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## Statistical Analysis Of The Effect Of Work Conditions On Safety And Health In The U.s. Long-Haul Trucking Industry: Evidence From The Niosh Survey Data

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**STATISTICAL ANALYSIS OF THE EFFECT OF WORKING CONDITIONS ON  
SAFTY AND HEALTH IN THE U.S. LONG-HAUL TRUCKING INDUSTRY:  
EVIDENCE FROM THE NIOSH SURVEY DATA**

by

**TAKAHIKO KUDO**

**DISSERTATION**

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

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2019

Major: ECONOMICS

Approved By:

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Advisor

Date

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Completing my journey to a Ph.D. degree, I cannot help recalling a passage from Jane Eyre written by Charlotte Bronte: 'Well has Solomon said--"Better is a dinner of herbs where love is, than a stalled ox and hatred therewith." I would not now have exchanged Lowood with all its privations for Gateshead and its daily luxuries.' The passage precisely describes what I feel leaving this department. How enjoyable was honorable poverty at this program! Thank you, Wayne State. Good bye, Detroit.

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## **CHAPTER 1 INTRODUCTION**

### **1. Background and Motivation**

#### **1.1. Truck Driver Safety and Work Conditions**

Truck drivers have a high probability of suffering from work place hazards. According to Smith (2015), 756 truck drivers died due to work-related injuries in the U.S., and more than 65,000 private sector truck drivers suffered from work-loss occupational injuries in 2012. Smith also points out that truck drivers are more than seven times more prone to fatal occupational injuries than the average American worker. In the trucking industry, fatal occupational injuries result mainly from transportation incidents, typically highway crashes.

Scholars have tried to analyze the causes of truck crashes. From an economist's perspective, the relationship between drivers' compensation and safety performance is a particular interest. The theory of human capital states that workers' compensation relates to their human capital, in other words, job-related skills (Becker, 1964). Because of this, employers need to offer higher compensation to hire more skilled workers. In the context of the trucking industry, the theory of human capital predicts that more highly paid drivers have higher driving skills. This suggests that more highly paid drivers may have higher safety performance. Moreover, higher compensation means larger opportunity cost of poor safety performance. Since truck crashes can damage the freight and certainly make it late for delivery, trucking firms may fire drivers when they cause truck crashes. In such circumstances, highly compensated drivers lose more money and benefits. This being the case, higher compensation may motivate drivers to operate trucks more safely.

In addition, higher compensation may encourage drivers to work long hours if income effect is strong enough. As Belzer and Sedo (2018) show, drivers work fewer hours in response to a wage increase if their pay rates are sufficiently high. On the other hand, studies indicate that long work hours can harm drivers' road safety by shortening sleep hours and intensifying fatigue. Lin et al. (1993) find that longer work hours are associated with a higher probability of truck crashes. If so, higher compensation may contribute to lowering the risk of crashes by reducing drivers' work

hours. Monaco et al. (2005) observe that short sleep hours, which are associated with long work hours, increase the risk of truck crashes. Consistent with Monaco et al., Crum and Morrow (2002) show that the difficulty of finding a place to rest intensifies the subjective perception of fatigue, which implies that that long work hours can be a primary factor of fatigue.

In particular, Rodríguez et al. (2003) and Rodríguez et al. (2006) test the hypothesis that drivers who are more highly paid are less likely to have truck crashes. In these studies, they use the data obtained from a trucking firm, J.B. Hunt, which experienced an increase in drivers' pay rates. They interpret the increase in pay rates as a natural experiment and examine its effect on the probability of truck crashes. They find that the increase in pay rates decreased the probability of crashes among drivers in J.B. Hunt.

## **1.2. Truck Drivers' Health and Work Conditions**

Studies demonstrate that truck drivers seem to have high health risks relative to other jobs. Sieber et al. (2014) and Thiese et al. (2015) observe that truck drivers have the higher rate of obesity than the general population. Sieber et al. show that 69 percent of U.S. truck drivers are obese, compared with 31 percent of the U.S. adult population. Thiese et al. show that 53 percent of truck drivers are obese. Saltzman and Belzer (2002) write that truck drivers also face other health risks regularly, such as diabetes and high blood pressure.

A suspected cause of truck drivers' poor health is fatigue. A panel convened by the National Academy of Science, Engineering, and Medicine (2016) indicates that fatigue may cause certain reversible physiological changes to human bodies, which can increase a number of health risks. Although there is little standard measure to quantify fatigue, work hours are used relatively commonly as a proxy for fatigue (National Academy of Science, Engineering, and Medicine, 2016). Dembe et al. (2005) show that workers who work longer than 12 hours a day or 60 hours a week have significantly higher risk of job hazards including occupational illnesses. Saltzman and Belzer (2002) also suggest that long work hours and sleep loss can increase the risk of certain illnesses including high blood pressure and diabetes.

Indeed, truck drivers' work is characterized by long work hours. According to a survey conducted by the University of Michigan Trucking Industry Program (UMTIP), truck drivers' mean and median weekly work hours are 65.7 hours and 62.0 hours, respectively (Belman et al., 2004). Compared with the national average of less than 40 hours, 60 hours of weekly work is abnormally long (Bureau of Labor Statistics, 2010). Such long work hours can potentially fatigue drivers and deteriorate their health. From the perspective of health economics, hours of resting to recover from fatigue is health investment, and households always face a tradeoff between health investment and income due to time constraints. Judging from their work hours, it seems that the average driver invests little time in health to earn higher income.

### **1.3. Truck Drivers' Work Hours and Compensation**

The previous subsections mentioned that truck drivers tend to work long hours, and excessively long work hours may harm truck drivers' safety and health. Why do truck drivers work such long hours? The paper that analyzes this question is by Belzer and Sedo (2018). They hypothesize that truck drivers have a target level of income which they struggle to achieve. Until drivers achieve the target level of income, they work as strenuously as possible. Once drivers achieve the target level of income, they begin to work fewer hours. As a result, drivers work fewer hours when their mileage rate is sufficiently high. Belzer and Sedo call this mileage rate a "safe rate" because research has linked long work hours with higher safety risk, and this pay rate is associated with limitations in working time. Belzer and Sedo's empirical analysis supports this hypothesis. Their result is also consistent with Camerer et al. (1997), who find that taxi drivers work fewer hours when they are more highly paid.

## **2. Contribution**

### **2.1. How Does Truck Drivers' Compensation Affect Safety?**

Although Rodríguez et al. (2003) and Rodríguez et al. (2006) reveal that higher mileage pay rates are associated with higher safety performance, these studies have several limitations. These studies do not control for fringe benefits, which can potentially relate to drivers' human

capital and safety incentives. Indeed, some studies imply that fringe benefits may affect drivers' human capital accumulation and safety incentives. Werner et al. (2016) argue that trucking firms which offer retirement plans for employees may have higher safety performance in comparison with those which do not offer retirement plans. Using firm level data, Rodríguez et al. (2004) find that drivers' average contribution to employment-based health insurance is positively related to safety performance of trucking firms. Both Werner et al. (2016) and Rodríguez et al. (2004), however, rely on firm level data, which are aggregated for each trucking firm. Therefore, these studies do not consider individual differences among drivers. For example, individual drivers' compensation can be different from each other even in the same firm, depending on their human capital. In the first paper, I analyze, using individual level data, how cash compensation and fringe benefits affect truck drivers' safety performance. Thus, the second paper provides a different implication from firm level studies on how drivers' entire compensation package affects their safety performance.

## **2.2. The Effect of Truck Drivers' Compensation on Safety Performance**

In the previous section, I mentioned that long work hours can increase health risks, and truck drivers tend to work excessively long hours. However, few studies address the linked relationship between these work hours and health specifically in the trucking industry, using regression analysis with ample control variables. Certainly, researchers have studied the linkage between hypertension and long work hours in general, but they do not examine the same linkage among truck drivers. Since truck drivers work much longer hours than the general population, it is important to examine how their work hours are related to hypertension. Using the NIOSH survey data, I investigate the linkage between work hours and hypertension with many controls.

## **2.3. The Effect of Truck Drivers' Non-Driving Pay on Work Hours: Evidence from the NIOSH Survey Data**

Belzer and Sedo (2018) imply that drivers may have a target level of income which they try to achieve and that they work significantly fewer hours after achieving the target. As a result,

drivers' labor supply curve is backward-bending. The third paper in the current dissertation examines this hypothesis from a different perspective. In the third paper, I analyze how non-driving pay, a unique compensation practice in the trucking industry, affects drivers' work hours. In general, truck drivers are assigned non-driving duties in addition to driving trucks. Typically, non-driving duties include loading, unloading, waiting for dispatch directions, waiting to load or unload, and performing ancillary task like regulatory and business requirements such as record-keeping and both maintenance and repair. Non-driving pay is the remuneration for such non-driving duties. Importantly, some trucking firms pay for non-driving work while others do not. Moreover, if firms pay for non-driving work, they remunerate drivers only for a part of it. For example, some firms may pay for loading and unloading (often in piecework form), but they may not pay for other non-driving duties.

If non-driving duties are unpaid, drivers need to pay a higher opportunity cost of time while doing non-driving duties. To compensate for the loss of income, drivers who are not paid for non-driving work may work longer than those who are paid. This hypothesis appears to be more realistic given that drivers have a target level of income, as Belzer and Sedo (2018) discuss. Belzer and Sedo certainly show that the length of unpaid time increases drivers' total work hours significantly. However, this may be due to the mathematical truism that total work hours increase because unpaid work hours simply add extra work hours. Hence, the fact that unpaid work hours increase work hours may not necessarily imply that the absence of non-driving pay induce them to work longer hours. My third paper fills this gap by examining the direct linkage between non-driving pay and work hours. Moreover, the NIOSH survey data collected in 2010, which I use, are the most recent data on truck drivers' occupational safety with various control variables. Since the data which Belzer and Sedo use were collected in 1996-1997, they may be slightly obsolete.

### **3. Data**

In the three papers, I commonly use the National Survey on Long Haul Truck Drivers (NIOSH survey), which collected by National Institute of Occupational Safety and Health (NIOSH)

in the Centers for Disease Control and Prevention (CDC) in 2010. The NIOSH survey is the most recent data on truck drivers' work conditions, safety and health. The dataset contains drivers' demographic information. The NIOSH survey covers only long-haul truck drivers. Short-haul and local truck drivers are not covered by this survey.

#### **4. Significance**

As stated above, truck drivers have a high risk of occupational injuries and illnesses, both of which threaten their life and quality of life. Truck drivers' safety and health can also affect the welfare of the public. The social cost of truck crashes is high. On average, the cost of crashes by a truck with a gross vehicle rating of 10,000 pounds is \$91,112 per truck involved (U.S. Department of Transportation, 2007). Treatment of hypertension costs \$1,131 per person annually (Balu and Thomas, 2006), which does not appear to be negligible.

Drivers' poor health may also threaten road safety because these two issues may be related. In other words, drivers' health conditions affect not only drivers themselves but also the public welfare. Ronna et al. (2016) show that truck drivers with cardiovascular illnesses, which are related to hypertension, have a significantly higher risk of crashes. Anderson et al. (2012) find that obesity is also associated with the higher probability of crashes. Therefore, it is important to frame the public policy to enhance drivers' safety and health. Analyzing what part of work conditions affect drivers' safety and health is a prerequisite for investing an effective countermeasure to this problem. This dissertation is an attempt to analyze this prerequisite and call for further research on it.

## **CHAPTER 2 THE EFFECT OF TRUCK DRIVERS' COMPENSATION ON SAFETY**

### **1. Introduction**

Truck driving has a high incidence of occupational hazards. In a recent study, Smith (2015) mentions that during 2012, 756 truck drivers died due to work-related injuries in the United States (U.S.), and more than 65,000 private sector truck drivers suffered from work-loss occupational injuries. Smith also writes that truck drivers have more than seven times higher probability of having fatal occupational injuries than the average U.S. worker. Most of these fatal occupational injuries are caused by transportation incidents, typically highway crashes.

A number of safety studies have tried to analyze the determinants of truck drivers' safety. Researchers have analyzed the relationship between truck drivers' compensation and safety (Rodríguez et al., 2004; Rodríguez et al., 2003; Rodríguez et al., 2006; Williams and Monaco, 2001; Nafukho et al., 2007). On several grounds, economic theory also suggests there can be a relationship between driver compensation and safety. First, efficiency wage theory suggests that employers need to pay greater than the market-clearing compensation to prevent workers from shirking. That is, more highly compensated workers are more motivated to work diligently for employers and are less likely to shirk. Hence, when worker labor is unobservable and when employers find it difficult to supervise workers closely, they may improve performance by offering greater than the market-clearing compensation. Likewise, more highly compensated truck drivers may have greater incentive to operate trucks safely.

Second, greater compensation attracts more productive job applicants. Workers with greater human capital may be more productive and have superior job skills, which allows firms to pay them higher compensation (Becker, 1964). That is, if employers do not pay sufficient compensation, high human capital workers may choose other jobs. In the case of trucking, if drivers' compensation is not high enough, drivers with higher human capital may choose other jobs with similar qualifications. As a result, only low quality workers may apply for truck driver jobs. Higher



compensation prevents this situation by encouraging better job candidates to seek careers in trucking.

This paper investigates how compensation, including employment benefits, affect truck drivers' safety. As a proxy for safety, I employ moving violations which truck drivers commit. This paper reveals that truck drivers to whom companies provide employment-based health insurance are less likely to commit moving violations than those who do not have such insurance. We use the National Survey of Long Haul Truck Drivers, which is the newest national survey data on long-haul truck drivers' occupational safety and health, and which contain data on fringe benefits.

## **2. Related Literature**

A number of papers analyze the effect of drivers' compensation on truck driver road safety. Rodríguez et al. (2003) and Rodríguez et al. (2006) examine how employee truck drivers' pay affects their road safety. In these studies, the authors use drivers' individual data in a large trucking firm, J.B. Hunt. The data set includes the periods before and after J.B. Hunt raised pay rates to its drivers. The authors interpret the change in pay rates as a natural experiment. Employing negative binomial and zero-inflation models, they find that higher pay for drivers can diminish the probability of highway crashes. Using a truck-stop-based survey conducted by the University of Michigan Trucking Industry Program (UMTIP), Williams and Monaco (2001) also find that drivers with higher mileage pay rates are less likely to be involved in accidents or commit Hours-of-Service (HOS) violations. Monaco and Williams (2000) and Monaco et al. (2005) find that truck drivers' annual wages are negatively related to the probability of falling asleep while driving, which can raise the probability of truck crashes. On the other hand, Nafukho et al. (2007) find that there is a positive relationship between truck drivers' income and crashes. However, since income can increase as a result of increasing work hours, it is hard to conclude from this study that high compensation increases the incidence of crashes. Most recently, Belzer and Sedo (2018) use the UMTIP survey data to estimate drivers' propensity to work long hours, which is associated with

safety. Belzer and Sedo reveal that drivers' work hours can be predicted by their pay rates. They conclude that drivers work fewer hours when their pay rates are sufficiently high.

The effect of fringe benefits on safety performance in the trucking industry has been examined less thoroughly, even though fringe benefits are an important part of workers' compensation. Rodríguez et al. (2004) employ firm level data from the three sources to analyze the safety performance of truck firms.<sup>1</sup> The authors do not find a significant relationship between average mileage pay rate and safety performance of trucking firms. However, the authors observe that drivers' average contribution to employment-based health insurance is positively related to safety performance of trucking firms. That is, firms in which drivers pay higher insurance contributions have higher safety performance. In general, high quality health insurance charges high insurance premiums on the insured and drivers may forego a significant part of their compensation to buy good health insurance. If so, risk-averse truck drivers may choose to work in firms that provide high quality health insurance. Since risk-averse drivers are less likely to cause crashes, firms that pay drivers more, in the form of health insurance, may have superior safety performance.<sup>2</sup> Clearly, more research is needed.

Werner et al. (2016) also employ firm level insurance claim data to analyze the effects of retirement plans on the safety performance of trucking firms. They measure the safety performance of each firm by its property and liability insurance cost per mile driven. This is based on their assumption that firms with worse safety records pay higher insurance premia. The result suggests that trucking firms which offer retirement plans for drivers may pay a lower insurance cost. This implies that firms with retirement plans have superior safety performance. They argue that

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<sup>1</sup> The data on truck crashes come from the Motor Carrier Management Information System (MCMIS) collected by the U.S. Department of Transportation (DOT). The data on financial performance and firm size come from the Motor Carrier Financial and Operating Statistics (F&OS) Program by the U.S. Department of Transportation's Bureau of Labor Statistics (BLS). The data on compensation come from compensation data collected by Signpost, Inc.

<sup>2</sup> Nonetheless, Rodríguez et al. do not have the data on the quality of health insurance of each firm. Hence, they note that this conclusion is not definitive.

providing retirement plans may attract truck drivers with specific types of preferences. That is, drivers who prefer to invest money in a retirement plan rather than spend it immediately, in the form of wages, may be more risk-averse as Lazear (1990) says. Intuitively, such risk-averse drivers are less likely to have crashes.

The contribution of this current paper is to analyze the effect of truck drivers' compensation on safety by using individual level data on truck drivers. In this paper, compensation includes fringe benefits as well as cash. Rodríguez et al. (2004) and Werner et al. (2016) analyze firm-level data instead of individual drivers' data. By the nature of firm level data, these studies cannot consider individual difference among drivers. For example, drivers' wages are different even in the same firm, but the difference in individual drivers' wages are ignored in the firm level data analysis. Other studies cited above are based on individual level data (Rodríguez et al., 2006; Rodríguez et al., 2003; Monaco and Williams, 2000; Williams and Monaco, 2001; Nafukho et al., 2007). However, these studies do not study the effect of fringe benefits thoroughly. These studies mainly focus on cash compensation. Certainly, Belzer et al. (2002) use individual level data and drivers' health insurance status, but they analyze other fringe benefits. Moreover, the data that they employ were collected between 1997 and 1999. The current paper provides new evidence with newer data on how compensation including cash and fringe benefits are related to truck drivers' safety.

### **3. Theory**

Belzer (2012) provides theoretical explanations for the relationship between truck drivers' safety and compensation. Reviewing the literature of labor economics, Belzer argues that truck drivers' compensation can be linked with their driving safety because compensation is related to professional drivers' human capital and safety incentives. He says that one of the important arguments is based on the efficiency wage theory, which was proposed by Yellen (1984).

The efficiency wage theory assumes that the productivity of firms depends on worker effort. To elicit effort when effort is unobservable, businesses may need to offer above market-clearing wages. Because workers sometimes are hard to observe, businesses face a special principal-agent

problem. Belzer and Swan (2011) suggest that to avoid safety problems in drayage, these firms may pay an efficiency wage that compensates workers to elicit greater safety and attention to security. When their current job pays better than the next-best alternative, workers lose more money and suffer future career damage when they are fired because of a safety or other performance problem. Thus, highly paid workers are less likely to shirk and are more likely to drive safely.

In the context of the trucking industry, efficiency wage theory predicts that higher compensation may encourage truck drivers' safety performance because their safety records follow them and better jobs go to safer drivers. Safety performance presumably is important for the productivity of trucking firms since they need to pay for the damage caused by crashes and crashes lead to damaged freight and late deliveries. Research suggests that the net present value of experienced, better paid truck drivers provides firms with positive return on investment, net of their higher compensation (Faulkner and Belzer, 2019).

Efficiency wages may also improve the quality of truck driver job candidates. Employers compete in the labor market to recruit capable employees. To hire superior candidates, employers need to offer higher wages than their competitors. In the labor market, trucking firms also compete with firms in other industries like the manufacturing and construction industries, which do not require a high level of education. Although manufacturing jobs are lower paid in general (Monaco and Brooks, 2001; Monaco et al., 2006), some blue collar jobs, such as oil rig workers, are paid relatively well. To employ high quality workers, trucking firms need to offer wages high enough to compete with such jobs in other industries.

Originally, the theory of efficiency wage did not necessarily consider non-wage compensation or fringe benefits. However, the theory can be applied to a broad sense of compensation other than wages because fringe benefits are an important part of the compensation package and motivate them to perform well. Indeed, conducting a survey for selected trucking firms, Min and Lambert (2002) find that fringe benefits as well as cash compensation are an important

factor for drivers' retention in trucking firms. This finding suggests that the impact of fringe benefit on drivers' human should not be ignored.

The shape of the labor supply curve may also contribute to truck driver safety. Belzer and Sedo (2018) find that truck drivers' work incentive is determined by pay rate. They show that truck drivers' labor supply curve is backward bending. Thus, when pay rate is sufficiently high, drivers work fewer hours due to a strong income effect relative to the substitution effect. This implies that high compensation can prevent truck drivers from working excessively such that they become fatigued and have crashes. Previous studies show how fatigue is an important factor of crashes are shown in the National Academy of Science, Engineering, and Medicine (2016).

#### **4. Data**

This paper uses the National Survey on Long Haul Truck Drivers, conducted by the National Institute for Occupational Safety and Health (NIOSH) of the Centers for Disease Control and Prevention in 2010. The survey collected data on long-haul truck drivers' occupational safety and health conditions. A similar survey on long haul truck drivers was conducted by the University of Michigan Trucking Industry Program (UMTIP), although that survey focused more broadly on driver work-life issues of interest to labor economists. The UMTIP data set may be slightly outdated since it was conducted in 1997 (Belman et al., 2004).

Long-haul truck drivers are drivers of trucks having a capacity of at least 26,000 pounds Gross Vehicle Weight (GVW), and freight delivery routes requiring them to take at least one mandatory ten-hour rest period away from home during each delivery (NIOSH, 2015; Chen et al., 2015). Drivers who have driven less than 12 months in their careers are excluded from the NIOSH survey (Chen et al., 2015).

The NIOSH survey includes both employee drivers' and owner operators' data, and employee drivers account for roughly 60 percent of the sample. We use only employee drivers' data since owner operators responsibilities and working conditions are different from those of employee drivers. Owner operators finance all or most of operating cost by themselves (Belzer,

2009; Hooper and Murray, 2017). The operating cost includes, but is not limited to, capital cost, fuel and maintenance cost, insurance, tolls and electronic devices (for example, satellite receivers, transmitters and transponders). In addition to these costs, owner operators often need to pay for licenses and permits. Such unobserved differences in economic pressures and working conditions may disturb the result, so we limit the sample to employee drivers. Eliminating the observations with missing data, we obtain the sample of 704 employee drivers.

## **5. Descriptive Statistics**

Table 2-1 shows the descriptive statistics of continuous variables. Figure 2-1 shows the histogram of the number of moving violations. This shows that 80 percent of drivers have no moving violations. The maximum number of moving violations is five, which suggests that moving violations are relatively rare events, which approximately follow Poisson or negative binomial distribution. The mean and median incidence of moving violations per million miles is 3.46 and 0 respectively.

The mean and median annual income are roughly \$52,500 and \$50,000 respectively, which is higher than other jobs that do not require higher education. However, long-haul truck drivers average about 3,275 hours of work per year, so the high earnings come at a price. The mean and median of annual mileage driven are 114,716 miles and 120,000 miles respectively. By using the annual mileage driven and income, we calculated the pay per mile driven. The mean and median pay rates are \$0.69 and \$0.43 dollars respectively. This estimation of pay per mile driven likely is biased upward, however, because drivers' income in the NIOSH survey includes income from non-driving work, such as loading and unloading, while, actual pay per mile driven does not include remuneration for non-driving work. While the median driver is not paid for any of this work, nearly half are paid flat rates (piecework) for some non-driving tasks.

Figure 2-1 Distribution of the Numbers of Moving Violations

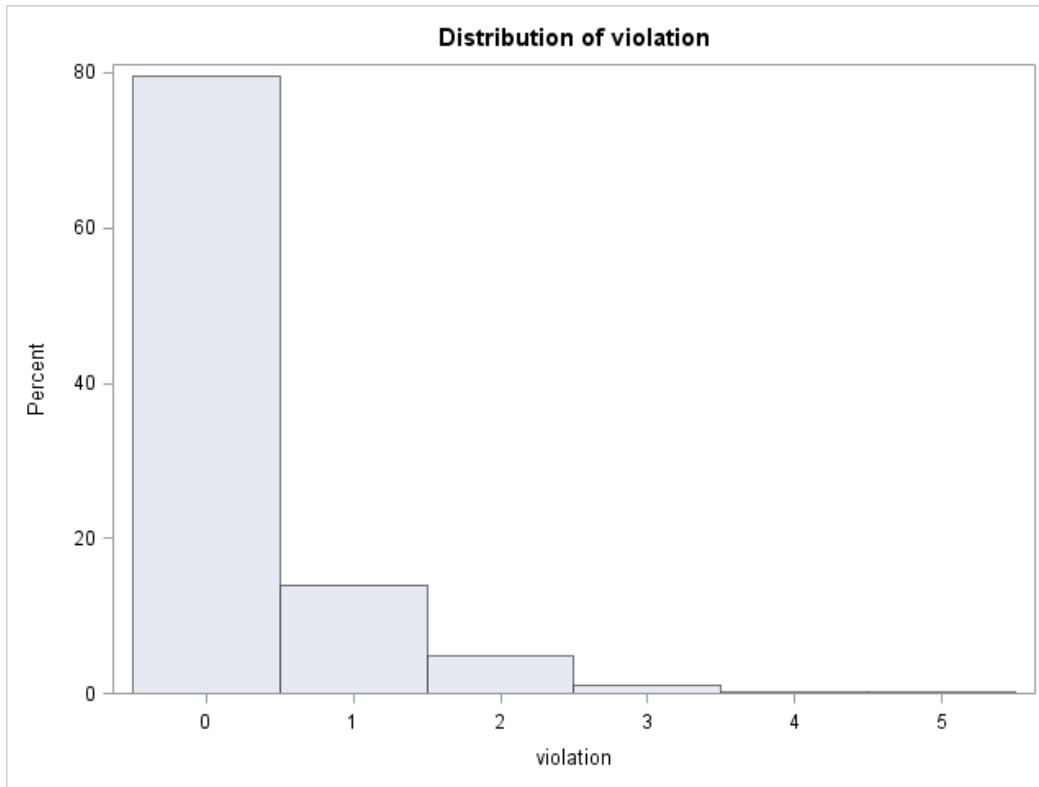


Table 2-1 The Descriptive Statistics of Continuous Variables

Variable	Mean	Median	Std Dev
Moving Violations	0.29	0	0.67
Annual Income	52516.81	50000.00	29347.34
Annual Mileage Driven	114715.8	120000.00	42235.63
Annual Work Weeks	49.99	52.00	4.80
Weekly Non-driving Duty Hours	15.11	10.00	16.87
Moving Violations per 1,000 Miles Driven	3.40	0	14.70
Pay/Mile	0.69	0.43	1.52

Notes: Moving Violations are those during 12 months prior to the survey. Pay/Mile is given by Annual Income/Annual Mileage Driven.

Table 2-2 shows the descriptive statistics of indicator variables. Approximately, 63 percent of employee drivers answer that their employers or union offer employment-based health insurance. In the NISOH survey data, the original questions on health insurance are “Does your employer or union offer you health insurance?” and “Are you covered by any type of health insurance or health care plan? Include coverage provided by your spouse or partner’s plan.” For drivers who are offered employment-based health insurance but covered by no health insurance, we treat them as not having

employment-based health care. It is still possible that drivers who are offered employment-based health insurance and have some form of health insurance may be covered by other health insurance, such as their spouses' health insurance. However, the information to identify such drivers is not available in the NIOSH survey data.

Approximately 46 percent of drivers are provided retirement benefit by their employers or union: either pension or 401K retirement plan or both. It should be noted that the NIOSH survey does not contain clear information about whether drivers who answered that they are provided pension or 401K retirement plan are vested. Therefore, a number of these drivers are still not vested for pension or 401K retirement plan though their employers provide it. Moreover, the employers' contribution to a 401K retirement plan is unknown in the NIOSH survey. Though it is likely many employers make some contribution as they provide a retirement plan, it is totally unknown from this survey how much they contribute.

Non-driving Pay is an indicator variable which equals one if drivers are paid for non-driving duties and equals zero otherwise. Approximately half of long-haul truck drivers (48.34 percent) are paid for such non-driving duties, according to the NIOSH survey data. This percentage seems to be consistent with the UMTIP survey data. In the UMTIP survey data, the non-driving duty which is paid most frequently is loading and unloading: 46 percent of non-union drivers are paid for loading and unloading (Belman et al., 2004).<sup>3</sup>

Non-driving duties which are not paid can make drivers work for longer hours to compensate for the loss of income. It may intensify their fatigue and probability of crashes. Moreover, drivers who are not paid for non-driving duties may feel less loyalty to their employers, which can diminish their incentive for safe driving and increase the probability of turnover.

Even if truck drivers are remunerated for non-driving labor, it does not mean that trucking firms remunerate them for all of their non-driving duties. For instance, it is possible that drivers are

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<sup>3</sup> Again, I refer to non-union employee drivers because over 95 percent of the sample in the current study are non-union employee drivers.



remunerated for loading or unloading duties even though they are not remunerated for waiting for dispatchers' directions; commonly, long-haul truck drivers are paid by the stop (piecework) rather than by the hour, thus making their effective hourly compensation rate contingent on other unpaid time. Indeed, UMTIP found that 44.7% of truck drivers are remunerated for loading and unloading, but only 21.2% of truck drivers are remunerated for dropping and hooking (Belman et al., 2004).<sup>4</sup> This fact suggests that there is a large difference in the percentage of drivers who are paid for each non-driving duty, depending on the types of tasks and employers.

Unfortunately, there is no information in the NIOSH survey data on what parts of non-driving duties are remunerated. The partial or total amount of non-driving pay is also not known in the NIOSH survey data. Thus, I use an indicator variable to distinguish drivers who are remunerated for non-driving duties at least partially from those who are not remunerated at all.

Long-haul trucking comprises the less-than-truckload (LTL) and truckload (TL) sectors. The LTL sector handles relatively light freight shipments (150-10,000 pounds per shipment) and carries multiple clients' freight shipments on one truck. The TL sector carries relatively heavy freight shipments (over 10,000 pounds per shipment) and typically carries a single owner's freight on one truck (Burks et al., 2010). In this table, LTL is an indicator variable which equals one if drivers work in the LTL sector and equals zero otherwise. Approximately, 20 percent of drivers work in the LTL sector.

Team is an indicator variable which equals one if drivers operate trucks as team drivers and equals zero otherwise. Some truck drivers drive trucks with another driver. While one driver is operating a truck, the other driver is sleeping. This work practice is called "team driving". Roughly 14 percent of drivers work in teams.

Union is an indicator variable which equals one if drivers are union members and equals zero otherwise. Only 2.6 percent of drivers are union members in the NIOSH survey. According

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<sup>4</sup> These numbers are not additive since they are counted as separate pieces of work. That is, some drivers are paid for all of these duties, but others are paid for only one of them or neither.

to Hirsch and Macpherson (2018), the proportion of union membership among truck drivers (SOC 9130) was 12.0 percent in 2010, which is higher than in the NIOSH survey. The difference may be explained by the fact that unlike the NIOSH survey, Hirsch and Macpherson include driver/sales workers and local and short-haul truck drivers in addition to long-haul truck drivers.

High School is an indicator variable which equals one if drivers hold high school diplomas or equals zero otherwise. In the original NIOSH survey data, drivers' history of education is classified more in detail: 8<sup>th</sup> grade or less, 9<sup>th</sup>-12<sup>th</sup> grade (no diploma), GED or equivalent, high school graduate (diploma), some college (no degree), associate degree (vocational), associate degree (academic), college degree or higher. Relatively small proportions of drivers have college or associate diplomas while a relatively large number of drivers finished high school but did not enter college or dropped out of high school. Therefore, we converted educational background into an indicator variable for high school diploma. Roughly, 80 percent of drivers have high school diploma.

White is an indicator variable which equals one if drivers are white or zero otherwise. In the original NIOSH survey, ethnicities are categorized more in detail, such as white, African, Asian, Hispanic and many other ethnic groups. However, white drivers account for 70% of all drivers, so other ethnic drivers are minor in terms of demographic proportions. Type is an indicator variable which equals one if the truck type is an enclosed van, which occupies approximately half of the trucks in the sample. Male is an indicator variable which equals one if drivers are male and zero otherwise. Approximately 93 percent of drivers are male.

Table 2-2 Descriptive Statistics of Indicator Variables

Variable	Percentage
Retirement Benefit	46.45
Health Insurance	62.93
Non-driving Pay	48.01
Less-than-Truckload	20.17
Team	13.78
Enclosed Van	50.28
Married	52.27

White	70.6
Male	93.07
Union	2.56
High School Diploma	78.84

Note: Retirement Benefit equals one if drivers are provided pensions by labor union or employers and equals zero otherwise. Health insurance equals one if drivers are provided health insurance by their employers and equals zero otherwise. Some drivers are offered health insurance by their employers, but they answer that they have no health insurance. This implies that they do not accept employment-based health insurance. These drivers are counted as health insurance=0 since these drivers are not covered by employment health insurance. That is, I do not treat these drivers as being provided employment-based health insurance. Non-driving pay equals one if drivers are paid for non-driving duties at least in part and equals zero otherwise. If non-driving pay is paid, drivers are not necessarily paid for all non-driving duties. As long as they are paid for some non-driving duties, Non-driving equals one. Less-Than-Truckload equals one if drivers work in the Less-Than-Truckload sector and zero otherwise. Team equals one if drivers are team drivers and zero otherwise. Enclosed Van equals one if drivers operate enclosed vans and zero otherwise. Married equals one if drivers are married and equals zero otherwise. White equals one if drivers are white and equals zero otherwise. Union equals one if drivers are union members and zero otherwise. High School Diploma equals one if drivers have high school diploma and equals zero otherwise.

## 6. Analysis

The most ideal candidate to proxy safety is the number of crashes which drivers have experienced during a certain period. Compared with other safety outcomes, truck crashes are particularly life-threatening and quite observable. Indeed, analyzing the effect of drivers' mileage pay rate on safety, Rodríguez et al. (2003) and Rodríguez et al. (2006) use the number of crashes that drivers experienced though the definition of crashes in these studies are different from that in the NIOSH survey data. Rodríguez et al. (2003) and Rodríguez et al. (2006) count crashes which involve \$1,000 of actual or estimated damages. The NIOSH survey data uses DOT reportable crashes, which cause one of the following consequences: a fatality; an injury to a person which requires immediate medical treatment away from the scene of the crash; or disabling damage to a vehicle, which needs to be towed.

Using the number of crashes in the NIOSH survey also can be problematic because the NIOSH survey asks drivers the number of crashes which drivers have experienced during their professional life (not just during a specified period). On the other hand, the data on compensation and control variables are those at the time the NIOSH survey was conducted. Since one can assume

that truck drivers' compensation has changed over time, the use of the number of crashes can yield a misleading result.

We therefore use the number of moving violations instead of crashes. In the NIOSH survey, drivers were asked to report the number of moving violations during the preceding twelve months. Some previous studies also employ moving violations as well as crashes as a proxy for safety performance (Monaco and Williams, 2000). Indeed, Murray et al. (2006) find that certain types moving violations are positively associated with crashes among truck drivers. Hence, moving violations seem to be a decent proxy of safety.

Using moving violations as the dependent variable, we construct the following Poisson and negative binomial regressions:

$$\begin{aligned} \ln[E(Y|X)] = & \alpha + \beta_1 \times \ln(\text{Pay/Mile}) + \beta_2 \times \text{Nondriving Pay} \\ & + \beta_3 \times \text{Health Insurance} + \beta_4 \times \text{Retirement Benefit} \\ & + \beta_5 \times \text{Union} + \beta_6 \times \text{Work Weeks} + \beta_7 \times \text{LTL} + \beta_8 \times \text{Married} \\ & + \beta_9 \times \text{Team} + \beta_{10} \times \text{Enclosed Van} \\ & + \beta_{11} \times \text{High School} + \beta_{12} \times \text{White} + \beta_{13} \times \text{Male} \\ & + \beta_{14} \times \text{Experience} + \beta_{15} \times (\text{Experience})^2. \end{aligned}$$

In the equation above,  $Y$  is the number of moving violations during the last 12 months prior to the survey, and  $X$  is the vector of all independent variables on the left-hand side of the equation. In general, the Poisson and negative binomial models are used when dependent variables are count variables and equal zero for many subjects. Section 5 shows that in the NIOSH survey data, roughly 80 percent of the subjects have zero moving violation, and the maximum number of moving violations is five. Such characteristics of the data justify the use of these models. The Poisson model assumes that the conditional mean of  $Y$  equals the conditional variance of  $Y$ , but the negative binomial model does not assume that the conditional mean and variance are equal. The negative binomial model is preferred when the Poisson model suffers from over-dispersion. Observing a

Pearson chi-square statistic, we test the null hypothesis that the Poisson model does not suffer from over-dispersion. If the hypothesis is rejected, the negative binomial model is preferred. Moreover, using adjusted Vuong and Clark sign tests, we examine whether the zero-inflated Poisson or zero-inflated negative binomial model is preferred to the Poisson or negative binomial model.

On the left-hand side,  $\ln[E(Y | X)]$  represents the expected value of the number of moving violations committed during the twelve months. On the right-hand side,  $\ln(\text{Mileage Pay})$  represents the natural logarithm of mileage pay, which is computed by dividing drivers' annual income by annual miles driven. Mileage pay rates computed as such may not always be accurate. In the NIOSH survey, both annual income and miles driven may suffer from measurement errors since drivers are not asked to check their written record of income or miles driven. The other independent variables are defined in the same way as section 5 mentioned. The reasons why these variables should be included in the regression are explained below. The linear specification for mileage pay rate follows Rodríguez et al. (2003); Rodríguez et al. (2006) and is based on the intuition that human capital monotonically increases with pay, as human capital theory implies.

**Non-driving Pay:** The variable is included because unpaid non-driving duty hours can induce drivers to work longer to compensate for the loss of income. This can intensify drivers' fatigue and cause crashes. According to Belzer and Sedo (2018), the length of unpaid time per mile increases drivers' work hours, though this result is not the primary interest of their paper. Likewise, the U.S. Department of Transportation Office of Inspector General (2018) suggests that the length of detention time may increase the risk of truck crashes. This may possibly be because longer detention time, which can be associated with unpaid non-driving duty hours, can increase the opportunity cost of time and induce drivers to work longer.

**Health Insurance:** As section 5 shows, some trucking firms make a contribution to drivers' health insurance premium under employment-based health insurance although the NIOSH survey does not specify the fraction contributed by trucking firms. Since employment-based health

insurance makes health care more affordable to drivers, it may raise the opportunity cost of losing their jobs due to poor safety performance. Thus, it motivates drivers to operate trucks safely. Moreover, high quality drivers prefer to work for firms which provide employment-based health insurance, adding to their overall compensation level. In addition, employment-based health insurance may attract risk-averse drivers to the trucking firms because risk-averse drivers prefer to purchase health insurance. Rodríguez et al. (2004) suggest that trucking firms which charge higher health insurance contribution on drivers have the lower risk of crashes possibly because risk-averse drivers may prefer to have high quality but expensive health insurance plans.

The data on the quality of drivers' health insurance are not available in the NIOSH survey data. The coverage of health insurance is diverse among different plans in the U.S. insurance market. For instance, some insurance plans cover contraceptives, osteopathic care, or chiropractic care, but others do not. It is possible that drivers who are offered high quality insurance are less likely to leave jobs and have greater safety motivation.

**Retirement Benefit:** Drivers with retirement benefits may have higher human capital. As with health insurance, retirement benefits are an important part of compensation packages. Moreover, drivers with retirement benefits are more likely to be current or former union members, who may work under better conditions. Even if they are not union members currently, former union drivers may have more human capital than non-union drivers (Hirsch, 1993). Union drivers may also have longer job experience and tenure. That is, union drivers may be more skilled, which may decrease the risk of crashes. The variable of retirement benefit also captures these current and former union members' human capital stock.

Drivers who qualify for pensions may not be working currently within joint labor-management pension plans that provide most trucking pensions. However, drivers who worked for a unionized firm after being vested and who moved to a non-union firm may still have pensions, or expect to receive them. The variable of pension also captures these former union members' human capital stock.

**Work Weeks:** This is the number of weeks which drivers work annually. This variable is included to measure the exposure to moving violations. Intuitively, if drivers work longer, they are more exposed to moving violations. Ideally, the exposure should be measured by the annual mileage driven, but the annual mileage driven is used to calculate mileage pay rates in this study. Because of this, using the annual mileage driven with mileage pay rates in the same model can cause strong collinearity, which can mislead the result. Therefore, I use the number of weeks drivers work annually.

**Less-than-Truckload (LTL):** Owing to the higher entry barrier and unionization rate, LTL truck drivers may work under better conditions than TL truck drivers. Indeed, LTL drivers in the NIOSH survey data seem to work fewer hours. In this NIOSH survey sample, LTL drivers' median weekly work hours are 60 hours whereas TL drivers' median weekly work hours are 65 hours. In addition to weekly work hours, LTL drivers have less delivery schedule tightness, which can intensify job stress and fatigue. Indeed, Belzer (2018) suggests that work pressure increases the probability of crashes. In the NIOSH survey, 34.86 percent of LTL drivers answer that they have never been given an unrealistically tight delivery schedule. On the other hand, 21.80 percent of TL drivers answer that they have never been given an unrealistically tight delivery schedule. If so, LTL drivers may be exposed to less fatigue and stress than TL drivers.

**Union:** Union members may have better working conditions thanks to collective bargaining power. A previous study indicates that union drivers have better safety performance than non-union drivers (Corsi et al., 2012). Such higher performance among union drivers may be because of the difference in human capital stock. Belman et al. (2004) report that 87.6 percent of union drivers have driven five years or longer and that 62.1 percent of them have driven more than fifteen years; on the other hand, 47.2 percent of non-union drivers have driven five years or longer and that 32.9 percent of them have driven fifteen years or longer. Since union drivers have more work experience, drivers may have higher human capital than non-union drivers. Indeed, studies suggest that more experienced drivers tend to operate trucks more safely (Kaneko and Jovanis, 1992; Lin et al., 1993).

In the NIOSH data, current union drivers have longer job experience than current non-union drivers, but the difference is insignificant. Current union drivers' mean job experience is 15.94 years, and current non-union drivers' mean job experience is 14.38 years. The t-test cannot reject the null hypothesis that their mean job experience is equal. Nonetheless, union members may have human capital which cannot be measured by experience. Booth et al. (2003) write that among male British workers, union members are more likely to have safety training than non-union workers.

Team: Theoretically, the effect of team driving on health is not obvious. On one hand, team drivers may sleep longer. On the other hand, they may operate more continuously at night changing the role of driving, which can cause job stress. Moreover, team drivers normally need to sleep in the sleeper berth in the moving truck, which may lower the quality of sleep. Thus, team driving may affect drivers' health either negatively or positively. Though the total effect on health is ambiguous, we control for the effect of this work practice and incorporate this variable in the model.

We also employ demographic controls: High School, White, Experience, and Enclosed Van.<sup>5</sup>

## 7. Results

Table 2-3 shows the results for negative binomial regressions under different specifications. We chose the negative binomial model as an appropriate model over Poisson model due to over-dispersion. The Poisson model is more appropriate when there is no over-dispersion: the conditional mean equals the conditional variance. In the presence of over dispersion, the negative binomial model is more appropriate. The presence of over-dispersion is tested based on the Pearson Chi-square statistics. The null hypothesis of the test is that there is no over-dispersion. If the Pearson Chi-square statistics exceed the critical value at the 5 percent level, we reject this null hypothesis. Performing the test, we find that the null hypothesis is rejected at the 5 percent level, which means

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<sup>5</sup> The percentage of non-driving work is not included in the regression due to the problem of collinearity. The percentage needs to be calculated by dividing non-driving work hours by total work hours, which are correlated with compensation. Because of this, I excluded this variable in this model.



that the Poisson model suffers from over-dispersion. Since the data include a large number of zero crash cases, we also checked if the zero-inflated negative binomial is appropriate. To this end, I used the Vuong test and Clarck Sign test. In either test, Akaike- and Schwarz-adjusted Vuong and Clarck statistics suggest that overall, the negative binomial model outperforms the zero-inflated negative binomial model for both specifications: Negative Binomial (1) and Negative Binomial (2); unadjusted Vuong and Clarck statistics are not used since they are biased (Desmarais and Harden, 2013).<sup>6</sup> Therefore, we present the results for the negative binomial model in Table 2-3.

In Negative Binomial (1) and (2), the coefficient for pay per mile driven is negative and significant at the 5 percent level. The coefficient for employment-based health care is also negative and significant at the 5 percent level in both specifications.

The Pearson correlation coefficients between dependent variables are shown in Appendix A. Based on the coefficients, collinearity between independent variables is small.

Table 2-3 The Results for the Negative Binomial Regressions

Variables	Negative Binomial (1)	Negative Binomial (2)
Intercept	-1.01 (0.18)	0.23 (1.03)
ln(Pay/Mile)	-0.29** (0.14)	-0.31** (0.15)
Retirement Benefit	-0.25 (0.20)	-0.23 (0.21)
Health Insurance	-0.43** (0.20)	-0.40** (0.20)
Non-driving Pay	-0.22 (0.18)	-0.21 (0.18)
Annual Work Weeks		-0.024 (0.017)
Less-than-Truckload		-0.16 (0.22)
Team		0.12

<sup>6</sup> Akaike-adjusted Vuong statistics supports the zero-inflated model for Negative Binomial (1), but it is not statistically significant. The same statistics significantly support the negative binomial model for Negative Binomial (2). Schwarz-adjusted Vuong statistics significantly supports the negative binomial model for both Negative Binomial (1) and Negative Binomial (2). Likewise, Akaike- and Schwarz-adjusted Clark statistics support the negative binomial model for both specifications. In sum, the zero-inflated model is not supported in a statistically significant way while the negative binomial is supported by most statistics.

		(0.25)
Enclosed Van		-0.21 (0.18)
Married		-0.070 (0.17)
White		-0.28 (0.18)
Male		0.46 (0.39)
Union		-1.73 (1.06)
Edu		-0.13 (0.21)
Experience		-0.0027 (0.027)
Experience <sup>2</sup>		-0.0001 (0.0007)
N	704	704
Degree of Freedom	699	688
Pearson Chi-Square	685.32	695.98
AIC (smaller is better)	956.28	966.33
BIC (smaller is better)	983.62	1043.80

Notes: \*\*\*p< .01; \*\*p< .05; \*p< .1. All p values are for two-tailed test.

## 8. Discussion

Two variables are significant factors for moving violations: pay per mile driven and employment-based health insurance. That is, drivers who are more highly paid per mile driven are less likely to commit moving violations. In this analysis, retirement benefits and non-driving pay are insignificant, as are all the controls. Likewise, drivers who are offered employment-based health insurance are less likely to commit moving violations. There are two explanations for the results.

First, as the efficiency wage theory predicts, higher mileage pay rate and employment-based health insurance may attract drivers with higher human capital and motivate them to operate safely. The result for mileage pay is consistent with Rodríguez et al. (2003) and Rodríguez et al. (2006). The statistical significance in the current study is weaker possibly due to the quality of the NIOSH survey data, in which mileage pay rate is computed from annual miles driven, not even

probed based on weekly miles driven. Moreover, Rodríguez, et al. employ data obtained from a single firm. In particular, certain firm-level characteristics, such as safety culture, may affect drivers' safety performance. Such characteristics are often hard to quantify and not observed in the data. Since Rodríguez, et al.'s data include drivers in a single firm, their study is less influenced by such characteristics.

Interpreting the result for employment-based health insurance requires a little more meticulousness. Traditionally, efficiency wage theory does not thoroughly discuss nonmonetary compensation including fringe benefits. However, efficiency wage theory is also concerned about compensation in general, which is not limited to monetary compensation. It intuitively makes sense that offering fringe benefits like health insurance can also attract workers with higher human capital since fringe benefits can improve workers' utility. Particularly in the U.S., where universal health care is absent, employment-based health care plays an integral role in making health care affordable to workers. Thus, it may not be surprising that offering employment-based health care attracts more skillful drivers with lower propensity for turnover and motivates them to be safer drivers. Indeed, Kim and Philips (2010) find that employment-based health insurance raises workers' retention in the U.S. construction industry whether the plans are provided by union or non-union contractors. This implies that employment-based health insurance may contribute to accumulating human capital.

The NIOSH survey data, however, do not contain information about the quality of health insurance. In addition, drivers' status of health insurance is somewhat problematic. In the NIOSH survey, two questions on health insurance are asked: "Does your employer or union offer you health insurance?" and "Are you covered by any type of health insurance or health care plan? Include coverage provided by your spouse or partner's plan." Certainly in the current study, drivers who are offered health insurance by employers but are not covered by any health insurance are treated as not having employment-based health insurance. However, drivers who are offered employment-

based health insurance and covered by some health insurance may be covered by their spouses' health insurance instead of their own employment-based health insurance.

Nonetheless, drivers who are offered employment-based health insurance can operate safely even if they are covered by other health insurance. According to the efficiency wage theory, offering higher compensation attracts high quality job candidates partly because higher compensation is a signal for high quality jobs. Judging the job quality, job candidates observe not only monetary compensation but the entire compensation package offered by employers. If so, trucking firms which offer no employment-based health insurance are likely to give a signal to job candidates that their jobs are very low quality. That is, job candidates anticipate that working conditions in general are poor in such firms. High quality truck drivers may avoid applying for such jobs even if they are covered by other health insurance plans.

Second, risk-averse drivers may prefer to work in trucking firms which provide employment-based health care. As Rodríguez et al. (2004) argue, trucking firms charge a part of health insurance premium to drivers. Facing the tradeoff between wages and health insurance, drivers who care about the risk of having illnesses choose to work for trucking firms which offer health care and offer somewhat lower wages. It is plausible that such drivers may be more risk-averse and commit fewer moving violations. However, this explanation does not sound persuasive regarding this data set. Checking the median wages of drivers with or without employment-based health insurance, I find that the median wages of these two groups are nearly equal: the median wage of drivers with health insurance is 15.27 dollars, and the median wage of drivers without health care is 15.18 dollars. The difference in wages does not seem to be high enough to justify this explanation that risk-averse drivers choose to work with employment-based health insurance as a result of the tradeoff between wages and health insurance. Rather, drivers with employment-based health insurance are likely to be more generously compensated in terms of their entire compensation package given that firms pay their contribution to insurance. This fact, however, may not lead us to conclude that employment-based health insurance does not attract risk-averse drivers

because drivers also have an option to work for other blue color jobs. That is, if drivers choose between trucking and other blue color jobs which pay higher wages and provide no health insurance, risk-averse drivers may choose to work for trucking firms which provide employment-based health insurance. Such drivers' occupational choice at the margin should be a subject of future research.

## **9. Conclusion**

In this paper, I analyzed how truck drivers' compensation affects their safety performance. This study finds that truck drivers who are provided employment-based health insurance are less likely to commit moving violations. The result provides a partial support for the hypothesis that trucking firms need to offer high compensation to attract drivers with high human capital and motivate them to operate safely.

Nonetheless, there are some limitations in this study. First, the quality of data on income and mileage driven is poor. In the NIOSH survey, drivers are not asked to check their pay check or tax record, which means that the reported income largely depends on drivers' memories. Annual mileage driven is also reported based on drivers' memories. In the NIOSH survey, drivers are not asked to check their driving record to check their mileage driven. Because of the lower accuracy of these data, mileage pay rates calculated in this study can suffer from a measurement issue. Furthermore, the information on the quality of drivers' health insurance is unavailable, and information also is not available on the proportion of the health insurance cost paid by the employer. Since the quality of health insurance is diverse in the U.S. insurance market, drivers with higher human capital work in firms which provide higher quality health insurance, which includes broader coverage and more generous payment of medical expenses.

Albeit having such limitations, this paper provides new evidence that compensation can be related to the road safety in trucking industry. A policy implication of this paper is that the issue of truck drivers' road safety may be linked to the issue of compensation. To further investigate this issue, it is essential for policy makers to collect higher quality data on truck drivers' safety

performance and compensation. Since truck crashes are hazardous for both drivers and other highway users, the author advocates the need for such further collection of the data.

## **CHAPTER 3 EXCESSIVE WORK HOURS AND HYPERTENSION: EVIDENCE FROM THE NIOSH SURVEY DATA**

### **1. Introduction**

Hypertension is a common illness among commercial motor vehicle (CMV) drivers. Studies show that CMV drivers are more likely to suffer from hypertension than people in other occupations. Bus drivers (Ragland et al., 1989) and taxi drivers (Kurosaka et al., 2000) are more susceptible to hypertension than comparable groups with other occupations. Reviewing the literature extensively, Apostolopoulos et al. (2012) write that CMV drivers' poor health can be attributed to their working conditions, including long and sedentary work hours. Indeed, long-haul truck drivers' job is characterized by long work hours due to relatively low wage rates (Belzer and Sedo, 2018). We hypothesize that excessive work hours are an important cause of hypertension among drivers. However, scholars have not examined how work hours affect the risk of hypertension among CMV drivers, particularly long-haul truck drivers. While studies examine how work hours and wages affect the incidence of hypertension among workers in general, results are mixed. Yang et al. (2006) and Yoo et al. (2014) indicate that longer work hours are positively related to the risk of hypertension. Nakanishi et al. (2001) claim there is little evidence that long work hours are associated with the incidence of hypertension.

In this study, we explore the linkage between work hours and hypertension among long-haul truck drivers in the U.S. Hypertension raises individuals' vascular mortality and risk of stroke (Prospective Studies Collaboration, 2002; Thrift et al., 1996). Hence, it is important to analyze the causes of hypertension to inform policy designed to enhance truck driver health.

### **2. Related Literature**

Work hours are an important factor that may be associated with the probability of suffering from hypertension. Studies show that long work hours are positively related to hypertension. Chankaramangalam et al. (2017) conducted a physical examination of 175 truck drivers in Southern India. They find that 40 percent of the subjects suffer from hypertension, and the longer duration

of driving is associated with the higher probability of hypertension among truck drivers. They also show that the difference in the susceptibility to hypertension cannot be explained by age and race. Yang et al. (2006) analyze the Public Use File of the 2001 California Health Interview Survey (CHIS2001), which is a telephone survey conducted in California in 2001. They analyze the 24,205 working age individuals in the survey data. Applying a logistic regression, Yang et al. find that work hours are positively associated with the probability of hypertension. Yoo et al. (2014) analyze longitudinal data of 10,254 subjects in South Korea. Employing survival analysis, they find that the susceptibility to hypertension is positively proportional to weekly work hours. They also find that the hazard ratio is higher among women than among men.

Nakanishi et al. (2001) observe that there is a negative association between work hours and hypertension among male white collar workers in a building contractor in Osaka Japan. However, it is hard to conclude from this study that working long hours decreases the probability of hypertension in general because the subjects of the study are white collar workers, whose quality of work is different from blue collar workers. The authors themselves point out that certain job groups—researchers and architects—tend to work longer hours than other groups, and researchers and architects are less susceptible to hypertension. They argue that researchers and architects may work longer but feel less job stress since they may feel higher satisfaction than other job groups in the same firm.

Long work hours can cause fatigue particularly due to sleep loss, which is related to the incidence of hypertension. The National Academy of Science, Engineering, and Medicine (2016) and Czeisler (2015) review the existing studies on the effect of sleep loss and fatigue on health risks. They argue that sleep loss can cause fatigue and physiological changes to human bodies, which can increase a number of health risks including hypertension. Citing Spiegel et al. (1999) and Leproult et al. (1997), Saltzman and Belzer (2002) also point out that the loss of sleep can exacerbate the severity of age-related illnesses, including hypertension. Particularly for hypertension, Suka et al. (2003) find that persistent insomnia, which causes sleep loss, can be an



important factor predicting hypertension. They use the data from annual health examinations in a telecommunication firm in Japan. Their descriptive statistics shows that subjects with persistent insomnia are approximately 10 percent more likely to suffer from hypertension. The result implies that sleep loss can increase the probability of having hypertension.

Truck drivers work long hours, on average 63 hours a week (Belman et al., 2004). This finding is consistent with that in the NIOSH survey data (Sieber et al., 2014), which shows that on average, truck drivers work slightly more than 63 hours a week (see Table 3-2 below). According to the Bureau of Labor Statistics (2010), on average Americans worked 38 hours a week in 2010. This means that long-haul truck drivers work 25 hours (66%) longer than the national average. Belzer and Sedo (2018) write that truck drivers work such long hours because of low wages and a backward-bending labor supply curve. With backward bending labor supply, truck drivers work fewer hours if their wages are high enough to purchase leisure. In other words, lower wages can induce drivers to work excessively, which leads to shorter sleep hours and intensifies their fatigue.

### 3. Theory

The theoretical background of this paper is given by Grossman's model. In Grossman's model, households face a tradeoff between income and health under a time constraint. Households need to work to earn income. Households also need to invest time to improve their health conditions. That is, health is a product of health investment. In the context of the trucking industry, health investment particularly implies taking enough sleep and rest to recover from their fatigue.

Mathematically, truck drivers face the following utility maximization problem.

Maximize  $U(C, H)$  subject to the constraints:

$$C \leq wL,$$

$$L + I \leq T, \text{ and}$$

$$H = f(I) = I^\alpha, \text{ where } 0 < \alpha < 1.$$

Truck drivers' utility function  $U$  is an increasing function of consumption goods  $C$  and health  $H$ :  $\partial U / \partial C > 0$  and  $\partial U / \partial H > 0$ . We ignore the disutility of labor in this model to simplify

the analysis. The marginal utility for either good is decreasing for each good:  $\partial^2 U / \partial C^2 < 0$  and  $\partial^2 U / \partial H^2 < 0$ . This first constraint requires that truck drivers' purchase of consumption goods lies within their income. In the first constraint,  $w$  and  $L$  represents wages and work hours respectively. The second constraint represents the time constraint. In the second constraint,  $I$  is the time for investing in health, and  $T$  is the total endowment of time. Truck drivers need to work and invest in health within the time endowment. The third constraint is the output of health as a return to health investment ( $I$ ). The production function of health is increasing for health investment, and its marginal return is diminishing in health investment:  $f' > 0$  and  $f'' < 0$ .

Combining the three constraints, we cancel  $L$  and  $I$  and obtain the frontier of feasible consumption of consumption goods and health:

$$\frac{c}{w} + H^{1/\alpha} \leq T.$$

Since  $dc/dH < 0$  and  $d^2C/dH^2 < 0$ , the locus of this constraint is given by the downward sloping concave curve. The optimal quantities of consumption goods and health are given by the point where the indifference curve of  $U(C, H)$  and the constraint are tangent to each other.

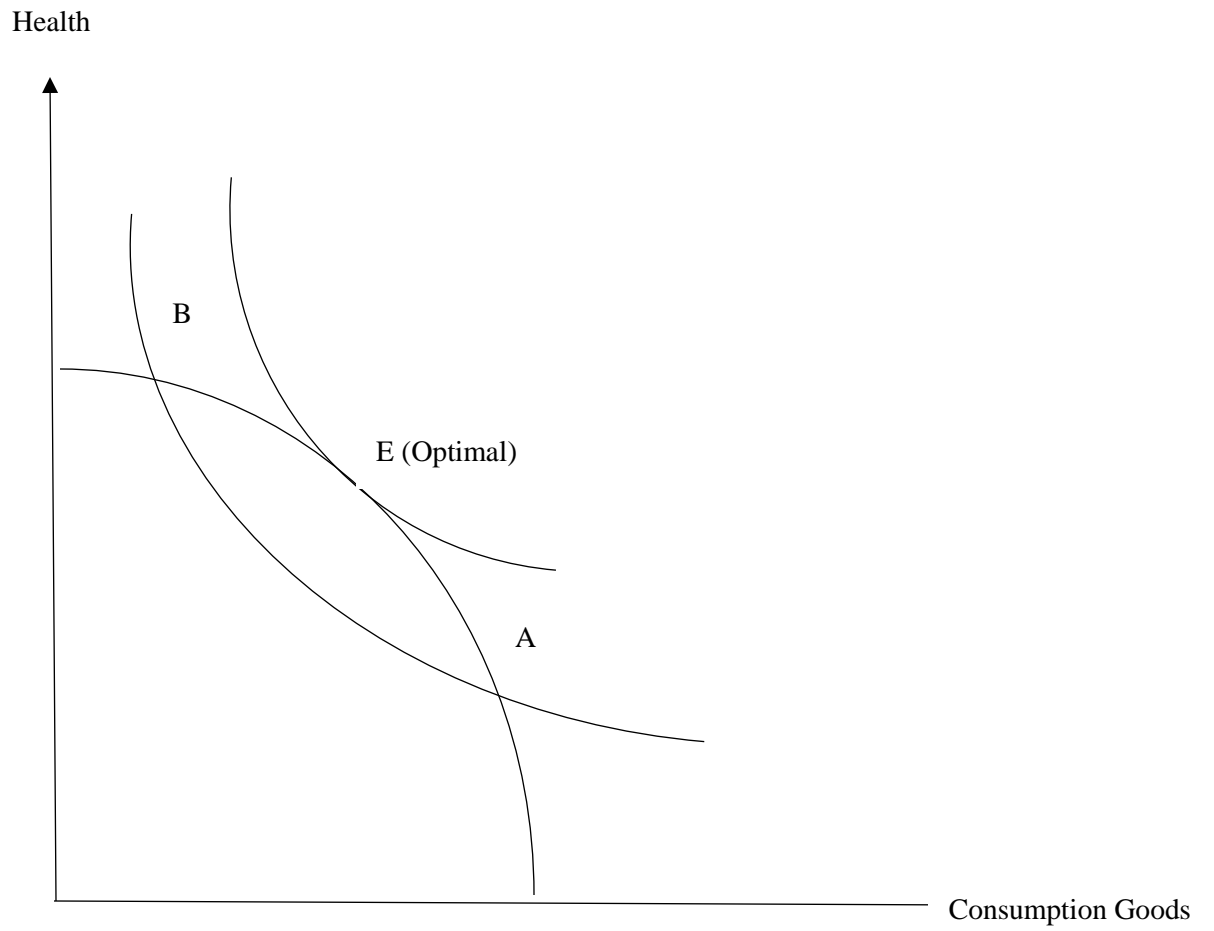
Realizing that working fewer hours is good for health, truck drivers may trade leisure for work hours in an attempt to maximize their utility. In other words, they need to decide how many hours to work to buy consumption goods and how many hours to invest in health. Nonetheless, since drivers' work depends on their employers' and clients' demands, they have a limited control over their work hours. Hence, their work hours may not be optimal.

This utility maximization problem is depicted in Figure 3-1. The horizontal axis represents drivers' income, and the vertical axis represents drivers' health. The convex curves are the indifference curves of their utility function. The concave curve represents their frontier of feasible combinations of income and health. The frontier of feasible combinations is concave for two reasons. First, drivers have a time constraint. Therefore, they face the tradeoff between income and

health. Working longer hours, truck drivers must give up the same hours of resting. This makes the frontier become downward sloping. Second, the marginal returns for health investment diminishes as health investment increases. This is based on the intuition that if an unhealthy person improves her life style somewhat, her health improves substantially. On the other hand, if a relatively healthy person does the same thing, her health improves to a lesser extent. Because of this, the frontier of feasible consumptions bends down and slopes downward.

Ideally, truck drivers choose the combination of consumption goods and health at point E, which is the optimal combination of the two goods. In fact, drivers cannot necessarily choose the optimal combination of income and health because drivers' work hours largely depend on the tasks which trucking firms assign. That is, once truck drivers are dispatched, they need to do one delivery after another. Doing multiple deliveries consecutively, they often need to be away from home for weeks. In such circumstances, drivers accept the combination of the goods at a point like A in Figure 3-1. At point A, drivers accept poorer health for more consumption goods than the optimal level. Drivers may often have to accept the combination at a point like B. That is, they want to work longer and earn higher income, but they stop working because they are not assigned a task. However, it is plausible to say that such a case is very rare given the fact that drivers work more than 60 hours a week (Belman et al., 2004). When drivers are not assigned tasks for a certain period, they are most likely to wait away from home for directions from the dispatchers and accept more work. As a result, they rarely choose a combination at a point like point B.

Figure 3-1 Truck Drivers' Maximization



The autonomy to choose work hours may depend on trucking firms. Some trucking firms may have worse employment practices than others. If so, some drivers are forced to choose combinations that are further way from the optimal combination while others choose combinations relatively close to the optimal one. As a consequence, some drivers work longer than others, so that they are more likely to suffer from health risks. In the context of the current study, such drivers are more likely to have hypertension.

Below, we examine the hypothesis that work hours are positively associated with the probability of hypertension. In the context of health economics, hours of rest can be regarded as the time investment in health to heal their fatigue. If drivers work longer, they have less time for resting to recover from fatigue or fewer hours of health investment.

#### **4. Data**

We use the National Survey of Long-Haul Truck Driver Health and Injury (the NIOSH survey data). The NIOSH survey was collected by the National Institute for Occupational Safety and Health (NIOSH) in the Centers for Disease Control and Prevention (CDC) in 2010. The purpose of the NIOSH survey was to gather data on long-haul truck drivers' occupational safety and health conditions. The NIOSH survey covers only long-haul drivers of "heavy and tractor-trailers (trucks having a capacity of at least 26,000 pounds Gross Vehicle Weight (GVW))" with "freight delivery routes [that] require them to sleep away from home" (NIOSH, 2015). Moreover, the long-haul truck drivers in this survey drove a truck with three or more axles as their main job for at least 12 months and took at least one mandatory 10-hour rest period away from home during each delivery (Chen et al., 2015). These NIOSH survey data are the most recent data on truck drivers' working conditions and occupational health.

The NIOSH survey data include both employee drivers and owner operators. Employee drivers are the majority and account for approximately 60 percent of the entire survey sample. I exclude owner operators from the sample because employee and owner operator drivers work under different conditions. Such a difference in work conditions may be linked to certain characteristics

which are not observed in the data but affect the result. Unlike employee drivers, owner operators normally finance various types of operating cost out of their pocket: capital cost, fuel and maintenance cost, insurance, tolls, electronic devices (for example, satellite receivers, transmitters and transponders), license, and permits (Belzer, 2009; Murray et al., 2006). Therefore, we restrict analysis to employee drivers.

## 5. Descriptive Statistics

In the NIOSH survey, there are two questions regarding drivers' hypertension history. The first question is whether truck drivers take anti-hypertensive medications currently. The second question is whether they have been diagnosed with hypertension by health care professionals. The NIOSH survey has three types of hypertension history among truck drivers. The first type is the drivers who have been diagnosed with hypertension and are taking anti-hypertensive drugs currently. The second type is the drivers who have been diagnosed with hypertension and are not taking anti-hypertensives currently. The third type is the drivers who have not been diagnosed with hypertension (see Table 3-1).

Table 3-1 Hypertension History

Hypertension History	Number	Percentage
Taking Medication	186	25.76
Diagnosed but not Taking Medication	64	8.86
No Hypertension History	472	65.37

The Federal Motor Carrier Safety Administration (2017) requires that drivers take medical exams every two years to continue to operate, and this exam measures blood pressure; this provides some reliability at least beyond a two-year window. Approximately 34 percent of drivers have been diagnosed with hypertension. As Table 3-1 reports, 25.76 percent of drivers are taking anti-hypertensive medication, while 8.86 percent of drivers have been diagnosed with hypertension but are not taking medication. It should be noted that this percentage is not the percentage of drivers

who really have hypertension, because some number of drivers likely have hypertension but have not been diagnosed, probably because they became hypertensive during the two-year interval and may not yet have been diagnosed with hypertension.

To compare with the general population, we grouped drivers by age groups and computed the hypertension prevalence in each age group: 18-39, 40-59, and 60 or older. Yoon et al. (2015) demonstrate the hypertension prevalence among the public in the U.S. based on the National Health and Nutrition Examination Survey. According to them, hypertension prevalence is 7.3 percent in the age group of 18-39; 32.2 percent in the age group of 40-59; and 64.9 percent in the age group of 60 or older. These percentages include controlled hypertension. In the NIOSH survey data, approximately 25 percent of drivers of 18-39 years old have hypertension; approximately 36 percent of drivers of 40-59 years old have hypertension; and approximately 51 percent of drivers of 60 years old or older have hypertension. Relative to the general population, hypertension is observed more frequently in the young cohort of truck drivers.

Table 3-2 shows the descriptive statistics of continuous variables of the entire sample of employee drivers and each category of hypertension: No Hypertension History, Hypertension without Medication, and Hypertension with Medication. The first category shows the samples that exclude and include the medicated drivers. The importance of this distinction will become clear below when we explain some descriptive statistics by hypertension histories. For the time being, we point out that both samples do not look much different in terms of aggregate statistics. The mean and median of employee drivers' work hours are roughly 63-64 hours a week whether we include medicated drivers in the sample or not. This is different from Sieber et al. (2014), who write that the average weekly hours are 60 hours. The samples are different in their paper because the current paper excludes owner operators' data. Furthermore, Sieber et al. use the weight based on the truck stops where interviews are conducted. However, we do not use such a weight. Theoretically, the weight based on survey locations is justified when each location is expected to have certain tendency about work hours. That is, drivers who stop at one truck stop tend to work longer than

those who stop at another truck stop. However, long-haul truck drivers stop at different truck stops across the U.S. depending on their origins and destinations. Thus, it is not clear that drivers who stop at certain truck stops on the date of the NIOSH survey have particular tendency in terms of work hours.

Another important finding is that the truck drivers' mean Body Mass Index (BMI) is approximately 30, which is the medical threshold value to distinguish obesity with overweight. Hege et al. (2017) show that the prevalence of obesity among U.S. long-haul truck drivers is 64 percent. In the NIOSH survey, roughly 60 percent of employee drivers are obese, which is consistent with their finding despite the difference in the sample size.

Table 3-2 also shows weekly work hours, age, BMI and weekly non-driving duty hours by hypertension history. On average, drivers who take anti-hypertensive drugs currently work fewer hours than the other two types of driver. This seemingly puzzling statistic can be due to the effect of hypertension on work hours. Drivers who need medication currently are likely to have relatively serious symptoms of hypertension. Such drivers may avoid working long hours, being anxious about the further progress of hypertension, which can eventually lead to cardiovascular disease, including stroke. Intuitively, these drivers may have been advised by their medical provider that they should work fewer hours. If drivers being treated for hypertension, including taking anti-hypertensive drugs, work fewer hours, they lower the average work hours of drivers with hypertension.

Table 3-2 Employee Drivers' Weekly Work Hours, Age, BMI and Weekly Non-driving Duty Hours by Hypertension History

	Variable	Mean	Median	Std Dev
All (N=722)	Weekly Work Hours	63.15	63.00	24.23
	Age	46.52	47.00	10.28
	BMI	32.41	31.43	7.13
	Weekly Non-Driving Duty Hours	15.19	10.00	16.90
No Hypertension (N=472)	Weekly Work Hours	62.88	62.00	23.36
	Age	44.72	45.00	10.07
	BMI	31.52	30.51	7.01



		Weekly Non-Driving Duty Hours	14.87	10.00	15.62
Hypertension Medication (N=64)	without	Weekly Work Hours	72.62	70.00	27.54
		Age	44.81	45.50	10.38
		BMI	31.90	29.98	7.83
		Weekly Non-Driving Duty Hours	20.13	13.5	24.7
Hypertension with Medication (N=186)		Weekly Work Hours	60.58	60.00	24.54
		Age	51.68	53.00	9.00
		BMI	34.84	34.36	6.64
		Weekly Non-Driving Duty Hours	14.30	10.00	16.55

Table 3-3 shows the descriptive statistics of indicator variables. Non-driving pay is an indicator variable which equals one if drivers are paid for non-driving duties or equals zero otherwise. In the trucking industry, many drivers are assigned not only driving duties but also non-driving duties: loading, unloading, waiting for dispatch directions, waiting to load or unload, performing ancillary tasks like regulatory and business responsibilities (such as record-keeping), and both maintenance and repair. Approximately half of truck drivers are not paid for such non-driving duties.

It should be noted that when truck drivers are paid for non-driving labor, they are not necessarily paid for all non-driving duties assigned. For instance, even if drivers are paid for loading or unloading duties, they probably are not paid to wait for their dispatchers' directions. Indeed, some types of non-driving duties are more likely to be paid than others. The survey which University of Michigan Trucking Industry Program conducted in 1997 reveals that 44.7 percent of truck drivers are paid for loading and unloading, but only 21.2 percent of truck drivers are paid for dropping and hooking (Belman et al., 2004).<sup>7</sup>

These descriptive statistics suggest that there is a large difference in the percentage of paid drivers depending on the types of task. Unfortunately, the data do not distinguish which non-driving

<sup>7</sup> These numbers are not additive since they are counted as separate pieces of work. That is, some drivers are paid for all of these non-driving duties, but others are paid for only one of them or neither.

duties in the data set are paid and which are not. It is also not known in the data how much they are paid for non-driving duties in total. Hence, the best thing that we can do to quantify non-driving pay is to set the indicator variable to distinguish drivers who are paid at least partially with those who are not paid at all for non-driving duties.

Health insurance is an indicator variable which equals one if employers provide health insurance for drivers or equals zero otherwise. Employment-based health insurance is offered to roughly 60-62 percent of employee drivers. In the NIOSH survey data, there are two questions related to drivers' status of health insurance: "Does your employer or union offer you health insurance?" and "Are you covered by any type of health insurance or health care plan?" Some drivers are offered employment-based health insurance, yet are covered by no health insurance. Since these drivers do not have employment-based health insurance, they are treated as zero in constructing the indicator variable. On the other hand, drivers can be offered health insurance by their employers and decline the coverage (for which they may have to pay out of pocket), yet be covered by some health insurance other than their own employment-based health care. These drivers may be covered, for example, by their spouses' health insurance. The NIOSH survey does not have the information to distinguish such drivers from those who are covered by employment-based health insurance. Therefore, we treat these two types of drivers as one in constructing the indicator variable. This variable also does not measure the quality of health insurance. In reality, the coverage of health insurance plans is diverse in the U.S. insurance market depending on insurance plans. Though such a difference in the qualities of insurance plans can affect drivers' health care utilization, this survey does not report detailed data on health insurance plans.

Long-haul trucking comprises less-than-truckload (LTL) and truckload (TL) sectors. The LTL sector deals with comparatively light freight shipments (150-10,000 pounds per shipment) and carries multiple clients' properties on a single truck. On the other hand, the TL sector conveys comparatively heavy freight shipments (over 10,000 pounds per shipment) and usually carries a single owner's cargo on one truck (Burks et al. 2010). LTL is the indicator variable which equals

one if drivers work in the LTL sector or equals zero otherwise. LTL drivers account for roughly 20 percent of the sample.

Some truck drivers operate trucks with another driver. While one driver is driving a truck, the other driver is sleeping. This practice is called team driving. Team is the indicator variable which equals one if drivers operate trucks as team drivers or equals zero otherwise. Team drivers account for approximately 14-15 percent of drivers.

Union is the indicator variable which equals one if drivers are a member of a labor union or equals zero otherwise; 2.62 percent of drivers are union drivers. In the 1997 UMTIP survey data, 15.5 percent of employee drivers are union members. The data suggest a sharp decline in union density among drivers between 1997 and 2010. The change in truck drivers' union density becomes clearer by comparing it with that of the general population. Hirsch and Macpherson (2017), reporting data from the Current Population Survey (CPS), show that the union membership rate for driver/sales workers and truck drivers was 19.6 percent in 1997 and 12.8 percent in 2017. The CPS category of driver/sales workers and truck drivers contains a wider range of jobs, such as short haul and local jobs. In this sense, the union membership rates in the NIOSH survey and Hirsch and Macpherson are not perfectly comparable, but the membership rates in the two data are consistently falling during this period.<sup>8</sup>

Table 3-3 Descriptive Statistics of Categorical Variables

	Variable	Percentage
All (N=722)	Non-driving Pay	48.34
	Health Insurance	62.33
	Less-than-Truckload	20.36
	Team	13.57
	High School	78.67
	White	70.64
	Married	51.66
	Male	93.35
	Union	2.63

<sup>8</sup> Importantly, Hirsch and Macpherson (2017) include all truck drivers, including driver/ sales workers driving trucks whereas the NIOSH survey data cover employee long-haul truck drivers. That is, the sample of the NIOSH survey data are narrower than that of CPS.

No Hypertension (N=472)	Non-driving Pay	48.52
	Health Insurance	59.11
	Less-than-Truckload	22.03
	Team	14.62
	High School	78.81
	White	68.64
	Married	48.52
	Male	91.74
	Union	2.54
Hypertension with Medication (N=64)	Non-driving Pay	43.75
	Health Insurance	68.75
	Less-than-Truckload	14.06
	Team	17.19
	High School	73.44
	White	73.44
	Married	50
	Male	93.75
	Union	3.13
Hypertension without Medication (N=186)	Non-driving Pay	49.46
	Health Insurance	68.28
	Less-than-Truckload	18.28
	Team	9.68
	High School	80.11
	White	74.73
	Married	60.22
	Male	97.31
	Union	2.69

Notes: Non-driving pay distinguishes drivers who are paid for non-driving duties at least in part from those who are not paid at all for non-driving duties. If non-driving labor is compensated, drivers are not necessarily paid for all non-driving work. As long as they are paid for some non-driving duties, the variable equals one. "Health insurance" distinguishes drivers who are offered health insurance by their employers and actually covered by some health insurance; people who are offered health insurance by their employers but have no insurance are treated as not having employment-based health care. Less-than-Truckload distinguishes drivers working in the Less-than-Truckload sector and those working for Truckload sector. Team distinguishes team drivers. High School distinguishes drivers who have a high school diploma from those who do not have it. White distinguishes white drivers from non-white drivers. Married distinguishes drivers married drivers. Male distinguishes male drivers from female drivers. Union distinguishes union and non-union members.

## 6. Analysis

In section 3, the theoretical model treats health as a deterministic product of health investment. That is, if individuals input a certain quantity health investment, they generate a certain

quantity of health deterministically. In fact, individuals' health conditions are not determined solely by health investment. Some people can suffer from hypertension despite working fewer hours. Others, on the other hand, do not suffer from hypertension though they work quite long hours. In other words, the effect of work hours on the incidence of hypertension is not deterministic but probabilistic. Health investment does not guarantee that drivers stay healthy, but it raises the probability of staying healthy.

To explore if wages affect the probability of hypertension, we employ a multinomial logit regression model, which measures the contribution of each factor to the probability of an event. The reference group is drivers with no hypertension history. The regression estimates the effect of each independent variable on the probability of having hypertension and taking medication and the probability of having hypertension but not taking medication in reference to having no hypertension history. The multinomial logistic regression equation is formulated in the following way:

$$\begin{aligned}
 & \text{Probability} \left( i = k \left| \begin{array}{l} k = \text{no hypertension, hypertension with medication,} \\ \text{or hypertension without medication} \end{array} \right. \right) \\
 & = \alpha + \beta_1 \times \ln(\text{Work Hours}) + \beta_2 \times \text{Nondriving Pay} + \beta_3 \times \text{Health Insurance} \\
 & \quad + \beta_4 \times \text{LTL} + \beta_5 \times \text{White} + \beta_6 \times \text{Age} + \beta_7 \times \text{Team} \\
 & \quad + \beta_8 \times \text{Union} + \beta_9 \times \text{BMI} + \beta_{11} \times \text{High School} \\
 & \quad + \beta_{11} \times \text{Male} + \beta_{12} \times \text{Married} + \varepsilon
 \end{aligned}$$

On the right-hand side, the variable of interest is the natural logarithm of weekly work hours,  $\ln(\text{Work hours})$ .<sup>9</sup> Weekly work hours, which are reported in the NIOSH survey data, may not be representative work hours for all drivers because those in the NIOSH survey are those working during seven days prior to the survey date. Truck drivers' work hours are contingent on their work shift, which is dictated by their task assigned. Truck drivers are typically assigned multiple deliveries and pickups one after another once they are dispatched. That is, when they finish one delivery, they may be given another delivery without going home. For this reason, truck drivers'

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<sup>9</sup> We take the natural log to control observations with extremely long work hours.

work hours are quite irregular depending on their employers' demand. This means that the wages calculated from weekly work hours are rough estimates.

The rationale for using each control is given in the following.

**Non-driving Pay:** Non-driving duties which are not paid can make drivers work for longer hours to compensate for the loss of income. It may increase their work hours and health risks.

**Health insurance:** The effect of health insurance on hypertension is ambiguous. On one hand, health insurance decreases the probability of suffering from hypertension because truck drivers with employment-based health insurance are more likely to visit doctors and obtain medical advice to prevent or treat hypertension. On the other hand, if truck drivers visit doctors, hypertension is more likely to be detected, which increases the probability of reporting hypertension. Whichever way health insurance may affect hypertension, controlling the effect is essential. Though drivers are legally required to take a physical examination every 24 months (Federal Motor Carrier Safety Administration, 2017), they may become hypertensive during the 24 months between exams.

**Less-than-Truckload (LTL):** LTL drivers may work under more generous conditions than Truckload (TL) drivers, including greater schedule predictability, and the NIOSH LHTDS may under-sample over-the-road LTL drivers because of the minimum requirement to spend three layovers away from home. If so, LTL drivers may be exposed to lower job stress than TL drivers. While the median LTL driver works 60 hours weekly, the median TL driver works hours 65 hours weekly. In addition to weekly work hours, LTL drivers are less exposed to a tight delivery schedule, which can cause job stress and fatigue. In my final sample of employee drivers, 34.86 percent of LTL drivers say that they have never been assigned an unrealistically tight delivery schedule while 21.80 percent of TL drivers say that they have never been assigned an unrealistically tight delivery schedule.

Such differences in drivers' working conditions can be attributed to a couple of institutional differences between the two sectors. First, while both sectors are quite competitive, the intensity of

competition in the LTL sector is lower than that in the TL sector. In the LTL sector, trucking firms need to operate terminals where they load and unload the freight. The cost of obtaining and managing terminals, and the cost of operating a pickup-and-delivery network to service the terminals, bars new entry to the LTL sector. Second, the LTL sector has been more unionized than TL sector traditionally (Burks et al., 2010). This may help drivers bargain collectively for a healthy work environment. Though the percentage of union drivers is quite small (4.3 percent in the LTL sector), collective bargaining leads to better working conditions.

**Team:** Theoretically, the effect of team driving on health is not obvious. On one hand, team drivers may sleep longer. On the other hand, they may operate more continuously at night changing the role of driving, which can cause job stress. Moreover, team drivers normally need to sleep in the sleeper berth in the moving truck, which may lower the quality of sleep. Thus, team driving may affect drivers' health either negatively or positively. Though the total effect on health is ambiguous, we control for the effect of this work practice and incorporate this variable in the model.

**Union:** We expect that union members have better working conditions than non-union members owing to greater bargaining power. Thus, union drivers may be less exposed to harsh work conditions that can harm drivers' health. Although few studies analyze the effect of union status on drivers' health, there are studies which indicate that labor union possesses bargaining power on compensation (Belzer, 2000; Belzer, 1995; Ge, 2014; Gabriel and Schmitz, 2014). Given that labor union maintains the bargaining power on wages, it may also have the bargaining power on healthy work conditions.

**BMI:** BMI is inserted in the model since a study finds that there is a positive correlation between BMI and the incidence of hypertension (Thiese et al., 2015).

We also use several demographic controls: High School Diploma, White, Age, Gender, and Marital Status.

## 7. Results

Table 3-4 shows the results for the multinomial logit regressions presented in section 3. In both Multinomial Logit (1) and Multinomial Logit (2), the reference group is the drivers who are not diagnosed with current hypertension. The column “Medicated” shows the effect of independent variables on the probability of taking anti-hypertensive drugs, and the column “Not Medicated” shows the effect of independent variables on the probability of having hypertension but not taking anti-hypertensive drugs.

Work hours do not significantly affect the probability of having anti-hypertensive drugs (Multinomial Logit (1)). However, more work hours significantly raise the probability of having hypertension but not having anti-hypertensive drugs (Multinomial Logit (2)). The magnitude of its marginal effect on the probability of having hypertension but not taking medication is also very close in both models. The magnitude of the marginal effect of work hours is approximately 0.1 percent at the mean work hours of 63.<sup>10</sup> That is, if work hours increases from 63 to 64, the probability of having hypertension rises by roughly 0.1 percent. The effect of health insurance is significant in Multinomial Logit (1), but it becomes insignificant when controls are added in Multinomial Logit (2). Age and BMI are positively and significantly associated with a higher probability of having anti-hypertensive drugs. Nonetheless, they do not influence the probability of having hypertension but not having anti-hypertensive drugs.

Appendix B gives the Pearson correlation coefficients between independent variables. Based on the results, multi-collinearity between does not seem to be large.

Table 3-4 The Results for the Multinomial Logit Regressions (Reference Group=Drivers with No Hypertension)

Coefficient	Multinomial Logit (1)		Multinomial Logit (2)	
	Not Medicated	Medicated	Not Medicated	Medicated

<sup>10</sup> We converted the coefficient into the marginal effect following the method shown in Greene (2011). Converting the coefficient into the marginal effect, we obtain approximately 0.07. Therefore, a unit increase in work hours (not in logarithmic scale) leads to  $7 * (\ln(X+1) - \ln(X)) = 7 * \ln(1+1/X)\%$ . Then at the mean of  $X=63$  hours, if work hours increase from 63 to 64, we have  $7 * (\ln(1+1/64)) = 0.13\%$ .



Intercept	0.43	-5.84***	-8.22***	-6.61***
ln(Work Hours)	-0.37	0.89**	-0.17	0.90**
Non-driving Pay	-0.055	-0.16	-0.091	-0.16
Health Insurance	0.41**	0.39	0.25	0.37
Less-than-Truckload	-0.19	-0.43	0.058	-0.43
Team	-0.45	0.24	-0.034	0.34
Age			0.081***	0.0044
High School Diploma			0.046	-0.23
White			0.064	0.26
Married			0.13	-0.037
Male			1.11**	0.36
Union			-0.3	0.0022
BMI			0.081***	0.0067
N	722		722	
Likelihood Ratio Test				
Statistics	25.02 (p=0.0053)		131.3329 (p<0.0001)	

Notes: \*p< .01; \*\*p< .05; \*\*\*p< .1. All p values are for two-tailed test. The variables are defined in the notes in Tables 2 and 3.

## 8. Discussion

Longer work hours are associated with a higher probability of suffering from hypertension but not taking hypertension medication. The positive relationship between work hours and hypertension implies that long work hours decrease the time for drivers to rest and recover from fatigue, which can be an intermediate linkage between work hours and hypertension. In terms of the economic model in section 3, drivers choose portfolios of higher income (relative to other jobs, such as production workers) and poorer health. This can be interpreted in two ways. First, drivers choose high income (by working long hours) and poor health because they are forced to choose suboptimal portfolios. Drivers are not allowed to choose such work hours at will since they need to stay away from home for a long period of time. Hence, they may have to choose work hours that are longer than the optimum. Second, drivers may choose the optimal work hours, but the optimal work hours may be excessive such that it damages their health.

The magnitude of the effect of work hours is, however, relatively small based on our result. The small magnitude may be explained by the quality of the data on work hours. In the NIOSH

survey, work hours are weekly work hours seven days prior to the survey, which may not represent each driver's average weekly work hours. Some drivers may have worked either longer or fewer hours than usual.

The result also has a policy implication: reducing drivers' work hours is essential to decrease the susceptibility to hypertension. To this end, two policies may be necessary. First, policy makers need to regulate drivers' mileage pay rates. As Belzer and Sedo (2018) point out, drivers tend to work fewer hours when their pay rate is higher; at a "safe rate" they start to trade leisure for income. If so, setting a sufficiently high minimum mileage pay may reduce drivers' work hours and susceptibility to hypertension. Second, the current HOS regulation may need to be changed so that it can control drivers' work hours. Under the current HOS regulations, drivers are not allowed to drive after 60 hours on duty in 7 consecutive days. Since the median driver works more than 60 hours, this may increase drivers' risk of hypertension.

On the other hand, it is counter-intuitive that longer work hours are not associated with the higher probability of taking anti-hypertensive drugs. This may be because hypertensive drivers whose symptoms are so serious work fewer hours for fear of the further progress of hypertension. Hence, even if longer work hours increase the probability of hypertension, the coefficient for work hours is not significantly positive. Moreover, drivers taking medication are older and more obese than drivers who have been diagnosed with hypertension but are not having medication. Such specific characteristics among medicated drivers can also disturb the significance of the effect of work hours on hypertension. This also implies that some previous studies that show a negative relationship between work hours and hypertension can be misleading. For example, Nakanishi et al. (2001) show a negative relationship between work hours and hypertension and conclude that association between long hours may not be associated with hypertension. However, the result can be due to the fact that people who realize that their blood pressure is high may change their behavior and work less. If so, it cannot be concluded that long work hours are not related to hypertension.

The coefficient for employment-based health insurance significantly increases the probability that drivers have medication in the absence of other controls. However, the significance disappears when the regression includes the controls. Hence, this effect of employment-based health insurance may be a product of omitted variable bias.

## **9. Conclusion**

In this paper, we examined how employee truck drivers' work hours affect the probability that they suffer from hypertension. If we limit the sample in drivers who are not taking medication currently, the results show that there is a positive relationship between truck drivers' work hours and incidence of hypertension. Since drivers seem to reduce their work hours when they are prescribed medication, including drivers under medication nullifies the statistical significance of the effect of work hours on the probability of hypertension. This is likely to be because medicated drivers may decrease work hours for fear of the further progress of hypertension.

An important limitation of this study is that the incidence of hypertension is based on the number of drivers who are diagnosed with hypertension by health care professionals. As is true of other health survey data, this can understate the real number of patients of hypertension in the sample. Although truck drivers are required to have physical examinations every 24 months, there may still be cases that they have hypertension but do not realize it during the two years. At least, we cannot deny this possibility conclusively.

Despite this problem, the ample data of the NIOSH survey enables this paper to analyze the relatively large sample with many controls. As Saltzman and Belzer (2002) write, the truck drivers' health conditions are problematic. This issue should be recognized as a negative externality in the trucking industry since health problems like hypertension threaten drivers' lives and public safety, as well as worker health. According to the current paper, a part of the negative externality may be caused by truck drivers' work hours. Hence, it is an urgent need to investigate further the association between work hours and health in the trucking industry.

## **CHAPTER 4 THE EFFECT OF TRUCK DRIVERS' NON-DRIVING PAY ON WORK HOURS: EVIDENCE FROM THE NIOSH SURVEY DATA**

### **1. Introduction**

The purpose of this paper is to explore the effect of non-driving pay on truck drivers' work hours. One of the compensation practices which is peculiar to the trucking industry in the United States (U.S.) and other some countries is payment based on miles driven. According to Friswell and Williamson (2013), nearly 66 percent of Australian long-haul truck drivers are paid based on miles driven. The truck drivers' job is to carry freight to certain destinations. In the majority of cases in the U.S., trucking firms pay only for driving duties based on the miles driven or a percentage of revenue.

However, driving is only one of the duties to which trucking firms assign drivers. In fact, truck drivers' duties include non-driving work, including loading and unloading; waiting to load or unload; performing ancillary tasks like regulatory and business requirements such as record-keeping; and performing or waiting for both maintenance and repair. According to a survey by the University of Michigan Trucking Industry Program, the sample average of truck drivers' work hours per day is 11.4 hours; on average truckers drive 8.4 hours per day, and the sample average of hours of non-driving duties per day is 3.1 (Belman et al., 2004). This suggests that roughly speaking, 27% of the average truck driver's work hours are devoted to non-driving duties, which usually are unpaid.

Truck drivers often are not paid for non-driving duties. Moreover, when drivers are paid for non-driving duties, they are not necessarily paid for all non-driving duties which they are assigned. According to Belman et al. (2004) cited above, 44.7% of truck drivers are paid for loading and unloading, and 21.2% of truck drivers are paid for dropping and hooking. This fact implies that most truck drivers have a substantial amount of time during which they are working for free. From the truck drivers' perspective, such unpaid non-driving duties waste the opportunity cost of their

time. Being paid for miles driven, the time expended on unpaid non-driving work could otherwise have been spent putting on the miles, which earns them money.

How do truck drivers behave if they face such a waste of time? Drivers may work longer hours to compensate for the loss of income. Conversely, if drivers are paid for non-driving labor, they may work less. Is this story true? In this paper, we examine how the remuneration for non-driving duty affects truck drivers' work hours. The effect of overall income and wages on work hours is also examined to benchmark previous studies.

There are few previous papers that study the effect of truck drivers' compensation, in general, on their work hours. Belzer and Sedo (2018) published the only paper that analyzes the effect of truck drivers' compensation on their work hours. Their paper estimates the truck drivers' labor supply curve with respect to mileage rates. The current paper focuses more on how non-driving pay, which is a unique compensation practice in the trucking industry, affects drivers' work hours.

We show that pay for non-driving work can decrease truck drivers' work hours. In other words, truck drivers paid for non-driving responsibilities work fewer hours than those not paid for this work. Furthermore, higher wages can also decrease their work hours. These results are important because long work hours may be related to drivers' crashes and health problems. If pay for non-driving duties decreases drivers' work hours, it may provide a rationale for requiring pay for non-driving labor in order to improve public health and safety outcomes.

## **2. Literature and Contribution of this Paper**

The trucking industry has unique compensation practices, which many industries do not have. In other industries, workers' pay is based on work hours, and only to a limited extent on piecework. Schildkraut (2003) shows that less than 5 percent of business establishments adopt piece rates or incentive pay as a compensation scheme in the general population. In contrast, long-haul truck drivers' pay primarily is based on miles driven or on a percentage of motor carrier revenue. Long-haul truck drivers paid based on an hourly basis are a small minority (mainly United Parcel

Service, a Teamster-represented company). Non-driving duties, such as loading and unloading, are paid or unpaid depending on employer pay packages and carrier operations.

Such a unique compensation system is an interesting subject of economic analysis. In particular, how truck drivers change their work hours based on compensation structure appears to be thought-provoking. Oddly enough, there are few studies which tackle this issue. Belzer and Sedo (2018) seem to have produced the only study that analyzes the effect of compensation on drivers' work hours. Using a two-stage least-squares model, they estimate truck drivers' labor supply curve with respect to mileage rates. They find that the truck drivers' labor supply curve is backward-bending. This suggests that drivers have a target level of income, which they struggle to achieve. Until drivers achieve their target level of income, they continue to work, leading half of all long-distance truck drivers to exceed general legal limits. Once drivers achieve their targets, they significantly reduce their work hours. This further implies that drivers work shorter hours when the mileage rate is higher than the backward-bending point, at which drivers start to purchase leisure by sacrificing income.

Similar to Belzer and Sedo (2018), some studies analyze the effect of taxi drivers' pay on work hours. Camerer et al. (1997) demonstrate that taxi drivers' labor supply curve also slopes negatively with respect to wages. That is, taxi drivers also have a target level of income, which they also struggle to achieve. Once they achieve the target, they decrease their work hours significantly. Thus, taxi drivers' labor supply curves slope backward once drivers achieve income that is high enough to purchase leisure with work hours—trading labor for leisure, as economic theory predicts. Crawford and Meng (2011) support this conclusion, finding that taxi drivers' daily work hours are negatively related to daily cumulative income. This provides further support for the hypothesis that more highly paid drivers work shorter hours. Likewise using data on taxi drivers in San Francisco and New York, Martin (2017) also finds that the probability that drivers stop working for a day increases with daily shift income. Nonetheless, applying the implications of these studies to truck drivers may require caution because work practices differ between these two occupations.

Compared with taxi drivers, truck drivers often need to be away from home for weeks, dispatched from one delivery to another as required by their employer and freight transport demand.

The phenomenon that more highly paid workers work less can also be seen among workers in general. Indeed, Drakopoulos and Theodossiou (1997) use data on general workers in six regions in Britain and reveal that workers who earn more than their expected income significantly reduce work hours.

None of these studies, including Belzer and Sedo (2018), focuses on the effect of non-driving pay on work hours, which is a compensation practice peculiar to the trucking industry. Certainly, Belzer and Sedo (2018) show that the length of unpaid time increases truck drivers' work hours, but they do not use non-driving pay as an independent variable. Thus, it is not clear if the result is due to the absence of non-driving pay. In other words, an increase in work hours may be a simple arithmetic truism that drivers work longer because they are assigned longer unpaid work time. Therefore, it should still be subject to a statistical study on whether the absence of non-driving pay induces drivers to work more.

Investigating the effect of non-driving pay on work hours is important because it is related to truck drivers' safety and health. According to Belman et al. (2004), truck drivers work approximately 64 hours a week on average. Similarly, Chen et al. (2015) report that the average long-haul truck driver works 60 hours per week. These numbers show that truck drivers overwork, which can cause fatigue and create safety and health problems (National Academy of Science, Engineering, and Medicine, 2016). In particular, studies indicate that long and irregular shifts threaten workers' safety and health (Jovanis et al., 2012; Kaneko and Jovanis, 1992; Dembe et al., 2005; Dembe et al., 2006; Dembe et al., 2004; Brachet et al., 2012; Lin et al., 1993). If non-driving pay is related to truck drivers' work hours, it may also be linked to their safety and health. Motivated by this concern, this paper studies how non-driving pay affects drivers' work hours.

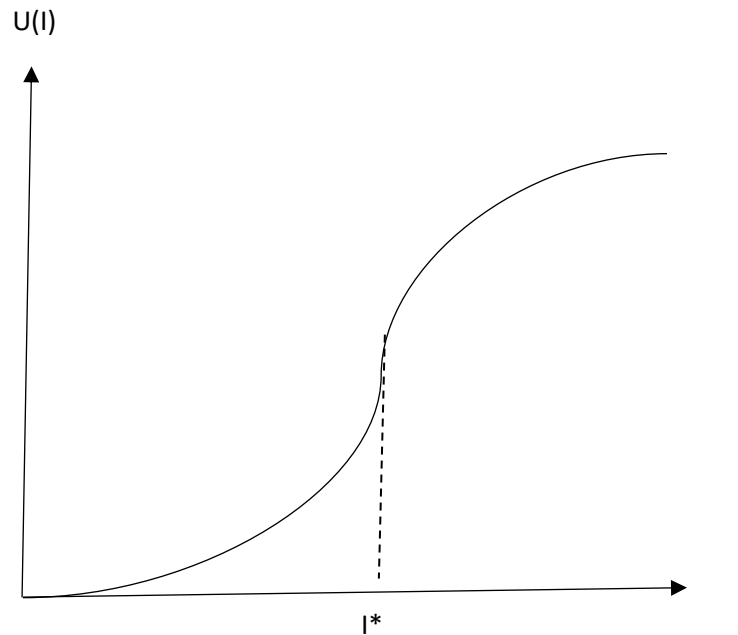
### 3. Theory

In this section we provide a theoretical framework with which to analyze how non-driving pay affects truck drivers' work hours. Some empirical studies imply that commercial motor vehicle (CMV) drivers, such as truck drivers and taxi drivers, may have a certain target level of income which they try to achieve (Belzer and Sedo, 2018; Camerer et al., 1997; Crawford and Meng, 2011). These studies also imply that drivers' work hours decline once their income reaches the target level. Given this hypothesis, pay for non-driving labor time can reduce long-haul truck drivers' work hours since it makes it easier for drivers to achieve a target level of income without having to extend their work week unnecessarily. Because truck drivers' pay mostly is based on piece rates, unpaid non-driving work hours create an opportunity cost of time for drivers. This may lead truck drivers to work longer to achieve a target level of income. Non-driving pay decreases the opportunity cost of non-driving duties by making it possible to achieve the target level of income in fewer hours of work.

A mathematical interpretation of the target income hypothesis can be given by the utility function which has the point of regime change: the level of income at which marginal utility of income decreases acutely if income exceeds it. For example, an S-shaped function may describe this feature of the utility function precisely. In this function, the slope of the tangent line increases until the level of income reaches the critical point. Once income exceeds the critical point, the slope of the tangent line starts to decrease. The critical inflection point represents the target level of income. Under this utility function, drivers work until they achieve the target level of income since the marginal utility of income increases until income reaches the target level. Drakopoulos and Theodossiou (1997) propose a utility function which has a kinked point at which marginal utility turns out to decrease in a discontinuous way. An S-shaped utility function is an extension of Drakopoulos and Theodossiou's utility function in the sense that marginal utility decreases at some point, but it does not need to happen discontinuously. Figure 4-1 shows the graphical expression of an S-shaped utility function.



Figure 4-1 S-Shaped Utility Function



Note: In figure 4-1,  $I$  represents income;  $U(I)$  represents the utility of income; and  $I^*$  represents the target level of income.

The target income hypothesis, as well as neoclassical labor supply, also assumes that drivers have the liberty of choosing work hours and leisure. As Belzer and Sedo (2018) point out, truck drivers possess such liberty only to a limited extent. That is, once long-distance truck drivers leave home and begin a tour of duty, they may need to make one delivery after another if trucking firms assign multiple sequential loads. As a result, they may need to be away from home for weeks. Therefore, it is plausible to say that drivers exercise the liberty of choosing work hours in limited situations. For example, they may possibly be given a choice to haul another load or to go home when other drivers who drive in the adjacent area currently can do the same delivery instead. At least, at the margin, they may have the liberty to decline an additional load when they are approaching their legal work-hour limit.

#### **4. Data**

We use the National Survey of Long-Haul Truck Driver Health and Injury (the NIOSH survey data), which was conducted by the National Institute for Occupational Safety and Health (NIOSH) in the Centers for Disease Control and Prevention (CDC) in 2010. The NIOSH survey aims at collecting the data on long-haul truck drivers' occupational safety and health. The survey focuses on long-haul drivers. Short-haul and local truck drivers are not included in this survey.

The NIOSH survey defines long-haul truck drivers thus: "Long-haul truck drivers are drivers of heavy and tractor-trailers (trucks having a capacity of at least 26,000 pounds Gross Vehicle Weight (GVW)). Their freight delivery routes require them to sleep away from home" (NIOSH, 2015). NIOSH provides an additional specification in Chen et al. (2015). Chen et al. state that the long-haul truck drivers in the NIOSH survey drove a truck with three or more axles as their main job for at least 12 months and took at least one mandatory ten-hour rest period away from home during each delivery. Drivers who have driven less than 12 months in their careers are, therefore, not covered by the NIOSH survey.

The NIOSH survey contains both employee drivers and owner operators. We exclude owner operators from our sample since their income seems to be incomparable with that of employee drivers. Owner operators normally pay the cost of operation on their own whereas employee drivers do not. The cost of operation includes but is not limited to capital cost, fuel and maintenance cost, insurance, tolls, electronic devices (for example, satellite receivers, transmitters and transponders), truck license, and permits (Hooper and Murray, 2017; Belzer, 2009). Such difference in compensation may lead to different behaviors between employee and owner-operator drivers, as well as different earnings calculations.

Eliminating the subjects with missing data, we obtained the final sample of N=715.

#### **5. Descriptive Statistics**

The descriptive statistics of the variables in the model are shown in Table 4-1 and Table 4-2. Table 4-1 shows the summary statistics for the continuous variables: work hours, income, job

experience, and age. The median and mean weekly work hours are approximately 63. This is consistent with the University of Michigan Trucking Industry Program (UMTIP) survey data, which report that employee drivers' mean and median weekly work hours are 65.7 hours and 62.0 hours respectively (Belman et al., 2004). This implies that truck drivers work for long hours relative to average American workers, who work slightly fewer than 40 hours (U.S. Bureau of Labor Statistics, 2015). Moreover, the median work hours imply that many drivers may violate the spirit of the hours-of-service (HOS) regulation, if not the letter. HOS regulations state that drivers are not allowed to drive after 60 hours on duty in 7 consecutive days and can work no more hours than that. Nevertheless, drivers still can legally work more than 60 hours a week by taking 34 consecutive hours off-duty after they reach this limit, after which they can reset cumulative work hours to zero. This allows them to work as many as 84 hours per week legally (Saltzman and Belzer, 2007). They also can evade weekly HOS limits by logging their non-driving labor off duty, further extending their effective work hours, and they can do so while using electronic logging devices. Nonetheless, the purpose of the HOS regulation is to control drivers' fatigue and prevent truck crashes. Working more than 60 hours a week, including non-driving duties, can be against the purpose of the HOS regulation to control drivers' fatigue.

The NIOSH survey shows that mean and median annual income are approximately \$51,622 and \$50,000 respectively, which appears to be higher than other jobs which do not require extensive education. For example, U.S. production workers' mean and median income is approximately \$33,000 and \$29,000 respectively. The mean and median annual miles driven are 114,546 miles and 120,000 miles respectively, and such mileage figures support the contention that truck drivers are working the long hours reported in the survey.

Using the NIOSH data, we calculate mileage rates by dividing annual income by annual miles driven. The mean and median mileage rates thus calculated are \$0.68 and \$0.48 respectively. Strictly speaking, mileage rate calculated in this way is not the same as what drivers are paid per mile driven. Because the NIOSH survey data do not contain mileage rates set by trucking firms,

we use the ratio of annual earnings to annual miles driven as a rough approximation. The UMTIP dataset also measures the ratio of annual earnings to annual miles driven. According to UMITP in 1997, the mean and median ratios of annual earnings to miles driven are \$0.50 and \$0.42 respectively for non-union employee drivers and \$0.60 and \$0.62 respectively for union employee drivers.<sup>11</sup> Unlike the NIOSH survey, UMTIP also collected the mileage rates which are set by trucking firms in addition to the ratio of annual earnings to annual miles driven. The mean and median estimated mileage rate is \$0.38 for non-union employee drivers. For non-union drivers, the mean and median are \$0.65 and \$0.50 respectively.<sup>12</sup>

In the NIOSH data, the mean and median percentages of non-driving duties hours out of total work hours are approximately 22 percent and 18 percent. In the UMTIP survey, roughly speaking, the mean and median percentages of non-driving duty hours are 27 percent and 18 percent, which are quite close to the percentages in the NIOSH survey data.<sup>13</sup>

Table 4-1 Descriptive Statistics of Continuous Variables

Variable	Mean	Median	Std Dev
Weekly Work Hours	63.03	62.00	24.21
Annual Income	51,622.14	50,000.00	20798.29
Annual Miles Driven	114,546.70	120,000.00	42250.34
Mileage Rate	0.68	0.43	1.50
Age	46.48	47.00	10.32
Weekly Non-Driving Duty Hours/Weekly Work Hours	21.79	17.64	17.54

Notes: Mileage Rate is the ratio of (Annual Income/Annual Miles Driven). Type distinguishes drivers who drives enclosed vans from those who drive other trucks.

<sup>11</sup> Using 2010 as the base year, we adjusted for inflation the mean and median ratios of annual earnings to miles driven. According to UMITP in 1997, non-union employee drivers' mean and median ratio of annual earnings to annual miles driven is \$0.37 and \$0.31 respectively, and those of union employee drivers are \$0.44 and \$0.38 respectively (Belman et al., 2004). On the other hand, the U.S. city average of Consumer Price Index for All Urban Consumers (CPI-U) is 160.5 in 1997 and 218.056 in 2010 (U.S. Bureau of Labor Statistics, 2017). Obtaining the inflation rate from 1997 to 2010 (218.056/160.5) and multiplying the numbers by the inflation rate yields the values above.

<sup>12</sup> Likewise, we adjusted the mean and median mileage rates for inflation using 2010 as the base year. In the UMTIP survey data, both mean and median mileage rates set by firms are roughly \$0.28 for non-union employee drivers in 1997; the mean and median mileage rates for union employee drivers are \$0.48 and \$0.37 respectively in 1997 (Belman et al., 2004). Multiplying these numbers by the inflation rate (218.056/160.5) yields the values above.

<sup>13</sup> This rough estimates are computed from Belman et al. (2004), who show that the mean and median total work hours in 24 hours are 11.4 hours and 11 hours respectively, and the mean and median non-driving duty hours are 3.1 hours and 2 hours respectively.

Table 4-2 shows the summary statistics of indicator variables. The percentages on the table are those of drivers for whom each indicator variable equals one. Approximately half of the drivers are paid for at least some non-driving work. For instance, drivers may be remunerated for loading or unloading duties whereas they are not remunerated for waiting for dispatchers' direction; commonly, long-haul truck drivers are paid by the stop (piecework) rather than by the hour, thus making their effective hourly compensation rate contingent on other unpaid time. Indeed, the University of Michigan Trucking Industry Program found that 44.7% of truck drivers are remunerated for loading and unloading, and 21.2% of truck drivers are remunerated for dropping and hooking (Belman et al., 2004).<sup>14</sup> This fact suggests that there is a large difference in the percentage of drivers who are paid for each non-driving task, depending on the types of tasks and employers. The NIOSH survey data do not contain information on which non-driving duties are paid: loading and unloading; waiting to load or unload; and performing ancillary task like regulatory and business requirements such as record-keeping and both maintenance and repair. In addition, the NIOSH survey data do not contain information on the amount of non-driving pay that drivers receive if they are paid for non-driving duties. Therefore, the indicator variable of non-driving pay equals one as long as drivers are remunerated for at least some non-driving duties.

Team driving is a work practice of driving trucks with another driver. While one driver is operating a truck, the other driver is sleeping. Team driving is employed so that drivers can carry freight for longer distances without stopping. Roughly 13 percent of all employee drivers work in teams.

Union drivers account for approximately 2 percent of the sample. In Hirsch and Macpherson (2018) based on the Current Population Survey (CPS), union membership among truck drivers was 12 percent in 2010, when the NIOSH survey was conducted. The difference may be explained by the fact that Hirsch and Macpherson's statistics includes short-haul and local truck

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<sup>14</sup> These numbers are not additive since they are counted as separate pieces of work. That is, some drivers are paid for all of these duties, but others are paid for only one of them or neither.

drivers and driver/sales workers whereas the NIOSH survey includes only long-haul truck drivers. Indeed, the UMITP survey shows that 11 percent of long-haul truck drivers were union members in 1997 while Hirsch and Macpherson show that 21 percent of truck drivers are union members. This seems to provide indirect support for the view that the difference in union drivers' percentage representation in the survey is due to the definition of truck drivers included used by NIOSH. However, we do not have any evidence on this issue. We also note that Hege et al. (2017) find that 3.5 percent of long-haul truck drivers have union membership though their sample is relatively small (N=260).

Long-haul trucking is segmented into less-than-truckload (LTL) and truckload (TL) sectors. The LTL sector carries relatively light freight (typically 150-10,000 pounds per shipment). The LTL sector also carries multiple clients' freight on one truck. The TL sector carries relatively heavy freight (typically over 10,000 pounds per shipment). The TL sector also carries a single owner's freight on one truck (Burks et al., 2010). LTL drivers account for roughly 20 percent of employee drivers.

High School is an indicator variable which equals one if drivers have high school diploma and equals zero otherwise. In the original survey, drivers' education is categorized more in detail: 8<sup>th</sup> grader or less, 9<sup>th</sup>-12<sup>th</sup> grade (no diploma), GED or equivalent, high school graduate (diploma), some college (no degree), associate degree (vocational/technical), associate degree (academic), bachelor's degree or higher. Relatively many drivers graduate from high school, but fewer drivers have bachelor or associate degree. Hence, we converted the variable into a binary variable which distinguishes drivers with a high school diploma from those without one.

Table 4-2. Descriptive Statistics of Categorical Variables

Variable	Percentage
Non-driving pay	48.53
Team Drivers	13.57
Union	2.52
Less-than-Truckload	20.28
Enclosed Van	50.35

White	70.63
High School Diploma	78.74
Male	93.15
Married	51.89

Notes: Non-driving pay distinguishes drivers who are paid for non-driving duties at least in part from those who are not paid for non-driving duties at all. If non-driving pay is paid, drivers are not necessarily paid for all non-driving duties. As long as they are paid for a piece of non-driving duties, the variable equals one. Enclosed Van distinguishes drivers who drive enclosed vans from those who drive other trucks. Education distinguishes drivers who have a high school diploma from those who do not have one.

## 6. Analysis

We formulate the model in the following way:

$$\begin{aligned} \ln(WH) = & \alpha + \beta_1 \times \text{non-driving} + \beta_2 \times \ln(\text{mileage rate}) + \beta_3 \times LTL \\ & + \beta_4 \times \text{Team} + \beta_5 \times \text{Union} + \beta_6 \times \text{Enclosed Van} + \beta_7 \times \text{white} + \beta_8 \times \text{High School} \\ & + \beta_9 \times \text{age} + \beta_{10} \times \text{age}^2 + \epsilon \end{aligned}$$

The dependent variable,  $\ln(WH)$ , is the natural logarithm of weekly work hours. The independent variables are defined as follows.

Non-driving represents an indicator variable which equals one if drivers are paid for non-driving duties at least in part. This is the coefficient of primary interest.

We use other variables defined in Section 5. The rationale for incorporating each variable in the model is the following.

$\ln(\text{mileage rate})$  represents the natural logarithm of mileage rates, which is calculated by dividing annual income by annual miles driven. As the previous section mentions, this is a rough estimate of mileage rate. In contrast with Belzer and Sedo (2018), we do not use a quadratic specification for mileage rate since the coefficient for the quadratic term is statistically insignificant.

Union: This variable is included to control for the bargaining power of the labor union, though the percentage of union members in the survey is quite small. The t-test also does not indicate a statistically significant difference in mileage rate between union and non-union drivers. However, Belzer and Sedo's mileage rate equation shows that union drivers receive higher pay than

non-union drivers (Belzer and Sedo, 2018). This implies that union drivers may work under more generous conditions though some of these conditions cannot be observed.

Team: The effect of team driving on work hours is not clear theoretically. Team driving may decrease work hours because drivers may be able to sleep longer. On the other hand, team driving can be used to operate trucks longer, particularly at night time, which may increase work hours. The previous literature does not analyze the effect of team driving on work hours. Though the effect is not clear, we control for it in the regression model.

Less-than-Truckload (LTL): Drivers in the LTL sector may be relatively better paid than those in the TL sector. There are a couple of reasons for this. First, though both sectors are competitive, the competition is less intensive in the LTL sector than in the TL sector due to higher entry barriers (Burks et al., 2010). With less competition and higher freight rates per ton-mile in this sector, LTL drivers may work under better conditions. Though mileage rates in the LTL and TL sectors are not significantly different, other unobservable difference in working conditions may exist between the two sectors. Second, the LTL sector carries relatively expensive freight (Burks, et al., 2010), which may induce LTL trucking firms to offer drivers more generous work conditions to hire drivers with higher human capital.

We also employ other controls: Enclosed Van, High School, White, and age.

Finally, we use an OLS to estimate the regression. Theoretically, mileage rate and work hours can be determined simultaneously. Thus, these two variables can be endogenous, which normally justifies the use of a two-stage least square model (2SLS). That is, we should make the fitted values of mileage rates by using instruments and employ the fitted mileage rates, as done by Belzer and Sedo. However, the F-statistics of the first stage regression is lower than 2 with the instruments available in the data. In addition, the R-squared for the first stage regression is smaller than .10. This suggests that the 2SLS may suffer from statistical bias due to weak instruments. Therefore, we employ an OLS instead of 2SLS in this study. The result for the first stage regression also is shown in at the end of section 7 to reveal the weak instrument problem. This auxiliary result



for the first pay rate equation is shown in section 7 to show that the 2SLS is not an appropriate statistical method in the context of this study.

## 7. Results

Table 4-3 shows the result for the OLS estimation of the regression. The coefficient for non-driving pay is negative and statistically significant at the 1 percent level. The coefficient for Less-than-Truckload is significant at the 5% percent level. The other coefficients excluding the intercept are insignificant.

Appendix C provides the Pearson coefficients between independent variables. The result indicates that the Pearson correlation coefficients are quite small. Thus, multi-collinearity does not seem to be very serious in this model.

Table 4-3 The Results for the Work Hours Equations: Dependent Variable= $\ln(\text{Weekly Work Hours})$

Variables	Model (1)	Model (2)	Model (3)
Intercept	4.08*** (0.03)	4.10*** (0.036)	4.51*** (0.29)
Non-driving Pay	-0.093*** (0.034)	-0.089*** (0.034)	-0.089*** (0.034)
$\ln(\text{Mileage Rate})$	-0.029 (0.026)	-0.023 (0.026)	-0.022 (0.026)
Less-than-Truckload		-0.10** (0.042)	-0.10** (0.042)
Team		-0.0084 (0.05)	-0.034 (0.052)
Union		-0.11 (0.10)	-0.11 (0.10)
Enclosed Van		0.0037 (0.034)	-0.0036 (0.034)
White			-0.042 (0.037)
Education			-0.078 (0.041)
Male			-0.004 (0.069)
Married			0.0063 (0.034)
Age			-0.01

			(0.012)
Age <sup>2</sup>			0.000081 (0.00013)
N	715	715	715
F-statistic	4.34**	2.67**	2.10*
R-squared	0.012	0.022	0.034
Adjusted R-squared	0.0093	0.013	0.018

Notes: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . All p values are for two-tailed tests. Non-driving pay distinguishes drivers who are paid for non-driving duties at least in part from those who are not paid for non-driving duties at all. If non-driving pay is paid, drivers are not necessarily paid for all non-driving duties. As long as they are paid for some non-driving duties, the variable equals one.  $\ln(\text{Mileage Rate})$  is the natural log of the ratio of (Annual Income/Annual Miles Driven). Enclosed Van distinguishes drivers who drives enclosed vans from those who drives other trucks. Education distinguishes drivers who have a high school diploma from those who do not have one. Male distinguishes male drivers from female drivers.

## 8. Discussion and Limitation

The results show that paying for non-driving work curtails truck drivers' work hours significantly, supporting the target income hypothesis. Since non-driving pay enables drivers to achieve their target level of income more quickly, drivers who are paid for non-driving responsibilities work fewer hours. In the absence of non-driving pay, drivers try to compensate for the loss of their income by working longer hours. This result and hypothesis are consistent with Belzer and Sedo (2018), who find that unpaid time increases drivers' work hours. The U.S. Department of Transportation Office of Inspector General (2018) also reports that longer detention time significantly increases the risk of truck crashes. This may be due to increased work hours and fatigue, which are caused by unpaid non-driving time—especially when such non-driving labor exceeds two hours at a time.

Unlike Belzer and Sedo (2018), mileage rate does not have a significant effect on work hours. This may be due to the quality of the NIOSH data on mileage rate. As discussed above, in the current paper, mileage rate is a rough approximation which is computed from annual income and annual miles driven. The mileage rate thus computed includes the remuneration (or lack of it)

for non-driving work. Belzer and Sedo, in contrast, can use the mileage rate rate which is paid specifically for driving work and which varies depending on freight because the data they use provide a specific rate. This difference in the quality of the data may disturb our result.

Though it is not a primary interest of this study, the result also shows that LTL drivers seem to work fewer hours. This may be due to the fact that the LTL sector may be less exposed to competition than the TL sector but it also may be due to operational characteristics of LTL. While most LTL carriers operate across specific intercity routes between regular and predictable loading and unloading points, many TL carriers operate on irregular routes and provide much less predictability to the driver. An indirect support for this hypothesis is that in the LTL sector, fewer drivers report that they have been assigned unrealistic time delivery schedules by their employers or clients. In the NIOSH data survey, 22.46 percent of TL drivers answer that they have never been assigned unrealistic delivery schedules while 31.72 percent of LTL drivers answer that they have never been assigned unrealistic delivery schedules.

A limitation of this study is that the quality of the data on work hours may not be high. Weekly work hours in the NIOSH survey data are those in seven days counted from the date of the survey. In whichever sector drivers may work, their work is based on work shifts. Truck drivers' work hours can vary depending on their tasks. Once they leave their original domicile, they may need to do one delivery after another, depending on employer requirements. Therefore, work hours which are reported in the NISOH survey may not be representative.

## **9. The Policy Implication**

The policy implication of this study is that remunerating drivers for non-driving duties can potentially prevent drivers' excessive work, which may reduce drivers' safety and health problems. As Saltzman and Belzer (2002) point out, both of these problems should be recognized as negative externalities caused by drivers' excessively long hours. This analysis shows that more than half of all long-haul truck drivers work 63 hours a week or more, and these drivers may violate the HOS regulations. This implies that more than half of the drivers are in a condition perilous to the public

as well as themselves. In particular, as Williams and Monaco (2001) point out, truck drivers who violate the HOS regulation are more likely to have crashes. If so, resolving drivers' excessive long hours seems to be an urgent policy agenda. As Jensen and Dahl (2009) suggest, the HOS regulations contribute to improving safety.

## CHAPTER 5 CONCLUSION

The three papers analyzed how working conditions and compensation affect safety and health. The first paper suggests that more generous compensation leads to better safety performance. Drivers with higher mileage rate and employment-based health insurance have a lower probability of committing moving violations. The second paper suggests that drivers working longer hours are more susceptible to hypertension. The third paper suggests that drivers remunerated for non-driving work tend to work fewer hours.

The implication of these papers is that generous compensation and working conditions may enhance safety performance and health among drivers. This implication is supported by previous studies. For example, Rodríguez et al. (2003) and Rodríguez et al. (2006) suggest that better compensation decreases the probability of having crashes. Belzer and Sedo (2018) find that greater compensation may make drivers work fewer hours, which may result in better safety performance. Yang et al. (2006) and Yoo et al. (2014) find that longer work hours are associated with higher risk of hypertension. While Nakanishi et al. (2001) argue that there is no positive correlation between work hours and risk of hypertension, this may be because patients with serious symptoms work fewer hours for fear of further progress of hypertension. With these previous studies, the current papers support the hypothesis that compensation and work conditions play an integral role in safety performance and health among drivers.

The current papers have several limitations. First, the quality of the data on compensation and working conditions is less than ideal. For example, due to the unavailability of the data on mileage rates, we used annual income per mile driven as its approximation, which was calculated by dividing annual income by annual miles driven. Because annual income includes remuneration for non-driving work, annual income per mile driven is biased upward relative to mileage rate, which is paid specifically for driving trucks. Moreover, we did not know important information about fringe benefits. For instance, the quality of employment-based health insurance is totally unknown, which is a problem common to Rodríguez et al. (2004). Second, though the third paper

finds that work hours are negatively related to health, the relationship between compensation and health is not clear. We have not found a significant relationship between compensation and health in the NIOSH survey. Previous studies, however, find a linkage between compensation and health (Leigh and Du, 2012; Kim and Leigh, 2010; Lenhart, 2017). It is not clear if the absence of their linkage in the current paper is due to the quality of data as mentioned in the first point.

In the current papers, we used classic generalized linear models: OLS, count variable regressions, and binary response models. Assuming the linear relationship between them, we estimated the marginal effect of independent variables on a dependent variable. This is the same approach as studies cited throughout the current papers. A different approach may also be possible. Safety performance and health are unobservable latent variables which are partly explained by observable variables, such as moving violations and hypertension. Latent variables may be modeled as structural equation (SEM) models. The benefit of SEM models is that we can analyze the complicated causal paths and direct and indirect effects explicitly. The application of SEM models to safety and epidemiological studies has a plethora of examples (Siu et al., 2004; Seo et al., 2015; Barling et al., 2002). For example, work conditions affect safety performance directly whereas it affects safety performance indirectly via an intermediate factor, such as health. Indeed, some studies show that obesity may be related to safety performance (Anderson et al., 2012; Zhu et al., 2006; Cantor et al., 2010). The application of SEM to the analysis of truck driver safety may produce interesting results and implications.

## APPENDIX A. THE PEARSON CORRELATION COEFFICIENTS (CHAPTER 2)

Variable	ln(Pay/Mile)	Retirement Benefit	Health Insurance	Non- driving Pay	Annual Work Weeks	Less- than- Truckload	Team	Type	Married	White	Male	Union	Edu	Experience
ln(Pay/Mile)														
Retirement Benefit	0.036													
Health Insurance	-0.067	0.22												
Non-driving Pay	-0.015	0.15	0.18											
Annual Work Weeks	-0.15	0.070	0.080	0.0087										
Less-than- Truckload	0.065	-0.029	-0.10	0.052	-0.0053									
Team	0.11	0.071	-0.022	0.0037	-0.12	0.073								
Type	-0.035	0.068	0.037	0.044	0.024	0.11	-0.066							
Married	0.028	0.037	0.076	0.063	0.0074	-0.052	0.0037	0.047						
White	-0.027	-0.10	0.038	-0.021	0.037	-0.048	-0.061	-0.058	0.12					
Male	0.0040	0.024	0.046	0.013	0.061	-0.018	-0.22	0.045	0.077	0.037				
Union	0.037	0.10	0.052	-0.030	0.015	0.053	0.094	-0.072	0.012	-0.015	0.044			
Edu	-0.0082	0.043	0.0010	0.0080	-0.027	-0.036	-0.037	-0.032	-0.079	0.018	-0.040	-0.028		
Experience	0.035	-0.050	0.047	0.032	-0.0015	-0.047	-0.19	-0.12	0.069	0.10	0.075	0.022	-0.063	

## APPENDIX B. THE PEARSON CORRELATION COEFFICIENTS (CHAPTER 3)

Variable	In(Work Hours)	Non-driving Pay	Health Insurance	Less-than-Truckload	Team	Age	Education	White	Married	Male	Union	BMI
In(Work Hours)												
Non-driving Pay	-0.094											
Health Insurance	0.073	0.17										
Less-than-Truckload	-0.091	0.061	-0.10									
Team	-0.021	-0.011	-0.025	0.070								
Age	-0.071	0.0091	0.051	-0.023	-0.16							
Education	-0.072	0.0097	-0.00011	-0.030	-0.040	0.031						
White	-0.050	-0.0031	0.032	-0.044	-0.064	0.096	0.020					
Married	-0.010	0.070	0.094	-0.047	0.0030	0.13	-0.077	0.12				
Male	0.0020	0.013	0.044	-0.016	-0.21	0.040	-0.043	0.035	0.075			
Union	-0.032	-0.037	0.056	0.045	0.086	0.039	-0.041	-0.026	0.0031	0.043		
BMI	-0.073	0.027	0.078	-0.13	-0.0080	-0.062	0.022	0.017	0.11	-0.0097	-0.0048	



## APPENDIX C. THE PEARSON CORRELATION COEFFICIENTS (CHAPTER 4)

Variable	Non-driving Pay	ln(Mileage Rate)	Less-than-Truckload	Team	Union	Enclosed Van	White	Education	Male	Married	Age
Non-driving Pay											
ln(Mileage Rate)	-0.013										
Less-than-Truckload	0.060	0.066									
Team	-0.00061	0.11	0.074								
Union	-0.031	0.039	0.052	0.092							
Enclosed Van	0.035	-0.032	0.11	-0.064	-0.072						
White	-0.0066	-0.020	-0.048	-0.067	-0.013	-0.044					
Education	0.0052	-0.017	-0.035	-0.043	-0.025	-0.016	0.025				
Male	0.019	0.0035	-0.014	-0.21	0.043	0.040	0.031	-0.046			
Married	0.066	0.022	-0.050	0.0054	0.011	0.057	0.12	-0.076	0.082		
Age	0.0062	0.033	-0.034	-0.16	0.045	-0.068	0.10	0.031	0.038	0.12	

## REFERENCES

- Anderson JE, Govada M, Steffen TK, et al. (2012) Obesity is Associated with the Future Risk of Heavy Truck Crashes among Newly Recruited Commercial Drivers. *Accident Analysis and Prevention* 49: 378-384.
- Apostolopoulos Y, Sönmez S, Shattell M, et al. (2012) Environmental Determinants of Obesity-associated Morbidity Risks for Truckers. *International Journal of Workplace Health Management* 5: 120-138.
- Balu S and Thomas J, III. (2006) Incremental Expenditure of Treating Hypertension in the United States. *American Journal of Hypertension* 19: 810–816.
- Barling J, Loughlin C and Kelloway EK. (2002) Development and Test of a Model Linking Safety-Specific Transformational Leadership and Occupational Safety. *Journal of Applied Psychology* 87: 488-496.
- Becker G. (1964) *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, Cambridge: Harvard University Press.
- Belman D, Monaco KA and Brooks TJ. (2004) *Sailors of the Concrete Sea: A Portrait of Truck Drivers' Work and Lives*, Lansing: Michigan State University Press.
- Belzer MH. (1995) Collective Bargaining after Deregulation: Do the Teamsters Still Count? *Industrial and Labor Relations Review* 48: 636-655.
- Belzer MH. (2000) *Sweatshops on Wheels: Winners and Losers in Trucking Deregulation*, New York: Oxford University Press.
- Belzer MH. (2009) OOIDA 2003-2004 Cost of Operations Survey: Report of Results. Detroit: Wayne State University.
- Belzer MH. (2012) The Economics of Safety: How Compensation Affects Commercial Motor Vehicle Driver Safety
- Belzer MH. (2018) Work-stress Factors Associated with Truck Crashes: An Exploratory Analysis. *Economic and Labour Relations Review* 29: 89-307.

- Belzer MH, Rodriguez DA and Sedo S. (2002) Paying for Safety: An Economic Analysis of the Effect of Compensation on Truck Driver Safety. Washington, DC: Federal Motor Carrier Safety Administration.
- Belzer MH and Sedo SA. (2018) Why Do Long Distance Truck Drivers Work Extremely Long Hours? *Economic and Labour Relations Review* 29: 59-79.
- Belzer MH and Swan PF. (2011) Supply Chain Security: Agency Theory and Port Drayage Drivers. *Economic and Labour Relations Review* 22: 41-64.
- Booth AL, Francesconi M and Zoega G. (2003) Unions, Work-Related Training, and Wages: Evidence for British Men. *Industrial and Labor Relations Review* 57: 68-91.
- Brachet T, David G and Drechsler AM. (2012) The Effect of Shift Structure on Performance. *American Economic Journal: Applied Economics* 4: 219-246.
- Bureau of Labor Statistics. (2010) *2010 Annual Averages: Household Data: Tables from Employment and Earnings (Persons at Work in Nonagricultural Industries by Class of Worker and Usual Full- or Part-Time Status)*. Available at: [https://www.bls.gov/cps/cps\\_aa2010.htm](https://www.bls.gov/cps/cps_aa2010.htm). (accessed 21 April 2019).
- Burks SV, Belzer MH, Kwan Q, et al. (2010) Trucking 101: An Industry Primer. In: Board TR (ed). Washington, DC: Transportation Research Board.
- Camerer C, Babcock L, Loewenstein G, et al. (1997) Labor Supply of New York City Cabdrivers: One Day at a Time. *Quarterly Journal of Economics* 112: 407-441.
- Cantor DE, Corsi TM, Grimm CM, et al. (2010) A Driver Focused Truck Crash Prediction Model. *Transportation Research Part E* 46: 683-692.
- Chankaramangalam MA, Ramamoorthy V, Muthuraja D, et al. (2017) Factors Associated with Hypertension among Truck Drivers: A Cross Sectional Study at a Check Post on a National Highway in South India. *International Journal of Medical Research and Health Sciences* 6: 126-129.

- Chen GX, Sieber WK, Lincoln JE, et al. (2015) NIOSH National Survey of Long-haul Truck Drivers: Injury and Safety. *Accident Analysis and Prevention* 85: 66-72.
- Corsi TM, Grimm CM, Cantor DE, et al. (2012) Safety Performance Differences between Unionized and Non-union Motor Carriers. *Transportation Research Part E* 48: 807-816.
- Crawford VP and Meng J. (2011) New York City Cab Drivers' Labor Supply Revisited: Reference-Dependent Preferences with Rational-Expectations Targets for Hours and Income. *American Economic Review* 101: 1912-1932.
- Crum MR and Morrow PC. (2002) The Influence of Carrier Scheduling Practices on Truck Driver Fatigue. *Transportation Journal* 42: 20-41.
- Czeisler C. (2015) Duration, Timing and Quality of Sleep are Each Vital for Health, Performance and Safety. *Sleep Health* 1: 5-8.
- Dembe AE, Erickson JB and Delbos R. (2004) Predictors of Work-Related Injuries and Illnesses: National Survey Findings. *Journal of Occupational and Environmental Hygiene* 1: 542-550.
- Dembe AE, Erickson JB, Delbos RG, et al. (2005) The Impact of Overtime and Long Work Hours on Occupational Injuries and Illnesses: New Evidence from the United States. *Occupational & Environmental Medicine* 62: 588-597.
- Dembe AE, Erickson JB, Delbos RG, et al. (2006) Nonstandard Shift Schedules and the Risk of Job-related Injuries. *Scandinavian Journal of Work, Environment & Health* 32: 232-240.
- Desmarais BA and Harden JJ. (2013) Testing for Zero Inflation in Count Models: Bias Correction for the Vuong Test. *The Stata Journal* 13: 810-835.
- Drakopoulos SA and Theodossiou I. (1997) Job Satisfaction and Target Earnings. *Journal of Economic Psychology* 18: 693-704.
- Faulkner MR and Belzer MH. (2019) Returns to Compensation in Trucking: Does Safety Pay? *Economic and Labour Relations Review*.

- Federal Motor Carrier Safety Administration. (2017) *DOT Medical Exam and Commercial Motor Vehicle Certification*. Available at: <https://www.fmcsa.dot.gov/medical/driver-medical-requirements/dot-medical-exam-and-commercial-motor-vehicle-certification>. (accessed 21 April 2019).
- Friswell R and Williamson A. (2013) Comparison of the Fatigue Experiences of Short Haul Light and Long Distance Heavy Vehicle Drivers. *Safety Science* 57: 203-213.
- Gabriel PE and Schmitz S. (2014) A Longitudinal Analysis of the Union Wage Premium for US Workers. *Applied Economics Letters* 21: 487-489.
- Ge Y. (2014) Do Chinese Unions Have "Real" Effects on Employee Compensation? *Contemporary Economic Policy* 32: 187-202.
- Greene WH. (2011) *Econometric Analysis, 7th Edition*, Upper Saddle River, NJ: Prentice Hall.
- Hege A, Lemke MK, Apostolopoulos Y, et al. (2017) US Long-haul Truck Driver Work Organization and the Association with Cardiometabolic Disease Risk. *Archives of Environmental and Occupational Health* 72: 303-310.
- Hirsch BT. (1993) Trucking Deregulation and Labor Earnings: Is the Union Premium a Compensating Differential? *Journal of Labor Economics* 11: 279-301.
- Hirsch BT and Macpherson DA. (2017) *Union Membership and Coverage Database from the CPS*. Available at: <http://www.unionstats.com/>. (accessed May 8th 2018).
- Hirsch BT and Macpherson DA. (2018) *Union Membership and Coverage Database from the CPS*. Available at: <http://www.unionstats.com/>. (accessed 19 April 2019).
- Hooper A and Murray D. (2017) An Analysis of the Operational Costs of Trucking: 2017 Update. American Transportation Research Institute.
- Jensen A and Dahl S. (2009) Truck Drivers Hours-of-Service Regulations and Occupational Health. *Work* 32: 363-368.
- Jovanis PP, Wu K-F and Chen C. (2012) Effects of Hours of Service and Driving Patterns on Motor Carrier Crashes. *Transportation Research Record* 2281: 119-127.

- Kaneko T and Jovanis PP. (1992) Mutiday Driving Patterns and Motor Carrier Accident Risk: A Disaggregate Analysis. *Accident Analysis and Prevention* 24: 437-456.
- Kim D and Leigh JP. (2010) Estimating the Effect of Wages on Obesity. *Journal of Occupational and Environmental Medicine* 52: 495-500.
- Kim J and Philips P. (2010) Health Insurance and Worker Retention in the Construction Industry. *Journal of Labor Research* 31: 20–38.
- Kurosaka K, Daida H, Muto T, et al. (2000) Characteristics of Coronary Heart Disease in Japanese Taxi Drivers as Determined by Coronary Angiographic Analyses. *Industrial Health* 38: 15-23.
- Lazear EP. (1990) Pensions and Deferred benefits as Strategic Compensation. *Industrial Relations* 29: 263-280.
- Leigh JP and Du J. (2012) Are Low Wages Risk Factors for Hypertension? *European Journal of Public Health* 22: 854–859.
- Lenhart O. (2017) Do Higher Minimum Wages Benefit Health? Evidence from the UK. *Journal of Policy Analysis and Management* 36: 828–852.
- Leproult R, Copinschi G, Buxton O, et al. (1997) Sleep Loss Results in an Elevation of Cortisol Levels the Next Evening. *Sleep* 20: 865-870.
- Lin T-D, Jovanis PP and Yang C-Z. (1993) Modeling the Safety of Truck Driver Service Hours Using Time-Dependent Logistic Regression. *Transportation Research Record* 1407: 1-10.
- Martin V. (2017) When to Quit: Narrow Bracketing and Reference Dependence in Taxi Drivers. *Journal of Economic Behavior and Organization* 144: 166-187.
- Min H and Lambert T. (2002) Truck Driver Shortage Revisited. *Transportation Journal* 42: 5-16.
- Monaco K, Olsson L and Hentges J. (2005) Hours of Sleep and Fatigue in Motor Carriage. *Contemporary Economic Policy* 23: 615-624.
- Monaco K and Williams E. (2000) Assessing the Determinants of Safety in the Trucking Industry. *Journal of Transportation and Statistics* 3: 69-80.

- Monaco KA and Brooks TJ. (2001) Deregulation and Wages in Trucking: A Time Series Phenomenon: A Time Series Approach. *Research in Transportation Economics* 6: 55-69.
- Monaco KA, Brooks TJ and Bitzan J. (2006) A Time Series Analysis of Wages in Deregulated Industries: A Study of Motor Carriage and Rail. *Journal of Applied Economics* 9: 105-118.
- Murray D, Lantz B and Keppler S. (2006) Predicting Truck Crash Involvement: Developing a Commercial Driver Behavior Model and Requisite Enforcement Countermeasures. *Transportation Research Board 2006 Annual Meeting*.
- Nafukho FM, Hinton BE and Graham CM. (2007) A Study of Truck Driver and their Job Performance Regarding Highway Safety. *Performance Improvement Quarterly* 20: 65-78.
- Nakanishi N, Yoshida H, Nagano K, et al. (2001) Long Working Hours and Risk for Hypertension in Japanese Male White Collar Workers. *Journal of Epidemiology and Community Health* 55: 316-322.
- National Academy of Science E, and Medicine,. (2016) *Commercial Motor Vehicle Driver Fatigue, Long-Term Health, and Highway Safety*, Washington, D.C.: The National Academy Press.
- NIOSH. (2015) *The National Institute for Occupational Safety and Health (NIOSH): Long-haul Truck Drivers*. Available at: <https://www.cdc.gov/niosh/topics/truck/default.html>. (accessed 19 April 2019).
- Prospective Studies Collaboration. (2002) Age-specific Relevance of Usual Blood Pressure to Vascular Mortality: A Meta-analysis of Individual Data for One Million Adults in 61 Prospective Studies. *Lancet* 360: 1903-1913.
- Ragland DR, Winkleby MA, Schwalbe J, et al. (1989) Prevalence of Hypertension in Bus Drivers. *AAOHN Journal* 37: 71-79.
- Rodríguez DA, Rocha M and Belzer MH. (2004) The Effects of Trucking Firm Financial Performance on Driver Safety. *Research in Transportation Economics* 10: 35-55.
- Rodríguez DA, Rocha M, Khattak AJ, et al. (2003) Effects of Truck Driver Wages and Working Conditions on Highway Safety: Case Study. *Transportation Record* 1883: 95-102.

- Rodríguez DA, Targa F and Belzer MH. (2006) Pay Incentives and Truck Driver safety: A Case Study. *Industrial and Labor Relations Review* 59: 205-225.
- Ronna BB, Thiese MS, Ott U, et al. (2016) The Association between Cardiovascular Disease Risk Factors and Motor Vehicle Crashes among Professional Truck Drivers. *Journal of Occupational and Environmental Medicine* 58: 828–832.
- Saltzman GM and Belzer MH. (2002) The Case for Strengthened Motor Carrier Hours of Service Regulations *Transportation Journal* 41: 51-71.
- Saltzman GM and Belzer MH. (2007) Truck Driver Occupational Safety and Health: 2003 Conference Report and Selective Literature Review. Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health.
- Schildkraut JL. (2003) NCS Reviews the Effectiveness of Variable Pay Collection. *Monthly Labor Review*, April 2003. (accessed 21 April).
- Seo H-C, Lee Y-S, Kim J-J, et al. (2015) Analyzing Safety Behaviors of Temporary Construction Workers Using Structural Equation Modeling. *Safety Science* 77: 160-168.
- Sieber WK, Robinson CF, Birdsey J, et al. (2014) Obesity and Other Risk Factors: The National Survey of U.S. Long-Haul Truck Driver Health and Injury. *American Journal of Industrial Medicine* 57: 615–626.
- Siu O-I, Phillips DR and Leung T-w. (2004) Safety Climate and Safety Performance among Construction Workers in Hong Kong: The Role of Psychological Strains as Mediators. *Accident Analysis and Prevention* 36: 359-366.
- Smith SM. (2015) Workplace Hazards of Truck Drivers in 2012. *Monthly Labor Review* 138.
- Spiegel K, Leproult R and Cauter EV. (1999) Impact of Sleep Debt on Metabolic and Endocrine Function. *Lancet* 354: 1435-1439.
- Suka M, Yoshida K and Sugimori H. (2003) Persistent Insomnia is a Predictor of Hypertension in Japanese Male Workers. *Journal of Occupational Health* 45: 344-350.



- Thiese MS, Moffitt G, Hanowski RJ, et al. (2015) Commercial Driver Medical Examinations. *Journal of Occupational and Environmental Medicine* 57: 659-665.
- Thrift AG, McNeil JJ, Forbes A, et al. (1996) Risk Factors for Cerebral Hemorrhage in the Era of Well-Controlled Hypertension. *Stroke* 27: 2020-2025.
- U.S. Bureau of Labor Statistics. (2015) *Time Spent Working by Full- and Part-time Status, Gender, and Location in 2014*. Available at: <https://www.bls.gov/opub/ted/2015/time-spent-working-by-full-and-part-time-status-gender-and-location-in-2014.htm>. (accessed 19 April 2019).
- U.S. Bureau of Labor Statistics. (2017) *Table 24. Historical Consumer Price Index for All Urban Consumers (CPI-U): U. S. City Average, All Items-Continued*. Available at: <https://www.bls.gov/cpi/tables/historical-cpi-u-201709.pdf>. (accessed 19 April 2019).
- U.S. Department of Transportation. (2007) *Unit Costs of Medium and Heavy Truck Crashes*. Available at: <https://www.fmcsa.dot.gov/advisory-committees/mcsac/unit-costs-medium-and-heavy-truck-crashes-2007-zaloshnja-miller>. (accessed 21 April 2019).
- U.S. Department of Transportation Office of Inspector General. (2018) *Estimates Show Commercial Driver Detention Increases Crash Risks and Costs, but Current Data Limit Further Analysis*. Available at: <https://www.oig.dot.gov/library-item/36237>. (accessed 19 April 2019).
- Werner S, Kuate CS, Noland TR, et al. (2016) Benefits and Strategic Outcomes: Are Supplemental Retirement Plans and Safer Driving Related in the U.S. Trucking Industry? *Human Resource Management* 55: 885-900.
- Williams E and Monaco K. (2001) Accidents and Hours-of-Service Violations among Over-the-Road Drivers. *Journal of Transportation and Research* 40: 105-115.
- Yang H, Schnall PL, Jauregui M, et al. (2006) Work Hours and Self-Reported Hypertension among Working People in California. *Hypertension* 48: 744-750.

- Yellen J. (1984) Efficiency Wage Models of Unemployment. *American Economic Review: Papers and Precedings* 74: 200-205.
- Yoo DH, Kang M-y, Paek D, et al. (2014) Effect of Long Working Hours on Self-reported Hypertension among Middle-aged and Older Wage Workers. *Annals of Occupational and Environmental Medicine* 26: 25.
- Yoon SSS, Fryar CD and Carroll MD. (2015) Hypertension Prevalence and Control among Adults: United States, 2011–2014. *NCHS Data Brief* 220: 1-8.
- Zhu S, Layde PM, Guse CE, et al. (2006) Obesity and Risk for Death Due to Motor Vehicle Crashes. *American Journal of Public Health* 96: 734-739.

**ABSTRACT****STATISTICAL ANALYSIS OF THE EFFECT OF WORK CONDITIONS ON SAFTY AND HEALTH IN THE U.S. LONG-HAUL TRUCKING INDUSTRY: EVIDENCE FROM THE NIOSH SURVEY DATA**

by

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Chapter 1 reviews the literature which analyzes the effect of compensation and working conditions on safety and health.

Chapter 2 analyzes how truck drivers' compensation affects their safety performance, using moving violations as a proxy for safety. In addition to drivers' pay per mile driven, we employ fringe benefits as independent variables. The result suggests that the rate of pay per mile driven, and employment-based health insurance, significantly decrease the probability of moving violations. The result provides support for the hypothesis that high compensation for drivers improve drivers' safety performance, though other forms of compensation are not significantly related to the incidence of moving violations.

Chapter 3 analyzes how truck drivers' working conditions affect health. We use hypertension as a proxy for health. Hypertension is a common illness among commercial motor vehicle drivers, including long-haul truck drivers. Few studies analyze how working conditions, including wages and work hours, might lead to hypertension among long-haul truck drivers. We hypothesize that long-haul truck drivers' hypertension is due to excessive work hours rather than age or BMI. Using a multinomial logit model, we find that that longer work hours are associated with a higher probability of suffering from hypertension, as expected. However, drivers who take medication for hypertension also work fewer hours per week, suggesting that they are proactive in

reducing their work intensity as well as taking their medicine in order to combat this illness. Since drivers face trade-off between income and health, drivers who take medication for hypertension also seem to accept lower overall earnings by working fewer hours in order to forestall worsening hypertension.

Chapter 4 analyzes how non-driving pay affects drivers' work hours. In the trucking industry, truck drivers' duties include not only driving trucks but also non-driving labor. However, non-driving work is not necessarily paid. This paper analyzes how the payment for non-driving duties (non-driving pay) affects truck drivers' work hours. This study finds that remunerating drivers for non-driving duties decreases drivers' work hours. The policy implication of this result is that paying non-driving pay can prevent drivers from working excessively long hours, which may mitigate fatigue. Thus, pay for non-driving labor may possibly enhance their safety and health.

Chapter 5 is the conclusion.

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2013-2019 Ph.D. in Economics, Wayne State University, Detroit, USA; Fields: Labor Economics and Industrial Organization (Dissertation: Statistical Analysis of the Effect of Work Conditions on Safety and Health in the U.S. Long-haul Trucking Industry: Evidence from the NIOSH Survey Data)

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