Logistic Regression Approach to Predicting Truck Driver Turnover

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Logistic Regression Approach to Predicting Truck Driver Turnover

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John F. Kros, Marketing and Supply Chain Management Department, East Carolina University, Greenville, North Carolina, USA

ABSTRACT

The purpose of this study is to identify those constructs that lead to driver turnover. The theory of reasoned action (TRA), originating in the social psychology literature is the theoretical approach in this study. Interviews with drivers were conducted using the intercept method to develop a survey instrument. The survey was then administered to drivers at large truck stops. This study makes contributions on two fronts. From a managerial perspective the study results indicate that companies can use a technique such as this model as part of their driver retention efforts in order to create competitive advantage by increasing efficiency and cutting costs. The resulting logistic regression model, based on four factors, accounts for eighty eight percent of the variance and accurately predicts which drivers or driver classes are most at risk of turning over.

Keywords: Driver Turnover, Logistics, Supply Chain Management, Theory of Reasoned Action (TRA), Truck Driver Retention

INTRODUCTION

One of the most important and complex problems facing both motor carriers and supply chains is the high rate of driver turnover (Patton, Park, & Lockridge, 2011) which currently exceeds 100 percent (McNally, 2013). The Advanced Center for Transportation Technologies at Clark College (2006) estimated that driver shortages and turnover costs the U.S. economy between $1.8 and $3 billion annually. Min and Lambert (2002) put these numbers in perspective and estimated that it costs between $3000 to $12,000 to replace a driver depending on the amount of time and money that the company must invest in the hiring, orientation, and training. During the course of this study we found that this figure now ranges from $7,000 to $10,000 to hire an experienced driver with no orientation or training costs to between $20,000 and $27,000 if these services are provided. This updated finding is generally supported by an industry report which placed the cost of replacing a driver at $25,000 (Refrigerated Transporter, 2007). High driver turnover rates have been found to increase carriers’ operating costs, reduce driver productivity and result in reductions in service quality and highway safety (Corsi & Fanara, 1988; Curtis & Wright, 2001; Suzuki, 2007). High driver turnover rates have
also been found to impact shippers when carriers are unable to meet pick-up and delivery schedules due to a lack of drivers or when frustrated or overworked drivers simply walk away and leave their trucks sitting on the side of the road (Keller & Ozment, 1999a; LeMay, Williams, & Garver, 2009).

Consequently, driver turnover and retention has been studied from many perspectives. These perspectives include but are not limited to driver recruitment and retention practices (LeMay, Taylor, & Turner, 1993; Gupta, Jenkins, & Delery, 1996; Stephenson & Fox, 1996; Keller & Ozment, 1999b; Keller, 2002; Min & Lambert, 2002; Suzuki, Crum, & Pautsch, 2009), driver training (Mejza & Corsi, 1999; Mejza, Barnard, Corsi, & Keane, 2003), work conditions (Rodriguez & Griffen, 1990; LeMay et al. 1993; Richard, LeMay, & Taylor, 1995; Stephenson & Fox, 1996; Keller & Ozment, 1999a; Keller, 2002; Min & Lambert, 2002; Suzuki et al. 2009), equipment (Garver, Williams, & Taylor, 2008), compensation (Rodriguez & Griffen, 1990; LeMay et al. 1993; Richard, LeMay, & Taylor, 1995; Gupta et al. 1996; Shaw, Delery, & Jenkins, 1998; Stephenson & Fox, 1996; Keller & Ozment, 1999b; Keller, 2002; Min & Lambert, 2002; Suzuki et al. 2009), demographic characteristics (Beilock & Capelle, 1990; Shaw et al. 1998; Min & Lambert, 2002; Suzuki et al. 2009), employment stability and past safety behavior (Cantor, Corsi, Grimm, & Ozpolat, 2010), driver needs (Williams, Garver, & Taylor, 2011), the role of dispatchers or driver managers (Richard et al. 1995; Gupta et al. 1996; Stephenson & Fox, 1996; Keller & Ozment, 1999ab; Keller, 2002; Suzuki et al. 2009), dispatching procedures (Taylor & Whicker, 2010), drivers’ relationship with top management (LeMay & Taylor, 1988), justice in the workplace (Cantor et al 2011), and driver satisfaction and frustration (Keller & Ozment, 1999b; Johnson, Bristow, McClure, & Schneider, 2010; LeMay et al. 2009). Other research in this area has looked at predicting which drivers are most at risk of turning over (Richard et al 1995; Min & Emam, 2003; Garver et al 2008; Suzuki et al. 2009). Readers may also gain useful insights from Crum & Morrow (2002).

Given the fact that driver turnover rates are increasing yet again due to the improving economy and regulatory mandates the purpose of this study is to determine why truck drivers turn over or churn. To accomplish the stated objective of this study the next section will address the research hypotheses which are based on the theory of reasoned action. The research hypotheses were tested using logistic regression. Logistic regression was chosen for this study due to its ability to analyze a combination of scale and categorical variables for the purpose of prediction and because it has been used for similar purposes in the job performance (e.g. Jackofsky, Ferris & Breckenridge, 1986), job turnover (e.g Mano-Negrin & Kirschenbaum, 1999), and driver health (Dahla, Kaerlev, Jensen, Tuchsen, Hannert, Nielsen, & Olsen, 2009; Valway, Jenison, Keller, Vega-Hernandez & McCree, 2009) literature. The authors then provide a discussion of the study results that were obtained from a survey of 154 Class 8 truck drivers that were employed by a diverse group of long haul truck load carriers across the United States. Discourse is then provided on study findings, managerial recommendations, implications for future research, and study conclusions.

This study contributes to the driver turnover and retention literature by presenting and empirically testing the influence of the four constructs identified in this study. This study contributes to the practice by speaking to the need for managers to develop programs in order to better manage the perceptions of their internal stakeholders (truck drivers) in order to reduce the costly negative impacts associated with high rates of driver turnover. The next section presents an overview of the theory of reasoned action which provides the theoretical support for our research hypotheses.
THEORY AND HYPOTHESES

Theory of Reasoned Action

The theory of reasoned action (TRA) originated in the social psychology literature and was developed by Ajzen and Fishbein (1980) and Fishbein and Ajzen (1975). The TRA focuses specifically on behavior and is comprised of three general constructs: behavioral intention (BI), attitude (A), and subjective norm (SN). TRA suggests that a person’s behavioral intention depends on the person’s attitude about the behavior and the corresponding subjective norms (BI = A + SN). Accordingly, if a truck driver intends to change jobs then it is likely that they will do so. However, this theory also recognizes that there are situations (or factors) that limit the influence of attitude on the intended behavior. For example, if a truck driver’s attitude leads them toward changing jobs but they do not have access to a new job the lack of a new job will prevent them from quitting. In this regard TRA can be applied to each of the four constructs (effectiveness of driver management programs, work life balance, quality of management and equipment) that were used in the development of the research hypotheses.

Effectiveness of Driver Management Programs

During the interview phase of this study drivers consistently noted that planning factors related to the effectiveness of driver management emerged. These factors included: the amount of work, steadiness of work, the amount and frequency of home time, routes driven and unpaid detention time as customer locations. These findings generally mirrored those reported by Crum & Morrow (2002) and Patton, Park, & Lockridge (2011).

Effectiveness of driver management is very important to both companies (Mejza et al. 2003) and drivers. Companies focus on the effectiveness of their driver management programs in order to generate profits. Alternatively, drivers need to provide for their families but also want and need to spend time with them and anything that causes them to spend time away from home and does not generate income creates frustration and ultimately relational problems at home (De Croon et al. 2004). Suzuki et al. (2009) found that companies may be able to predict which drivers are most at risk of turning over based in part on certain aspects of driver management programs such as the number of miles driven per week.

Driver interviews also suggest that poor driver management programs may also lead to driver fatigue, frustration and higher accident rates similar to Crum and Morrow (2002) and Larsen (2004). One driver in particular stated:

If they don’t do a better job of making their customers get me loaded and unloaded faster I going to quit because it’s costing me money sitting there doing nothing.

This statement by a frustrated driver is rather telling in that it provides support for the use of TRA as it suggests that this driver believes that their current situation will not improve unless they change carriers. Discussions with driver hiring managers provide additional anecdotal support for this finding as they reported that their internal company exit interviews consistently support the drivers’ position. Hence, effectiveness of driver management programs is defined as:

The extent to which management is able to effectively manage those areas under its control while satisfying competing objectives such as customer service, profit expectations, driver satisfaction and regulatory compliance.

This definition then provides the basis for $H_1$:

$H_1$: Drivers that rate their firm’s driver management program’s effectiveness higher are less likely to turnover.
Table 1. Summary of driver management literature

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Steadiness of work</td>
<td>FMCSA 2003ab; Richard et al. 1995; Schulz, 2011; driver interviews</td>
</tr>
<tr>
<td>Amount of work</td>
<td>FMCSA 2003ab; Richard et al. 1995; Crissey, 2011abc; driver interviews</td>
</tr>
<tr>
<td>Predictability of home time</td>
<td>Keller 2002; Richard et al. 1995; McElroy et al. 1993 ; Traub, 2011</td>
</tr>
<tr>
<td>Length of home time</td>
<td>Keller, 2002; Richard et al. 1995; McElroy et al. 1993 ;</td>
</tr>
<tr>
<td>Frequency of home time</td>
<td>Keller, 2002; Richard et al. 1995; McElroy et al. 1993</td>
</tr>
<tr>
<td>Routes driven</td>
<td>Min &amp; Lambert, 2002; driver interviews</td>
</tr>
<tr>
<td>Unpaid time at customer’s locations</td>
<td>Min &amp; Lambert, 2002; driver interviews</td>
</tr>
</tbody>
</table>

Based on this combination of anecdotal evidence and the extant literature the following items (see Table 1) were selected to measure the effectiveness of driver management construct. The following section will address the second construct of interest work life balance.

Work Life Balance

During the driver interview process factors related to work life balance were an important theme. The need to achieve a balance between work and quality of life is well supported in both the extant academic and trade press literature. A work life balance is also very personal in nature and varies from driver to driver as it does in the general population. The preponderance of the work life balance literature suggests that factors that relate to the relationship between compensation and quality of life play a key role in a driver’s intent to turnover (Garver et al. 2008). Other research by LeMay et al. (1993); Keller (2002); and Min and Lambert (2002) in addition to countless industry reports (Patton et al., 2011; Schulz, 2011; Traub, 2011) provide further support for this relationship.

However, it must be noted differences in pay do not adequately explain why drivers consistently leave one job for another with equal pay. Driver interviews and research by Min and Lambert (2002) indicates that other factors such as total compensation (e.g. insurance and retirement plans) and personal factors such as vacation / holiday time are also important factors related to this construct. Research by Dobie et al., (1998); Min and Lambert (2002) and Chrissey (2011c) indicate that many drivers have families and that companies need to take a broader perspective when developing driver employment packages. These findings are supported by both TRA and the following statement from one of the responding drivers which indicates that this driver is giving serious consideration to what is best for his family.

I really like driving for ____ because I get plenty of miles but I may have to quit because they can’t get me home on a regular basis. It’s been pretty hard on my family with me being gone so much.

Work life balance is therefore defined as:

A personal sense of self worth and accomplishment resulting from meaningful daily accomplishment and enjoyment derived from one’s work and life.

Based on this evidence H2 is provided:

**H2:** Drivers that rate their work life balance more positively will be less likely to turnover.

The following items (see Table 2) were identified for use in measuring the work life
Table 2. Summary of work life balance literature

<table>
<thead>
<tr>
<th></th>
<th>Garver et al. 2008; Min &amp; Lambert, 2002; Keller, 2002; Crissey, 2011c; Park, 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate of pay</td>
<td>Suzuki et al 2009; Min &amp; Emam, 2003; Min &amp; Lambert, 2002; Crissey, 2011b; Kulisch, 2011</td>
</tr>
<tr>
<td>Bonus programs</td>
<td>Suzukiet al 2009; Min &amp; Lambert, 2002</td>
</tr>
<tr>
<td>Medical / dental insurance</td>
<td>Suzukiet al 2009; Min &amp; Lambert, 2002</td>
</tr>
<tr>
<td>Retirement programs</td>
<td>Suzukiet al 2009; Min &amp; Lambert, 2002; McElroy et al 1993</td>
</tr>
<tr>
<td>Holiday / vacation time</td>
<td>Min &amp; Lambert, 2002; McElroy et al 1993</td>
</tr>
</tbody>
</table>

balance construct. The next section will be devoted to the quality of company management construct.

Quality of Company Management

The third construct that consistently emerged during the driver interviews related to the quality of firm’s management. There are a number of factors that were identified by drivers during the interview process and were generally supported by the extant literature which relate to the overall management of the company. These factors include company reputation (FMCSA 2003ab; Min & Lambert, 2002), new employee orientation (Richard et al. 1995); company sponsored training (Beilock & Capelle, 1990); their recruiter’s truthfulness (Dobie et al. 1998); drivers relationships with their dispatcher or driver manager (Keller, 2002; Taylor, 1991); recommendations from other drivers (Deierlein, 1996) and company size (anecdotally from conversations with driver hiring managers (larger is better due to the perceived ability of the firm to weather economic downturns and their ability to provide drivers with paying loads). Keller and Ozment (1999b) found that truck drivers penalize companies through decreased productivity and increased turnover that perform poorly in these areas.

This stream of research is also supported by TRA and the following driver statement which appears to indicate that this driver reasons that their quitting is justified given the fact that they feel that their driver manager has consistently lied to them.

If my driver manager doesn’t quit lying to me about why I get all the bad loads and deadhead (empty unpaid miles) miles I am going to quit.

Quality of Management is defined as:

The ability of management to effectively direct the organization, as a whole, in order to produce a high quality product or service while meeting stakeholder needs.

Based on this support H3 is provided:

H3: Drivers that rate the quality of their firm’s management higher are less likely to turnover.

The following items (presented in Table 3) were identified for use in this study. The next section will provide discourse on the equipment construct.

Equipment

The condition of the tools or equipment that drivers use has also been linked to their intentions to stay with a firm (Garver et al. 2008). Research by Stephenson and Fox (1996) and LeMay et al. (1993) note the importance of drivers having reliable equipment that is in good working condition as there is a direct relationship between the availability and condition of equipment and drivers’ ability to meet schedules and earn a living. Not surprisingly, Min and Lambert (2002) found that equipment ranks second in importance to drivers behind
Table 3. Summary of quality of company management literature

<table>
<thead>
<tr>
<th>Company size</th>
<th>Driver interviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>The company’s reputation</td>
<td>Keller, 2002; Min &amp; Lambert, 2002</td>
</tr>
<tr>
<td>New employee orientation</td>
<td>Min &amp; Eman, 2003; driver interviews</td>
</tr>
<tr>
<td>Company sponsored training</td>
<td>Min &amp; Lambert, 2002; McElroy et al. 1993</td>
</tr>
<tr>
<td>The recruiter’s truthfulness</td>
<td>Keller, 2002; Min &amp; Eman, 2003; Taylor, 1994; driver interviews</td>
</tr>
<tr>
<td>Relationship with driver manager / dispatcher</td>
<td>Garver et al. 2008; Keller, 2002; Taylor, 1991; driver interviews</td>
</tr>
<tr>
<td>Recommendations from other drivers</td>
<td>Richard et al 1995; driver interviews</td>
</tr>
</tbody>
</table>

pay in terms of driver turnover. Consequently, many companies have shortened their equipment cycles so that drivers have newer and more comfortable equipment (Crissey, 2011b). These findings should not be surprising given the fact that the vast majority of drivers are paid by the loaded mile driven and non-serviceable equipment negatively impacts a driver’s ability to earn income (Johnson et al. 2010). Support for the use of this construct is also provided by TRA and the following driver statement which conveys both the cause of their frustration and the driver’s reasoned intent to act on this problem.

_If they don’t fix this truck I am going to walk away and leave it sitting on the side of the road the next time it breaks down._

For the purpose of this study equipment is defined as:

Those hard assets which when combined with their related operational characteristics, requirements and availability enable the production of a good or service.

Based on this support the authors provide \( H_a \):

\[ H_a: Drivers \text{ that rate their employer’s equipment more highly are less likely to turnover.} \]

Based on the preceding discussion the following items (see Table 4) were utilized in this study. Table 4 will be followed by a brief discussion of potential moderators that have been suggested by past research.

Support for the preceding hypotheses is also found in the mainstream business literature as evidenced by Albacete-Saez, Fuentes-Fuentes & Bojica (2011) who noted the impact of management quality on firm performance, Munoz-Doyague & Nieto (2012) who successfully linked employee relationships with

Table 4. Summary of equipment variables

| Age of trucks                          | Suzuki et al 2009; driver interviews |
| Condition of trucks                   | Keller, 2002; Min & Lambert, 2002; LeMay et al 1993; driver interviews |
| Make / model of trucks                | Min & Lambert, 2002; Deierlein, 1996 |
| Age of trailers                       | Driver interviews |
| Condition of trailers                 | Min & Lambert, 2002; LeMay et al 1993 |

**Potential Moderating Variables**

Past research by and Min & Emam (2003) and Suzuki et al. (2009) which was anecdotally supported by the driver interviews indicates that there are other variables which may have a moderating effect on a driver’s propensity or intent to change jobs. The most commonly cited moderating variables include: the number of miles driven annually, total years of driving experience, the number of employers that they have had during their driving career and the driver’s age.

Academic and anecdotal evidence provide strong support for including each of these variables in any model whose focus is on predicting driver turnover. Driver interviews indicate that the number of miles they are able to drive annually has a direct impact on their earnings because most truck drivers with at least three years of experience are paid between 34 and 36 cents per loaded mile which equates to about $36,000 for drivers that average 100,000 miles annually (Schulz, 2011). Drivers that are not getting enough miles (less than 100,000) may feel that their ability to earn a living wage has been negatively impacted in accordance with TRA. Our interviews with driver managers suggest that drivers that are getting more miles (100,000 or more) may be more satisfied assuming that they are still able to get home on a regular basis.

Other research by Mobley et al. (1979) and Fukami & Larson (1983) found that age, and tenure with the current employer is related to propensity to turnover. More specifically, they found that older drivers are less likely to change jobs than younger drivers; drivers with more experience are generally less likely to change jobs than less experienced drivers who are more likely to become frustrated due to the rigors of the job. Support for these finding can be found in TRA because older more experienced drivers have a greater depth of knowledge and are better able to evaluate their current situation and take the appropriate action. Similarly, the TRA framework would suggest that drivers who have a history of changing jobs on a regular basis can be expected to repeat their job switching behavior in the future. Based on this information the following hypotheses are presented.

**H3:** More experienced drivers are less likely to turn over than less experienced drivers.

**H4:** Drivers that have driven for fewer companies will be less likely to turnover.

**H5:** Drivers that have been with their current employer longer are less likely to turnover.

**H6:** Drivers that get at least 100,000 miles annually are less likely to turnover.

**RESEARCH METHODS**

The research methods include the survey questionnaire, the sample, and methods of data analysis.

**Survey Questionnaire**

The survey development portion of this study began with the lead author who has driven Class 7 and 8 trucks and supervised truck drivers asking 21 truck drivers what they would look for in an employer. Interviews were conducted using the intercept method while the drivers were refueling their trucks at major truck stops in North Carolina, Virginia, Tennessee, Illinois, Missouri, Arkansas, and Oklahoma. Each of these interviews began with a series of open ended questions about the four constructs of interest and lasted between 15 to 20 minutes. These discussions lead to the development of a 30 item survey instrument. The survey instrument was then reviewed by the coauthors and
six drivers who were not previously interviewed. The results of these reviews indicated that only minor grammatical changes were needed to aid in clarity.

**Data Collection**

A pencil and paper version of the survey was then administered to 154 truck drivers who were contacted using the intercept method while they were either refueling, waiting to pay for their fuel or were waiting for their trucks to be repaired at large truck stops located on I-95 in Virginia, North Carolina and Georgia. Individual truck stops were chosen based on their size to ensure a greater diversity of potential respondents. No identifying personal information (i.e. names, driver number, etc.) was collected from any of the study participants to ensure anonymity. Drivers were qualified prior to administering the survey (only long haul truck load drivers were accepted). Approximately 1 in 3 drivers agreed to participate in the study. None of the drivers participated in more than one phase of the study and none were offered a financial incentive for their participation beyond the ability to voice their concerns. Responding drivers were generally the sole respondent from each company and no company had more than 3 respondents.

**Analysis**

Overall, the surveyed drivers averaged 14.7 years of experience, have driven for 5.6 companies and have been with their present employer an average of 2.6 years. The average age was 45.7 and 99% were male. The demographics identified in this research are similar to those provided by the American Trucking Association (ATA) (http://www.truckline.com/StateIndustry/Documents/ATADriverShortageStudy05.pdf, 2005) with the exception of the percentage of female drivers which was approximately one percent in this study compared to four percent reported by the ATA. More current industry studies suggest that these demographics are still valid as there is no indication that they have changed (Crissey, 2011c).

**Findings**

Twenty four explanatory variables were developed to assess driver attitudes on each of the variables using a seven-point scale anchored by 1 = not at all important to 7 = very important with neither important nor unimportant (4) as a mid-point response. The dependent variable was derived from the seven-point scale anchored by 1 = very likely to 7 = very unlikely scale “How likely you are to change firms within the next year.” This item was selected based on the theory of reasoned action and research by Lee & Mowday (1987) and Richard et al. (1995) which found that intent to leave is the best predictor of an employee actually leaving. The relationship between intent and actual driver turnover is also supported by Paille, Fournier, & Lamontagne (2011). Similar to past research the demographic items used in this study were number of miles driven annually, total years of driving experience, the number of employers that they have had during their driving career and the driver’s age.

**Variable Multicollinearity**

The potential for multicollinearity exists in any multi-variable survey instrument. Correlation analysis was completed on the variables and high inter-correlations were discovered. For example, Company Size was significantly correlated with 12 of the 24 variables. In order to eliminate possible multicollinearity associated with the individual variables used in the study, a factor analysis was conducted. Factor analysis is a data reduction method that allows multiple variables to be summarized by a smaller set of underlying dimensions called factors. Individual variables that measure the same dimension will statistically “load” on the same factor. These “loadings” can be interpreted as the correlation between that individual variable and all the other variables of a particular factor. In turn, variables with high “loadings” all measure the same construct and that construct can then be used as a single factor to express all the variables having significant “loadings” on that
factor (Pedhazur & Schmelkin, 1991). Finally, the results of the factor analysis are combined with logistic regression to develop a predictive model for driver turnover.

**Construct Development and Unidimensionality**

Construct unidimensionality was established through principal components analysis using a maximum likelihood and varimax rotation on the 24 items to determine if the items loaded on the appropriate construct as hypothesized. The results of this analysis indicated that all of the items loaded on the appropriate construct and achieved a factor loading of at least 0.40 which is the recommended cutoff (Netemeyer et al. 2003). All of the items were found to correspond to one and only one construct with 17 out of 24 items having factor loadings of greater than .6 and only one item had a factor loading of less than 0.5. The results of this portion of the analysis also indicate that study findings were consistent with expectation. The results of this analysis are provided in Table 5.

**Reliability Analysis**

Having established construct unidimensionality the authors examined each of the scales for reliability using Cronbach’s Alpha in SPSS 17.0. The resulting alpha values ranged from a low of 0.855 to a high of 0.907 indicating that the scales are both reliable and consistent in quality (Nunnally & Bernstein, 1994).

Variables were created for each of these four constructs using a summed scale. This summed scale is a composite value for a set of items calculated by taking the average of the items that were identified as having the highest loadings per that construct (Hair et al. 2009). The four demographic variables were also used which resulted in a total of eight possible independent explanatory variables for the logistic regression model.

**Logistic Regression**

A binary logistic regression model was developed to help explain the significance of the four constructs and the demographic variables (e.g., age, miles driven, number of employers, years of experience) on intent to turnover. Intent to turnover was defined as a 0-1 binary variable based on the survey question “How likely are you to change jobs within the next 12 months?” which necessitated the use of binary logistic regression.

The general form of the logistic regression model is as follows in Equation 1:

\[
Y_n = \frac{1}{1 + \exp(-Z)}
\]

where

\[
Z = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n
\]  (1)

The logistic relationship can be characterized by the curved line in Figure 1.

The logistic curve is sometimes referred to as an S-curve as it takes on that shape. The curve itself does not actually ever reach 0 or 1 but only approaches from above or below, respectively.

The question “Likelihood of changing jobs” is based on a 7 point likert scale that is commonly used in the management literature because it enables the respondent to more accurately express their true feelings without introducing other forms of respondent bias (e.g., social desirability bias). Responses to the question were transformed into two groups. A high intent to turnover group and low intent to turnover group were formed to construct the binary (i.e., 0 = high intent to turnover and 1 = low intent to turnover) dependent variable. The intent to turnover responses were divided at the response mean (mean = 4.9) with responses below 4.9 coded as a 0 or high intent to turnover and responses above 4.9 coded as 1 or low intent to turnover (Hair, et al., 2009). In
Table 5. Factor analysis results

<table>
<thead>
<tr>
<th>Survey Items</th>
<th>Effectiveness of Driver Management</th>
<th>Work Life Balance</th>
<th>Quality of Company Management</th>
<th>Equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company size</td>
<td>.169</td>
<td>-.054</td>
<td>.699</td>
<td>-.009</td>
</tr>
<tr>
<td>Company reputation</td>
<td>.074</td>
<td>.423</td>
<td>.662</td>
<td>.166</td>
</tr>
<tr>
<td>New employee orientation</td>
<td>.179</td>
<td>.243</td>
<td>.801</td>
<td>.144</td>
</tr>
<tr>
<td>Company sponsored training</td>
<td>.199</td>
<td>.117</td>
<td>.816</td>
<td>.171</td>
</tr>
<tr>
<td>Recruiter’s truthfulness</td>
<td>.380</td>
<td>.223</td>
<td>.598</td>
<td>.213</td>
</tr>
<tr>
<td>Relationship with driver mgr.</td>
<td>.354</td>
<td>.212</td>
<td>.521</td>
<td>.292</td>
</tr>
<tr>
<td>Recommendations from other drivers</td>
<td>.264</td>
<td>.030</td>
<td>.472</td>
<td>.287</td>
</tr>
<tr>
<td>Rate of pay</td>
<td>.444</td>
<td>.593</td>
<td>.148</td>
<td>.086</td>
</tr>
<tr>
<td>Bonus programs</td>
<td>.428</td>
<td>.657</td>
<td>.101</td>
<td>.154</td>
</tr>
<tr>
<td>Medical / dental insurance</td>
<td>.148</td>
<td>.856</td>
<td>.097</td>
<td>.057</td>
</tr>
<tr>
<td>Retirement plans</td>
<td>.115</td>
<td>.842</td>
<td>.148</td>
<td>.070</td>
</tr>
<tr>
<td>Holiday / vacation time</td>
<td>.451</td>
<td>.652</td>
<td>.180</td>
<td>.122</td>
</tr>
<tr>
<td>Steadiness of work</td>
<td>.591</td>
<td>.477</td>
<td>.181</td>
<td>.149</td>
</tr>
<tr>
<td>Amount of work</td>
<td>.521</td>
<td>.455</td>
<td>.214</td>
<td>.141</td>
</tr>
<tr>
<td>Predictability of home time</td>
<td>.836</td>
<td>.222</td>
<td>.241</td>
<td>.170</td>
</tr>
<tr>
<td>Length of home time</td>
<td>.832</td>
<td>.226</td>
<td>.300</td>
<td>.115</td>
</tr>
<tr>
<td>Frequency of home time</td>
<td>.828</td>
<td>.212</td>
<td>.227</td>
<td>.108</td>
</tr>
<tr>
<td>Routes driven</td>
<td>.595</td>
<td>.091</td>
<td>.228</td>
<td>.196</td>
</tr>
<tr>
<td>Unpaid wait time at customer’s location</td>
<td>.625</td>
<td>.208</td>
<td>.116</td>
<td>.097</td>
</tr>
<tr>
<td>Age of trucks</td>
<td>.169</td>
<td>-.042</td>
<td>.180</td>
<td>.759</td>
</tr>
<tr>
<td>Condition of trucks</td>
<td>.295</td>
<td>.009</td>
<td>.075</td>
<td>.746</td>
</tr>
<tr>
<td>Make / model of trucks</td>
<td>.004</td>
<td>.108</td>
<td>.046</td>
<td>.819</td>
</tr>
<tr>
<td>Age of trailers</td>
<td>.035</td>
<td>.188</td>
<td>.196</td>
<td>.740</td>
</tr>
<tr>
<td>Condition of trailers</td>
<td>.257</td>
<td>.269</td>
<td>.288</td>
<td>.640</td>
</tr>
</tbody>
</table>

*Principal Component Analysis, Varimax Rotation, Rotation converged in 6 iterations

Table 6. Reliability analysis

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Cronbach’s Alpha</th>
<th>Number of Survey Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality of Company Management</td>
<td>0.907</td>
<td>7</td>
</tr>
<tr>
<td>Work Life Balance</td>
<td>0.893</td>
<td>5</td>
</tr>
<tr>
<td>Effectiveness of Driver Management</td>
<td>0.891</td>
<td>7</td>
</tr>
<tr>
<td>Equipment</td>
<td>0.855</td>
<td>5</td>
</tr>
</tbody>
</table>
Figure 1. The logistic curve

In the study, 64 responses coded as 0 and 90 responses coded as 1.

The independent variables tested in the model are listed in Table 7. The table displays the variable name, a description, and scale used to characterize the variable.

Stepwise regression was employed to identify the set of independent variables that have a significant impact on the dependent variable and so that the relative impact of each variable could be more clearly observed. After four iterations, a set of significant independent variables was discovered. A Chi Square ($\chi^2$) statistic was

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management Quality</td>
<td>Construct 1</td>
<td>1-7</td>
</tr>
<tr>
<td>Compensation</td>
<td>Construct 2</td>
<td>1-7</td>
</tr>
<tr>
<td>Effect of Driver Management</td>
<td>Construct 3</td>
<td>1-7</td>
</tr>
<tr>
<td>Equipment</td>
<td>Construct 4</td>
<td>1-7</td>
</tr>
<tr>
<td>Years Experience</td>
<td>The number of years experience driving</td>
<td>0-45</td>
</tr>
<tr>
<td>Number of Employers Career</td>
<td>The total number of employers the driver has had over the life of their driving career</td>
<td>1-24</td>
</tr>
<tr>
<td>Age</td>
<td>Current age</td>
<td>24-73</td>
</tr>
<tr>
<td>Miles Driven per Year</td>
<td># of paid miles driven in the last year</td>
<td>880-1800k</td>
</tr>
</tbody>
</table>
Table 8. Stepwise regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-7.7051</td>
<td>1.711</td>
<td>0.000</td>
</tr>
<tr>
<td>(x_1) = Management Quality</td>
<td>0.7348</td>
<td>0.195</td>
<td>0.000</td>
</tr>
<tr>
<td>(x_2) = Number of Employers Career</td>
<td>-0.1394</td>
<td>0.049</td>
<td>0.005</td>
</tr>
<tr>
<td>(x_3) = Age</td>
<td>0.0559</td>
<td>0.019</td>
<td>0.004</td>
</tr>
<tr>
<td>(x_4) = Miles Driven per Year</td>
<td>0.0019</td>
<td>0.001</td>
<td>0.004</td>
</tr>
</tbody>
</table>

used to gauge whether all the variables in the model have a significant effect. The \(\chi^2\) value for the overall model was 37.117, was significant at \(p<0.001\) and explained 84% of the model’s variance. In short, the overall logistic regression model performs well. Table 8 contains the statistical results of the significant variables from the stepwise regression analysis.

Table 8 shows that only one of the hypothesized constructs and four of the moderating variables were statistically significant: management quality \((x_1)\), number of employers in a driver’s career \((x_5)\), age \((x_4)\), and miles driven per year \((x_3)\). Each of these variables was significant at the \(p<0.001\) level. The results of this analysis provided both expected and unexpected results as demonstrated by the fact that only four of the eight hypotheses were supported.

\(H_1\): Not supported
\(H_2\): Not supported
\(H_3\): Supported
\(H_4\): Not supported
\(H_5\): Not supported
\(H_6\): Supported
\(H_7\): Supported
\(H_8\): Supported

Using these variables, the logistic regression model is as follows:

\[
\begin{align*}
Y_n &= \frac{1}{1 + \exp(-Z)} \\
Y_n &= \frac{1}{1 + \exp(-(-7.7051 + 0.7348x_1 - 0.1394x_2 + 0.0559x_3 + 0.0019x_4))}
\end{align*}
\]

where

\[
Z = -7.7051 + 0.7348 \times 5.5 - 0.1394 \times 5.5 + 0.0559 \times 46 + 0.0019 \times 1230 = 0.478
\]

In addition, no significant correlation was found between any of the four final explanatory variables. In short, the model coefficients tell the story of how the independent variables affect the likelihood to turnover. Essentially from Equation 2, it can be said that drivers who rate management quality lower have a higher likelihood of turnover, drivers with more employers throughout their career tend to turnover more, younger drivers have a higher likelihood to turnover, and drivers that drive less miles per year tend to turnover more.

**DISCUSSION**

To illustrate how the model performs an “average” driver from this study will be used to test the model. The average driver in our study is characterized as follows in Table 9:

Using these values for the independent variables we see the following logistic regression model:

\[
Y_n = \frac{1}{1 + \exp(-Z)}
\]

where

\[
Z = -7.7051 + 0.7348 \times 5.5 - 0.1394 \times 5.5 + 0.0559 \times 46 + 0.0019 \times 1230 = 0.478
\]

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Table 9. Average variable values

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$ = Management Quality</td>
<td>5.5</td>
</tr>
<tr>
<td>$x_2$ = Number of Employers Career</td>
<td>5.5</td>
</tr>
<tr>
<td>$x_3$ = Age</td>
<td>46</td>
</tr>
<tr>
<td>$x_4$ = Miles Driven per Year (in 00)</td>
<td>1230</td>
</tr>
</tbody>
</table>

and therefore,

$$Y_n = \frac{1}{1 + \exp(-0.478)} = 0.6173$$

Since the logistic regression model returned a value greater than 0.50, the average respondent from our survey is less than likely to turnover. However, to just look at an average driver would be shortsighted. The average driver profile needs to be compared to a somewhat different driver profile (i.e., different values for the independent variables). To illustrate the effects of a different respondent profile the values for management quality, number of employers career, and miles driven per year are held the same as in the previous example but the age of the respondent is decreased by 10 years from 46 to 36 years of age (approximately a 20% reduction in age). Using these values for the independent variables results in the following logistic regression model:

$$Y_n = \frac{1}{1 + \exp(-Z)}$$

where

$$Z = -7.7051 + 0.7348 \times 5.5 - 0.1394 \times 5.5 + 0.0559 \times 36 + 0.0019 \times 1230 = 0.081$$

and therefore,

$$Y_n = \frac{1}{1 + \exp(-(-0.081))} = 0.4798$$

Overall, since the logistic regression model returned a value lower than 0.50, the average respondent from our survey is more than likely to turnover. In comparison to the average driver profile, a reduction in age to 36 years results in changing the likelihood to turnover from less than likely to turnover to more than likely to turnover. In another brief example of independent variable impact, all variables are set back to their average level except for management quality rating which is reduced by 20% akin to the previous example. The lower management quality rating returns a value for the logistic regression model of 0.4182. Since this value is lower than 0.50 the likelihood to turnover would be higher than the average driver profile case. In other words, lower management quality ratings lead to higher likelihoods of driver turnover. If management is concerned about identifying driver turnover, it might be said that they should definitely concentrate on drivers who give lower management quality scores, drivers who have had more employers over their career, drivers who are younger, and drivers who drive less miles per year. Thus, the model is supported by the extant driver turnover literature.

**CONTRIBUTIONS AND IMPLICATIONS**

The results of this study provide a number of important contributions and implications for managers in the trucking industry. The most
important managerial contribution provided by this study is the development of a model that will enable managers to identify those individual drivers or classes of drivers that are most at risk of turning over. This finding is especially important given the most recent Hours of Service (HOS) limitations implemented by the Federal Motor Carriers Safety Administration (FMCSA) which reduces allowable operating hours still further which makes it even harder for even the safest drivers to reach the 100,000 mile threshold. Consequently, recent industry reports indicate that record numbers of safest and best producing drivers are now seeking employment outside the trucking industry (Jones, 2013ab).

The authors also specifically recommend that carriers focus their hiring efforts on reducing the hiring bottleneck so that more potential drivers can be transitioned from applicants to actual drivers, working to develop employment packages that focus on the drivers’ work life balance, and attracting drivers from non-traditional sources such as drivers that have left the field but wish to return and retirees that want to drive on a part time basis. The authors also suggest that carriers collaborate with shippers in order to increase operational efficiency and decrease the negative impacts associated with driver shortages.

LIMITATIONS, FUTURE RESEARCH IMPLICATIONS AND CONCLUSIONS

The primary limitation of this study stems from the snap shot approach which looked a single period of time instead of the more preferred longitudinal approach to see if the model holds over time. A second potential limitation of this study stems from its exploratory nature and relatively small sample size in terms of the number of respondents. However, this limitation is at least partially offset by the diversity and number of carriers represented and the fact that this driver segment is a relatively homogeneous group. These limitations notwithstanding this study make important contributions to both the extant literature and to the trucking industry as a whole.

The results of this study provide important implications for future research. One of the primary research implications indicated by this study resulted from the unexpected results. Given the significant results provided by this study’s factor and reliability analysis and the mixed results obtained from past research one may conclude that driver turnover and retention is an infinitely more complex process than was previously thought. This would then seem to imply that driver turnover should be viewed as an ongoing process in which drivers gradually transition from an inactive job search to actively searching for a position, to accepting said position, the ongoing reevaluation of said position and the ultimate transition to becoming a satisfied employee or moving on to yet another carrier. If true, this should prove to be a fertile field for future research given the expected increase in turnover rates for the industry overall.

The purpose of this study was to identify those constructs that ultimately lead to driver turnover. Study findings indicate that carriers can predict with a reasonable degree of certainty which drivers or classes of drivers are most at risk of changing jobs. Theoretically, carriers that adopt this model and take corrective action based on its results should gain competitive advantage in terms of cost reduction, customer satisfaction, and improved efficiency through decreased driver turnover rates.

REFERENCES


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