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Abstract

This paper explores the safety consequences of increasing truck driver pay. The test case the authors examine involves a large over-the-road truckload firm that on February 25, 1997, raised wages an average of 39.1%. An analysis that controls for demographic and operational factors, including prior driving experience and experience acquired on the job, suggests that for drivers employed during the lower pay regime and retained in the higher pay regime, crash incidence fell. A higher pay rate also led to lower separation probability, but this indirect effect only translated into fewer crashes by increasing the retention of older, more experienced drivers. These findings suggest that human capital characteristics are important predictors of driver safety, but that motivational and incentive factors also are influential.

KEYWORDS: Pay Incentives, Truck Driver Safety

PAY INCENTIVES AND TRUCK DRIVER SAFETY: A CASE STUDY

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This paper explores the safety consequences of increasing truck driver pay. The test case the authors examine involves a large over-the-road truckload firm that on February 25, 1997, raised wages an average of 39.1%. An analysis that controls for demographic and operational factors, including prior driving experience and experience acquired on the job, suggests that for drivers employed during the lower pay regime and retained in the higher pay regime, crash incidence fell. A higher pay rate also led to lower separation probability, but this indirect effect only translated into fewer crashes by increasing the retention of older, more experienced drivers. These findings suggest that human capital characteristics are important predictors of driver safety, but that motivational and incentive factors also are influential.

Trucking safety has become an increasingly important transportation policy concern in recent years. This concern was heightened by sizeable increases in trucking activity following economic deregulation of the interstate trucking industry in 1980, deregulation of the intrastate trucking industry in 1995, and the enactment of NAFTA (Wilson 2001). Despite growing awareness of the complexity of firms' operating environments and the stochastic nature of crashes, studies of large truck safety continue to focus on human factors, load characteristics, vehicle characteristics and maintenance, and roadway and environmental conditions. Recent research, however, demonstrates an increasing interest in how market pressure on the trucking industry may manifest itself in historically low real freight rates, tightened schedules to meet shipper demands, increased interfirm competition, and negative safety outcomes (GAO 1991; Hensher et al. 1992; Quinlan 2001; Traynor and McCarthy 1993). In particular, changes in wage structures and increased competition caused by

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By the terms of a confidentiality agreement with J.B. Hunt, the authors cannot freely dispense the data used in the study. With Hunt's permission, however, release of the data for limited use may be possible. Contact the first author at City & Regional Planning, University of North Carolina, New East Hall Room 317, CB#3140, Chapel Hill, NC 27599-3140; danrod@unc.edu.

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economic deregulation in the industry have heightened researchers' interest in the role that employee compensation and industrial relations play in the trucking industry (Belzer et al. 2002; Belman and Monaco 2001; Belzer 1995; Hunter and Mangum 1995; Rodriguez et al. 2004).

Hypothesizing a link between wage structures and crash incidence, in 1990 the National Transportation Safety Board (NTSB) called for a review of trucking industry structure and conditions that may create incentives for unsafe driving behaviors (National Transportation Safety Board 1990). Recent studies have shown that low pay is associated with a higher probability of commercial driver crash involvement (Belzer et al. 2002; Monaco and Williams 2000) and higher crash frequency (Rodriguez et al. 2003). These studies have brought issues of compensation and driver behavior to the forefront of the trucking policy debate. However, identification of pay as an important factor does not make clear the causal pathways through which it influences safety outcomes. In this study we focus on a specific aspect of the relationship between pay and safety: in a group of drivers who experience a pay increase, does the higher pay affect driver safety performance? We also test for an indirect path of influence: could it be that drivers who view their jobs as more valuable because of a pay increase drive more safely in order to retain those jobs—leading to longer tenure and further development of skills associated with safe driving? Even though increased safety is an outcome commonly shared by both causal paths, the policy implications may differ depending on the paths' relative importance.

To examine the effect of a pay increase on the safety outcomes of a group of drivers, we use panel data from J.B. Hunt, a large over-the-road truckload firm.[1] We observe the same set of drivers before and after they receive a pay increase. Using a two-stage approach, we isolate the direct effect of the pay increase on the probability of monthly crash involvement for each driver from the indirect effect that such an increase may have on crashes by improving driver retention and enabling the accumulation of human capital.

Expected Safety Consequences of Changes in Driver Pay Level

Human capital theory suggests that variations in human capital across individuals and firms should in part explain differences in worker performance (Becker 1962). For example, we expect greater job experience to enhance worker productivity and to be associated with greater safety. Because pay level differences proxy human capital differentials, we expect higher compensation to correlate with superior employee performance (Abowd et al. 2002). For trucking firms, in a market in which labor supply appears to be highly elastic (Hirsch 1988; Rose 1987), high pay likely attracts drivers with desirable human capital characteristics, such as extensive driving experience and a low number of prior crashes and moving violations. This occurs if drivers with superior human capital receive better compensation packages or if those with greater human capital are able to obtain better-paying positions in the industry. In either case, we expect that certain driver human capital characteristics will correlate with better driving outcomes, such as greater productivity, on-time performance, customer relations, and safety.

In addition to influencing the quality of drivers attracted to the firm, higher driver pay should, according to efficiency wage theory, influence the behavior of a firm's existing pool of drivers by providing incentives for more professional performance and disincentives for unprofessional conduct if the latter leads to dismissal. We examine drivers before and after a substantial wage increase to isolate the motivational and behavioral effects of higher pay on existing drivers from the human capital

[1] A truckload (TL) motor carrier hauls shipments larger than 10,000 pounds (see Belzer 2000 for a glossary). This is just a threshold, however; the typical semi-trailer will carry between 40,000 and 45,000 pounds of freight.

effects of attracting a new set of drivers to the firm. To study the impact of a pay raise on a given set of drivers, we develop a framework that parallels the standard labor-leisure model. In this case, we assume drivers trade work time (and earnings) against leisure. Consider a driver's utility function, represented as

$$U = U(X, -E), \tag{1}$$

where U is the strictly quasi-concave and twice (continuously) differentiable utility of a driver, X is a composite of all goods and services consumed by a driver, and $-E$ is leisure, or the negative of driving effort E. We assume utility is increasing in X and $-E$, and therefore as effort increases, leisure decreases. If H is defined as the driving hours worked and v as the average driving speed, then $vH = E$, and leisure increases with fewer hours worked or by driving slower when working.[2] We further assume drivers maximize the above utility function subject to the constraint

$$X = RE + Y, \tag{2}$$

where R is the real per mile pay rate of drivers, Y is the real income from non-labor activities, and E is as defined above. A point of utility maximization is guaranteed as long as the marginal rate of substitution between $-E$ and X is diminishing, which is a standard assumption.[3] Maximizing equation (1) subject to equation (2) yields the labor supply function

$$H = \mathrm{f}(R,Y). \tag{3}$$

The effect of a pay rate increase on hours worked is summarized by $\delta H / \delta(R)$. Analytically, this follows the standard labor-leisure model, with no clear prediction of how income or leisure will respond to a change in pay rate because the net impact of a change in mileage rates will be composed of a substitution effect and an income effect.

Our model assumes that drivers have some freedom to control how much work they accept. Although the assumption holds more directly for owner-operators and leased owner-drivers than for employees of for-hire truckload firms, the latter also have some say in accepting or rejecting loads; at least they have control over the bundle of labor and leisure offered by specific employers and within the industry generally. The regularity with which some of them choose to exceed federally mandated hours of service limits is one indirect indication of drivers' ability and propensity to choose how many hours they work. These regulations, which might reasonably have been expected to dissuade drivers from working too many hours, are violated frequently.[4] Indeed, Belman and Monaco (2001) suggested that for their sample of drivers, annual miles driven correlated with having violated the ten-hour driving rule in the previous thirty days.

Because they are paid by the mile, truck drivers face labor-leisure choices quite different from the standard ones faced by most other workers. First, firms (and drivers) are exempt from the maximum-hours regulation of the Fair Labor Standards Act (FLSA), which means that in a regular workweek drivers legally can work any number of hours without payment of overtime premia. Instead, the Hours of Service rules promulgated by the U.S. Department of Transportation regulate driving hours.[5]

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[2]Notice that vH has a fixed maximum value because H and v independently have fixed maximum values. If H is the hours of work and T the total time available, then $T - L = H$. Similarly, the characteristics of the tractor, the road, the weather, traffic congestion, and speed limits govern the maximum driving speed.

[3]Normally, the assumption is

$$\frac{\partial^2 U}{\partial X \partial E} < 0,$$

which is equivalent to assuming a diminishing marginal rate of substitution between X and E.

[4]This was true particularly for hours of work during the period covered by this study. On January 4, 2004, hours-of-service regulations changed such that drivers may not drive after an elapsed time of fourteen hours per shift each day, including breaks. Longstanding practice was much more lax (see Belzer 2000).

[5]49 CFR Parts 385, 390, and 395. Hours of Service of Drivers; Driver Rest and Sleep for Safe Operations.

Second, unscheduled truck drivers have greater uncertainty about expected monthly earnings than regular workers do. Most workers have a relatively fixed monthly paycheck, which allows them to budget expenditures and adjust financial commitments to income. Unscheduled truck drivers face similar monthly commitments (for example, food, rent, and utilities) but have lower certainty about expected income.

This uncertainty about monthly income has led some researchers to posit that such workers aim for a target income (for taxi drivers, Camerer et al. 1997; for truck drivers, Drakopoulos and Theodossiou 1998). Drivers who have target incomes may care about their incomes relative to a reference point or level of aspiration, and they may revise such targets periodically. If drivers are unable to earn their target incomes during any pay period, they face the tradeoff between adjusting their effort in order to reach the target and experiencing—perhaps subconsciously—a higher crash probability, or accepting lower earnings. A higher crash probability could stem from exceeding existing hours of service limits, driving in bad weather, driving faster than permitted, driving while fatigued, or compromising on required equipment safety checks. In the context of the labor-effort model, the income effect of a pay raise may reduce pressure on drivers to put in extra hours.

Connection between Pay, Separation, and Driver Safety

Drivers' pay raises can lead indirectly to better safety records through pay's influence on driver retention rates. Higher pay may increase retention rates, thereby allowing drivers to accumulate general and firm-specific human capital. The more familiarity a driver has with his equipment, his work responsibility, his customers, and his route, the lower the probability of injury. For example, Belzer et al. found that at J.B. Hunt, prior experience and tenure at Hunt were independent predictors of crash probability (Belzer et al. 2002:82–86). As such, higher pay may influence driver safety outcomes indirectly through increased accumulation of firm-specific skills.

This indirect relationship between pay and safety is relevant because certain segments of the trucking industry tend to exhibit very high turnover rates (Lemay et al. 1993). Belman and Monaco (2001) estimated for their sample that while the median truck driver had been driving for twelve years, median tenure with the current employer was only eighteen months. These high rates of turnover tend to result from drivers continually looking for better job opportunities or from disciplinary actions by firm management. Human capital theory also can be used to explain individuals' job separation probability and to link this probability with driver safety outcomes; prior research suggests that the probability of leaving a firm will decrease as the driver accumulates firm-specific skills (Strober 1990). If tenure with the firm is low and the probability of separation is high, we expect firm-specific skills to be low and crash probability to be high. By contrast, low separation probability reverses the relationship.

Empirical research has shown that high employee pay is correlated with a low probability of separation (for example, Cotton and Tuttle 1986; Holzer 1990; Leonard 1987; Munansinghe 2000). Similar results have been reproduced for truck drivers (Gupta et al. 1996; Lemay, Stephen, and Turner 1993; Richard and Lemay 1995; Taylor 1991). At the same time, high labor turnover rates have been associated with negative safety outcomes (Rinefort and Van Fleet 1998; Feeny 1995; Bruning 1989).

In summary, although there are reasons to believe that higher pay will elicit better driver performance, including better safety outcomes for both current and new employees, a model paralleling the labor-leisure tradeoff suggests that the expected safety impact is not clearly identifiable, partly because driver preferences for time off and work vary as pay varies. Likewise, we expect higher pay to decrease a driver's willingness to leave the firm, which translates into higher firm-specific human capital and, plausibly, into better crash outcomes. In this study we attempt to isolate the influence of the pay increase on current drivers from the effect that such an increase may have on driver retention and the development of human capital on the job.

Data Description

We observe demographic, operations, compensation, and crash data for a population of 2,368 unscheduled over-the-road J.B. Hunt drivers who received pay increases during a period of up to 25 months between 1995 and 1998. J.B. Hunt is one of the three largest nonunion truckload trucking and logistics firms operating in North America. The data cover two one-year periods: September 1995–September 1996, and March 1997–February 1998, inclusive. No data are available for the four months from October 1996 through February 1997. The end of the first period marks the month the firm announced its new wage policy, and the beginning of the second period coincides with the implementation of changes in the firm's human resource practices designed to improve driver safety and reduce driver turnover rates. Of particular interest to this study are substantial increases in the mileage pay rate of drivers. Hunt implemented the pay increase by assigning raises of different percentages to drivers at different pay rates, depending on the pay at which the driver was hired. Drivers at the low end of the pay scale whom Hunt retained received a larger percentage increase in pay than did drivers at the high end. Thus, only drivers whom Hunt hired before the announcement and who remained with the firm until the pay raise became effective experienced a pay increase. These drivers are the ones included in this study.

Drivers in the sample are observed for an average of 17.7 months, with some drivers present since the first month of observation (September 1995) and others hired as late as September 1996, before Hunt made the announcement of the pay rate increase. Sixteen percent of drivers left the firm while under observation, and we observed 71.6% of drivers for more than 12 months. The figures confirm the importance of driver turnover rates for the trucking industry, where more than two-thirds of firms have voluntary turnover rates exceeding 30% (Lemay, Stephen, and Turner 1993), and many firms experience turnover rates greater than 100% (Cox 2004); Hunt's yearly turnover in this division was 105% at the time it announced the change, and the average in the truckload industry during the first quarter of 2005 was 120% (Nguyen 2005). The figures also are consistent with the view that truckload driver jobs are not desirable jobs and that better understanding of driver separation behavior is important for the industry.

Driver Compensation and Crash Outcomes

We focus on J.B. Hunt's unscheduled or irregular-route over-the-road drivers pulling dry van trailers. We emphasize unscheduled drivers for two reasons. First, this was the target group for Hunt, which wanted to provide a compensating wage differential that made this work—which is so difficult because it is irregular and involves extended time away from home—as attractive as scheduled work. We also emphasize irregular route drivers because they implicitly have a higher level of uncertainty about their ability to cover recurring expenditures with their monthly income than dedicated or scheduled drivers do. They may be more willing, therefore, to work more hours when work is available to ensure that they make their targets; they may systematically work even harder than necessary to ensure against this uncertainty. The regularity of scheduled work means that dedicated drivers can count more firmly on monthly earnings in order to cover expenses, and they can schedule their personal lives more reliably; by the same token, this choice denies them some opportunities for supplemental earnings.

Furthermore, by observing dry van drivers we attempt to mitigate the fact that it is difficult to observe job-specific human capital skills and specialized trades. Drivers hauling specialized freight, like bulk commodities that may require special handling skills (such as dump truck unloading, bulk liquid pumping, dry bulk pressurized blowing, food grade handling, and continuously moving loads in non-baffled liquid tanks), hazardous materials knowledge (special handling requirements of flammable and corrosive chemicals), and automobiles (loading, unloading, and securement of high-value products), tend to require more specific skills than dry van drivers. Therefore, some of the human capital accumulated from tenure with specialized haulers will be occupation-specific but not necessarily firm-specific. Firm-specific human capital stems from familiarity with equipment and knowledge of firm practices, fleet management characteristics, and locations and special demands of shippers and consignees.

The outcome of interest to our study is the occurrence of a crash (regardless of fault) involving $1,000 or more of actual or estimated damages. The dollar figure constitutes the firm's out-of-pocket costs associated with each crash (including bodily injury, property damage, recording and towing costs to all parties, and adjustor expenses) or the firm's actuarial estimates of the cost based on data for past crashes with similar characteristics. These costs exclude the impact of crash events on health and liability insurance costs and workers' compensation costs. J.B. Hunt's drivers were involved in 826 crashes during the period observed, corresponding to an average of 0.35 crashes per driver, but 74% of drivers did not have a reported crash exceeding the $1,000 dollar value. We considered different crash cost cutoff points, such as $200 and $2,000, but results were very similar to those presented below.

For compensation information, we observe each driver's base pay rate (cents/mile) when hired by the firm (BasePay) and the new pay (NewPay) reflecting the increases for each driver at the beginning of the second period. Consistent with theory (Abowd et al. 2002; Becker 1962), we view the base pay rate as a proxy for drivers' human capital characteristics (unobserved to us), such as prior moving violation and crash records, substance abuse records, and expected driver productivity. The average base pay for drivers in this study is 27.9 cents/mile (Table 1). Likewise, we view the increase in driver pay for each individual at the end of February 1997 as the exogenous stimulus that may lead to a reassessment of driving effort on the part of each driver. On average, drivers in this sample experienced a pay rate increase of 39.1%.

J.B. Hunt implemented other changes in compensation policies concurrently with the pay increase. Notably, it instituted a system of bonus pay for adequate safety performance and for productivity, and promised greater efforts to return drivers to their homes at the completion of each run, when so requested. Unfortunately, we do not have data to control for these bonuses or returns home. To the extent that such bonuses and home visits correlate with any of our independent variables, the effects estimated will be biased. Two mitigating factors are important, however. First, even though bonuses provide additional income to drivers, by far the greatest part of a driver's income results from pay rate and miles driven. Second, we attempt to account for policies implemented simultaneously with the pay rate increase by including a dummy variable (After) indicating whether the driving activity of each driver occurred before or after the changes in compensation policy. Admittedly, this is a blunt way to control for concurrent changes, but given the data limitations, it is the preferred way to proceed.

Other Relevant Variables

Control variables for each driver include activity data and demographic characteristics. Driver activity data include average miles driven up to the beginning of each month (MilesToDate), miles driven at the end of the current month (Miles), number

Table 1. Descriptive Statistics Summarized at the Individual Level.[a]

Variable	*Description*	*Mean or Percentage*	*Standard Deviation*	*Min*	*Max*
MONTHS	Months observed	18.3	7.2	2	26
AGE	Age at $t = 0$ (years)	40.7	9.5	20	70
SEX	1 = Female	2.4%	15.5%		
RACE	1 = White	73.2%	44.3%		
SINGLE	1 = Single	39.1%	48.8%		
BASEPAY	Base pay rate (cents/mi.) when hired	27.9	4.2	17	37
NEWPAY	Pay rate (cents/mi.) per month, time-varying	38.1	3.1	21	48
EXPERIENCE	Total driving experience (yrs.), time-varying	5.0	4.6	0.2	37.8
MILES	Miles driven per month (000s), time-varying	9.3	2.7	0.2	21.8
MILESTODATE	Average miles driven up to beginning of observed month (000s), time-varying	8.2	3.0	0.1	23.0
DISPATCHES	Dispatches per month, time-varying	16.3	4.3	1	41
WINTER	1 = Driving activity during winter month, time-varying	30.5%	11.7%		
AFTER	1 = Driving activity after compensation policy change, time-varying	52.1%	18.4%		
PEAK	1 = Driving activity during peak season, time-varying	25.5%	9.7%		

N = 2,368 (aggregated from 42,725 driver-month observations).
[a]For variables that change with time, such as MILES and NEWPAY, summary statistics at the individual level may provide a skewed depiction.

of dispatches (DISPATCHES) during each month we observe a driver, and the total number of crashes recorded during prior months (PRIORCRASHES), which is set to zero when we observe each driver initially. One can interpret the variable MILESTODATE as a proxy for driver productivity and earnings during the months prior to the current month of activity. The sign expected for DISPATCHES is positive because we expect drivers with greater unpaid and unproductive waiting time and more pulling in and out of traffic conflict zones, such as docks and urban areas, to have higher crash probability. We also expect that drivers with a greater number of dispatches make shorter runs and operate in conflict zones more often than drivers with fewer dispatches, all else held equal.

By using information on the month of the year when the driving activity occurred, we control for possible seasonal effects of weather on crash probability. For weather, the variable WINTER equals one if the driving occurred in the months of December through March and zero otherwise. Admittedly, weather varies greatly during these months among regions, but these drivers operate in 48 states and Canada, and we do not have geographic information on the region in which the driving activity occurs.

Demographic and human capital data include age, race, marital status, sex, and driving experience when hired (EXPERIENCE). EXPERIENCE increases with time, and therefore it measures total driving experience when observed initially as well as experience accumulated throughout the observation period. The fact that we measure the accumulation of experience is critical for interpreting the coefficient of NEWPAY as the safety consequence of the pay increase, net of its effect on time on the job. We include AGE with both linear and quadratic terms to account for potential nonlinearities with crash probability, while

Table 2. Comparison of Drivers with and without Crashes.[a]

Variable	*No Crashes*	*One or More Crashes*	*t-Statistic*[b]	*P-Value*
AGE	40.7	40.8	–0.12	0.91
SEX (F)	2.6%	1.9%	0.95	0.34
RACE (W)	73.9%	71.2%	1.33	0.19
SINGLE	38.2%	41.7%	–1.57	0.12
BASEPAY	28.1	27.2	4.69	0.00
NEWPAY	38.1	38.2	–0.82	0.41
EXPERIENCE	5.17	4.45	3.22	0.00
MILES	9.20	9.69	–4.31	0.00
DISPATCHES	16.13	16.94	–4.50	0.00
WINTER	30.4%	30.6%	–0.37	0.72
AFTER	52.7%	50.6%	2.57	0.01
PEAK	25.5%	25.4%	0.87	0.39

N = 2,368 (aggregated from 42,725 driver-month observations).

[a]Average per driver used for time-varying covariates, except for NEWPAY, for which we used the value of pay after the pay increase.

[b]For continuous variables, t-tests were used to compare the two groups. The Wilcoxon rank sum test, yielding a z-test statistic, was used for binary variables. All tests are two-tailed.

we use dummy variables to indicate other demographic characteristics.

A host of other potential factors not adequately captured by the data used for this study can influence a driver's crash propensity, and we acknowledge this limitation. For example, to the extent that a correlation exists between vehicle and environmental factors influencing driver safety and demographic and occupational variables, the coefficients estimated for the latter two sets of variables would be biased. A driver's age and rate of pay, for example, might correlate with the type of tractor driven. Certain trucks may be safer or better maintained than others and their use may correspond to higher or lower crash risk. Thus, not accounting for the type of tractor can yield biased coefficients for age, pay, or both. However, we have no reason to believe that a relationship exists between the type of tractor and the seniority or pay of the driver in this dataset. At the time of the study, J.B. Hunt used relatively new cab-over-engine tractors, still under manufacturer's warranty. This guarantees that performance variation, including safety characteristics, was very limited, and decreases the possibility of bias due to this unobserved variable.

An initial descriptive overview of the data, focusing on comparisons among drivers, will help illustrate the character of the data and highlight some apparent patterns. The first comparison we draw is between drivers with and without crashes (Table 2). Drivers with no crashes tended to have higher base pay and more driving experience when we observe them initially than drivers with one or more crashes. Likewise, those with no crashes drove fewer miles and had fewer dispatches. Table 2 indicates no consistent association between driver demographic characteristics and crash involvement. A limitation of Table 2 is that it does not show when such crashes occurred relative to the pay increase. The empirical crash hazard function (Figure 1) more aptly depicts differences in crash involvement over time.

The empirical crash hazard function summarizes the fraction of drivers during each month who experienced a crash during that month, without controlling for other covariates. Because the trend is decreasing over time, Figure 1 confirms that the crash hazard decreases with duration before and after the pay increase, and that crash probability after the pay raise appears to be lower than crash probability before the pay raise. However, Figure 1 does not show

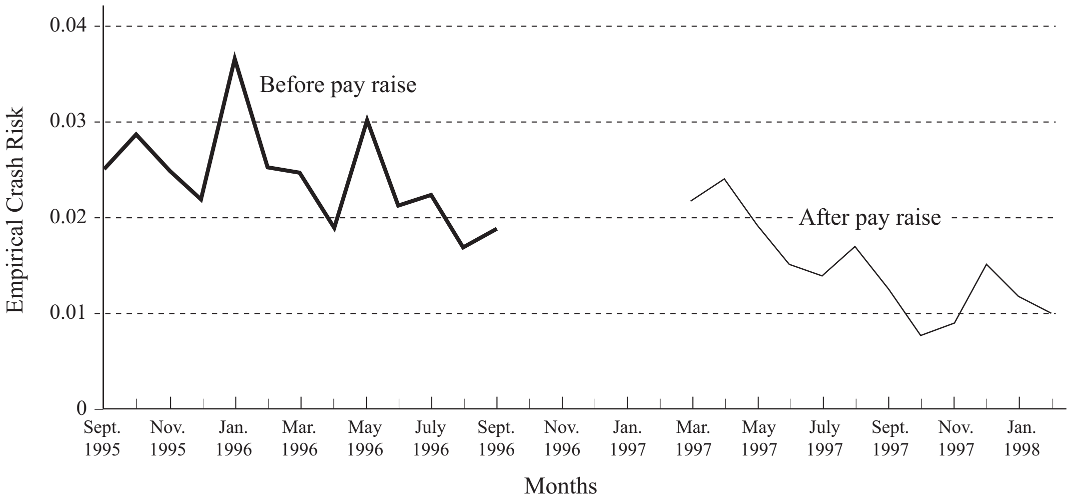

Figure 1. Empirical Crash Risk for J.B. Hunter Drivers before and after the Pay Raise.

clearly whether the decreasing trend only stems from having observed drivers for longer periods or if the pay increase *per se* explains part of the decrease. For example, we expect drivers with long recorded durations in the sample (those toward the right-hand side of Figure 1) to have a higher concentration of characteristics that can lead to lower crash risk. One such characteristic is accumulated experience on the job, which may be partly responsible for the observed decrease in the crash hazard. Thus, we should explore with more sophisticated econometric tools the degree to which any differences in crash hazards before and after the pay raise result from the pay change, while controlling for other variables. We address this topic in the next main section ("Crash and Separation Probability Models").

Ability to Generalize from Current Data

In adopting a firm- and industry-specific focus, we trade off the generality of results obtained from intra- and inter-industry, multi-firm, and multi-occupation research for the better definition and data resolution provided by this narrow focus. To examine potential limits to our ability to generalize from the data to other truckload industry sub-sectors, we compare the current dataset with two additional sources of information for the TL sector (Table 3). The first source of information is a survey conducted by the University of Michigan Trucking Industry Program (UMTIP) (for details, see Belman and Monaco 2001 and Belzer et al. 2002). The UMTIP data used in this study include details on 233 full-time employee drivers paid by the mile. We exclude owner-operators and hourly paid drivers. The second data source is a survey of firms included in the National Survey of Driver Wages published by Signpost, Inc. Signpost surveys approximately 200 truckload firms of various sizes, including most major TL carriers and a sample of medium-sized and smaller carriers. This study uses data from 102 firms, with employee drivers paid by the mile, who responded to the UMTIP survey of Signpost respondent firms (see Belzer et al. 2002).

The J.B. Hunt data differ modestly from the other sources of data with respect to drivers' demographic characteristics (race and marital status), and a major difference appears in miles driven per dispatch. More

Table 3. Comparison between Current Dataset and Selected Datasets.

Independent Variable	*J.B. Hunt*[a]	*UMTIP Driver Survey*[b]	*Signpost and UMTIP Firm Survey*
AGE (years)	40.7	42.2	n.a.
RACE (white)	74%	86%	n.a.
SINGLE	39%	31%	n.a.
Driving Experience (yrs.)	5.0	3.46	n.a.
Base Pay (cents/mi.)	27.9	28.6	28.6
Miles per Dispatch	571	858.0	905.9

[a]This study.
[b]Tenure at the firm, not driving experience
n.a. = not available.

J.B. Hunt drivers tend to be married and non-white than average, using the UMTIP survey as a benchmark. The differences detected for miles per dispatch may result from the firm's reliance on rail transportation for hauling freight over long distances. However, figures from a 1999 survey conducted for the Truckload Carriers Association are close to J.B. Hunt's figures, showing an average of 550 miles per dispatch (Martin Labbe Associates 1999).

The potential limitations of using a single firm's data should not deter us from analyzing the relationship between pay changes and safety outcomes. Such analysis may indicate the usefulness of engaging in a general equilibrium analysis. Furthermore, because we control for human capital and occupational characteristics experimentally or quasi-experimentally, the examined relationship between pay changes and safety may be representative of similar relationships for other trucking firms. Other strengths of the dataset include its reliance on the firm's database, and not on driver recall—a known source of bias present in survey data.

Crash and Separation Probability Models

Given the longitudinal nature of the data, we apply a multivariate methodology to examine crash probability based on semiparametric hazard modeling techniques (see Meyer 1990; Prentice and Gloeckler 1978). We first present our econometric approach for modeling crash occurrence. Because the crash model is general enough, we use it as a starting point for our presentation of the driver separation probability model.

Crash Involvement Model

We define T_i as a discrete random variable representing the duration of stay in a non-crash state for driver i. Further, we model distributions of durations in a non-crash state as transition probabilities between a non-crash state and a crash state. The calendar time is not the same for all drivers, and therefore we measure duration on person-specific clocks that are set to zero when we begin to observe each individual. The recorded duration is the interval (t_i-1, t_i) for truck driver $i = 1,\ldots,N$, all of whom are initially in the non-crash state at time 0. We also record whether drivers had a crash during the interval or (the "censored cases") remained in the non-crash state. If a crash is recorded, we assume the driver begins in a non-crash state the following period.

Given the conditional probabilities of moving into a crash state having survived until t in a non-crash state (h_{it}), we can express the likelihood for drivers moving into a crash state and for drivers remaining in a non-crash state as

$$(4)\qquad \sum_{i=1}^{n} \delta_i * \log\left[\frac{h_{i\tau+s_i}}{(1-h_{i\tau+s_i})}\right] + \sum_{i=1}^{n}\sum_{t=\tau}^{\tau=s_i} \log(1-h_{it}),$$

where h_{it} is the hazard rate at time t for driver i, and $\delta_i = 1$ for non-censored cases and 0 otherwise (for details, see Jenkins 1995).

In order to specify the likelihood function fully, it is necessary to identify an expression of h_{it} for this particular process. This specification will have a substantial effect on the inferences made about the process, since the interpretation of the covariates varies according to the hazard specification selected. For this study, a complementary log-log specification was used for the crash hazard rate, which results in a model that is the discrete time counterpart of the continuous time proportional hazards model (Jenkins 1995; Prentice and Gloeckler 1978). A proportional hazards specification refers to the influence of any covariate having a multiplicative effect on the baseline hazard function. This specification has been used elsewhere in transportation safety research (see Chang and Jovanis 1990; Jovanis and Chang 1989; Mannering 1993).

Even without a compelling reason to support specifying proportional hazards vis-à-vis non-proportional hazards, our model specification assumes proportionality. We test this assumption empirically by including an interaction of each time-invariant explanatory variable with a time variable measuring the length of time observed for each driver. A test of the hypothesis that the coefficient on the interacted term is zero is a test of the proportional hazards assumption for the time-invariant explanatory variable. Rejection of such a test leads to the inclusion of the interacted term as an explanatory variable.

We account for the duration dependence of the hazard rate semi-parametrically with dummy variables for time periods during which drivers are observed (Box-Steffensmeier and Jones 1997). We assume that the probability is constant during the period captured by each dummy variable. Thus, dummy variables provide information on how the baseline probability rate changes across periods, thereby explicitly allowing for occurrences of periodic heterogeneity.

Finally, our modeling approach makes several simplifying assumptions. We assume independence in the crash hazard across periods, conditional on the variables observed. If one or more unobserved variables induce correlation across periods, this will bias the estimated coefficients. Likewise, we assume that the risk of a crash for a given driver is unaffected by earlier crash occurrences. We take two steps to address the implications of this assumption. First, we follow Oakes's suggestion to include an explicit variable capturing this dependence (Oakes 1992), using the variable PriorCrashes as described in the previous section. The coefficient for this variable determines the change in crash risk from being involved in prior crashes. Second, even if the risk of a future crash remained related to previous crashes due to unobserved factors, we correct our standard errors using White's robust variance estimates, by allowing for clustering within each driver (White 1980).

Separation-from-the-Firm Model

We use an approach similar to that in the previous section for crash models to derive the estimator for examining separation probability (for example, quits and discharges). Because separation from the firm is a discrete outcome that occurs in time, researchers interested in employee turnover and separation behavior have begun to realize the usefulness of applying duration models to examine such behavior (for example, Dolton and Van Der Klaauw 1999; Lindeboom and Kerkhofs 2000; Morita et al. 1993; Somers 1996). In our analysis we experimented with several model specifications, including a split population survival model (Schmidt and Witte 1989), but rejected these models in favor of the discrete time proportional hazards approach shown in equation (4).

For the separation probability model, modifications to the estimation sample and several exclusions of variables are necessary. First, we exclude from the estimation sample drivers who left the firm and who recorded a crash during the month they left or during the previous month. This mitigates concern over the possibility of endogeneity between crash probability and the separation probability, and partially ensures that drivers who leave the firm do so for reasons other than being at fault for a crash. As a result, we exclude 77 drivers (3.26% of all drivers) and 361 driver-months (1.3% of all driver-months during this pe-

Table 4. Driver Discrete Time Proportional Risk Probability Models for Separation and Crash.[a]

	Model 1 (dep. variable: separation = 1)			*Model 2 (dep. variable: crash = 1)*			*Model 3 (dep. variable: crash = 1)*		
	Coefficient	*Standard Error*	*z-Statistic*	*Coefficient*	*Standard Error*	*z-Statistic*	*Coefficient*	*Standard Error*	*z-Statistic*
AGE	–0.006	0.007	–0.85	–0.067***	0.010	–6.42	–0.067***	0.010	–6.44
AGE^2				0.002***	0.000	6.92	0.002***	0.000	6.93
SEX	0.217	0.300	0.72	–0.254	0.237	–1.07	–0.250	0.238	–1.05
RACE	–0.025	0.127	–0.20	–0.349***	0.071	–4.91	–0.350***	0.071	–4.91
SINGLE	0.226*	0.117	1.93	–0.105	0.068	–1.55	–0.103	0.068	–1.52
BASEPAY	–0.025	0.019	–1.35	–0.024	0.018	–1.38	–0.024	0.018	–1.36
NEWPAY	–0.092***	0.015	–6.00	–0.267***	0.028	–9.53	–0.264***	0.028	–9.33
$NEWPAY^2$				0.009***	0.001	9.23	0.009***	0.001	8.46
EXPERIENCE	0.012	0.019	0.65	–0.077***	0.024	–3.26	–0.075***	0.024	–3.16
$EXPERIENCE^2$				0.002***	0.001	3.18	0.002***	0.001	3.12
MILES				–0.129***	0.018	–7.00	–0.129***	0.018	–7.01
MILESTODATE	–0.268***	0.042	–6.33	0.075***	0.018	4.20	0.075***	0.018	4.19
DISPATCHES				0.012	0.009	1.34	0.012	0.009	1.31
WINTER				0.063	0.091	0.70	0.058	0.090	0.64
AFTER				0.215	0.252	0.85	0.288	0.301	0.96
PEAK	–0.593***	0.181	–3.28						
PRIORCRASHES				0.154*	0.084	1.84	0.155*	0.084	1.85
PR_SEPARATION							–1.266	2.789	–0.45
Baseline Hazard-Only Log-Likelihood		–1572.3			–7,958.7			–7,958.7	
Log Likelihood at Convergence		–1480.2			–3,962.9			–3,962.8	
P > X^2: Wald Test—Full Model		0.000			0.000			0.000	
Driver-Months		19,890			42,725			42,725	
Drivers		2,360			2,437			2,437	
P > X^2: LR Test of Model 3 vs. Model 2								0.79	

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.
[a]For model details see Meyer (1990). Standard errors of crash models corrected using White's robust variance estimator (White 1980).

riod) from the estimation sample for the driver separation model. Because it is not possible to isolate the drivers who leave the firm due to a crash from those who leave for other reasons and happen to have had a recent crash, endogeneity may remain a concern, though a small one given the small fraction of drivers. Second, we estimate the separation model using data for the twelve months following the implementation of the compensation change. This is because, by design, the dataset contains no separations before the compensation change. Separations only occur when drivers leave after the pay increase.

Third, several variables (DISPATCHES, MILES, WINTER, AFTER, and all quadratic terms) are excluded from the separation model specification. Since DISPATCHES and MILES vary from month to month, it would be inappropriate to include them in the driver separation model, because they will tend to have low values for drivers who leave the firm during a given month. This is true in part because drivers can terminate at any time during a month. We exclude WINTER on theoretical grounds because there is no particular expectation that the weather will have an effect on individual separation probabilities. We also exclude AFTER, the indicator of whether driving activity occurs before or after the compensation policy change. This coefficient is not identifiable by design because none of the drivers in the dataset left the firm before the pay rate changed. We tested the significance of quadratic terms for AGE, NEWPAY, and EXPERIENCE but none was significant at standard levels of confidence. In the interest of model parsimony, we excluded these quadratic terms from the separation equation.

Finally, we include an additional dummy variable in the separation equation (PEAK) that we do not include in the crash model. This variable accounts for seasonal variation in the demand for trucking services expected during the months before the shopping season of December begins. During these months, because of exogenous changes in the demand for trucking, drivers can expect steady work and should be less likely to leave the firm (and too valuable for the firm to let go). The variable PEAK takes a value of one if driving activity occurs between September and December and zero otherwise.

Results and Discussion

We report estimates from three different models in Table 4: the separation probability model (model 1), the crash model (model 2), and the same crash model including predicted separation probability per month as an independent variable (model 3). Appendix 1 contains the coefficients of the baseline hazard estimated for these three models. We cannot reject the proportionality of hazards assumption for the crash models at standard levels of confidence. This means that the effect of NEWPAY on crashes does not vary over time.

Driver Separation Model

Results suggest that the driver separation model is statistically significant at a 99% level of confidence. This parsimonious model explains about 6% of the variance with no driver, compensation, or activity explanatory variables. Although this figure is low, it seems satisfactory given that 382 drivers left the firm during the period after the pay raise (less than 3% of drivers during any month). The coefficient for driver pay (NEWPAY) confirms our initial expectation that as monthly pay rate increases, the probability of separation decreases. Evaluated at the mean pay rate when drivers were hired, one cent per mile higher pay corresponds to an 8.8% lower separation risk, which translates into an elasticity of –2.45. This estimate is net of the effect of the pay rate at which Hunt hired the drivers (BASEPAY), and net of other explicit measures of human capital such as AGE and EXPERIENCE. Of the demographic variables, only SINGLE is statistically significant. Single individuals apparently are more likely than married individuals to leave the firm.

Unlike demographic variables, the two driving activity variables are relevant in predicting an individual's probability of separation from the firm. Conforming to our expectations, the estimated coefficient for MilesToDate is negative and statistically significant, suggesting that since mileage determines driver earnings, the higher the earnings to date, all else held equal, the lower the risk of leaving the firm. Specifically, at the mean, for every additional thousand miles driven each month (or about $381 in earnings at the mean pay rate), the separation probability is 23.5% lower. At mean values shown in Table 1, this suggests a separation elasticity with respect to monthly miles driven of –1.93. Also corresponding to our initial expectations, the coefficient for Peak suggests that drivers are 44.7% less likely to leave the firm during peak activity months than at other times. Finally, we find no detectable duration dependence from observing the semi-parametric baseline hazard (Appendix 1); only two of the time dummy variables are statistically different from zero at a 90% level of confidence. This suggests that the underlying separation hazard, controlling for the variables observed, does not change over time.

Once estimated, the coefficients of the separation equation were used to calculate each driver's probability of leaving the firm after the pay raise (PR_Separation), which then became an independent variable in a crash model (model 3). Because several variables (MilesToDate, Experience, Dispatches, and NewPay) vary from month to month, so does the predicted probability of leaving the firm. For the months prior to the pay increase, we restrict the predicted probability of separation to zero since, by design, no driver in our sample is at risk of leaving the firm before the implementation of the pay increase.

Driver Crash-Involvement Models

The driver crash models have substantially better fit than the separation model, with models 2 and 3 explaining 49.7% of the log-likelihood share of a model estimated only with the semi-parametric baseline hazard. Coefficient signs and statistical significance are consistent across the two crash models for all variables, but the likelihood ratio statistic for testing model 2 versus model 3 (using unadjusted standard errors) suggests that model fit improvement does not warrant the addition of PR_Separation as an explanatory variable in model 3 (p = 0.69). Therefore, the following discussion emphasizes the coefficient estimates from model 2, unless otherwise noted.

The coefficients of the compensation variables help us distinguish the effect of the pay increase on safety from the effect of pay through the accumulation of human capital. The coefficients for NewPay and its squared term are statistically significant and exhibit opposite signs, as we would expect. This means that as pay rises, the crash probability becomes lower, but at a decreasing rate. Considering together the contribution of pay and its squared term at the average pay when drivers were hired, and all variables held constant at their median values, the coefficients suggest that a 1% increase in pay rate corresponds to a 1.33% decrease in crash risk.[6] Figure 2 shows the change in crash probability as NewPay varies from 17 cents per mile to 47 cents per mile, with BasePay held at 17 cents per mile and all variables held at their median. At low pay levels, the net effect of a higher pay rate is lower crash risk, though the effect reduces incrementally and eventually reverses, controlling for other factors.

It is possible that the motivational effect of higher pay decreases over time, or that drivers adjust their recurrent financial commitments upward in the relatively short run after a pay increase. Do the safety effects of a pay increase attenuate over time? We tested this hypothesis by including an interaction term between NewPay and time observed after the raise, but the estimated coefficient is not statistically significant, indicating that the decrease in crash probability related to the pay raise does not

[6]The values for all explanatory variables in the model except the time dummies used in calculating the point elasticity are as follows: Age = 42, Sex = 0, Race = 1, Single = 0, BasePay = 27.9, Pay = 27.9, Experience = 4, Miles = 10.32, MilesToDate = 8.89, Dispatches = 18, Winter = 0, After = 1, and PriorCrashes = 0.

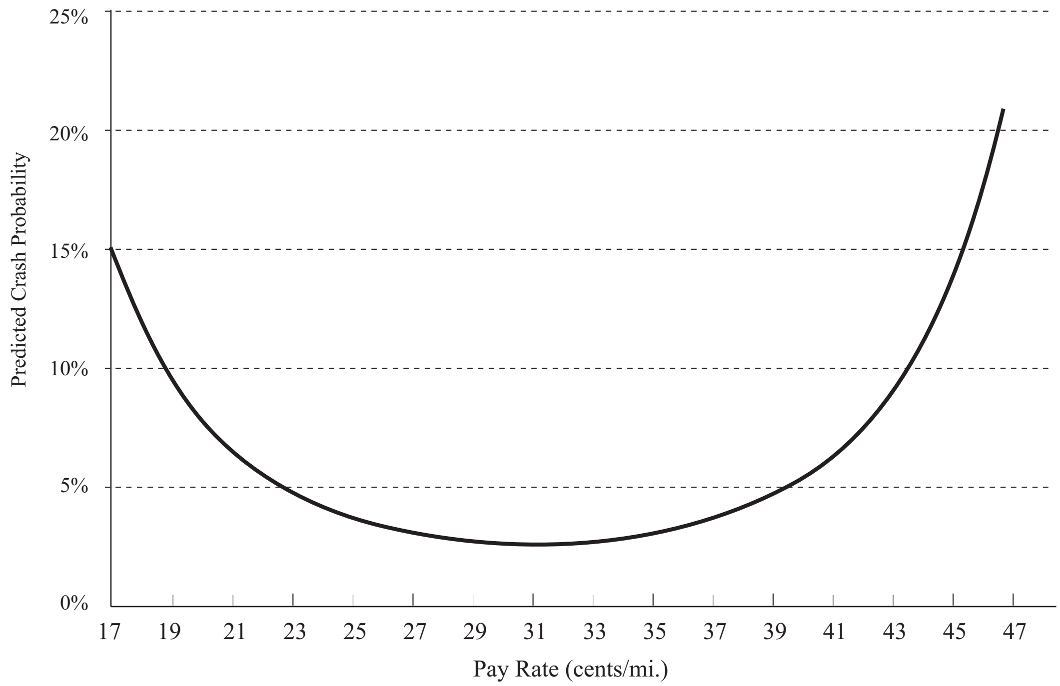

Figure 2. Predicted Crash Probability and Pay Rate.

change over the time observed (results not shown).

In contrast with the previous results, the coefficient on BasePay suggests that drivers' human capital characteristics, unobserved by us but observed by those making hiring decisions, do not correspond to crash outcomes. Initially this seems a surprising result because we expect initial driver pay levels, as a proxy for different levels of human capital, to be related to better employee outcomes (Abowd et al. 2002), particularly in the case of trucking firms, for which labor supply appears to be highly elastic (Hirsch 1988; Rose 1987). Inquiries with company officials revealed a likely explanation for this unexpected result. Before the change in the company's compensation policies, J.B. Hunt's practice was to hire drivers with little or no truck driving experience, and then train them. BasePay thus is measuring unobserved human capital characteristics rather than trucking experience. Because most human capital associated with truck driving is specific to driving skills, BasePay likely measures unobserved characteristics that may be less relevant to trucking safety, or may be uniform across all drivers hired as "students" and trained by Hunt.

We assess the relevance of the indirect link between pay and safety, through its effect on separation probabilities, with the coefficient on PR_Separation in model 3. Using White's robust variance estimator, we find the coefficient estimated is not statistically significant at standard levels of confidence ($p = 0.65$), suggesting that even though the pay raise motivated people to remain employed with the firm for a longer time (model 1), this did not translate into lower crash risk, once the analysis controls for variables such as Age and Experience.

One concern is that the coefficient on Experience is absorbing all the effect of accumulated human capital gained by remaining employed with the firm. We tested additional models in which the numerical value of EXPERIENCE was set to the experience of each driver when hired, without allowing it to change (accumulate) over time. With this change, the coefficient on PR_SEPARATION remained statistically insignificant at standard levels of confidence (results not shown).

These results imply that strategies that keep drivers at a company for longer periods of time do not necessarily provide the added benefit of decreasing driver crash risk. On the one hand, if these strategies lead to the retention of experienced drivers, then crash outcomes will improve as the carrier selects among existing employees with superior human capital. On the other hand, we find that driver retention in itself does not contribute to safety beyond certain driver characteristics observed here, such as age and experience. More broadly, however, the results suggest that human resource strategies based on efficiency wages, which reduce turnover, may have positive effects on crash outcomes only if they lead to an increase in driver age and experience. Furthermore, the results support the idea that individual pay also has an important motivational component for drivers in this sample, reflected in better safety outcomes.

While our primary interest lies with the relationship between pay and crash outcomes, it is also useful to examine the relationship between other variables and crash risk. Results for these variables can provide further insight regarding the connection between demographic, human capital, and occupational factors and driver safety. The coefficients on demographic variables tend to be consistent with prior expectations and existing empirical evidence (Blower 1996; Campbell 1991). The coefficients on AGE and its quadratic term suggest that as age increases, crash risk decreases but at a decreasing rate. Human factors research has long demonstrated declining driver performance as drivers pass the age of 50, and our results are consistent with that research (Brock 1996). For white drivers, the probability of being involved in a crash is 29.5% lower than the crash probability of drivers of other races. We speculate that the race variable is picking up differences in human capital characteristics across races and their effect on labor market outcomes. We detect no gender differences, a result that also is consistent with recent crash research for the population at large (Lourens et al. 1999).

Driving experience (EXPERIENCE), the only explicit measure of human capital we use, exhibits a quadratic relationship with respect to crash probability. While the estimates suggest that an inexperienced driver faces a crash risk similar to that of a driver who has slightly more than 31 years of driving experience, remember we control for other factors that may offest this effect. Human resource managers and policy-makers may want to keep this tradeoffs in mind as they consider the value of career retraining. Although we cannot explain definitively why crash risk initially decreases and then increases with driving experience, some researchers and trucking professionals have suggested driver complacency and loss of key driving skills may be responsible; drivers may forget some of what they have learned. We do control for driver age in the current study, and thus there may be other explanations for the relationship between crash risk and experience, independent of age.

Only two of the five occupational variables are statistically significant. The coefficient on MILESTODATE suggests that the greater the average miles driven up to each month, the higher the crash likelihood for the following month. We speculate that this can reflect how prior miles driven predicts future exposure and can also reflect the accumulation of fatigue, with these drivers "pushing their luck" by pushing the limits of their endurance over time. Likewise, the coefficient for MILES suggests that as the number of miles driven during a month increases, crash probability decreases. This result is not surprising, because crashes can occur at any time of a given month, and therefore on average MILES will tend to have low values for drivers who had a large crash during the month measured. A large crash leads to the loss of productive time resulting from reassigning the driver to a different truck, disability leave, and other factors that would lead to lower driving miles for a month in which a driver experienced a crash.

The coefficient on PriorCrashes suggests an association between the total number of crashes in which the driver was involved prior to an observed month and the probability of a crash during that month, all else held equal. The results suggest each previous crash increases the risk of a future crash by 16.7%. We surmise that this relationship would be stronger if we had information regarding at-fault crashes only. Nonetheless, this result supports the usefulness of using historical data on crash involvement to predict future crash risk, a common practice in the vehicular insurance industry.

The baseline hazard function contains additional information of interest, resulting from the time dummy variable coefficients for models 2 and 3 (Appendix 1). The coefficients suggest that the baseline crash hazard decreases the longer we observe a driver in our data set, even after controlling for the variables described previously. This means that the longer we observe a driver, the lower the crash probability, and it indicates the existence of characteristics correlated with lower crash risk beyond the characteristics measured here. For example, while gains in earnings may not influence safety indirectly through lower separation probabilities, improved non-wage benefits not observed by us would certainly lead to the retention of high-quality drivers. The baseline hazard may be detecting such a situation.

One final concern with these results is the possibility that unobserved heterogeneity in the sample is biasing the estimated coefficients toward negative duration dependence (Heckman and Singer 1985). This would be the practical consequence if, as we expect, recruiters hire drivers based on traits not observed by us, such as prior moving violations, prior employment history, character, or disposition, which can explain crash outcomes of drivers and which are not captured by our human capital proxy, BasePay.[7] We attempted to address the problem of unobserved heterogeneity by parameterizing a heterogeneity term that imposes a Gaussian mixture distribution and a gamma mixture distribution, as suggested by Meyer (1990) and implemented by Jenkins (1995). Unfortunately, neither of the parameterizations resulted in reliable estimates of the coefficients.[8]

Conclusions

Increases in trucking activity following economic deregulation of the industry in the 1980s and 1990s, the ratification of NAFTA, the development of Just-in-Time logistics, and increasing globalization have heightened the safety concerns regarding trucking operations. In this study we developed a model of truck driver behavior that incorporates effort and driver pay rates to examine the relationship between driver compensation and safety outcomes. The comparative statics of the model yielded ambiguous results and provided a testable hypothesis about how safety outcomes vary with changes in driver compensation. We then empirically examined this relationship using a sample of drivers who received a pay increase averaging 39.1% while working for a nonunion truckload, over-the-road firm. We used this rich disaggregate

[7]A solution to addressing the problem of heterogeneity, other than incorporating additional variables into the model, is to generalize the hazard rate specification to include an additive error-term ε_i at the individual level with mean zero and uncorrelated with the vector of explanatory variables, X_{it}. We can then assume the error term for the sample follows a parametric distribution, and by integrating it out of the likelihood function we may estimate a model. This requires imposing a distribution, such as normal, lognormal, or gamma, on failure-prone individuals, with a different distribution for those less "vulnerable" (see Jenkins 1995 and Lancaster 1990).

[8]It is possible that the numerical methods used in estimating the coefficients are not reliable due to the large number of individuals observed over time (2,368) and the high correlation that exists for each driver over time.

set of data on drivers involved in crashes and drivers not involved in crashes, observed for time periods ranging between 2 and 25 months, to estimate duration models of crash probability.

Results suggest that the pay increase influenced safety by modifying the behavior of current drivers. The data indicate that drivers had better crash records after the pay increase, when the analysis controls for demographic, occupational, and human capital characteristics. It is unclear whether the improvement in the drivers' safety records was the result of more careful driving, perhaps due to the increased opportunity cost of leaving the firm, a desire for less effort (a labor-leisure tradeoff), or other related behavioral adjustments. Although the precise causal chain through which such increases in safety occurred cannot be isolated using the current dataset, additional study of how drivers trade labor for leisure at different pay rates and under different operating circumstances may contribute to understanding the behavioral links between compensation, target earnings, and crash outcomes. It may also suggest alternate mechanisms through which policy-makers might encourage compliance with truck driver hours-of-service policies designed to reduce the incidence of truck-related highway crashes.

We find mixed evidence regarding the influence of human capital characteristics on crash outcomes. On the one hand, we determined that the relationship between crash risk and driving experience was U-shaped. At low driving experience levels, marginal increases in driving experience decreased crash risk. At high levels of experience, however, marginal increases in experience increased crash risk. These results lend support to the value of driver re-training programs. On the other hand, our proxy for other human capital characteristics, observed by the person making hiring decisions but not by us, did not correspond with crash outcomes. We attribute this to the fact that the firm hired drivers directly from training school, with little job-specific human capital.

Other empirical results of interest to human resource managers emerge from our model specification, allowing driver compensation to influence crash outcomes directly or, through its impact on driver separation probability, indirectly. We did not detect a statistically significant relationship between separation probability and crash outcomes, after controlling for variables such as driver age and experience. Thus, driver safety appears to be one of the benefits resulting from lower driver turnover, but only if the carrier retains older and more experienced drivers. By itself, a reduction in driver turnover does not appear to be related to improved crash outcomes.

More broadly, the results of the theoretical and empirical models provide insights relevant to current efforts to improve safety for trucking operations. First, the findings of this research with respect to pay and safety tend to support regulatory efforts to limit truck driver hours of work. Likewise, to the extent that drivers can increase their wages and earnings by driving faster, firms' policies to control the maximum speed of tractors through the use of on-board governors seem justified.[9] Finally, the empirical analysis also serves partly to explain how unions contribute to safety by negotiating better earnings and working conditions; union drivers in the trucking industry have better safety records than non-union drivers, even if with similar exposure levels. The 1997 National Master Freight Agreement per mile rate for 5-axle tandems is $0.453, slightly lower than the rate paid by J.B. Hunt to its higher-paid drivers after the pay increase.

Although this partial equilibrium analysis applies to J.B. Hunt only, other carriers may find its implications relevant, particularly regarding their driver-hiring practices. Comparisons between J.B. Hunt and other large firms in the sector

[9]See also Belzer et al. (2002) for a cross-sectional analysis demonstrating this effect.

suggest that J.B. Hunt is more representative of the average large firm than originally expected. Thus, to the extent that we can make generalizations about the truckload sector from this study, our findings suggest that although human capital characteristics can be important predictors of driver safety, motivational and incentive factors related to driver pay also play an important role in determining safety outcomes.

Appendix 1
Estimated Baseline Hazard for Separation and Crash Risk Models

	Model 1[a]		*Model 2*[b]		*Model 3*[b]	
Time	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
time3			0.154*	0.084	–0.271*	0.150
time4			–0.271*	0.150	–0.274	0.167
time5			–0.278*	0.168	–0.149	0.161
time6			–0.152**	0.162	–0.353**	0.174
time7	–1.418*	0.755	–0.360***	0.175	–0.544***	0.196
time8	–0.576	0.487	–0.543***	0.196	–0.689***	0.203
time9	–0.003	0.385	–0.687*	0.202	–0.303*	0.181
time10	0.029	0.401	–0.304**	0.181	–0.491**	0.198
time11	0.440	0.388	–0.492***	0.198	–0.630***	0.204
time12	0.086	0.421	–0.634***	0.204	–0.825***	0.229
time13	0.037	0.433	–0.821***	0.229	–0.630***	0.223
time14	–0.134	0.463	–0.624***	0.222	–0.903***	0.333
time15	0.343	0.435	–0.883**	0.330	–0.683**	0.306
time16	0.125	0.472	–0.672***	0.304	–1.332***	0.386
time17	0.450	0.457	–1.314***	0.383	–1.529***	0.405
time18	–0.043	0.502	–1.518***	0.404	–1.284***	0.353
time19	0.778*	0.446	–1.261***	0.349	–1.123***	0.278
time20	0.212	0.463	–1.107***	0.274	–0.737***	0.251
time21	0.031	0.483	–0.717***	0.248	–1.218***	0.286
time22	0.012	0.495	–1.196***	0.279	–1.337***	0.311
time23	–0.514	0.554	–1.313***	0.306	–1.531***	0.339
time24	0.440	0.490	–1.502***	0.333	–1.384***	0.325
time25	–0.042	0.587	–1.365***	0.322	–2.070***	0.430
time26	0.437	0.560	–2.041***	0.425	–2.005***	0.456
time27	–0.321	0.672	–1.982***	0.452	–1.602***	0.394
time28	0.194	0.551	–1.573***	0.388	–1.108***	0.338
time29	0.389	0.543	–1.091***	0.335	–1.616***	0.412
Time30	0.290	0.567	–1.602***	0.410	–1.634***	0.439

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

Notes: time6 is the baseline category for the separation risk model (model 1). The variables time1 and time2 are the baseline category for the crash models (models 2 and 3).

[a]Proportional separation risk probability model.

[b]Proportional crash risk probability model. For details, see Meyer (1990). Standard errors of crash models corrected using White's robust variance estimator (White 1980).

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