator signup observations with a preventable incident entry during the study period were coded one while the rest (12,006) of the operator signups were assigned zeros. Finally, in the third step, the PA status logit model was then estimated.

5.4. Model Specification Issues

The MNL specification is based on a celebrated and restrictive property of independence of irrelevant alternatives (IIA). The IIA property is both a major strength and weakness of MNL. The IIA property implies or requires the assumption that the unobserved random error terms are independent from one safety outcome type to the other. This was not anticipated to be the case because some of the safety outcome types were likely sharing unobserved terms and therefore they were expected to be correlated. Surprisingly, it turns out that this hypothesis could not be supported by TriMet data.

The assumption of IIA was assessed using Hausman test and Small-Hsiao test. Hausman test was devised by Hausman and McFadden (1984). The Small–Hsiao test (also known as the likelihood ratio test) is provided in Small & Hsiao (1985). These are post-estimation tests in Stata software and were performed using the program written by Freese and Long (2000). The hypothesis that the odds (safety outcome-J verses safety outcome–k) are not independent of the other outcomes was rejected at $\alpha = 0.05$ level. This finding indicated that IIA assumption is not violated. When the IIA assumption is violated, the more flexible structure, known as nested logit, is preferred and has been used in safety analysis by Lee & Mannering, (2002) and Shankar et al., (1996) among others.

5.5. Model Interpretations

The estimated coefficients from the incident preventability models are not directly interpretable as is the case in the linear regressions models because the dependent variable for each outcome is expressed as the logarithm of the odds of an event. This complication is addressed by computing the relative risk ratio (or sometimes also known as odds ratio) for categorical variables and average derivatives for continuous variables (Crown, 1998; Zador et al., 2000).

According to Crown (1998) partial derivatives enable the effects of a particular variable on the probability of an event to be examined without the inconvenience and confusion introduced by the log of the odds formulation. The derivative indicates the change in probability of each discrete safety outcome with respect to a unit change in the independent variable. The relative risk ratio indicates how the probability of safety outcome i relative to zero or reference group changes if the independent variable is increased by one unit. The relative risk ratio was computed by exponentiation of the coefficient estimates of categorical variables. In contrast, average derivatives for continuous variables were computed using the formulation provided by Koppelman & Bhat (2006) and Crown (1998).

Direct partial derivative of the probability with respect to an independent variable within a particular equation is given as:

$$\frac{\delta P_i}{\delta X_{ik}} = P_i(1 - P_i)\beta_{ik} \quad \text{..} 4.0$$

While in another equation, the cross partial derivative of the probability of a given outcome with respect to an independent variable is expressed as:

$$\frac{\delta P_i}{\delta X_{IK}} = -P_i P_I \beta_{Ik} \quad \text{..} 4.1$$

In the case of logit models the odd ratios (or relative risk ratios) were computed for dummy variables using the formulation provided by Crown (1998). This is mathematically expressed as:

$$\text{Odd ratio} = \exp(\beta_k) \quad \ldots\ldots 4.2$$

In addition, the partial derivatives were computed for the continuous variables that were significant in the model using the formulation provided in equation 4.3.

$$\frac{\delta P_i}{\delta X_k} = \beta_k P_i (1 - P_i) \quad \ldots\ldots 4.3$$

Elasticity is the other measure used to quantify the extent to which the discrete outcome probabilities are influenced by changes in an independent variable (Koppelman and Bhat, 2006; Washington et al., 2003; Shankar and Mannering, 1996). In the multinomial logit model analysis, elasticity represents or measures the proportionate change in the probability of a safety outcome due to a proportionate change in the explanatory variable.

According to Washington et al. (2003) elasticities for continuous variables are computed from the partial derivatives for each observation as:

$$E_{X_j}^{P_J(i)} = \frac{\partial P_j(i)}{\partial X_j} \times \frac{X_j}{P_j(i)} \quad \ldots\ldots 4.4$$

Where P(i) is the probability of operator j being involved in safety outcome i, E represents the elasticity and X_j is the value of the variable being considered. When this equation is applied to the multinomial logit model in equation 3.8 above then the elasticity equation becomes:

$$E_{X_j}^{P_J(i)} = [1 - P(i)]\, \beta_i X_j \quad \ldots\ldots 4.5$$

The elasticity formula however is not applicable to indicator variables (those taking on one or zero values). A measure of the effect of the indicator variable is derived by computing pseudo– elasticity (Washington et al., 2003; Shankar and Mannering, 1996).

The pseudo-elasticity in the multinomial logit formulation is given as

$$E_{X_{KI}}^{P(i)} = \frac{\exp[\Delta(\beta i Xj)]\sum_{\forall I}\exp(\beta_{kI}X_{kI})}{\exp[\Delta(\beta_i X_i)]\sum_{\forall I_j}\exp(\beta_{kI}X_{kI}) + \sum_{\forall I \neq I_j}\exp(\beta_{kI}X_{kI})} - 1 \quad \ldots\ldots\ldots\ldots.4.6$$

Where I_j is the set of alternate outcomes with X_k in the function determining the safety outcome, and I is the set of all possible outcomes. These elasticity and pseudo-elasticity formulations have been applied in assessing effects of variables on various types of accident severity (Shankar and Mannering, 1996; Chang and Mannering, 1999).

5.6. Estimation Results and Discussion

Turning to the results, two sets of multinomial and binary logit models were estimated using maximum likelihood methods. The distinction between these models is that the modified specifications had main and lagged variables incorporated. In contrast, the standard specifications accounted only for the main variables. The structure of the multinomial logit model (with four safety outcomes: non-incident involved, preventable incident involved, non-preventable incident involved and other unclassified incident outcomes) was estimated.

The estimation process was carried out using STATA software with “non-incident involved” as the reference group. The estimated coefficients for modified multinomial and binary logit models are presented in Table 4. Also included are the computed odd ratios and average derivatives for the binary logit model.

The presentation in this section covers estimated parameters from the modified multinomial and binary logit models. However, the standard model results provided in Appendix C will be referenced as needed. Given the number of variables covered in the models, the discussion to follow will mainly focus on the estimated parameters from the modified multinomial logit model. The parameter estimates of the ordinary logit model will only be discussed where the estimates from the multinomial logit are counter-intuitive or less informative.

Table 4. Modified Multinomail and Logit Coefficient Estimates

ESTIMATION MODELS	MODELS WITH MAIN AND LAGGED VARIABLES					
	LOGIT			MULTINOMIAL LOGIT		
	PA Status			PA	NPA	UNC
VARIABLES & PARAMETERS	β (S.E)	ODD RATIO	AVE. DER	β (S.E)	β (S.E)	β (S.E)
OPERATOR DEMOGRAPHICS						
Age	−.0804* (.0360)	—		−.0845* (.0340)	−.0344 (.0351)	−.0408 (.0251)
Age^2	.0011* (.0003)	—	0.0130	.0012* (.0003)	.0004 (.0004)	.0004 (.0003)
Female	.1174 (.0951)	1.12500	—	.1471 (.0950)	.1823* (.0915)	.1269 (.0661)
African American	−.1853 (.1273)	0.83080	—	−.2250 (.1255)	−.2693* (.1209)	−.0706 (.0834)
Asian/Pacific Islander	−.5572* (.2673)	0.57280	—	−.5185 (.2656)	.3147 (.1893)	−.0933 (.1600)
Hispanic	.0216 (.2097)	1.02180	—	.0362 (.2093)	.1076 (.1987)	.0774 (.1458)
EMPLOYMENT STATUS CHARACTERISTICS						
Years of Experience	−.0701* (.0206)	—	-0.0034	−.0795* (.0208)	−.0372 (.0197)	−.0315* (.0144)
Years of $Experience^2$	.0009 (.0006)	—	—	.0010 (.0006)	.0007 (.0006)	.0005 (.0004)
Probationary Status	.4952* (.1960)	1.64100	—	.5152* (.1971)	.1331 (.2203)	.4900* (.1538)
ASSIGNED-WORK CHARACTERISTICS						
Unique Assignments	−.0021 (.0038)	—	−.00011	−.0067 (.0040)	−.0015 (.0039)	.0017 (.0028)
Split Shift	—	—	—	−.2571 (.1664)	−.0941 (.1623)	.0761 (.1151)
Lag Split Shift	.2279* (.1046)	1.25600	—	—	—	—
Total Hours Worked	.0024* (.0005)	—	0.00012	.0024* (.0006)	.0024* (.0005)	.0025* (.0004)
Weekend Hours	−.0012 (.0007)	—	−.00006	−.0015* (.0007)	−.0009 (.0007)	−.0005 (.0005)
Average Daily Span	.0312 (.0303)	—	0.00162	.0925* (.0416)	−.0467 (.0401)	−.0608* (.0283)
Daily Span CV	.4782 (.5723)	—	0.02480	.9921 (.6120)	.7720 (.5940)	.6184 (.4225)
Three Day/ 30 Hour Week	.2465 (.2943)	1.28000	—	.1976 (.2939)	.2172 (.3084)	.3260 (.2221)
Four Day/ 40 Hour Week	−1.225 (1.025)	0.29370	—	−1.437 (1.029)	−1.100 (1.028)	−.1101 (.4949)

Table 4. continues	PA Status β (S.E)	ODD RATIO	AVE. DER	PA β (S.E)	NPA β (S.E)	UNC β (S.E)
ASSIGNED-WORK CHARACTERISTICS - continues						
Short Term Absence Hours	—	—	—	.0063* (.0018)	.0009 (.0019)	.0024 (.0013)
Lag Short Term Absence Hours	.0078* (.0017)	—	0.00040	—	—	—
Merlo Garage	−.1658 (.1451)	0.84720	—	−.1910 (.1476)	−.4963* (.1576)	.0571 (.1037)
Powell Garage	− .1914 (.1025)	0.82580	—	− .1460 (.1031)	.1803 (.0964)	.0890 (.0713)
Secondary Radial Route	−.1525 (.1495)	0.85850	—	−.1413 (.1490)	.1634 (.1403)	−.0518 (.1074)
Crosstown Route	−.2321* (.1138)	0.79290	—	−.2569* (.1133)	−.0556 (.1053)	−.1353 (.0771)
Feeder Route	−.3342 (.2833)	0.71590	—	−.3045 (.3010)	.0639 (.2885)	.0190 (.2009)
Peak Express Hours	−.2388 (.3272)	0.78760	—	−.2438 (.3340)	−.2262 (.3720)	.1750 (.2371)
Shift Ends 4:00-7:00 pm	.0098 (.1202)	1.00990	—	.0696 (.1192)	−.1625 (.1127)	−.1111 (.0806)
Shift Ends After 7:00 pm	.0076 (.1442)	1.00760	—	−.0547 (.1444)	−.0002 (.1308)	−.1036 (.0963)
Low -Floor Bus	.0251 (.1491)	1.02550	—	.0423 (.1505)	.0712 (.1523)	.0451 (.1111)
Old Bus	−.1537 (.1942)	0.85750	—	−.1178 (.1966)	.1782 (.2027)	−.2097 (.1462)
Small Bus	.0552 (.2974)	1.05670	—	−.0188 (.3224)	−.6320 (.3477)	−.0724 (.2264)
SERVICE PERFORMANCE CHARACTERISTICS						
Boardings Per Revenue Hour	−.0014 (.0061)	—	−.00007	−.0005 (.0061)	.0106 (.0057)	.0038 (.0043)
Lifts Per Hour	1.001* (.3694)	—	0.05192	1.035* (.3546)	.4462 (.3580)	.6106* (.2624)
Ave.Max. Speed - Peer Speed	.0150 (.0330)	—	0.00078	.0186 (.0295)	.0184 (.0295)	.0550* (.0213)
Proportion Late Departs	1.227* (.4583)	—	0.06364	1.174* (.4691)	.4752 (.4659)	.9257* (.3371)
Proportion Early Departs	1.112 (.7067)	—	0.05769	1.138 (.7457)	1.011 (.6948)	.7514 (.5175)
Layover Proportion	.0391 (.0777)	—	0.00203	.0299 (.1396)	−.1282 (.2724)	−.7867* (.3392)
Security Requests	− .0111 (.0396)	—	−.00057	− .0031 (.0421)	.0539 (.0379)	.1065* (.0262)
Evasive Action Events	.2926 (.2175)	—	0.01517	.5624* (.2268)	1.409* (.1643)	.7140* (.1570)

Table 4. continues	PA Status			PA	NPA	UNC
	β (S.E)	ODD RATIO	AVE. DER	β (S.E)	β (S.E)	β (S.E)
CUSTOMER SERVICE INFORMATION						
Lag Unsafe Operation	.1772* (.0739)	—	0.00919	.1936* (.0710)	.0946 (.0704)	.1210* (.0520)
Unprofessional Treatment	.0377 (.0499)	—	0.00196	.0520 (.0490)	.1173* (.0440)	.1211* (.0322)
Lag Fit for Duty	-.0055 (.5491)	—	−.00028	-.0179 (.5264)	.1590 (.4457)	−.4106 (.3027)
Service Delivery Problem	.0994 (.0828)	—	0.00515	.0972 (.0848)	−.0654 (.0991)	−.1417 (.0782)
Commendation: Calls Stops	-.0149 (.0364)	—	−.00077	-.0185 (.0299)	−.0082 (.0280)	.0117 (.0196)
Commendation : Other	.0608 (.0547)	—	0.00315	.0901 (.0531)	.0919 (.0536)	.0608 (.0396)
TEMPORAL CHARACTERISTICS						
Fall Signup	.1628 (.1445)	1.17680	—	.1339 (.1427)	−.3400* (.1255)	−.0390 (.0930)
Spring Signup	.4049* (.1317)	1.49920	—	.3664* (.1295)	−.4817* (.1245)	.0622 (.0875)
Summer Signup	.3514* (.1318)	1.42100	—	.3324* (.1307)	−.3776* (.1223)	−.0237 (.0895)
2007	- .2737 (.1807)	0.76050	—	- .2319 (.1824)	.3280 (.1692)	.3326* (.1381)
2008	-.3667 (.1899)	0.69300	—	-.3228 (.1920)	.1408 (.1798)	.1592 (.1444)
2009	-.5827* (.2385)	0.55840	—	-.5322* (.2388)	.2313 (.2348)	.0038 (.1778)
Intercept	− 2.700* (.9646)	—	—	− 2.990* (.9533)	− 3.715* (.9535)	− 1.765* (.6832)
				BASE = NO-INCIDENT		
Sample Size	10,079	—	—	11,585	—	—
Wald Chi-square (49)	261.38	—	—	—	—	—
LR Chi- square (147)	—	—	—	830.95	—	—

Where *is significant at α =0.05 level; UNC is unclassified and AVE.DER is average derivative

The computed relative risk ratios and average derivates /marginal effects computed from estimated coefficients of the modified multinomial logit are provided in Table 5. In general, the signs of the computed parameters are plausible and they are generally consistent with prior expectations and what was established in the incident frequency models. An interpretation and discussion of the findings is presented next. Factors

Table 5. Average Derivatives and Computed Relative Risk Ratios

ESTIMATION MODELS	MODIFIED MULTINOMIAL LOGIT					
	PA	NPA	UNC	PA	NPA	UNC
VARIABLES & PARAMETERS	RRR	RRR	RRR	AVE. DERIVATIVES		
OPERATOR DEMOGRAPHICS						
Age					—	—
Age^2	—	—	—	0.0112	—	—
Female	1.1580	1.2000	1.1353	0.0058	0.0087	0.0116
African American	0.7985	0.7639	0.9319	−.0090	−.0125	−.00450
Asian/Pacific Islander	0.5954	1.3700	0.9110	−.0203	0.0218	−.00972
Hispanic	1.0370	1.1140	1.0805	0.0009	0.0054	0.0075
EMPLOYMENT STATUS CHARACTERISTICS						
Years of Experience				-0.0035	—	-0.0026
Years of $Experience^2$	—	—	—	—	—	—
Probationary Status	1.6740	1.1420	1.6322	0.0245	0.0013	0.0554
ASSIGNED-WORK CHARACTERISTICS						
Unique Assignments	—	—	—	−.00033	−.00008	0.0002
Split Shift	0.7733	0.9102	1.0790	−.01179	−.00484	0.0105
Total Hours Worked	—	—	—	0.0001	0.0001	0.0002
Weekend Hours	—	—	—	−.00007	−.00004	−.000042
Average Daily Span	—	—	—	0.0046	0.0027	−.00742
Daily Span CV	—	—	—	0.0411	0.0345	0.0549
Three Day/ 30 Hour Week	1.2180	1.2430	1.3855	0.0068	0.0091	0.0356
Four Day/ 40 Hour Week	0.2375	0.3330	0.8957	−.0371	−.03647	−.00200

Table 5. continues	PA RRR	NPA RRR	UNC RRR	PA AVE. DERIVATIVES	NPA AVE. DERIVATIVES	UNC AVE. DERIVATIVES
ASSIGNED-WORK CHARACTERISTICS - continues						
Short Term Absence Hours	—	—	—	0.0003	0.0000	0.0002
Merlo Garage	0.8261	0.6088	1.0587	−.00783	−.02382	0.0105
Powell Garage	0.8641	1.1980	1.0931	−.00784	0.0098	0.0092
Secondary Radial Route	0.8682	1.1780	0.9495	−.00659	0.0101	−.00587
Crosstown Route	0.7734	0.9460	0.8734	−.01067	−.00138	−.01237
Feeder Route	0.7375	1.0660	1.0192	−.01309	0.0042	0.0033
Peak Express Hours	0.7837	0.7976	1.1913	−.01091	−.01169	0.0232
Shift Ends 4:00-7:00 pm	1.0721	0.8500	0.8948	0.0045	−.00818	−.01120
Shift Ends After 7:00 pm	0.9468	0.9999	0.9016	−.00196	0.0009	−.01054
Low -Floor Bus	1.0430	1.0738	1.0461	0.0015	0.0034	0.0041
Old Bus	0.8890	1.1951	0.8108	−.00479	0.0120	−.02213
Small Bus	1.0190	0.5315	0.9302	0.0028	−.02645	−.00440
SERVICE PERFORMANCE CHARACTERISTICS						
Boardings Per Revenue Hour	—	—	—	−.00008	0.0006	0.0003
Lifts Per Hour	—	—	—	0.0442	0.0169	0.0561
Ave.Max. Speed - Peer Speed	—	—	—	0.0005	0.0006	0.0057
Proportion Late Departs	—	—	—	0.0488	0.0158	0.0888
Proportion Early Departs	—	—	—	0.0466	0.0461	0.0666
Layover Proportion	—	—	—	0.0066	−.00150	−.08373
Security Requests	—	—	—	−.00095	0.0022	0.0111
Evasive Action Events	—	—	—	0.0183	0.0695	0.0633

	PA	NPA	UNC	PA	NPA	UNC
Table 5. continues	RRR	RRR	RRR	AVE. DERIVATIVES		
CUSTOMER SERVICE INFORMATION						
Lag Unsafe Operation	—	—	—	0.0082	0.0037	0.0111
Unprofessional Treatment	—	—	—	0.0014	0.0053	0.0119
Lag Fit for Duty	—	—	—	−.00382	0.0058	0.0431
Service Delivery Problem	—	—	—	0.0057	−.00282	−.01535
Commendation: Calls Stops	—	—	—	−.00093	−.00047	0.0014
Commendation : Other	—	—	—	0.0036	0.0043	0.0053
TEMPORAL CHARACTERISTICS						
Fall Signup	1.1430	0.7117	0.9617	0.0079	−.0167	−.00288
Spring Signup	1.4430	0.6178	1.0642	0.0197	−.0252	0.0074
Summer Signup	1.3940	0.6855	0.9766	0.0187	−.01917	−.00242
2007	0.7930	1.3880	1.3945	−.01384	0.0163	0.0353
2008	0.7241	1.1512	1.1726	−.01614	0.0075	0.0183
2009	0.5873	1.2601	1.0038	−.02153	0.0150	0.0013

Where UNC represents unclassified incidents

considered were operator demographics and employment status, assigned-work characteristics, service performance, customer feedback and temporal factors.

Operator Demographics and Employment Status

The likelihood of an operator being involved in a preventable incident relative to non-incident involvement is estimated to decrease at a diminishing rate with respect to operator's age. It reaches a minimum when the operator is 35.21 years old; which is relatively lower than the sample average of 50.32 years. Presumably, this is what one would expect— a diminishing marginal safety returns relationship. Surprisingly, age was found to be insignificant in non-preventable and unclassified incident outcomes. It may be recalled that in the case of incident frequency analysis, the minimum expected collision and total incidents is reached when an operators is about 36.08 years old.

These results show that the negative-to-positive transition of the expected collisions and total incidents, as well as the likelihood of preventable incident involvement, is reached at about the same age – approximately when the operator is 35 years old. Holding age fixed, an operator's length of service was expected to be negatively correlated with the likelihood of preventable and non-preventable incident involvements.

The estimated parameters indicate that the probability of being involved in a preventable incident over non-incident involved is about 1.67 times higher for operators who are still on probation than regular operators. Similarly, the estimated probability of unclassified incident involvement over non-incident involved operators is about 1.63 times higher for those on probation than regular operators. The difference between the likelihood of non-preventable incident involvement for regular operators and those who are still on probation is relatively small. These results indicate that relative to regular bus operators, those operators who are still on probation are more likely to be involved in preventable and unclassified incidents than in the other safety outcomes.

Beyond initial probationary period of employment, operators' experience is estimated to be inversely related to the likelihood of preventable and unclassified incident involvements. More precisely, each additional year of operators experience is estimated to reduce the probability of being involved in a preventable incident over non-incident involved by 0.35 percentage points. In the case of unclassified incidents, the probability declines annually by 0.26 percentage points.

These results indicate that an experienced bus operator is relatively safe and has a higher likelihood of being involved in an unclassified than in preventable safety incidents. In contrast, operator experience was found to be insignificant in non-preventable incident occurrences, an indication that non-preventable incidents are relatively random events. These findings can be interpreted as validating TriMet's training and safety review process of classifying bus safety incidents as either PA or NPA. Indeed, NPA incidents are random events as involvement is not influenced by experience or operator's length of service.

Regarding gender, race and ethnicity, the estimated model results indicate that the female dummy variable is not significantly correlated with the probability of being involved in preventable and unclassified incidents. However, for unknown reasons, the probability of being involved in non-preventable over non-incident involved is 1.2 times higher for female than male counterparts.

As previously discussed in the incident frequency analysis section, female operators are may be more likely to report when involved in non-preventable incidents, or non-preventable incidents are more likely to be acknowledged to a female bus operator. The likelihood of preventable incident involvement relative to non-incident involved was found not to be associated with race and ethnicity indicators.

Similarly, the differences in likelihoods of non-preventable and unclassified incident involvement for African American, Asian, Hispanic and White operators are not significantly different from zero.

Assigned Work Characteristics

Turning to assigned work related factors, an operator's total hours of service during a signup was entered in the model to account for exposure to incident risk. The estimated coefficients for this variable were all positive and significantly different from zero at $\alpha = 0.05$, but the associated marginal effects varied across different outcomes. A unit increase of an operator's total hours of service is associated with a higher marginal effects on the likelihood of preventable incident involvement than non-incident involved, followed by unclassified and then non-preventable incident outcomes. The negative weekend hours marginal effect suggests that preventable incidents risk diminishes on days when regional traffic volumes are lower and congestion is less pronounced. Similarly, change in driving patterns may be at play.

Independent of operator's total hours of service, straight assignments are generally the most sought after assignment type among operators, while split assignment type, whether full or part time, are least desired. These preferences are not reflected in the likelihood of associated safety outcomes across run types. Similar findings were established in the incident frequency analysis, the exception being that in the total incidents' frequency model, the lag of split shift dummy variable was found to be positively correlated with expected total incident frequency. However, in the present binary analysis the lag of split shift dummy was dropped from the model because it was insignificant.

When binary logit model was estimated (see Table 4 and Appendix C) the lag of the split shift dummy variable was found to increase the likelihood of preventable incident involvement. This finding can be interpreted as signaling that fatigue in the last period has safety effects in the current period. Two dummy variables were also incorporated in the model to identify bus operators who worked compressed workweeks. The coefficients, however, are insignificant. An indication that the likelihood of being involved in any incident type versus non-incident involved, is not different between part-time operators on 3-day, 30-hour weeks, operators on 4-day, 40-hour weeks and those operators on standard workweeks.

An operator's average daily span of work hours is found to be positively related to the likelihood of preventable and unclassified incident involvement, but not with non-preventable incident outcome. An increase in work span by one more hour is estimated to increase the probability of preventable incident involvement over non-incident involved by 0.46 percentage points. On the other hand, a similar increase results in a decrease of unclassified incidents by 0.74 percentage points. Span variability was found to have insignificant effects.

The present findings are similar to the results established in the incident frequency analysis section. In particular, work span findings seem to be more relevant to bus operators on split shifts. More specifically, the findings suggests that an increase in the amount of time separating shifts not only contributes to greater preventable incident involvements over non-incident involved but also will increase the likelihood of the unclassified incidents. These findings indicate that the split shift effect on safety is not direct. Unlike in the collision incidents analysis, span variability was unexpectedly found to be insignificant in preventable incident outcomes.

Beyond operator work span effects, the model estimates reveal that variations in short duration absence hours are positively related with the likelihood of preventable incident involvement, but not with other incident outcomes. The estimated marginal effects associated with short duration absence hours can be interpreted as a contributor to probability of preventable incident involvement relative to non-incident involved. These findings are consistent with prior expectations (Wahlberg & Dorn, 2009) and resembles the empirical relationship uncovered in the collision frequency models.

Differences, however, were observed when instead of the present signup absence hours, the prior signup short duration absence hours was entered into model. While the lag of the short duration absence hours variable was positively correlated with the expected collision frequency, in the present binary analysis this variable was dropped from the model because it was found to be insignificant. When a different model specification was employed (see ordinary logit estimates in Table 4 and in Appendix C), the lag of short duration absence hours was found to have a significant positive effect on the probability of preventable incident involvement. The coefficient on the lag of short duration absence hours may be interpreted as a signal of diminishing job satisfaction (Strathman, et al., 2009), which in turn may compromise safety.

Turning to the time-of-day, the most desired runs or assignments are those that correspond to normal business hours, while the least desired are those in which operators have to deal with the evening commuting rush at the end of their shift. These considerations, however, are not reflected in the safety performance of bus operations as the two dummy variables identifying the time of day when an operator's run concludes were not significantly different from zero at α =0.05 level.

Work for operators is assigned out of three garage facilities, with Central serving as the primary garage, and Powell and Merlo serving as satellite facilities. Among the three garages, the likelihood for non-preventable incident involvement over non-incident involved is lower for buses dispatched from Merlo garage than those dispatched from Central garage (RRR= 0.6088, P = 0.002). In contrast, there is no significant difference in the safety performance of buses dispatched from Powell and those dispatched from Central garage. This finding suggests that although non-preventable incidents are known to be random events, they are deterministic to some level.

With respect to route typology, operators on frequent service radial routes with 15-minute or better service frequency to the Central Business District face elevated risk levels. Some of the risks are related to exposure to more traffic volumes, overload consequences from headway deviations, as well as greater interference from construction activity, downtown traffic and on-street parking. Therefore, it was anticipated that this would be reflected in safety performance differentials across alternate route types, including: secondary radials, feeders, peak expresses and crosstowns.

Surprisingly, model estimation results show that there are no safety differentials across route types. The crosstown routes are the only exception where the likelihood of preventable incident involvement is estimated to be lower than the frequent service radial routes (RRR = 0.7734, P = 0.023). A similar, pattern was ascertained in incident frequency models. Specifically, it was found that the expected total incidents on crosstown routes was 12% lower than the frequent service radial routes. On the other hand, the expected total incidents on frequent service radials and other route types were not significantly different from zero.

The operational safety effect of vehicle related factors was also examined. The estimated parameters indicated that the likelihood of preventable incident involvement over non-incident involved is not significantly different among low-floor buses and other bus types. Similar findings were also found in other incident types, non-preventable and unclassified incident outcomes. One dummy variable, a small bus indicator, was entered in the model to represent and capture vehicle size effects on safety outcomes. The results show that vehicle size is not correlated with safety performance. Similarly, safety performance for new and buses older than 15 years was found to be not significantly different.

In comparison with incident frequency estimates, the present results are relatively similar to what was found in collision and total incident models. In particular, it was established that the expected collision and total incident frequencies were not significantly different between new and older buses. On the other hand, the present binary model findings are different from the incident frequency model results. Specifically, an inverse relationship was established between older buses and expected non-collision frequencies. In contrast, the model estimates do not support the hypothesis that the likelihood of incident preventability over non-incident involved is different between newer and older buses ($\alpha = 0.05$ level).

Service Performance Characteristics

Turning to service performance related factors, passenger boardings were expected to have a positive influence on the likelihood of preventable incident involvement. This relationship was expected because a larger volume of passengers increases the exposure risk and the prospect for an occurrence of unpleasant incidents — especially those associated with braking and acceleration. As it turns out, more passenger boardings per revenue hour was not significant in preventable or non-preventable incident involvements.

Relative to non-incident involved, one more lift movement per hour is estimated to increase the probabilities of preventable and unclassified incident involvement by about 4.4 and 5.6 percentage points respectively. In the case of incident frequency models, lift movements were found to be positively related to the expected collision and non-collision frequencies, as well as to the total incident frequencies. However, unlike preventable incident outcomes, non-preventable incident involvement is not correlated with lift movements at $\alpha = 0.05$. This finding is consistent with the general observation that non-preventable incidents are relatively random events.

The positive marginal effects associated with lift movements in preventable incident outcome can be interpreted in a number of ways. But as observed in earlier bus transit studies (Strathman, et al., 2009; Dueker, et al., 2004) each lift operation adds 60-120 seconds to dwell time. Further, they also note that when lift operations occur with regularity, time can be added to the schedule to account for longer dwells. Conversely, when lift operations occur infrequently, schedules are not adjusted and delays from lift-extended dwells must be recovered. It can be argued that bus lift operation contributes to the likelihood of a bus running late. Consequently, this may serve as an incentive to the bus operator to pay less attention and to rush in an effort to adhere to the schedule. These actions in turn may increase the likelihood of preventable and unclassified incident involvement.

Speeding relative to peers represents a potential safety risk. Variations in speeding were expected to be positively related to the likelihood of preventable and non-preventable incident outcomes. Indeed, the estimated parameters reveal that speeding is positively correlated with the likelihood of unclassified incident involvement. However, this variable was found not to be empirically associated with the likelihood of preventable and non-preventable incident outcomes.

Independent of speeding and bus lift operation effects, two other variables, namely, proportion late and proportion early departures, were included in the model to capture the safety effects of operators' inability to adhere to a schedule. It was expected that operators who consistently depart from time points late compared to their peers serving the same route during the same time period would be associated with increased likelihood of preventable incidents. The estimated parameters are consistent with prior expectations. Specifically, the proportionate late variable is positively associated with preventable and unclassified incident outcomes.

Similarly, in the case of incident frequency models, positive relationships were established between this variable, the proportion late, and the expected collision and non-collision, as well as, in the expected total incidents frequency models. However, the present model estimates show that the likelihood of non-preventable incident involvement is not significantly correlated with the proportion late variable.

The variable, proportion early depart, was entered in the model to capture safety effects associated with operators early departures from time points relative to the peers. It was found to have insignificant effects on bus operations safety.

In comparison to the incident frequency model estimates, the early depart variable was insignificant in non-collision and total frequency models. On the other hand, it was found to have a positive influence on the expected collision frequency incidents.

Arguably, operators who consistently leave early, by more than one minute from time points relative to their peers may be motivated by a number of reasons. Some of the objectives according to Strathman. et al., (2009) are that early departures can pad the amount of layover time at the end of the route; early departures can also diminish actual headways, allowing operators to carry lighter passenger loads.

As stated in Section 4.2, literature has identified insufficient layover time as a contributor to operator fatigue and safety risk. Therefore, the proportion layover variable was expected to be empirically correlated with the likelihood of preventable and non-preventable incident involvement. Contrary to prior expectations, this variable was found to have insignificant effects not only on the likelihood of preventable incident involvement but also for non-preventable incident outcomes. For unknowns reasons, proportion layover variable was found to be inversely related to the likelihood of unclassified incidents. The negative marginal effects associated with this variable in unclassified over non-incident involved can be attributed to the sufficient layover time that TriMet builds into the actual run schedules.

The effects of the responsive actions taken by bus operators due to security and safety risk related concerns are explored by accounting for the number of pre-coded text messages sent to dispatchers requesting security personnel and reporting evasive action events. The occurrence of a security related incident was estimated to increase the probability of unclassified incident involvement over non-incident involved by about 1.1 percentage points. In contrast, the occurrence of security incidents was insignificant in preventable and non-preventable incident involvement outcomes.

Operator stress associated with navigating a large bus on routes through congested city traffic is compounded when operators have to take evasive actions to avoid crashes. The occurrence of an evasive action related incident is estimated to increase the probability of preventable incident involvement over non-incident involved by 1.83 percentage points. While in the case of non-preventable and unclassified incident involvements, the probabilities are estimated to increase by about 7% and 6% respectively. These results are similar to the findings established in non-collision and total incident frequency model. On the other hand, they are different from what was found in collision models. Precisely, the occurrence of an evasive action event was insignificant in the collision frequency model. In the present analysis, the occurrence of an evasive action event is estimated to increase the likelihood of preventable and non-preventable, as well as, unclassified incident outcomes.

Customer Service Information

Beyond the operator's service performance, customer feedback about an operator's bus operation is expected to be empirically correlated with safety outcomes. Passengers experience bus operators' delivery of service first-hand and some are motivated to report either complaints or make commendations on their bus ride experiences. Specifically, it was expected that the likelihood for preventable incident involvement would increase with the complaints but decrease with commendations. A complaint about unsafe operation of the bus and concern about an operator's fitness for duty were estimated to have a positive effect on the likelihood of preventable incident involvement in the standard models (specifications without lagged variables- see Appendix C). The standard models also reveal that the complaints related to rude or unprofessional treatment by an operator have a positive influence on the likelihood of non-preventable and unclassified incident involvements.

Positive association between customer complaint variables and safety incidents, as argued in the incident frequency section might arise because of previous customer experience of crash incidents, which may serve as a motivation for lodging a complaint. This simultaneity issue was addressed in the present binary models by lagging the complaint related variables that had significant influence on the likelihood of incident involvement.

The modified model estimated that a complaint in the prior signup about unsafe bus operation increases the probability of preventable incident involvement over non-incident involved by about 0.8 percentage points. On the other hand, the likelihood for unclassified incident involvement was estimated to increase by about 1.1 percentage points. The effect of complaints related to prior concerns about operators' fitness for duty was unanticipatedly found to be insignificant in preventable incident involvement.

The other variables that were found to be insignificant in the modified binary model include: service delivery problem complaints, commendations factors, such as prior commendations for stop announcement and commendations for other actions. These findings are relatively similar to what was established in the incident frequency models. Specifically, prior signup complaints related to unsafe operation of the bus were found to positively influence the expected collision and total incidents frequencies.

Similarly, the present binary model has established that prior signup complaints about unsafe operation of the bus have a positive influence on the likelihood of preventable and unclassified incident outcomes. As earlier argued, this finding suggests that passenger complaints about an operator's unsafe bus operation is not motivated by their prior experience with bus safety incidents, but may be signaling elevated habitual safety risk and associated consequences. In other words, this finding can be interpreted as suggesting that chronic complaints regarding operator unsafe bus operation elevates the risk of being involved in a preventable incident.

Temporal Characteristics

Safety performance was estimated to vary systematically with respect to temporal factors. In particular, regarding annual variations, the probability of unclassified incident involvement over non-incident involved is estimated to have been about 40% higher in the year 2007 than the year 2006. On the other hand, the likelihood for preventable incident involved over non-incident involved is estimated to have been lower in the year 2009 than in the year 2006 (RRR= 0.5873, P = 0.026).

Seasonality is evident as well. The likelihood for non-preventable incident involvement over non-incident involved is lower during fall and spring than in the winter signup. In contrast, the same is not true for preventable and unclassified incident outcomes. More precisely, during the study period, the probability for preventable incident involvement over non-incident involved is estimated to have been about 1.4 times higher in the summer than in the winter signup.

The higher likelihood of non-preventable incidents in the winter than fall and spring signup can be attributed to snow and the icy conditions that were experienced during the winter periods. The estimated increase in likelihood for preventable incident outcomes in summer over winter signups can possibly be attributed to the increase in exposure risks that is often evident in the summer periods. In particular, high levels and increased flow volumes of other road users, such as motorists and pedestrians, as well as, cyclists are usually common in the summer period; this might consequently contribute to more preventable incident outcomes.

These findings are different in a number of ways from what was established in the incident frequency models. First, all signup related variables were insignificant in the incident frequency models. In contrast, the present model estimates, clearly reveal existence of seasonality. Second, expected collision and total incidents frequencies were estimated to be higher in 2007 than in the year 2006. In contrast, the present model estimates reveal that the likelihood of preventable incident involvement was lower in the year 2009 than in the year 2006.

5.7 Methodological Considerations and Result Limitations

There are two main methodological limitations of this study which might affect the validity of the analyses: those limitations related to representation of the exposure variable in the study design and of inadequate control of the confounding effects of the covariates.

The most apparent shortcoming of the operator-based design is the challenge of correctly representing risk exposure. This was especially apparent given that the variable passenger boardings per revenue service hour was insignificant in all models at $\alpha = 0.05$ level. Given this finding, the total hours worked by the operator during each operator signup period was used as a proxy measure of risk exposure for all safety models. Total hours worked is an important risk exposure variable especially when bus service provision is in urban areas. Finer definitions or stratification of hours worked, such as using hours worked in peak and off-peak, may improve performance of this safety model because stratified total hours better captures variations in risk exposure between off-peak and peak periods.

As an alternative to total hours, future analyses can stratify/classify total hours worked into more detailed categories such as hours worked during early morning(before 7:00 am), hours worked in morning peak (7:00- 9:00 am), mid-day period (9:00 am- 4:00 pm) and evening hours (after 6:00 pm). These refinements may better capture variations in risk exposure and improve performance of the safety model.

Turning to risk exposure empirical findings in non-collision analysis, the two known risk exposure measures for non-collision incidents are total hours worked and number of passenger boardings per revenue hour of service. The variable passenger boarding per revenue hour would have been an ideal representation of risk exposure for non-collision incidents. But for unknown reasons it was insignificant in the models. The safety incident pattern earlier observed in Figure 4 (section 3.4) indicates that non-collisions incidents are mostly concentrated in afternoons, especially between 1:00pm-7:00 pm. The analysis also showed that the number of passenger boardings during the morning periods corresponds to the number of passenger boardings in the afternoon periods.

Therefore, from the observed pattern of non-collision incidents over time of the day and the insignificant finding for the passenger boarding variable, it can be speculated that what the passenger boardings variable is capturing or measuring is not homogenous. The condition of passengers /customers appears to be changing overtime or is unstable. Future research, can address this issue by stratifying the passenger boardings variable by time periods as proposed for the total hours variable above. The stratification of the number of passenger boardings per revenue hour will better account for passenger exposure and may improve the safety model performance.

The other limitations of this study are those related to the confounding effects of time of day variation of safety incidents with selected operator characteristics- for example, split shifts, hours worked, age and experience. One way to determine if these theoretical concerns are supported by data is to look for or to check if time of the day safety incidents are correlated with selected operator characteristics for stratified samples or subsamples with same level of risk exposure. The experience variable (measured in years) for a subsample of bus operators who run the same assignments, also known as unique assignments, was not significantly correlated to the frequency of safety incidents in all models. In addition, pairwise correlations between these study variables were very small at $\alpha = 0.05$ level.

It is possible, however, that safety incidents may be correlated with these study variables through a third variable, also known as extraneous/exogenous variable. In addition, some of the variables may be correlated with omitted variables (i.e. split shift and peak periods) and therefore omitted variable bias limitations. The feasible approaches to addressing correlations between study variables and the extraneous variable is through use of efficient designs and/or statistical analytical controls (Kish, 1959). Statistical controls for potential confounding factors were employed in the present study. The time of the day when an operator concludes the run (or shift end) and the variable that captures the shift type worked (split shift) were incorporated in the model, but shift period worked specifically was not included.

Nevertheless, morning and evening peaks have higher levels of traffic volumes than off-peak periods. Consequently they have higher levels of risk exposure. Use of the variable that accounts for the time of the day when an operator shift concludes is necessary, but not sufficient, to fully address the potential confounding effects that may exist. Therefore, stratification of these study variables may improve future analysis. For example, shift worked can be stratified into early morning peak, mid-day off-peak, evening peak and evening off-peak shift periods. These variable refinements and the stratification of other study variables may improve future model results. This observation suggests that confounding concerns have not completely been eased in the present study. Especially, the separation of the effect of time of day variation safety incidents from the selected operator variables is not well captured and/or controlled for in the present models. The implication is that the analysis/results must be interpreted with these considerations in mind. But as observed in an earlier study (Kish, 1959), “the perfect should not be the enemy of the good”.

CHAPTER 6.0: CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter provides a summary of the key findings that the study has established. In addition, the chapter presents concluding remarks and associated policy or practice implications, as well as the study's contributions and future research directions.

6.2. Summary, Conclusions and Implications

This study has examined how incident frequency and preventability is associated with bus operations at TriMet. Empirical analyses encompassed 4,631 incidents that occurred over a three-year period, from September 2006 through February 2009. Regression analysis identified twenty-four factors (summarized below in Table 5) that are empirically correlated with the frequency of collision, non-collision and total incidents, as well as those that are associated with preventable, non-preventable and other unclassified incident involvements.

In overall, this study has uncovered that there are numerous empirical relationships between operational factors and transit bus safety incidents. Specifically, safety incident frequency and preventability analysis has shown that bus operator age, experience and short duration absenteeism from work, as well as the operator's work span and variability in daily work span/assignments are correlated with bus safety incidents.

Table 6. Important Factors in Safety Performance Analysis at TriMet

OPERATOR DEMOGRAPHICS & EMPLOYMENT STATUS CHARACTERISTICS
Age Years of experience Probationary status
ASSIGNED- WORK CHARACTERISTICS
Total hours worked Weekend hours Split shift Average daily span Daily span coefficient of variation 3-day/30 hour week 4-day/40 hour week Short term absence hours Merlo garage Crosstown Shift end after 7:00 pm Old bus
SERVICE DELIVERY & PERFORMANCE CHARACTERISTICS
Lift operations per hour Proportion late departs Proportion early departs Security requests Evasive action events Boardings per revenue hour*
CUSTOMER SERVICE INFORMATION
Unsafe bus operation Unprofessional treatment Fit for duty

* This variable ideally represents exposure for non-collision incidents- may have to be stratified

In addition, this study has also shown that schedule adherence pressures and bus lift operations are related to safety incidents. The other factors that are empirically correlated with safety performance are operators' responsive action events and customer complaints about unsafe bus operation. These findings and their associated management or policy implications are discussed below.

First, the safety incident frequency and preventability analysis results indicate that beyond the initial probationary period of employment, there are diminishing marginal safety returns associated with both operator age and length of service. With respect to the age effect, the negative-to-positive transition of the expected collisions and total incidents, as well as the likelihood of preventable incident involvement, is reached at about the same age – approximately when the operator is 35 years old.

Traffic safety researchers have long recognized that drivers' motor and cognitive performance diminish with age, although the transition point estimated in this study occurs when bus operators are still relatively young. This finding may not surprise those who have studied the health and wellness of transit operators. However, health and wellness research in the transit industry has tended to focus on such outcomes as health expenses, workers' compensation costs, absenteeism costs, and operator turnover costs (Davis, 2004). As this study's findings indicate, safety outcomes and costs should also be a relevant concern associated with the aging of operators.

Regarding the experience effect, safety incident frequency analysis results indicate that negative-to-positive turning point in collision frequency is reached when operator length of service is approximately 30.8 years. This finding provides empirical evidence of diminishing marginal safety returns to operator length of service, and point to a need for more emphasis on regular refresher training – a practice that an industry survey by Moffat et al. (2001) found is utilized by only 36% of transit properties.

In the case of preventability analysis, the results indicate that an experienced bus operator is relatively safe and has a higher likelihood of being involved in an unclassified than in preventable safety incidents. In contrast, non-preventable incidents are not influenced by operator's experience, an indication that non-preventable incidents are relatively random events. These findings can be interpreted as validating TriMet's operator training program and safety review process of classifying bus safety incidents. As it stands now, four in five incidents that occurs during bus operations, the agency is not at fault, usually the other parties are. This shows that the rate of incidents preventability at TriMet is really low which is good news as it signals success of the agency's safety training program. Given TriMet's ability and resources, it should however, strive towards having zero preventable safety incidents.

Second, apart from transit industry concerns for bus operator absenteeism-related health expenses, labor costs and high labor turnover, absenteeism's contribution to safety incidents is also another area that needs attention. In particular, this study's findings suggest that absenteeism directly and indirectly contributes to undesirable safety outcomes and costs.

The evidence of direct effects is established in the estimated positive correlation between an operator's absence hours and expected collision frequency, as well as in the association with preventable incident outcomes. The evidence for indirect effects is established through the absence-driven demand for extraboard replacement operators, whose more varied daily work spans are estimated to contribute to greater collision frequency.

Third, there has also been a longstanding concern in the transit industry about the safety consequences of operator fatigue (Gertler et al., 2002). This study's findings offer empirical evidence that support this concern in a number of ways. Specifically, this study reveals that, holding operators total hours of service constant, an increase in the daily span of hours is found to increase the likelihood of preventable incident involvement, as well as the expected frequency of collisions. This finding is perhaps more relevant for split shift bus operators – as they often run extended spans of workdays. Given that the risk exposure is not fully accounted in this study, this interpretation should be treated with caution.

Another variable that captures the fatigue effect, split shift in prior signup, is not only positively correlated with expected total incidents but also increases the likelihood of preventable incident involvement. Similarly, fatigue-related concerns associated with the disruptive effects of variable work assignments are supported by the positive correlation between work span variability and expected collision frequency. This study’s findings demonstrate that the expected labor cost savings that motivate the use of such work assignments are at least partially compromised by higher safety costs.

Fourth, the safety risk of occupational stress has also been a serious concern in the transit industry. This study has uncovered that running late not only increases the likelihood of preventable incident outcomes, but also is found to be a significant contributor to the expected frequency of collision, non-collisions and total incidents. However, with the emergence and adoption of AVL systems at TriMet, schedulers now have access to running time data. The availability and use of running time data to inform scheduling reduces the likelihood that running late is a consequence of an unrealistic or improperly written schedule. But as Levinson (1991) observes, schedules are written to be compatible with the abilities of a “typical” bus operator.

The difference of abilities in relation to the typical operator implies that some operators will face greater challenge and pressure adhering to a schedule on a given route or time of day than others. In theory, safety performance may be improved by assigning work to operators so that the difference between the actual and typical abilities is minimized. However, in practice this alternative may not be feasible, as the union and management agreement allows bus operators to select work on the basis of seniority – which may or may not align actual and desired operator abilities.

Regarding running early effects, the early depart variable is positively correlated with the expected collision frequencies but not with incident preventability. However, relative to late depart estimates, it was found that while both are positively associated with the expected collision frequency, the elasticity for running late is almost double that of running early. This study's findings thus show that operator- related safety performance is more sensitive to running late than running early.

Previous literature has identified insufficient layover time as a contributor to operator fatigue and safety risk. Arguably, one motivation for running early is that it adds to the amount of layover time. This argument is however not supported by TriMet data as the estimated actual run cuts implemented during the study period yielded a layover share of 8.5 % more than the agreed minimum of 80 minutes in an 8-hour shift. Therefore, in practice, the data supports that the layover built into the run schedules at TriMet is reasonably sufficient to ensure that safety is not compromised.

Fifth, the model results also indicate that factors affecting operators' schedule maintenance pressures, such as lift usage, are empirically associated with safety outcomes. In particular, the lift operations variable was found to increase the likelihood of preventable and unclassified incident involvement. In the case of safety incident frequency models, lift movements were found to be positively related to the expected collision and non-collision frequencies, as well as to the total incident frequencies. When lift operation is infrequent and unpredictable, it is often treated as another contributor to random delay and is addressed indirectly in the recovery time that is built into a posited schedule.

The positive association established between lift operation and preventable incident outcomes, as well as with incident frequency may potentially be interpreted as a scheduling problem. Now the challenge is to figure out how this new insight can help improve safety performance. This study's finding indicates a need for a more detailed empirical analysis of lift activity at the route and trip levels to ascertain how the problem should be addressed in the schedule development process.

Analysis also established a positive correlation between lift operation and the expected frequency of non-collision incidents. This suggests that passengers with mobility impairments face unique safety risks that may be attributed to improper functioning and on-board securement of lifts. This study's finding indicates a need for continuing research on the design of lift and securement devices. In addition, it also points to a need for continuing review of practices intended to ensure safe travel of passengers with disabilities.

Sixth, beyond the safety risk concerns of occupational stress associated with schedule maintenance pressures and lift operations, operator response to risky and unsafe situations is also another area that needs attention. This study indicates that bus operator responsive actions to security incidents and risk situations are significant contributors to safety outcomes. Specifically, the number of security request incidents by the operator is positively correlated with the expected frequency of non-collision and total incidents. Similarly, the number of operator evasive action events is positively correlated with the expected frequency of non-collision and total incidents. However, comparison of the relative importance for these two operator responsive action related variables shows that the elasticity for evasive action events is roughly half the elasticity associated with security requests. This finding suggests that operator- related safety performance is more responsive or sensitive to security request incidents than evasive actions events.

Operator evasive action events were also positively associated with the likelihood of preventable, non-preventable and other unclassified incident outcomes. This study's finding may suggest that responsive actions should also be a relevant concern in bus operations at TriMet, especially since, operator responsive actions may themselves contribute to safety incidents. For example, taking evasive action itself may contribute to on-board safety or non-collision incidents. Similarly, a security request may occur as an outcome of an on-board safety incident, especially when consumption of alcohol or other substances is involved. With these issues at hand, this finding underscores a need for a more detailed empirical analysis of operator responsive actions at the trip and route level to determine how associated preventable collision and non-collision incidents can be reduced.

Seventh, customer commendations and complaints serve as a valuable source of information about the bus operator's attitude toward service delivery and safety issues. While operators are often rightfully skeptical of the validity of pieces of customer information, this study has found that patterns of customer information offer important insights into operators safety-related performance.

In particular, the model results indicate that the current and prior signup complaints related to unsafe operation of the bus is positively correlated not only with the likelihood of preventable incident outcomes, but also with the expected collision and total incidents frequencies. This finding suggests that passenger complaints about an operator's unsafe bus operation are signaling an elevated safety risk and associated consequences. This finding can be interpreted as suggesting that chronic complaints regarding operator unsafe bus operation elevates the risk of being involved in a preventable incident which may occur either in the present or future signup, and consequently increases collision frequencies.

Safety incident frequency analysis results indicate that interaction between short duration absence hours and fit for duty variables are positively correlated with expected collision frequency. This finding suggests that the safety consequence of fitness complaints about an operator are more pronounced in the presence of short duration absence hours. The general message for transit management represented in this study's findings may be summarized as follows: listen to and follow up on pieces of customer information, and act on patterns of information.

Finally, regarding ITS recovered data and transit safety improvement, this study provides an example of the contribution that transit ITS data can make in realizing more comprehensive safety analysis and greater understanding of safety risks, especially when combined with other information commonly maintained and archived in an agency's data warehouse. Surveys conducted by the U.S. Department of Transportation's (USDOT) Volpe Transportation Systems Center suggest that the transit industry has not fully tapped the potential of archived ITS data with respect to safety analysis and planning (USDOT, 2009). For example, a Volpe Center 2004 survey that queried transit agencies on their use of ITS data for accident analysis or prediction found that only 6 out of the 80 responding metropolitan area transit properties indicated that they had used their data for safety analysis.

The ability to realize the potential benefits of ITS data resources in safety and other applications may however be limited by a number of challenges: such as those related to ITS data validation, data integration, staffing and staff expertise in accessing and analyzing archived data. TriMet stands out as a unique exception for being one of a limited number of transit properties in the US that has managed to overcome these challenges (Strathman et al., 2008). TriMet's experience provides valuable lessons for other properties in promoting more effective utilization of transit ITS and other data resources in operations management, service planning and market research.

Moving forward, this study recommends that TriMet continue to maintain and improve upon their safety incident records. In the short run, the agency may want to ensure that their safety incident database at minimum has information on the above identified factors. In addition, the agency may want to clearly determine the definition or meaning of bus operator job dissatisfaction and identify how exactly this variable is measured in order to capture the information as appropriate.

Another safety issue that the agency may need to determine is related to operator work span. Specifically, the agency may need to establish whether it makes a difference to have operators resting 2-3 hours between shifts verses 5-6 hours. In other words: what time span between two operator split shifts is cost-effective? In addition, TriMet may want to conduct a cost-effectiveness study that compares the overall agency-wide cost of the current practice of having regular operators running split shifts verses using or hiring part-time operators to cover those shifts instead. Another study that may allow TriMet to ascertain the attributes that describe a "typical" operator may be essential in reduction of preventable incident outcomes related to scheduling.

As earlier observed in section 1.3 the transit operating environment is dynamic and highly complex. Ultimately, the safety performance of TriMet is subject to change over time. Therefore, this study recommends that in the long run (say after every twelve to sixteen signups) a similar study using the safety models that have been developed (random effects negative binomial and logit/multinomial logit) may be necessary to determine if there are any significant changes in operations that may be compromising operator-related safety performance.

6.3. Study Contributions and Future Research

This study established that there are numerous empirical relationships between operational factors and transit bus safety incidents. Specifically, it uncovered that bus operator age, experience and short duration absenteeism from work, as well as the operator's work span and variability in daily work span/assignments are correlated with bus safety incidents. In addition, schedule adherence pressures associated with running late and bus lift operations are empirically related to safety incidents. The other factors that influence safety performance are operators' responsive action events and customer complaints about unsafe bus operation.

These findings make some contributions to the understanding of the factors that are empirically related to the likelihood of preventable incident involvement, as well as those that influence the frequency of safety incidents. The findings also offer insights into operation practices and policies that hold promise for improving operator safety performance.

In addition to empirical and practical contributions, this research also contributes to our methodological knowledge. The developed operator signup-based methodology and econometric tools/models can be calibrated and adapted to estimate transit bus incidents for localities in which large and medium sized transit agencies provide bus service. The products and knowledge generated from this research together with what will be established in the above recommended studies (assuming they will be done) will allow to enhance existing transit safety countermeasures and to develop new ones which will lead to reductions in accidents and thus yield substantial cost savings in the form of reduced risk.

This study suffers from four important shortcomings. First, operator-habit related variables are not considered in the safety model. While it is difficult to measure and account for operator habit-related factors, it is obvious that habits are non-homogeneous across different bus operators. For example, some operators might take more risks than others. An appropriate analytical framework should control for differences in accident involvement likelihood across operators with different habits. Second, the safety effects of other modes (e.g., automobiles, bicycles, trucks.etc.) in the network have not been accounted for. Third, log-linear model specification has been assumed as the most appropriate formulation of the count data modeling framework. In practice, other model forms, such as additive formulations do exist. Ideally, data mining techniques can be used to identify the most appropriate model form, but this has not been explored. Fourth, risk exposure is not fully accounted or represented in this study especially in non-collision incidents.

Future safety research built on this study's findings can explore the effect of operator habit-related factors on safety performance in urban transit systems. Another potential study can examine the influence of operational characteristics on safety performance across various US urban transit systems.

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APPENDICES

Appendix A. Variable Definition and Measurements

Dependent Variables	**Definition &Measurement**
Collision incidents	Count of collision incidents during signup
Non-collision incidents	Count of non-collision incidents during signup
Total incidents	Count of all incidents during the signup
Non-incident involved	Count of all operator signup periods without an incident
Preventable incidents involved	Count of total preventable incidents that occurred in each operator signup.
Non-Preventable incidents involved	Count of total non-preventable incidents that occurred in each operator signup
Unclassified incidents involved	Count of total incidents that were uncategorized in each operator signup
Independent Variables	
Operator Demographic characteristics	
Age	Operator's age(in years) on the first day of signup
Male	A dummy variable equaling one if the operator is male and zero otherwise
Female	A dummy variable equaling one if the operator is female and zero otherwise
White	A dummy variable equaling one if the operator's race is white and zero otherwise
African American	A dummy variable equaling one if the operator's race is African American and zero otherwise
Asian	A dummy variable equaling one if the operator's race is Asian or pacific Islander and zero otherwise
Hispanic	A dummy variable equaling one if the operator's race is Hispanic and zero otherwise
Employment Status Characteristics	
Seniority /Years Experience	Operator's TriMet experience (in years) on the first day of the signup.
Probationary	A dummy variable equaling one when the operator's employmentstatus is "Probationary" on the first day of the signup and zero otherwise
Assigned Work characteristics	
Same Assignments	A dummy variable equaling one when the operator's assigned work is the same as in the previous signup and zero otherwise
Split Shift	A dummy variable equaling one when operator's assigned work is split between two distinct blocks of time during the workday and zero otherwise
Total Hours worked	Total hours worked by the operator during the signup
Weekend Service Hours	Total weekend service hours worked by the operator during the signup
Average Daily Work Span	Average daily work span worked by the operator during the signup.
Average Daily CV	Is the ratio of standard deviation to Average daily work span for the operator during the signup (coefficient of variation).
Three day/30 Hour wk	A dummy variable equaling one if the operator worked three-day/30 hour weeks and zero otherwise.
Four day/40 Hour week	A dummy variable equaling one if the operator worked four-day/40 hour weeks and zero otherwise.

Appendix A - continues	Definition &Measurement
Assigned Work characteristics-continues	
Short term Absence Hours	Short duration (three consecutive days or less) hours associated with sick leaves, unexcused absences, and leaves related to a serious medical condition.
Center Garage	A dummy variable equaling one when the operator's pullout during the sign-up is from the Center St. garage and zero otherwise
Powell Garage	A dummy variable equaling one when the bus operator's pullout during the sign-up is from the Powell Ave. garage and zero otherwise
Merlo Garage	A dummy variable equaling one when the bus operator's pullout during the sign-up is from the Merlo Dr. garage and zero otherwise
Frequent Service Radial Route	A dummy variable equaling one when the operator's assigned route is classified as a frequent service Trunk Radial (i.e., headways 15 minutes & under) and zero otherwise
Secondary Service Radial Route	A dummy variable equaling one when the operator's assigned route is classified as a secondary service Trunk Radial (i.e., headways greater than 15 minutes) and zero otherwise
Crosstown Route	A dummy variable equaling one when the operator's assigned route is classified as a Crosstown and zero otherwise
Feeder Route	A dummy variable equaling one when the operator's assigned route is classified as a Feeder and zero otherwise
Peak Express Service Hours	A dummy variable equaling one when the operator's assigned route is classified as a Peak Express and zero otherwise
Shift Ends Before 4:00	A dummy variable equaling one when an operator's scheduled pull-in for the sign-up occurs before 4:30 pm and zero otherwise
Shift Ends 4:00- 7:00pm	A dummy variable equaling one when an operator's scheduled pull-in for the sign-up occurs between 4:30 and 7:30 pm, and zero otherwise
Shift Ends After 7:00 pm	A dummy variable equaling one when an operator's scheduled pull-in for the sign-up occurs after 7:30 pm and zero otherwise
Low-Floor Bus	A dummy variable equaling one if bus type assigned a low floor bus and zero otherwise
Old Bus	A dummy variable equaling one if bus type assigned is old and zero otherwise
Small Bus	A dummy variable equaling one if the bus type assigned is small and zero otherwise
Standard Bus	A dummy variable equaling one if the bus type assigned is standard and zero otherwise
Service Perfomance Characteristics	
Boardings per Revenue Hour	Passenger boardings per revenue hour on service delivered by the operator during the signup
Lifts per Revenue Hour	Lift operations per revenue hour on service delivered by the operator during the signup
Av.Max. Speed vs.Peers Speed	Operators mean maximum speed between time points minus the mean maximum speed of peer operators (.i.e., traveling between the same time points during the same time period) during the signup.
Proportion Late Departures vs.Peers	Proportion of an operator's departures from time points that are late (i.e., more than five minutes late in relation to scheduled departure) minus the proportion of late departures of peer operators (i.e., serving the same time period) during the signup
Proportion Early Departures vs.Peers	Proportion of an operator's departures from time points that are early (i.e., more than one minute early in relation to scheduled departure) minus the proportion of early departures of peer operators (i.e., serving the same time period) during the signup
Actual average Layover Proportion or time	Operator's actual average layover time divided by actual average revenue service time per trip during the signup
Security response requests	Number of text-coded requests for security response transmitted by the operator to the dispatch center via the bus control head during the signup
Evasive Action Events	Number of incidents requiring the operator to take evasive action during the signup

Appendix A - continues	Definition &Measurement
Customer Commendations & Complaints	
Fit for Duty	Number of reported (e.g., by passengers , field supervisors) "Fit for Duty" incidents involving the operator during the signup.
Unsafe Operation	Number of incidents involving unsafe vehicle operation by the operator reported to Customer Relations during the signup
Unprofessional Treatment	Number of "unprofessional conduct" complaints involving the operator reported to Customer Relations during the signup
Service Delivery Problem	Number of complaints reported to Customer Relations involving a service delivery problem (e.g., missed stops & pass-ups, early departures) by the operator during the signup.
Commendations: Stop Announcements	Number of commendations reported to Customer Relations involving the announcement of stops over the bus intercom by the operator during the signup
Commendations: Other	Number of commendations of the operator for all other reasons reported to Customer Relations during the signup.
Temporal Characteristics	
Fall Signup	A dummy variable equaling one for a Fall signup and zero otherwise
Winter Signup	A dummy variable equaling one for a Winter signup and zero otherwise
Spring Signup	A dummy variable equaling one for a Spring signup and zero otherwise
Summer Signup	A dummy variable equaling one for a Summer signup and zero otherwise
Year 2006	A dummy variable equaling one when the operator's signup occurs in the year 2006 and zero otherwise
Year 2007	A dummy variable equaling one when the operator's signup occurs in the year 2007 and zero otherwise
Year 2008	A dummy variable equaling one when the operator's signup occurs in the year 2008 and zero otherwise
Year 2009	A dummy variable equaling one when the operator's signup occurs in the year 2009 and zero otherwise

Appendix B. Standard RENB Estimates and Elasticities

ESTIMATION MODELS	STANDARD RENB						
VARIABLES & PARAMETERS	(Std. Dev)	TOT β (S.E)	COL β (S.E)	NCOL β (S.E)	TOT E	COL E	NCOL E
Dependent Variables							
Total Incident Events (TOT)	0.316 (0.611)	—	—	—	—	—	—
Collision Events (COL)	0.184 (0.443)	—	—	—	—	—	—
Non-collision Events (NCOL)	0.132 (0.398)	—	—	—	—	—	—
Independent Variables							
OPERATOR DEMOGRAPHICS							
Age	50.0 (9.40)	−.0519* (.0151)	−.0401* (.0182)	−.0627* (.0241)			
Age^2	2589.0 (909.7)	.0006* (.0002)	.0005* (.0002)	.0006* (.0003)	0.810	0.990	−.270
Female	0.308 (0.462)	.0772 (.0421)	.0149 (.0507)	.1767* (.0674)	—	—	0.162
African American	0.140 (0.347)	−.1234 (.0549)	−.0955 (.0657)	−.1535 (.0884)	—	—	—
Asian/Pacific Islander	0.035 (0.184)	−.1060 (.1048)	−.1499 (.1267)	−.0646 (.1681)	—	—	—
Hispanic	0.038 (0.190)	.0421 (.0918)	.0210 (.1126)	.1364 (.1443)	—	—	—
EMPLOYMENT STATUS CHARACTERISTICS							
Years of Experience	10.35 (8.31)	−.0392* (.0091)	−.0440* (.0109)	−.0292* (.0148)			-0.302
Years of $Experience^2$	176.42 (252.90)	.0006* (.0003)	.0007* (.0003)	.0003 (.0005)	−2.72	−.300	—
Probationary Status	0.074 (0.262)	.2232* (.0728)	.1487 (.0923)	.3685* (.1121)	0.200	—	0.308
ASSIGNED-WORK CHARACTERISTICS							
Unique Assignments	11.45 (17.42)	−.0002 (.0016)	−.0030 (.0020)	.0035 (.0025)	—	—	—
Split Shift	0.301 (0.459)	−.0006 (.0659)	−.0470 (.0840)	.0536 (.1013)	—	—	—
Total Hours Worked	383.55 (125.82)	.0017* (.0002)	.0015* (.0003)	.0021* (.0003)	0.652	0.575	0.805
Weekend Hours	75.73 (79.87)	−.0009* (.0003)	−.0012* (.0004)	−.0005 (.0005)	0.068	−.091	—
Average Daily Span	9.45 (1.67)	.0073 (.0162)	.0638* (.0207)	−.0763* (.0249)	—	0.603	−.721
Daily Span CV	0.141 (0.116)	.3740 (.2382)	.8351* (.2972)	−.2170 (.3749)	—	0.118	—
Three Day/ 30 Hour Week	0.021 (0.145)	.3509* (.1209)	.2082 (.1590)	.5454* (.1774)	0.296	—	0.420
Four Day/ 40 Hour Week	0.003 (0.054)	−.5824 (.3534)	−2.238* (1.004)	.2463 (.3809)	—	-8.375	—

Appendix B -continues		TOT	COL	NCOL	TOT	COL	NCOL
ASSIGNED-WORK CHARACTERISTICS - continues	Mean (Std. Dev)	β (S.E)	β (S.E)	β (S.E)	E	E	E
Short Term Absence Hours	13.91 (21.59)	.0023* (.0008)	.0034* (.0010)	.0008 (.0013)	0.032	0.357	—
Interaction of Fit for Duty & Short Term Absence Hours	.117 (2.119)	—	.0238* (.0096)	—	—	0.357	—
Merlo Garage	0.218 (0.413)	−.1507* (.0631)	−.2153* (.0786)	−.0687 (.0989)	-0.160	-0.240	—
Powell Garage	0.341 (0.474)	.0116 (.0430)	.0523 (.0531)	−.0439 (.0675)	—	—	—
Secondary Radial Route	0.154 (0.361)	−.0193 (.0591)	−.0089 (.0731)	−.0641 (.0954)	—	—	—
Crosstown Route	0.238 (0.426)	−.1087* (.0442)	−.0882 (.0563)	−.1381* (.0682)	-0.110	—	-0.150
Feeder Route	0.059 (0.235)	−.0418 (.1207)	−.1080 (.1471)	.0635 (.1973)	—	—	—
Peak Express Hours	0.027 (0.162)	−.0280 (.1314)	−.0712 (.1501)	−.3493 (.2590)	—	—	—
Shift Ends 4:00-7:00 pm	0.501 (0.500)	−.0521 (.0484)	−.1160 (.0606)	.0375 (.0763)	—	—	—
Shift Ends After 7:00 pm	0.189 (0.391)	−.0470 (.0584)	−.1388 (.0738)	.0767 (.0904)	—	—	—
Low -Floor Bus	0.657 (0.475)	.0128 (.0596)	.0249 (.0748)	.0663 (.0942)	—	—	—
Old Bus	0.234 (0.423)	−.1849* (.0785)	−.1338 (.0973)	−.2707* (.1275)	-0.200	—	-0.310
Small Bus	0.046 (0.210)	−.1425 (.1355)	−.1254 (.1595)	−.2250 (.2378)	—	—	—
SERVICE PERFORMANCE CHARACTERISTICS							
Boardings Per Revenue Hour	43.37 (10.25)	.0027 (.0024)	.0004 (.0030)	.0066 (.0038)	—	—	—
Lifts Per Hour	0.286 (0.149)	.6364* (.1385)	.5210* (.1762)	.8490* (.2142)	0.182	0.149	0.243
Ave.Max. Speed - Peer Speed	0.045 (1.502)	.0074 (.0127)	−.0030 (.0152)	.0215 (.0207)	—	—	—
Proportion Late Departs	0.149 (0.103)	1.1303* (.1921)	.9147* (.2392)	1.321* (.3012)	0.168	0.136	0.197
Proportion Early Departs	0.054 (0.059)	.4313 (.3288)	1.142* (.3889)	−.6685 (.5517)	—	0.062	—
Layover Proportion	0.255 (0.310)	−.0798 (.1014)	−.0429 (.0947)	−.2376 (.2473)	—	—	—
Security Requests	0.499 (0.980)	.0527* (.0152)	.0217 (.0208)	.0797* (.0214)	0.026	—	0.040
Evasive Action Events	0.025 (0.163)	.5813* (.0606)	.0634 (.1107)	.9102* (.0755)	0.015	—	0.023

Appendix B -continues	Mean (Std. Dev)	TOT β (S.E)	COL β (S.E)	NCOL β (S.E)	TOT E	COL E	NCOL E
CUSTOMER SERVICE INFORMATION							
Unsafe Operation	0.207 (0.516)	.0691* (.0290)	.0839* (.0365)	.0692 (.0451)	0.014	0.017	—
Unprofessional Treatment	0.391 (0.814)	.0607* (.0188)	.0388 (.0246)	.0920* (.0278)	0.024	—	0.036
Fit for Duty	0.007 (0.084)	.2536 (.1635)	−.3029 (.3392)	.3138 (.2515)	—	2.816	—
Service Delivery Problem	0.114 (0.413)	.0089 (.0382)	.0100 (.0473)	.0313 (.0592)	—	—	—
Commendation: Calls Stops	0.687 (1.380)	.0129 (.0112)	.0083 (.0143)	.0228 (.0170)	—	—	—
Commendation : Other	0.302 (0.705)	.0550* (.0206)	.0641* (.0252)	.0394 (.0335)	0.017	0.019	—
TEMPORAL CHARACTERISTICS							
Fall Signup	0.252 (0.434)	−.0082 (.0440)	−.0781 (.0570)	.0908 (.0673)	—	—	—
Spring Signup	0.253 (0.435)	.0355 (.0496)	.0778 (.0622)	−.0395 (.0795)	—	—	—
Summer Signup	0.170 (0.376)	.0203 (.0497)	−.0056 (.0635)	.0562 (.0773)	—	—	—
2007	0.414 (0.493)	.1292* (.0557)	.1780* (.0720)	.0464 (.0851)	0.121	0.163	—
2008	0.345 (0.476)	−.0045 (.0600)	.0638 (.0772)	−.1288 (.0922)	—	—	—
2009	0.086 (0.280)	−.0833 (.0878)	−.1103 (.1119)	−.0369 (.1362)	—	—	—
Intercept	—	1.857 (.4894)	1.866 (.9677)	2.555 (.8313)	—	—	—
Parameter, a	—	163.446 (42.628)	603.734 (470.64)	114.86 (57.83)	—	—	—
Parameter, b	—	8.411 (1.281)	9.600 (2.553)	2.633 (.337)	—	—	—
Sample Size	13,796	13,796	13,796	13,796	—	—	—
Number of Groups	—	1,502	1,502	1,502	—	—	—
Walds chi-value	—	755.6	352.4	635.3	—	—	—
LR Test Vs. Pooled chi-value	—	75.68	19.13	142.5	—	—	—
Ratio of log-likelihood index(ρ^2)	—	0.278	0.261	0.476	—	—	—
Adjusted ratio log-likelihood (ρ^{-2})	—	0.264	0.254	0.470	—	—	—

* Variable is significant at α = 0.05 level and E represents Elasticity

Appendix C. Standard Multinomial and Logit Coefficient Estimates

ESTIMATION MODELS	Standard : Models Without Lag Variables					
	LOGIT			MULTINOMIAL LOGIT		
	PA Status			PA	NPA	UNC
VARIABLES & PARAMETERS	β (S.E)	ODD RATIO	AVE. DER	β (S.E)	β (S.E)	β (S.E)
OPERATOR DEMOGRAPHICS						
Age	-.0853* (.0311)	—		-.0871* (.0293)	−.0270 (.0314)	−.0391 (.0223)
Age^2	.0011* (.0003)	—	0.0114	.0011* (.0003)	.0003 (.0003)	.0004 (.0002)
Female	.0899 (.0849)	1.094	—	.0932 (.0847)	.0698 (.0832)	.1098 (.0598)
African American	-.1388 (.1106)	0.8704	—	-.1601 (.1103)	−.1873 (.1085)	−.1240 (.0774)
Asian/Pacific Islander	-.5497* (.2466)	0.5771	—	-.5066* (.2434)	.3469* (.1710)	−.1482 (.1513)
Hispanic	.0856 (.1913)	0.9179	—	- .0599 (.1905)	.0680 (.1834)	.1130 (.1302)
EMPLOYMENT STATUS CHARACTERISTICS						
Years of Experience	-.0669* (.0189)	—	-0.0055	-.0702* (.0189)	−.0325 (.0179)	−.0335* (.0133)
Years of $Experience^2$	.0009 (.0005)	—	—	.0009 (.0006)	.0006 (.0005)	.0005 (.0004)
Probationary Status	.5907* (.1577)	1.8053	—	.5843* (.1555)	.0698 (.0832)	.3716* (.1216)
ASSIGNED-WORK CHARACTERISTICS						
Unique Assignments	-.0035 (.0037)	—	−.00019	-.0038 (.0037)	−.0022 (.0036)	.0021 (.0026)
Split Shift	-.1668 (.1429)	0.8463	—	-.1620 (.1505)	−.0700 (.1467)	.0616 (.1057)
Total Hours Worked	.0014* (.0005)	—	0.00007	.0015* (.0005)	.0021* (.0005)	.0020* (.0003)
Weekend Hours	-.0011 (.0007)	—	−.00005	-.0012 (.0007)	−.0009 (.0007)	−.0006 (.0005)
Average Daily Span	.0855* (.0339)	—	0.0046	.0869* (.0365)	−.0279 (.0356)	−.0285 (.0253)
Daily Span CV	.5014 (.5079)	—	0.02697	.5710 (.5344)	1.0945* (.5137)	.2688 (.3787)
Three Day/ 30 Hour Week	.0971 (.2720)	—	0.00545	.0977 (.2729)	.3032 (.2812)	.2783 (.2008)
Four Day/ 40 Hour Week	-1.3965 (1.0109)	—	−.04247	-1.4756 (1.027)	−1.0684 (1.0258)	−.2462 (.4932)

	PA Status			PA	NPA	UNC
Appendix C-continues	β (S.E)	ODD RATIO	AVE. DER	β (S.E)	β (S.E)	β (S.E)
ASSIGNED-WORK CHARACTERISTICS - continues						
Short Term Absence Hours	.0060* (.0016)	—	0.00032	.0060* (.0017)	.0005 (.0018)	.0025 (.0013)
Merlo Garage	−.1260 (.1291)	0.8816	—	−.1488 (.1314)	−.4623* (.1419)	.0245 (.0942)
Powell Garage	− .2480* (.0933)	0.7804	—	− .2244* (.0936)	.2126* (.0882)	.0656 (.0655)
Secondary Radial Route	−.1702 (.1353)	0.8435	—	−.1798 (.1332)	.1185 (.1274)	−.0159 (.0961)
Crosstown Route	−.2325* (.1022)	0.7926	—	−.2501* (.1030)	−.0061 (.0955)	−.1466* (.0710)
Feeder Route	−.2034 (.2655)	0.816	—	−.2066 (.2664)	.0348 (.2578)	.0233 (.1810)
Peak Express Hours	−.0629 (.2635)	0.9391	—	−.0816 (.2651)	−.1434 (.3054)	.0602 (.2042)
Shift Ends 4:00-7:00 pm	.0274 (.1135)	1.0278	—	.0214 (.1104)	−.1400 (.1042)	−.1059 (.0755)
Shift Ends After 7:00 pm	−.0850 (.1332)	0.9185	—	−.0886 (.1336)	−.0264 (.1207)	−.1060 (.0902)
Low -Floor Bus	(.1314)	1.0352	—	(.1310)	(.1360)	(.0989)
Old Bus	−.3182 (.1704)	0.7275	—	−.3167 (.1702)	.0790 (.1779)	−.2552* (.1278)
Small Bus	(.2734)	1.0627	—	(.2851)	(.3038)	(.2014)
SERVICE PERFORMANCE CHARACTERISTICS						
Boardings Per Revenue Hour	−.0049 (.0055)	—	−.00026	−.0048 (.0054)	.0073 (.0051)	.0065 (.0038)
Lifts Per Hour	1.347* (.3143)	—	0.07246	1.3841* (.3033)	.4385 (.3159)	.6228* (.2324)
Ave.Max. Speed - Peer Speed	.0183 (.0294)	—	0.00098	.0196 (.0264)	.0174 (.0267)	.0406* (.0193)
Proportion Late Departs	1.405* (.3948)	—	0.07557	1.5194* (.4058)	1.062* (.4008)	1.280* (.2960)
Proportion Early Departs	1.086 (.6662)	—	0.05844	1.114 (.6983)	.9480 (.6519)	.6143 (.4937)
Layover Proportion	−.0042 (.0487)	—	−.00022	−.0098 (.1295)	−.0467 (.1583)	−.3455 (.2449)
Security Requests	− .0091 (.0375)	—	−.00049	.0071 (.0398)	.0720* (.0354)	.1136* (.0249)
Evasive Action Events	.3487 (.1843)	—	0.01876	.6052* (.1961)	1.3291* (.1473)	.6904* (.1408)

Appendix C-continues	PA Status			PA	NPA	UNC
	β (S.E)	ODD RATIO	AVE. DER	β (S.E)	β (S.E)	β (S.E)
CUSTOMER SERVICE INFORMATION						
Unsafe Operation	.1597* (.0660)	—	0.00859	.1718* (.0657)	.1054 (.0661)	.0714 (.0498)
Unprofessional Treatment	.0215 (.0469)	—	0.00116	.0368 (.0469)	.0986* (.0417)	.1005* (.0314)
Fit for Duty	.7374* (.3427)	—	0.03967	.7256* (.3471)	−.0996 (.4699)	.4550 (.2740)
Service Delivery Problem	.0619 (.0800)	—	0.00333	.0601 (.0807)	−.0291 (.0867)	−.1176 (.0700)
Commendation: Calls Stops	-.0146 (.0326)	—	−.00078	-.0145 (.0280)	.0084 (.0257)	.0192 (.0183)
Commendation : Other	.0317 (.0485)	—	0.001703	.0484 (.0481)	.0902 (.0475)	.0805* (.0344)
TEMPORAL CHARACTERISTICS						
Fall Signup	.0664 (.1083)	1.0686	—	.0545 (.1071)	−.1803 (.0958)	.0287 (.0734)
Spring Signup	.4329* (.1173)	1.5417	—	.4031* (.1159)	−.3873* (.1184)	.0973 (.0819)
Summer Signup	.3273* (.1172)	1.3872	—	.2971* (.1172)	−.2868* (.1152)	.0206 (.0834)
2007	.0261 (.1304)	1.0264	—	.0385 (.1290)	.0414 (.1166)	.2585* (.0936)
2008	-.0746 (.1391)	0.9281	—	-.0753 (.1382)	−.1160 (.1269)	.1274 (.0996)
2009	-.3918* (.1995)	0.6758	—	-.3897 (.2000)	−.0223 (.1980)	−.0642 (.1451)
Intercept	− 2.604* (.8527)	—	—	− 2.578* (.8167)	− 3.3956* (.8431)	− 1.988* (.6012)
				BASE = NO-INCIDENT		
Sample Size	12,006	—	—	13,796	—	—
Wald Chi-square (49)	314.23	—	—	—	—	—
LR Chi- square (147)	—	—	—	964.85	—	—
Prob > chi2	0.0000	—	—	0.0000	—	—

Where * is significant at α =0.05 level; UNC is unclassified and AVE.DER is average derivative

Appendix D. Average Derivatives and Computed Relative Risk Ratios

ESTIMATION MODELS	Standard : Models Without Lag Variables					
	MULTINOMIAL LOGIT			MULTINOMIAL LOGIT		
	PA	NPA	UNC	PA	NPA	UNC
VARIABLES & PARAMETERS	RRR	RRR	RRR	AVERAGE DERIVATIVE		
OPERATOR DEMOGRAPHICS						
Age					—	—
Age^2	—	—	—	0.0096	—	—
Female	1.0980	1.0723	1.1161	0.00370	0.00279	0.01090
African American	0.8520	0.8292	0.8834	−.0063	−.0086	−.01080
Asian/Pacific Islander	0.6025	1.4147	0.8622	−.0205	0.02520	−.01550
Hispanic	0.9419	1.0703	1.1197	−0.0038	0.00320	0.01252
EMPLOYMENT STATUS CHARACTERISTICS						
Years of Experience				-0.0042	—	-0.0041
Years of $Experience^2$	—	—	—	—	—	—
Probationary Status	1.7940	1.1164	1.4501	0.03150	0.00080	0.03817
ASSIGNED-WORK CHARACTERISTICS						
Unique Assignments	—	—	—	−.00019	−.00013	0.00027
Split Shift	0.8505	0.9324	1.0635	−.00793	−.0038	0.00824
Total Hours Worked	—	—	—	0.00006	0.00010	0.00019
Weekend Hours	—	—	—	−.00005	−.00004	−.000047
Average Daily Span	—	—	—	0.00440	0.00148	.00382
Daily Span CV	—	—	—	0.02310	0.05690	0.01741
Three Day/ 30 Hour Week	1.1030	1.3540	1.3210	0.00182	0.01590	0.02930
Four Day/ 40 Hour Week	0.2286	0.3435	0.7817	−.0388	−.0363	−.01546

Appendix D. contnues	PA RRR	NPA RRR	UNC RRR	PA	NPA	UNC
				AVERAGE DERIVATIVE		
ASSIGNED-WORK CHARACTERISTICS - continues						
Short Term Absence Hours	—	—	—	0.00028	− 0.00001	0.00022
Merlo Garage	0.8617	0.6298	1.0248	−.0060	−.0227	0.00662
Powell Garage	0.7990	1.2370	1.0678	−.01174	0.01230	0.00691
Secondary Radial Route	0.8354	1.1260	0.9842	−.00863	0.00750	−.00152
Crosstown Route	0.7787	0.9940	0.8636	−.01080	.0014	−.0139
Feeder Route	0.8134	1.0354	1.0236	−.0096	0.00240	0.00351
Peak Express Hours	0.9217	0.8664	1.0621	−.0039	−.0077	0.00820
Shift Ends 4:00-7:00 pm	1.0216	0.8693	0.8996	0.00220	−.0071	−.01053
Shift Ends After 7:00 pm	0.9152	0.9739	0.8995	−.0036	− 0.00045	−.01043
Low -Floor Bus	1.0351	1.0100	0.9963	0.00170	0.00046	−0.0007
Old Bus	0.7286	1.0822	0.7748	−.0134	0.00720	−.0250
Small Bus	1.0209	0.5783	0.9594	0.00270	−.0243	−.00143
SERVICE PERFORMANCE CHARACTERISTICS						
Boardings Per Revenue Hour	—	—	—	−.00030	0.00037	0.00068
Lifts Per Hour	—	—	—	0.06280	0.01550	0.05510
Ave.Max. Speed - Peer Speed	—	—	—	0.00066	0.00061	0.00410
Proportion Late Departs	—	—	—	0.06340	0.04490	0.12050
Proportion Early Departs	—	—	—	0.04801	0.04460	0.05220
Layover Proportion	—	—	—	0.00186	−.00006	−.0368
Security Requests	—	—	—	−.00060	0.00310	0.01170
Evasive Action Events	—	—	—	0.02130	0.06680	0.06090

Appendix D. contnues	PA RRR	NPA RRR	UNC RRR	PA	NPA	UNC
				AVERAGE DERIVATIVE		
CUSTOMER SERVICE INFORMATION						
Unsafe Operation	—	—	—	0.00770	0.00480	0.00584
Unprofessional Treatment	—	—	—	0.00087	0.00460	0.00990
Fit for Duty	—	—	—	0.03310	− 0.01102	—
Service Delivery Problem	—	—	—	0.00380	−.00094	−.0128
Commendation: Calls Stops	—	—	—	−.00086	.00037	0.00210
Commendation : Other	—	—	—	0.00159	0.00430	0.00770
TEMPORAL CHARACTERISTICS						
Fall Signup	1.1056	0.8350	1.0291	0.00310	−.01005	.00402
Spring Signup	1.4965	0.6789	1.1022	0.02230	−.02151	0.01035
Summer Signup	1.3460	0.7507	1.0208	0.01680	−.01560	.00201
2007	1.0393	1.0423	1.2950	.00009	0.00027	0.02780
2008	0.9275	0.8905	1.1359	−.00414	− 0.00701	0.01530
2009	0.6773	0.9779	0.9378	−.0163	0.00025	−0.0046

Where UNC represents unclassified incidents