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ORIGINAL ARTICLE

Follow the money: Trucker pay incentives, working time, and safety

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Abstract

Most truck drivers experience economic pressure in the form of low pay rates, no pay for non-driving work time, and long work hours. Unpaid working time, leading to low effective pay rates, encourages drivers to work excessive hours to pursue target earnings, which leads to fatigue and working time violations, and ultimately raises crash rates. This paper explores the complex relationship between regulatory violations, pay incentives, and crashes, to determine the effects of economic forces on carrier safety. We use data from 13,904 intrastate trucking companies in the United States, as well as median hourly truck driver wages from data published by the Bureau of Labor Statistics. We find that controlling for observed regulatory violations (hours of service, unsafe driving, and substance abuse), at the mean, 1% higher driver wages are associated with 1.04% fewer crashes. Stated differently, a 10% wage increase would be 5 times as effective as a 10% reduction in 'unsafe driving' or 2.5 times as effective as a 10% reduction in 'driver fitness' violations. This unit elasticity between driver pay and crashes suggests that higher compensation will bring direct and commensurate worker and public safety benefits. Every unit in higher pay, at the mean, will lead to a corresponding unit improvement in safety. Our findings suggest that the most effective way for regulators to pursue their mission to reduce crashes, fatal or otherwise, would be to collect firm-level data on truck driver compensation and allow their methodology to follow sound science.

Keywords: efficiency wage; fair labour standards; labour market regulation; negative externalities; occupational safety; piecework; target earnings; truck driver safety; wages; working time

Background

The trucking industry is critical to the United States (US) economy because supply chains rely on trucking for about 80% of the value of freight transport. According to the US Department of Transportation (DOT) Bureau of Transportation Statistics (BTS), in 2019 (before COVID-19 supply chain disruptions), employment in transportation and warehousing accounted for 3.8% of the U.S. civilian labour force, and truck transportation accounted for 27% of the transportation and warehousing sector (US Department of Transportation Bureau of Transportation Statistics 2019). Supply chain disruptions emerging in 2020, and continuing in subsequent years, have revealed the extent to which the economy depends on reliable freight transport. In 2023, trucking contributed US$389.3 billion to the US Gross Domestic Product (GDP), or 29% of the entire contribution by all transport modes (US Department of Transportation Bureau of Transportation

Statistics 2019). While trucking was only about 1.8% of GDP in 2023, COVID-19 supply chain disruptions have shown the centrality of this activity for the rest of the economy, especially inflation.

Trucking safety measurement relies on data collected by the US DOT Federal Motor Carrier Safety Administration (FMCSA), which maintains the Motor Carrier Management Information System (MCMIS) database, with information on 892,078 for-hire carriers in May 2019. Approximately 30,000 trucking companies enter and exit the database every year. A National Academies panel estimated that about 550,000 carriers are active at any one time, of which approximately 200,000 report sufficient data to be included in the system-wide analysis (Panel on the Review of the Compliance Safety and Accountability (CSA) Program of the Federal Motor Carrier Safety Administration 2017). One may expect such a large industry to be concentrated and led by a few large firms, like railroads and airlines. However, 90% of all firms operated six or fewer trucks in 2018, according to MCMIS census data; most trucking companies are small, and the industry is fragmented.

Trucking also has restructured significantly since liberalisation of trucking economic regulation in 1980. 'Deregulation' of trucking caused the Common Carrier[1] sector of trucking to fracture and disappear, as intense competition broke trucking into three sectors reflective of freight shipment characteristics: less-than-truckload (LTL), using pickup and delivery systems to consolidate small shipments; truckload (TL), operating like the regulatory exempt sector did before 1980; and the package delivery sector, which the US Census has reclassified out of trucking and into the courier sector. Package delivery and freight integrators operate firms hauling everything from small packages and letters to full TLs, but in the small shipment sized network model (Belzer 2000). Carriers with different operational characteristics require operating authority and must report safety data to FMCSA, and all remaining part of trucking.

Truck driver compensation has declined significantly since economic deregulation in 1980. Low pay has become an important feature of truck driver labour markets and compensation remains so low that the industry complains of labour shortages and successfully pushed to increase hours of work and employ long-haul drivers as young as 18 in an effort to remedy the claimed shortage (Federal Motor Carrier Safety Administration (FMCSA) Department of Transportation (DOT) 2022). The FMCSA and many private analysts claim that this is a recruiting and retention problem because it is impossible for an actual labour shortage of truck drivers to persist for decades; such shortages develop only when human capital development takes many years of education and experience. Research suggests that low compensation is linked to low productivity, as well as trucking company safety and truck driver safety and health, so it has become a significant bellwether for workers subject to growing precarious work arrangements.

Literature review

Scholars believe the current highly competitive trucking industry market is the consequence of the Motor Carrier Act (MCA) of 1980, which broke down institutional barriers to interstate entry (Belzer 2000, 64–67) followed by the Federal Aviation Administration Authorization Act of 1994, which did the same for intrastate trucking, and deunionisation, which has been a long-standing process in the US. The International Brotherhood of Teamsters (IBT), which represented about 60% of trucking industry employees before 1980 (Hirsch 1988, 306), in 2023 represented 7.3% of 'truck transportation' industry employees and 9.3% of all 'driver/sales workers and truck drivers' (Hirsch et al 2023). Deregulation effectively promoted market competition and reduced driver compensation, both wages and benefits, as well as union density (Rose 1987; Hirsch 1993; Hirsch et al 1997; Monaco and Brooks 2001).

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Policy change such as this, however, creates winners and losers. One study published a decade after the passage of the MCA of 1980 concluded that while logistical efficiency probably improved due to the rationalisation of the freight transport sector and the share of freight transport cost declined relative to GDP, probably 60% of the savings was due to reduced driver compensation (Winston et al 1990), which many economists assumed were regulatory rents. Lower compensation may have been appropriate if drivers earned monopoly rents before deregulation, but high turnover and trucking's recruiting and retention challenges since the mid 1980s suggests the employment package made truck driving much less attractive to qualified drivers, moving trucking down the labour market queue. As Hirsch (1993) concludes, a substantial share of earnings *premia* before deregulation were not rents but instead returns to driver skills and experience.

In the classic supply and demand model, if more firms enter the market, the supply curve will shift outward, which drives the equilibrium price down. A rational trucker maximises profit when it sets the driver's wage at the minimum level required by the price of the transportation service; trucking companies set wages at the market-clearing equilibrium price at which the marginal cost equals the marginal revenue. When driver labour costs constitute a major share of motor carrier costs, cost minimisation forces drivers to absorb the burden of declining freight rates due to competition, as well as shifting the risk associated with inconsistent operational scheduling to the drivers (Belzer 1995, 648). However, if lower driver compensation leads to safety risk and if the cost of this safety risk is not captured in price, workers and the public may absorb the cost as an 'externality'. This static model therefore may not capture the full consequences of the decline in drivers' compensation, including safety costs, and poor truck driver health may be an even larger externality (Saltzman and Belzer, 2007).

In the past two decades, various studies have shown the relationship between pay incentives and commercial motor vehicle (CMV) driver safety. The University of Michigan Trucking Industry Program (UMTIP) surveyed long-haul truck driver compensation, demographics, use of logbooks, attitudes towards hours of service (HOS) regulations, and other issues in a survey administered at truck stops (Belman et al 2005). Using UMTIP cross-sectional data, Monaco and Brooks estimated the relationship among three safety measures and driver characteristics. They found that less sleep and more miles driven, both increase the probability of violating working time regulations and having crashes. Most importantly, the mileage pay rate and the payment method affect the probability of a logging violation or a crash (Monaco and Brooks 2001). Moreover, Monaco and Williams conclude that firm size matters, as large firms (1,000 to 4,999 employees) outperform small firms (25 or fewer employees) with lower probability of crash involvement, moving violations (traffic citation or 'ticket'), and violating logbook regulations (Monaco and Williams 2000).

Belzer, Rodriguez, and Sedo examine the relationship between the various compensation practices of motor carriers and safety outcomes. Their multi-level study gathered data from four sources: the National Survey of Driver Wages (NSDW, or 'Signpost'), the National Motor Carrier Directory, MCMIS, and the UMTIP truck driver survey, allowing three layers of analysis. In a cross-sectional study of 102 nonunion TL carriers, they combine NSDW and MCMIS with their own survey, finding that the inverse relationship between compensation and total motor carrier crashes is almost unit elastic – at the mean, 'a 10% increase in compensation would be estimated to cause an 9.2% decrease in crashes' (Belzer et al 2002, 64–71).

In a firm-level case study, they use individual driver data from J.B. Hunt – a very large nonunion TL motor carrier with 11,540 individuals and 92,528 observations – covering 26 months (September 1995—September 1996 and March 1997—February 1998), before and after a major wage increase. Using Cox survival analysis to estimate the probability of driver crashes month-to-month, this study shows the 38% pay increase led to a 50% decline

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in crashes year-over-year and a 75% decline in big crashes. 'At the mean rate of pay … this translates into an elasticity of −3.4' (Belzer et al 2002, 80).

In the third study, they test a subsample of all employee drivers who are paid by the mile in the UMTIP dataset and find that a 10% increase in the mileage rate reduces the probability of a crash by 21%. All three models show that driver pay is a strong predictor of driver safety. Since the elasticity varies across different model specifications, they estimate that the elasticity averages better than −2 across all studies. Their report, and the subsequent published papers (Rodriguez et al 2006; Belzer and Sedo 2018), lays the foundation on driver compensation and safety for multiple studies.

Belzer and Sedo look analytically at the long-haul truck drivers' response to pay rates, using UMTIP survey data. They start with efficiency wage theory, which asserts that firms that pay workers above the market clearing rate experience a higher level of effort and performance (Yellen 1984). They hypothesise that workers further are motivated to reach their target earnings (the amount they need to earn to pay their bills), and then will trade labour for leisure, declining additional work. They derive a backward bending labour supply curve, which estimates the labour-leisure trade-off for long-distance truck drivers (and hence the labour market for truck drivers). Their analysis suggests that a typical driver's preference for paying work (and their willingness to supply labour to the market) declines when they reach such targets – a concept applicable to all workers. Specifically, they find the income effect starts dominating the substitution effect at the tipping point when the representative driver receives an average of US$0.3075 cents per mile in 1997 dollars (US$0.59 cents per mile in 2023 dollars) while working 69.8 hours per week. They predict that CMV drivers who earn a higher rate will work fewer hours than lower paid drivers (Belzer and Sedo 2018). Although 69.8 hours per week is well beyond the legal limit of 60 hours, long working time is consistent with the findings of the National Survey of Long-Haul Truck Drivers conducted by the National Institute for Occupational Safety and Health (NIOSH) in 2010 (Chen et al 2015), and with Viscelli's finding that drivers have strong incentives to dodge the HOS mandatory 60-hour rule by using different 'logbook techniques' (Viscelli 2016) that allow them to work far more hours than the legal limit. These techniques include recording most unpaid non-driving working hours off-duty to conserve weekly hours that they can use to accept additional paying loads.

Kudo and Belzer used the 2010 NIOSH dataset and found that higher mileage payrates[2] and employment-based health insurance are significantly associated with a lower probability of moving violations, a proxy for safety. They do not explore the causality between moving violations and crashes because the survey data are cross-sectional (2019).

Although flaws and gaps in every dataset create challenging econometric problems, the results seem consistent. Compensation is a strong predictor of crashes; if the compensation is low, then the probability of crash or the crash count (depending on the model) will be high. In this paper, we explore this relationship in the intrastate property-carrying sector of the trucking industry in 2018 using MCMIS firm-level data.

Motivation

The foregoing literature suggests that the relationship between compensation and safety seems strong across multiple studies. Unfortunately, the datasets used in the previous studies are more than a decade old. This study aims to test the relationship between HOS violations and crashes and determine the relationship between compensation and crashes, using different statistical approaches and current datasets.

The National Academies convened a panel to evaluate the causality between fatigue and both crashes and commercial driver health. They concluded that working time regulations need to take into account the trade-off between the economic advantages of faster cheaper transportation and the disadvantages of more crashes (Panel on Research Methodologies and Statistical Approaches to Understanding Driver Fatigue Factors in Motor Carrier Safety and Driver Health 2016). A second panel study by the National Academies followed immediately, echoing the first, which recommended that the FMCSA collect data on compensation so that it could determine the effect of compensation on safety using a single dataset (Panel on the Review of the Compliance Safety and Accountability (CSA) Program of the Federal Motor Carrier Safety Administration 2017). Regulators have not implemented any of these recommendations.

This paper aims to make this trade-off more explicit by linking crash risk to the number of FMCSA HOS compliance violations, using the 2018 MCMIS dataset.

Theory and hypothesis

Deregulation in 1980 led to an intensively competitive environment. In the past two decades, only a few studies have focused on compensation and safety in the trucking industry. Given the importance of trucking labour in commerce – a fact that the COVID supply shock made clear – we should look at the role compensation plays in providing performance incentives.

Efficiency wage theory suggests that employers could pay higher than market-clearing compensation to attract, recruit, and retain truck drivers. The market-clearing wage in trucking, however, is obscured because long-haul truck driver pay is almost all piecework and trucking companies do not record hours of work because the Fair Labor Standards Act exempts from overtime pay truck drivers in interstate commerce (Belzer 2024, forthcoming). In addition to providing incentives for productivity, efficiency wages would create an incentive to drive safely in order to retain their jobs and improve their employability for future truck driving jobs (Akerlof et al 1988; Akerlof and Yellen 1990). This runs counter to the cost minimisation model that most trucking companies use.

The classic definition characterises the efficiency wage as the compensation package that a profit-maximising firm will offer an employee to minimise the labour cost per efficiency unit, which also equates to the firm's marginal product. However, the efficiency wage hypothesis (Yellen 1984) suggests that employers need to pay higher than market equilibrium compensation to prevent workers from shifting firms and induce greater labour productivity in some markets. This takes added salience in an industry that typically has 100% turnover annually. From an employer's perspective, efficiency wages will attract higher quality workers and reduce turnover, because workers testing the labour market cannot find a better alternative job. In the context of the trucking industry, the hypothesis suggests that above market-clearing wages can attract good drivers and thus improve safety performance.

In addition, higher pay creates an incentive for truck drivers to avoid fatigue and drive safely to retain their current job, while improving their employability for future good truck driving jobs. Higher wages, *ceteris paribus*, should improve driver and motor carrier safety performance without sacrificing profitability. Faulkiner and Belzer show that one of the largest US TL trucking companies, which raised long-haul truck driver wages by 38% to make irregular-route long-distance trucking employment equally attractive to regular-route trucking jobs, reduced recruiting and training cost by cutting turnover in half, and saved casualty cost by reducing major crashes fourfold. Higher paid, stable employees also were significantly more productive, logging 1,000 more productive miles (1,600 km) per month and earning the company higher return on investment (ROI). Indeed, higher paid experienced drivers annually earned their employers an estimated US$10,474 greater net present value than that earned by low-paid inexperienced truck drivers at the same firm (Faulkiner and Belzer 2019). An all-in profit maximisation model outperformed the cost minimisation model, accounting for all measurable potential externalities.

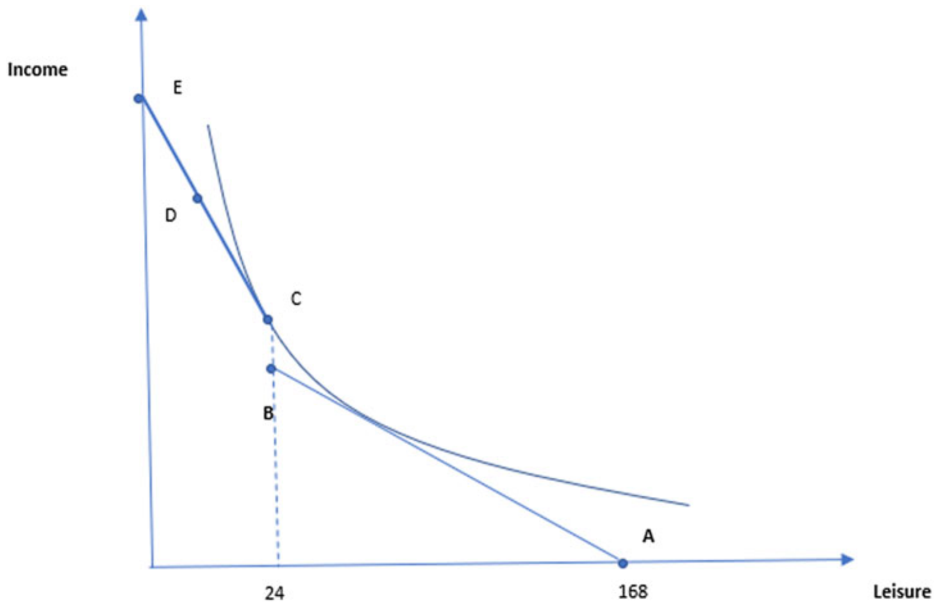

Figure 1. Labour leisure model.
Note: This figure technically shows the tradeoff between income and leisure on the premise that workers raise their income by resting fewer hours. Theoretical framework from Belzer and Sedo, 2018

The classic labour-leisure model shows the trade-off between work and rest. In trucking, the model is subject to the HOS constraint, which at least conceptually limits CMV drivers to 60 hours per 7 consecutive days. If most drivers are sensitive to earnings and have a target income higher than the market-clearing price, they have a strong incentive to work and drive more, violating the HOS regulations; these excess hours ultimately result in higher crash probability (Panel on Research Methodologies and Statistical Approaches to Understanding Driver Fatigue Factors in Motor Carrier Safety and Driver Health 2016). In other words, the mismatch between their target earnings and their relatively low pay rate will give them an incentive to work more hours than is legally allowable or safe.

The U.S. Fair Labor Standards Act (FLSA) prescribes a minimum hourly wage for most U.S. production workers, premium overtime pay (time-and-one-half after 40 hours per week), and requires employers to record labour time properly. Figure 1, adopted from Belzer and Sedo (2018), shows that truck drivers can choose work hours from E-D-C because they are substantially exempted from the FLSA and because total work hours depend on self-report without verification. This contrasts with the working time regime for a typical production worker in the U.S., who is subject to a practical constraint due to the influence of premium pay, as required by the FLSA, of A-B as well as recording and enforcement mechanisms required by the U.S. Department of Labor Wage and Hour Division. Point C shows the situation in which a driver is indifferent compared with a 40-hour FLSA-covered worker, while D is the point at which a driver can earn a higher income by exceeding the HOS limit.

This model shows that drivers have economic reasons to work extremely long hours in pursuit of higher earnings. However, if they are not satisfied with the difference between B and C, they can still work more but at the cost of greater HOS violation risk, which means trading safety and health against earnings (Belzer and Sedo 2018), as well as the risk of regulatory sanctions that may damage their driving records.

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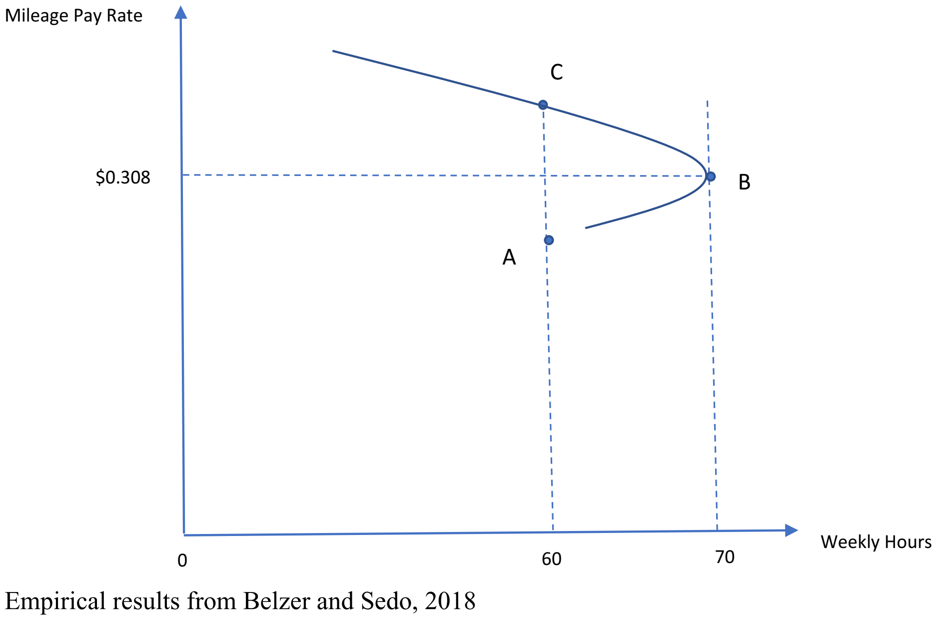

Figure 2. The estimated backward bending supply curve.

Based on the labour-leisure trade-off model, we define a driver's utility function as

$$U = U(C,\ L)$$

subject to:

$$C = wH + Y$$

$$T = H + L$$

where U is strictly quasi-concave and can be differentiated twice. C represents the total consumption of the driver; L is the hours of leisure; H is the hours of work; T is the time constraint; w is the hourly wage rate; and Y is the driver's autonomous income. If we assume the marginal rate of substitution between C and L is diminishing or $\frac{\partial^2 U}{\partial C \partial L} < 0$, thence maximising the driver's utility function subject to constraints, we can derive the labour supply function as $H = f(w, Y)$, where a change in hourly wages can be denoted as $\partial H \partial w$. The net impact of a marginal change in w on H is ambiguous since both income effect and substitution effect will be present. However, Belzer and Sedo show that this can be demonstrated empirically by a backward-bending labour supply curve, estimated in Figure 2.

The vertical axis in Figure 2 represents the mileage pay rate in 1996 nominal dollars (the year of the UMTIP truck driver survey) while the horizontal axis represents the work hours of a driver. From A to B, the substitution effect dominates the income effect; as the pay rate increases, the work hours increase, and the trucker drives more or works more non-driving hours, or both. From B to C, the income effect dominates the substitution effect and the trucker either drives less or works fewer nondriving hours, or both. The tipping point on the graph is B. If the market-clearing price is at point A, which represents the HOS rule of 60 hours per 7 days, and a typical driver has a target income at point B subject to other constraints, the driver has an incentive to work beyond 60 hours, exceeding the HOS rules and putting the truck driver and the public at risk. If the employer can increase the mileage pay rate to point C, then that representative trucker will work

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fewer hours and follow the HOS regulations (Belzer et al 2002; Belzer and Sedo 2018; Kudo and Belzer 2019). This pay rate – about US$0.75 per mile (2022 U.S. dollars) – might be considered a 'safe rate' in the US context, adhering to the spirit of the regulations limiting drivers to 60 hours of work. To be clear, almost all intercity and interstate US truck drivers are paid piecework – by theoretical estimated distance – and the median driver earns no pay at all for non-driving time.

This paper tests the hypothesis that HOS compliance violations (as a proxy for excessive and illegal working time predictably associated with low pay rates) lead to crashes for intrastate property carriers. Furthermore, we will validate the relationship between compensation and crashes, since recent studies show a significant impact.

Data and variables

As both National Academy Panel Studies report, there are significant weaknesses in the data on economic aspects of trucking operations – and hence, data on economic factors contributing to crash risk. Although compensation has been shown to be a strong predictor of crashes, neither FMCSA nor any other government agency collects regular reliable data on truck driver working time. Researchers must rely on one-off surveys to construct usable measures of truck driver compensation. For example, the Occupational Employment and Wage Statistics (OEWS), from the BLS, collects data on truck driver hourly wages, even though most truck drivers are paid piecework and do not earn an hourly wage. OEWS also reports annual earnings by multiplying the reported hourly wage by the standard 2080-hour standard American 40-hour work week. The UMTIP and NIOSH truck driver surveys, however, which report 50% higher weekly work hours, imply that this systematic understatement of truck driver working time substantially overestimates hourly earnings estimates while issuing annual earnings estimates of unknown quality. Researchers therefore must rely on multiple datasets and employ extensive statistical controls.

For this study, the primary data source is recent MCMIS data coming from field offices through SAFETYNET, Compliance Analysis and Performance Review Information (UGPTI 2024), and other sources. SAFETYNET is designed to manage and provide appropriate access to company-level safety data (US Department of Transportation 2024). The monthly release includes four key datasets: Census, Inspection, Violation, and Crash for both interstate and intrastate carriers. Unlike all previous datasets mentioned above, which are either proprietary (J.B. Hunt) or cross-sectional and survey based (UMTIP and NIOSH), the MCMIS dataset is monthly and freely available. All trucking companies authorised to operate must submit the MCS-150,[3] providing public information on all carriers with operating authority in intrastate and interstate operations. All crash, violation, and inspection data are at the incident level, which provides very granular information. Few researchers have fully utilised the MCMIS dataset for empirical studies because the dataset is so massive and difficult to use.

The FMCSA's mission is to prevent CMV-related injuries and fatalities (FMCSA 2024a). To this end, FMCSA uses the Safety Measurement System (SMS) (FMCSA 2024b) as the primary tool to identify motor carriers with safety compliance issues. SMS includes 899 possible violations that may arise from roadside inspections, and experts put them into six Behavior Analysis and Safety Improvement Categories (BASICs): Unsafe Driving, Hours-of-Service Compliance, Vehicle Maintenance, Controlled Substances/Alcohol, Hazardous Materials Compliance, and Driver Fitness.

In the current study, our primary data source is the 2017–2018 MCMIS dataset, merged across multiple monthly releases. The monthly release includes all four BASICs datasets for both interstate and intrastate carriers. Because all Census data are at the firm level and carriers often update once a year or two, we choose to do our analysis at the firm level

Table 1. Unique carrier observations

Year/Carrier Type	A	B	C	Grand Total
2015	49,508	2,078	30,219	81,805
2016	150,966	3,552	30,937	185,455
2017	265,282	5,361	57,231	327,874
2018	353,759	6,785	84,139	444,683
OBS	819,515	17,776	202,526	1,039,817

using annual numbers. To minimise the endogeneity issue, 2017 BASICs data are used for explanatory variables and 2018 crash data are used for the dependent variable.

The Census dataset includes information on more than one million interstate, intrastate hazmat, and intrastate non-hazmat motor carriers. Table 1 lists the distribution of observations across different types of carriers. FMCSA defines interstate carriers as Type A, intrastate hazmat carriers as Type B, and intrastate non-hazmat carriers as Type C. In this paper, our cross-sectional analysis will focus on intrastate carriers (Type B and C), which consisted of 62,592 observations in 2017. In addition to carrier operation type, the Census dataset also includes the DOT number, passenger-carrier flag, locations, MCS-150 update date, self-reported vehicle miles travelled (VMT), the corresponding VMT year, number of power units, and number of drivers.

Locations refer to a carrier's physical location, the mailing location, and the location of the FMCSA state branch office that oversees the carrier. A typical interstate carrier operates in multiple states, so it would be impossible to distinguish the reported VMT by state or location. For example, if an interstate carrier's reported VMT in MCS-150 is 1,000,000 miles, and the carrier's physical location is in California, we cannot assume that all miles are travelled within California; we also cannot allocate the mileage across states given limited information in the MCMIS dataset. We also incorporate truck driver wages by using average wages by state – something we could not do if we were studying interstate carriers. This is in response to the inadequate data on compensation – the issue that troubled the National Academy Panels. This study therefore will focus on intrastate freight carriers only. For intrastate carriers, those three locations must be the same, and the reported VMT means the mileage travelled in the carrier's operating state within the year. In addition, about 90% of intrastate trucking carriers have 8 drivers or fewer, while the rest may have 100 to 2,000 drivers. To learn how a typical intrastate carrier behaves in the market with more precision, we restrict our sample to truckers with 8 or fewer drivers; the lower number of observations reduces the sample size to 13,904 unique intrastate hazmat and non-hazmat property carriers.

The Inspection dataset includes incident-level information regarding the different levels of BASIC-related inspections, which are relevant to unsafe driving, HOS compliance, driver fitness, and vehicle maintenance. The dataset also includes the DOT number, state, and date, which we use for mapping.

The Violation dataset includes five BASIC-related violations. The Unsafe Driving violation refers to careless or reckless driving, such as speeding. The HOS Compliance violation is driving excess (illegal) hours or false logging. The Driver Fitness violation typically is driving without a commercial driver's license (CDL) due to a medical condition. The Controlled Substances/Alcohol violation means driving under the influence of alcohol or drugs. The Vehicle Maintenance violation is commonly caused by poor maintenance of the truck (FMCSA 2012).

The Crash dataset includes incident-level data such as fatalities, injuries, light conditions, and weather conditions. This dataset also has the DOT number, state, and date, which we use for mapping variables in this study.

In addition to these datasets from MCMIS, we get a wage dataset from the Occupational Employment and Wage Statistics (OEWS) Survey (Bureau of Labor Statistics 2024) by state and occupation, and population data from the US Department of Labor Bureau of Labor Statistics. As discussed above, the lack of compensation data in MCMIS requires researchers to develop novel methods to proxy truck driver wages. OEWS annually provides an update on the median wage of each occupation in the US, which also includes a wide range of classifications for a single industry. In this study, it is most relevant to look at truck transportation (NAICS 484000), and we narrow this down to 'Heavy and Tractor-Trailer Truck Drivers' (perhaps more artfully articulated as 'Drivers of Heavy and Tractor-Trailer Trucks'; OCC 53-3032) because intercity truck drivers usually drive these kinds of trucks. Furthermore, we choose the median hourly pay for these drivers in each state as our wage variable since we believe the wage of intrastate carriers for this most common occupation (commercially licensed drivers of large trucks) will be relatively consistent among firms within each state but differ among states. The heavy-duty truck driver labour market is among the most competitive in the country, so the median wage rate for this classification of driver by state will vary according to local labour market conditions, and differences among states will include differences in labour markets and the varying cost of living among them. Finally, we create a 'state' variable which is the rank order of states and territories[4] by population density per square mile in 2015 (the most densely populated state or territory is ranked 1), and we use it as a control variable and as a proxy for unique state and territory characteristics, such as the extent of urban crash exposure; these estimates come from the United States Census Bureau. We admit that this mechanism is noisy and second-best, and we would rather use carrier-level wage data, but in the absence of such data, the controls implemented for this analysis will allow us insight into the role wages play in predicting safety across carriers.

Descriptive data

Table 2 shows the top 10 HOS compliance violations in 2017 by weight, which account for about 87% of all HOS violations. Although violation codes are slightly different due to classification and local interpretation, they all fall into two broad categories. According to HOS regulations modified in 2014, property-carrying drivers cannot drive more than 11 hours after 10 consecutive hours off duty, nor can they drive after having worked 14 hours per day, including driving and non-driving on-duty hours. Further, exceptions to the rules allow them to work – but not drive – until their work assignment is complete, and a systematic exception now allows them to drive their trucks as 'personal conveyance' rather than for revenue, even if loaded, for unspecified additional time after they have gone off duty because they have exhausted their safety-related hours of work (Martinez and U.S. Department of Transportation - Federal Motor Carrier Safety Administration 2018). 'Regulatory Guidance Concerning Off-Duty Time', issued in 2013 (Ferro and U.S. Department of Transportation - Federal Motor Carrier Safety Administration 2013), further allows (and, in a competitive market, implicitly encourages carriers to require) drivers to log non-driving work time off duty, making it possible for drivers to extend their workday – and hence their workweek – almost at will.

Technically, the weekly work limit is 60 hours for 7 consecutive days and 70 hours for 8 consecutive days for a company operating seven days a week, though this does not include all the foregoing extra time in service to the employer or the work process. The original purpose of the eight-day schedule allowed long-haul drivers to cluster their off time on the weekend, for better recovery time. Under the current rules, as promulgated by FMCSA, if

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Table 2. Top 10 HOS compliance violations

HOS Violation Codes	SECTION_DESC (property carrying vehicle)	% of total
3958	Record-of-Duty Status violation (general/form and manner)	29.34%
3958F01	Driver's record-of-duty status not current	13.74%
3958E	False report of driver's record-of-duty status	9.80%
3953A3II	Driving beyond 8-hour limit since the end of the last off duty or sleeper period of at least 30 minutes	8.95%
3958K2	Driver failing to retain previous 7 days records-of-duty status	6.39%
3953A2PROP	Driving beyond 14-hour duty period	4.69%
3958F1	Driver's record-of-duty status not current	4.57%
3958A	No drivers record-of-duty status when one is required	3.59%
3958A	No driver's record-of-duty status	3.09%
3953A3PROP	Driving beyond 11 hour driving limit in a 14-hour period	2.79%
Subtotal		86.94%
Other violations		13.06%
Total		100.00%

they reach their 60-hour limit in less than seven days, they can take a 34-hour break to reset their clock (a feature created in 2004 to allow truck drivers to work legally up to 84 hours weekly) or wait until they pick up hours after their eighth day (as required before 2004). In theory, if a driver works 60 hours from 12:01 am Sunday and continues to work 14 hours a day, s/he will nearly run out of hours after working all day Thursday (at which time s/he will have worked 56 hours). If s/he takes a 34-hour break after running out of hours, s/he can go back to work and ultimately work 84 hours during the 7-day period between 12:01 am Sunday to 11:59 pm Saturday without committing an HOS violation (Saltzman and Belzer 2007). Obviously, this is far more than the 60 hours per 7-day week permitted by the core regulations and the spirit of the law. In practice, drivers (with their own motivation or at the urging of carriers) often log their non-driving work time as off duty (because, as the UMTIP and NIOSH surveys show, they do not get paid for this time), which allows them to work even more hours by working 'off the clock', as Viscelli (2016) implies.

According to an NIOSH survey conducted in 2010, long haul employee truck drivers (LHTDs) on average work 3,275 hours per year, or 62.6 hours per week, with the median employee driver working 62 hours, the bottom quintile of drivers working up to 45 hours, and the top quintile of drivers working 79.1 or more hours weekly (author calculations using NIOSH data). When LHTDs receive an unrealistically tight delivery schedule, they are more likely to drive faster and continue to drive despite fatigue, bad weather, or heavy traffic, even if they do not receive additional pay for the added work or risk (Kudo and Belzer 2019; Chen et al 2020).

Table 3 shows the descriptive statistics. Our focus on intrastate trucking companies with 8 or fewer drivers restricted us to 13,904 observations; we also excluded carriers that operate in both interstate and intrastate trucking, to avoid ambiguity. A substantial number of duplicates in the raw dataset further reduced the number of observations.

In addition to the BASICs, we believe it is essential to add earnings to the model, as studies have found statistical evidence that higher pay incentives correlate to fewer

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Table 3. Descriptive statistics

Variable	Mean	Std Dev	Min	Max	Label
CRASHES_2018	0.46	2.36	0.00	74.00	Crashes in 2018
HOS	0.35	2.30	0.00	72.00	HOS compliance violations in 2017
UNSAFE	0.48	2.01	0.00	48.00	Unsafe driving violations in 2017
DR_FIT	0.45	1.93	0.00	42.00	Driver fitness violations in 2017
SUBT	0.01	0.17	0.00	8.00	Controlled substances/alcohol violations in 2017
VM	8.52	24.09	0.00	566.00	Vehicle maintenance violations in 2017
WAGE*	20.61	1.63	17.71	26.09	Median hourly wage in the carrier's state in 2017
LVMT	10.13	1.81	0.69	17.56	Log of reported Vehicle Miles Traveled in 2017
HM_FLAG**	0.02	0.12	0.00	1.00	HazMat flag
STATE/TERRITORY INDICATOR***	27.66	13.31	1.00	56.00	2015 ranking of states/territories by population density
DRIVER_TOTAL	2.23	1.68	1.00	8.00	Reported Total Drivers per Carrier in 2017
NBR_POWER_UNITS	2.52	2.50	0.00	60.00	Reported Total Power Units in 2017

N = 13,904.
*State- or territory-level median hourly wage of 'Heavy and Tractor-Trailer Truck Drivers' (OCC 53-3032) from OEWS.
**1 for HazMat and 0 otherwise.
***1 = most populated.

crashes or lower probability of a crash or violation (Belzer et al 2002; Rodriguez et al 2006; Faulkiner and Belzer 2019; Kudo and Belzer 2019).

For an intrastate property carrier in 2017, the mean hourly wage for all fifty states and territories from the OEWS data was \$20.61 with a standard deviation of \$1.63, a low of \$17.71, and a high of \$26.09. As discussed above, however, while BLS collects wages from firms, most truck drivers are paid piecework, so wages must be estimates. Working time of truck drivers working for a company in interstate commerce is not recorded because the Fair Labor Standards Act does not apply fully to truck drivers, likely biasing all OEWS truck driver hourly wage estimates upwards significantly; the same caveat holds for an unknown proportion of intrastate drivers, though local labour markets probably contribute to wage setting. Real average wages, according to the UMTIP and NIOSH surveys, are much lower than this, simply because drivers of long-distance heavy-duty trucks average far more than 40 hours of work per week. This is important for labour market analysis because trucking employers are competing in a labour market with accurate hours of work reported for most occupations other than trucking. As of January 2024, average hourly earnings in the US were \$34.55, according to the U.S. Bureau of Labor Statistics (FRED 2019; US Bureau of Labor Statistics 2024). As long as income has not reached the driver's target level, the slope of the labour supply curve remains positive (Belzer and Sedo 2018), and the truck driver will choose to work more, so the actual wage rate matters.

In addition, drivers may be willing to commit small violations and adjust their hours by not recording unpaid non-driving work, which eventually can be associated with crashes (Viscelli 2016). We believe low real wages and piecework gives drivers an incentive to take more work assignments to pursue higher income and take the risk of getting caught violating HOS regulations, or having a crash.

Table 4. Zero-inflated negative binomial regression

Negative Binomial Part Coef. Std. Err. Z P>|z| 95% Conf. Interval Dependent variable: crashes_2018						
HOS	0.0021	0.0046	0.46	0.649	−0.007	0.011
UNSAFE	0.0089	0.0049	1.81	0.070	−0.001	0.019
DR_FIT	0.0198	0.0075	2.63	0.009	0.005	0.035
SUBT	−0.0455	0.0685	−0.66	0.507	−0.180	0.089
VM	0.0000	0.0005	−0.02	0.984	−0.001	0.001
WAGE	−0.0504	0.0153	−3.29	0.001	−0.080	−0.020
LVMT	0.0299	0.0122	2.44	0.015	0.006	0.054
1.HM_FLAG	0.1947	0.1322	1.47	0.141	−0.065	0.454
STATE_TERRITORY	−0.0005	0.0018	−0.27	0.785	−0.004	0.003
DRIVER_TOTAL	0.0100	0.0103	0.97	0.333	−0.010	0.030
_constant	2.8404	0.3399	8.36	0.000	2.174	3.507
Zero-Inflated Part Coef. Std. Err. Z P>|z| 95% Conf. Interval						
WAGE	0.2433	0.0292	8.33	0.000	0.1861	0.3006
STATE_TERRITORY	0.0234	0.0034	6.84	0.000	0.0167	0.0300
NBR_POWER_UNIT	−0.1221	0.0122	− 9.98	0.000	−0.1461	−0.0981
_constant	−2.2815	0.6129	−3.72	0.000	−3.4827	−1.0803
/lnalpha	−1.7227	0.0915	−18.82	0.000	−1.9021	−1.5432
alpha	0.1786	0.0163			0.1493	0.2137

Number of observations: 13,904.
Nonzero observations: 693.
Zero observations: 13,221.
Inflation model: logit.
LR chi2(10) = 42.35.
Log likelihood = −4672.465.
Prob > chi2 = 0.0000.
Likelihood-ratio test of alpha = 0: chibar2(01) = 497.14; Pr> = chibar2 = 0.0000.
Vuong test of zero-inflated negative binomial vs. standard negative binomial: z = 14.74; Pr>z = 0.0000.

In our sample, intrastate property carriers have an average 2.52 power units with a standard deviation of 2.50. While most carriers are small with 5 or fewer trucks, a few large intrastate trucking companies drive the standard deviation up, as the maximum is 1,273 power units. The MCMIS census dataset includes the number of drivers, but a high correlation exists between drivers and trucks, and we choose to use one in our negative binomial model and the other in the zero-inflated model. As Table 4 shows, the correlation coefficient between power units and driver total is 0.69, suggesting a high correlation between trucks and drivers and in line with our expectation; among small intrastate carriers, most trucks are driven by one driver. Other correlations are relatively low, however, resolving our concern about multicollinearity.

Based on the descriptive statistics shown above, on average, an intrastate carrier had a 0.46 crash measure (less than one reportable crash) in 2018. The count of crashes is purely based on distinct incident IDs, minimising the double-counting issue. Authorities and trucking companies cannot ignore a reportable crash because these crashes involve at least one fatality, one injury requiring transportation to a medical facility, or one vehicle towed from the scene. Finally, each BASIC violation count represents the number of violations that an intrastate carrier had in 2017 in that category.

HOS compliance violations have a firm-level mean of 0.35 and a standard deviation of 2.3, which suggests that 90% of the intrastate motor carriers had fewer than 4 violations. Unsafe driving violations have a mean of 0.48 and a standard deviation of 2.01, meaning that 90% of intrastate carriers had fewer than 3.79 violations (for a single carrier, the maximum number of violations can be as high as 48). Compared to other BASICs, the unsafe driving violations have the second-highest total number. Driver fitness violations have a mean of 0.45, and a standard deviation of 1.93, meaning 90% of intrastate motor carriers had fewer than 3.62 violations. Given the average fleet size of 2.5 in our sample, however, that suggests about 1.5 violations per driver, which is enough to raise red flags.

Controlled substances/alcohol violations have a mean close to 0 and a standard deviation of 0.29, meaning 99% of the intrastate had less than 1 violation, while for a single carrier, the maximum number of violations was as high as 8. This is the least common violation in the sample with a low mean and standard deviation.

Vehicle maintenance violations have a mean of 8.52, and a standard deviation of 24.09, while for a single carrier, the maximum number of violations was as high as 599.

Reported VMT has a mean of 25,043 per carrier in 2017, and we use a logarithm to minimise the excessive impact of large numbers.

The HM flag is an indicator for differentiating hazmat and non-hazmat carriers – 1 for hazmat and 0 otherwise. Driver total is the number of drivers reported by the carrier in 2017.

To sum up, our dependent variable is the log of crashes at the firm level. Our independent variables are five BASIC violations and average hourly pay for truck drivers by state, while the other three are control variables.

Regression analysis

All variables are mapped with a constraint on the year so that they are more aligned with each other than is the NIOSH survey. Indeed, while each firm is unique, in this paper, we want to test our hypothesis that moving violations are associated with crashes from a typical small carrier's perspective.

Since Table 3 shows that the distribution of crashes is not normal, using OLS will lead to biased results. Most carriers had zero crashes in 2018, and some carriers may not have operated at all (a chronic problem in MCMIS data), causing more excessive zeros.

The negative binomial model can be written as

$$\begin{aligned} Log(Crashes) = {} & \beta_0 + \beta_1\ HOS\ Viol + \beta_2\ Unsafe\ driving\ Viol + \beta_3\ Driver\ fitness\ Viol \\ & + \beta_4\ Substance\ alcohol\ Viol + \beta_5\ Vehicle\ maintenance\ Viol \\ & + \beta_6 (Hourly\ wage + \beta_7\ Log(VMT) + \beta_8\ Hazmat\ Flag \\ & + \beta_9 \left(State\_Territory\ Indicator\right) + \beta_{10}\ (Drivers) \end{aligned}$$

The zero-inflated logit model can be written as

$$Logit(0) = \beta_{11} + \beta_{12}\left(Hourly\ wage\right) + \beta_{13}\left(State\ Dummy\right) + \beta_{14}\ (Power\ Units)$$

Estimated results

From Table 4, the likelihood ratio test that alpha = 0 is significantly different from zero, which suggests that our data is over-dispersed and that a zero-inflated negative binomial model is more appropriate than a zero-inflated Poisson model. The Vuong test suggests that the zero-inflated negative binomial model is a significant improvement over a standard negative binomial model.

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The log odds of being an excessive zero would increase by 0.24 for every $1 increase in mean wage. In other words, a higher wage would mean it is more likely that the zero would be due to not having driven than to any safety explanation. On the other hand, the log odds of being an excessive zero would decrease by 0.122 for each of the carrier's power units.

Labour economists are interested in the extent to which higher compensation leads to an outcome associated with higher workforce quality or motivation. This analysis does not disappoint, and in fact this is the most important takeaway from the study. The sign of hourly pay is negative and statistically significant at the 1% level (the most statistically significant coefficient, controlling for BASICs). This estimation is consistent with our expectation and aligned with findings in the current literature: experienced drivers will react to the pay increase and drive more safely as the opportunity cost of crashes increases, and income gets closer to their target level (Monaco and Williams 2000; Belzer et al 2002; Rodriguez et al 2006; Belzer and Sedo 2018; Faulkiner and Belzer 2019; Kudo and Belzer 2019). For WAGE, the expected change in log(crash) for a one-unit increase in wage is –0.0504. This reduces the expected count of crashes for each $1 added to hourly wage, holding other variables constant, by 5%.[5] Since the mean of hourly wage is $20.61 in the sample, the elasticity is about −1.04[6]. Access to data on firm-level mean wages, as recommended by the 2017 Panel on the Review of the Compliance Safety and Accountability Program of the FMCSA, would allow more precise estimates on firm-level safety elasticities. This analysis is consistent with findings in Belzer, Rodriguez, and Sedo (2002, 64–71) and other prior research.

Enforcement regulators are interested in the extent to which their actions reduce crashes. This analysis does not disappoint them either, as critical enforcement elements also appear to reduce crashes. From the estimated results shown in Table 4, two BASICs are statistically significant at the 10% level or better in our model, with 13,904 observations of typical intrastate carriers with eight or fewer drivers. The wage variable is the most highly significant predictor of crashes, with very high Z scores. The test statistic z is the ratio of the coefficient to the standard error of the respective predictor. The z value follows a standard normal distribution, which is used to test against a two-sided alternative hypothesis that the coefficient is not equal to zero. A high Z score (low P value) shows strong confidence that the coefficient of Wage is unlikely to be zero due to chance. The dependent variable in the zero-inflated model is 0 crash due to non-observables, i.e. not driving at all (wage increases because non-driving increases), so the results in two models are aligned. Regulators' ability to identify unsafe carriers, therefore, is hampered by the lack of data on wages. Finally, HOS, controlled substances, and vehicle maintenance are not statistically significant at the 10% level.

The HOS violation variable is not statistically significant at the 10% level, but the parameter's sign is consistent with our prior expectations. The estimated result means that at the margin, we failed to accept the alternative hypothesis that if a small size intrastate carrier were to increase HOS violation by one count, the expected number of crashes in a year would increase by a factor of 1.0022 while holding all other variables in the model constant.[7] Intuitively, we would think, and FMCSA believes, that HOS-related violations, such as driving and working excessive and illegal hours, lead to fatigue and stress, and thus increases the probability of crashes. However, the data come from regulatory enforcement, not from a random sample of the population. Further, the enforcement community targets trucking companies and trucks that it suspects of operating dangerously on any of the BASICS dimensions. Because enforcement is not random, and BASICS violations are found in a targeted way, violations are systematically higher than they would be in the general population. In addition, this analysis is at the small-firm level, so the estimated result suggests the typical intrastate property carrier reacts to HOS violations on an annual basis. Even though results are biased towards

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carriers that enforcement has identified as likely to be dangerous, the findings for compensation will be applicable to this at-risk set of carriers.

The estimated parameter of unsafe driving violations has a positive sign, and it is statistically significant at the 10% level, consistent with our expectations, but it may be the effect rather than the cause of the problem. At the margin, if a small size intrastate carrier were to increase unsafe driving violation by one count, the expected number of crashes in a year would increase by a factor of 1.0089. Even without compensation incentives, this violation is behaviour related and relies heavily on the driver's habits; some drivers like speeding or following too closely, and they have been doing this for years, so eventually, they may be caught or involved in a crash. It too reflects the selection bias of enforcement discussed above, but at minimum, the wage effect will be applicable to those carriers.

The estimated parameter for driver fitness has a positive sign; the estimated factor on crash is about 1.020 at the 1% level. One of the most common violations in this category is driving without a CDL due to unacceptable medical conditions. Once caught, the driver can no longer drive for a living, so it decreases the probability of future crashes in general at the carrier level, but it also suggests lax management on the part of the carrier. Besides, drivers' inability to renew their CDL for health reasons implies that the condition is severe enough that they may drive less in exchange for health, willingly or unwillingly, or may exit FMCSA-regulated trucking. The existing medical condition may physically prevent them from driving more. The net impact therefore seems clearer in this study than the ambiguous finding in the NAS 2017 Panel report.

The estimated parameter of the controlled substances and alcohol violation is not statistically significant at the 10% level, so we failed to reject the null hypothesis. We expect a positive relationship between controlled substances and crashes. However, our estimate suggests that controlled substance violations are rare and were not predictive of crashes for intrastate carriers in 2018, which is also consistent with the findings in the NAS 2017 Panel report.

The estimated parameter of vehicle maintenance has a positive sign, but with a Z Score of −0.02, it is convincingly statistically insignificant. The coefficient is extremely small and close to 0.

State and territory population density is a control variable that aims to capture those characteristics. The estimated parameter is not statistically significant at the 10% level, suggesting that crashes are not more likely to happen in California than in Alaska, *ceteris paribus*. The data do not allow us to control for urban and rural truck travel miles of intrastate carriers or different topography, however, so this measure is less precise than we might prefer. One might expect that greater population means more vehicles and traffic within US states, increasing exposure, which would increase the likelihood of crashes, regardless of the carrier's role in the crash. This study suggests such expectation is ambiguous among small size intrastate carriers in the US.

The estimated parameter of vehicle mileage travelled has a positive sign and is statistically significant at the 5% level. Since we are focusing on intrastate carriers, the reported VMT by each carrier represents miles travelled within the state of operation. The current results confirm that more miles driven would be associated with more crashes, consistent with our expectation.

The estimated parameter of the HazMat flag, which indicates the current FMCSA classification of hazardous material carriers, is not statistically significant at the 10% level. Hazmat carriers are no safer than non-hazmat carriers. This is contrary to our expectations because we assume that hazmat drivers receive more training and more careful review.

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Total drivers is a control variable and is not significant at the 10% level. We cannot conclude that among small interstate carriers in the US, a carrier with more drivers will have more crashes, *ceteris paribus.*

Conclusion

In this paper, we do two things. The first involves testing FMCSA's BASICS to determine whether enforcement categories are associated with crashes. We find a weak relationship, as the most obvious driver factors – HOS violations – do not have a statistically significant relationship to crashes. Unsafe driving has a significant relationship, but unsafe driving is observed and charged only when it occurs, which not only violates all assumptions of random selection needed for OLS but it also probably occurs in conjunction with a crash or near miss. Driver fitness violation shows the strongest statically significance and impact on crash among five BASICs for small intrastate carriers.

Second, we estimate the relationship between truck driver wages and safety, using average wages for each state and territory, and linking safety performance of motor carriers in each state to the number of crashes estimated for each intrastate carrier. The results are striking. Wage is by far the strongest predictor of crashes compared with BASICs, both in terms of significance and in terms of the magnitude of the effect. While BASICs such as unsafe driving and driver fitness are significant and important, the effect of wages is much more robust than the effects of BASICs. A 10% increase in wages would be around 5 times as effective as a 10% reduction in unsafe driving or around 2.5 times as effective as a 10% reduction in driver fitness violations.[8] While data limitations have forced us to use a rather noisy estimator (average heavy truck driver wages by state), we still find a highly significant and powerful effect. These differences could be the result of unobserved state factors not directly associated with population density, but we believe that the controls for state characteristics minimise these possible confounding effects. Further research will be needed to isolate other possible factors associated with unmeasured state characteristics. Precise estimates can be made only at the motor carrier level with motor-carrier-level compensation data, but despite accepting the recommendation of the 2017 NAS Panel Report *Improving Motor Carrier Safety Measurement*, cited elsewhere, the FMCSA has not collected these data.

The results for hourly wage suggest that carriers paying higher wages have fewer crashes, and this finding is aligned with results across 25 years of our studies,[9] as well as those of others. The estimated elasticity is −1.04, which shows that the pay incentive is a main driver of safety because it takes advantage of the fundamental labour economics expectation that workers trade leisure for labour when they have reached their target earnings. This supports the recommendations from both National Academy Panel Reports: FMCSA should add wage and hour data to the SMS. Wage and hour data are not collected for most trucking jobs, and in this respect, truck drivers remain an outlier among all US production workers.

In sum, there are two sides to the story: proper compensation and enforcement of the rules. Our research suggests that both compensation and enforcement matter, and the FMCSA's safety mission requires wages, as well as enforcement of rules. Economic incentives to reduce hours worked should be combined with enforcement of BASIC regulations to reduce crashes effectively. FMCSA is quite justified in maintaining strong enforcement of limits on working time, while at the same time ensuring that truck drivers earn a living wage sufficient to reward and motivate safe driving. We also recommend FMCSA consider collecting and adding wage or mile pay rate to the MCMIS dataset for all future studies, in conformance of the recommendations of both NAS Panel studies.

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Notes

[1] During economic regulation, "common carriers" were like utilities offering their services to the public, transparently posting rates for consumers.
[2] Using NIOSH data, the mileage pay rate is a ratio of total annual earnings to the number of miles driven and does not include non-driving labour because the dataset did not allow controls for non-driving time.
[3] Every carrier uses MCS-150 to apply for a DOT number, and FCMSA requires carriers to update this file periodically, including changes in the number of power units, drivers, and annual miles.
[4] Data include 50 states, the District of Columbia, and five territories.
[5] $1 - e\wedge(-0.05039) = 5\%$.
[6] Mean of wage times −0.05039.
[7] Log(crashes) = 0.0021, crashes = exp(0.0021) = 1.0022.
[8] We calculated the factor of each by calculating exp(parameter):

	Est Coeff	Factor	1 minus factor			
unsafe	0.009	1.009	−0.009	A	−5.49	(C/A)
Fitness	0.020	1.020	−0.020	B	−2.45	(C/B)
Wage	−0.050	0.951	0.049	C		

[9] https://www.michaelbelzer-saferates.com/

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