U.S. DEPARTMENT OF TRANSPORTATION

OFFICE OF INSPECTOR GENERAL

Estimates Show Commercial Driver Detention Increases Crash Risks and Costs, but Current Data Limit Further Analysis

FMCSA

Report No. ST2018019

January 31, 2018

U.S. DEPARTMENT OF TRANSPORTATION
OFFICE OF INSPECTOR GENERAL

Highlights

Estimates Show Commercial Driver Detention Increases Crash Risks and Costs, but Current Data Limit Further Analysis

Required by the Fixing America's Surface Transportation Act of 2015

Federal Motor Carrier Safety Administration | ST2018019 | January 31, 2018

What We Looked At

The Fixing America's Surface Transportation Act of 2015 (FAST Act) directs FMCSA to issue regulations that cover the collection of data on delays experienced by CMV operators before the loading and unloading of their vehicles. The act also directs the Office of Inspector General (OIG) to report on the effects of driver detention. Accordingly, we conducted this audit to (1) assess available data on delays in motor carrier loading and unloading, and (2) provide information on measuring the potential effects of loading and unloading delays. In addressing our objectives, we also reviewed FMCSA's plan to collect data on driver detention.

What We Found

Accurate industrywide data on driver detention do not currently exist because most industry stakeholders measure only time spent at a shipper or receiver's facility beyond the limit established in shipping contracts. Available electronic data cannot readily discern detention time from legitimate loading and unloading tasks, and are unavailable for a large segment of the industry.

We estimated that a 15-minute increase in average dwell time—the total time spent by a truck at a facility—increases the average expected crash rate by 6.2 percent. In addition, we estimated that detention is associated with reductions in annual earnings of $1.1 billion to $1.3 billion for for-hire commercial motor vehicle drivers in the truckload sector. For motor carriers in that sector, we estimated that detention reduces net income by $250.6 million to $302.9 million annually.

FMCSA's plan to collect data on driver detention does not call for collection or detailed analysis of reliable or representative data, and the Agency has no plans to verify the data that motor carriers and drivers would provide. As a result, the data may not accurately describe how the diverse trucking industry experiences driver detention, which would limit any further analysis of impacts.

Our Recommendations

FMCSA concurred with our recommendation to improve future plans for collection of data on driver detention.

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U.S. DEPARTMENT OF TRANSPORTATION
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Memorandum

Date: January 31, 2018

Subject: INFORMATION: Estimates Show Commercial Driver Detention Increases Crash Risks and Costs, but Current Data Limit Further Analysis | Report No. ST2018019

From: Barry J. DeWeese
Assistant Inspector General for Surface Transportation Audits

To: Federal Motor Carrier Safety Administrator

According to the Federal Motor Carrier Safety Administration (FMCSA), approximately 415,000 crashes involving large[1] trucks occurred in 2015. Of these, 145,310 were severe enough to be recorded in FMCSA's Motor Carrier Management Information System (MCMIS),[2] which reports only crashes involving fatalities, significant injuries,[3] or vehicle towing. Also in 2015, 1.29 fatal crashes and 29.5 crashes causing injuries occurred per 100 million vehicle miles traveled by large trucks.

In 2007, FMCSA sponsored research that indicates that time at shipping and receiving facilities beyond that legitimately needed for cargo loading and unloading—referred to as driver detention—may reduce driving hours and cause income loss for commercial motor vehicle (CMV) drivers. The research also indicated that drivers who experience detention may also drive unsafely due to fatigue or desire to recover lost income—increasing the risk of crashes that result in fatalities, injuries, and financial costs.

FMCSA is responsible for establishing rules covering CMV operations and working with industry to ensure public safety on the Nation's highways. Furthermore, the Fixing America's Surface Transportation Act of 2015 (FAST Act) directs FMCSA to issue regulations that cover the collection of data on delays

[1] A large truck is a vehicle designed, used, or maintained primarily for carrying property, with a gross vehicle weight rating or gross combination weight rating of over 10,000 pounds, or any vehicle carrying hazardous materials that requires placarding, regardless of weight.
[2] All MCMIS data that we use in this report refer exclusively to carriers based in the United States.
[3] In this report, we define a significant injury as one that requires transportation of the affected individual from the accident scene for medical care.

experienced by CMV operators before the loading and unloading of their vehicles and at other points in the pick-up and delivery process. The act also directs the Office of Inspector General (OIG) to report on the effects of driver detention on the economy, the efficiency of the transportation system, motor carrier safety, and the livelihoods of motor carrier drivers. Accordingly, our objectives were to (1) assess available data on delays in motor carrier loading and unloading, and (2) provide information on measuring the potential effects of loading and unloading delays. In addressing our objectives, we also reviewed FMCSA's plan to collect data on driver detention.

We conducted our work in compliance with generally accepted Government auditing standards. To assess available data on driver detention, we reviewed Government and industry studies and interviewed representatives of industry stakeholders. To estimate safety impacts, given the limitations of available data on driver detention, we used statistical methods that enable estimation with limited information and measurement error. The data available to us included 2013 data assembled for a 2014 FMCSA-sponsored study of detention and FMCSA safety data. To provide information on the potential income effects of driver detention, we used data generated by an FMCSA simulation model, in combination with the study data, to estimate the effects associated with detention on the earnings of truckload (TL) drivers and motor carriers. We also interviewed FMCSA officials to understand the Agency's plan to address its mandate to collect data on driver detention. We did not examine the effects of detention on shippers or receivers, and our assessment of the effects on the efficiency of the transportation system was limited to the revenue impacts for motor carriers.

See exhibit A for additional information on our scope and methodology. See exhibit B for detailed explanations of the methodology for our analysis of the safety effects of detention, and exhibit C for additional information on the methodology for our analysis of the effects of detention on drivers' incomes and carriers' net revenues. Exhibit D lists the entities we visited or contacted.

We appreciate the courtesies and cooperation of Department of Transportation representatives during this audit. If you have any questions concerning this report, please call Barry J. DeWeese, Assistant Inspector General for Surface Transportation Audits, at (202) 366-5630.

cc: The Secretary
FMCSA Audit Liaison, MCPRS
OST Audit Liaison, M-1

Results in Brief

Accurate industrywide data on driver detention do not currently exist because most industry stakeholders measure only time spent at a shipper or receiver's facility beyond the limit established in shipping contracts—often 2 hours.

Commercial drivers and carriers do not capture time spent waiting prior to reaching the contractual threshold. Similarly, Industry, Government, and academic detention research has used dwell time—the total amount of time spent at a facility—when it exceeds 2 hours as a proxy for detention time. Furthermore, the research has relied on limited interview, survey, and electronic data. Available electronic data—collected and maintained by the motor carrier industry—cannot readily discern detention time from legitimate loading and unloading tasks, and are unavailable for a large segment of the industry. For example, in 2014, FMCSA sponsored a study of detention time that relied on electronic dwell time data representing only 29 medium and large carriers and 2 small carriers. Carriers with three or fewer trucks represent the large majority of motor carriers. Furthermore, the data collected for FMCSA's study covered only 7 months of 2013. Finally, FMCSA's study did not examine possible effects on safety of driver detention.

Driver detention is estimated to increase the expected rate of truck crashes, and drivers and motor carriers that experience detention may collectively earn approximately a billion dollars less each year.

Based on data from 2013,[4] we estimated that a fifteen-minute increase in average dwell time increases the average expected crash rate by 6.2 percent. The national crash rate per 100 power units[5] per year in FMCSA's Motor Carrier Management Information System (MCMIS) database for 2013 is 1.56,[6] so a 6.2 percent increase over this baseline implies an expected increase of one additional crash per 1,000 power units had average dwell times increased by 15 minutes. In 2013, freight-hauling motor carriers in MCMIS recorded a total of 104,318 crashes. For the entire commercial motor vehicle (CMV) cargo sector, we estimate that such an increase would have been expected to result in an additional 6,509 crashes in that year. We also found that, on average, every 5 percentage point increase in the

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[4] We used data on truck dwell time assembled for FMCSA's 2014 study on detention time—provided by the Virginia Tech Transportation Institute—in combination with data on motor carrier crashes from FMCSA's MCMIS database to produce our estimates.

[5] Power units are truck tractors and straight trucks. Straight trucks are commercial motor vehicles in which the power unit and cargo box are non-detachable.

[6] This crash rate, from FMCSA's Motor Carrier Management Information System (MCMIS), includes only crashes involving fatalities, significant injuries, or vehicle towing.

share of loading and unloading stops experiencing detention, results in a 4.7 percent increase in expected crash rates. In addition, based on our simulation analysis, we estimated that detention is associated with reductions in annual earnings of $1.1 billion to $1.3 billion—between $1,281 and $1,534 per driver per year—for for-hire[7] commercial motor vehicle drivers in the truckload (TL)[8] sector. For motor carriers in that sector, we estimated that detention is associated with net income reductions of $250.6 million to $302.9 million annually. We did not examine the effects of detention on the net income of shippers or receivers.

FMCSA's plan to collect data on driver detention limits any further analysis of impacts.

In response to a FAST Act directive, FMCSA plans to collect data on driver detention through use of a reporting form on its public website that drivers and carriers can use to voluntarily submit data on detention. However, FMCSA's plan does not call for collection or detailed analysis of reliable or representative data, and the Agency has no plans to verify the data that motor carriers and drivers would provide. According to an FMCSA official, the costs of rigorous data collection and analysis would likely outweigh the benefit and the Agency primarily views detention as a market efficiency problem best addressed by private industry rather than through government action. Because FMCSA lacks a plan to ensure the representativeness and accuracy of any driver detention data it collects, its data may not accurately describe how the diverse trucking industry experiences driver detention, which would limit any further analysis of impacts.

We made one recommendation to improve future plans for collection of data on driver detention.

Background

FMCSA's primary mission is to prevent CMV-related fatalities and injuries. It carries out this mission by issuing, administering, and enforcing a variety of regulations on Federal motor carrier safety, such as hours of service (HOS) requirements.[9] The Agency also gathers and analyzes data on motor carriers,

[7] Carriers are either for-hire or private. For-hire carriers transport cargo to the public on a fee basis, while private fleets transport only a company's own products.

[8] In the truckload sector, a truck transports a single shipper's cargo between two locations in a single trip, while a less-than-truckload (LTL) carrier transports cargo for multiple shippers in a single trip that may require loading and unloading at multiple locations.

[9] Federal HOS regulations restrict the amount of time that commercial motor vehicle drivers may operate their vehicles. Drivers are allowed 14 consecutive hours after coming on duty following 10 or more consecutive hours off-duty. During this 14-hour window, the regulations limit drivers to no more than 11 hours of actual driving time. However, these 11 hours may or may not be consecutive.

drivers, and vehicles; takes enforcement actions; and supports enforcement activities at the State level through Motor Carrier Safety Assistance Program grants.

The interstate commercial motor carrier cargo industry is extensive and includes a variety of stakeholders, including carriers, shippers, receivers, and intermediaries. Shippers are cargo owners that hire carriers to transport their cargo. Receivers are those scheduled to receive and take ownership of the cargo. Intermediaries arrange the transportation of goods between shippers and receivers. Finally, third-party logistical companies provide warehousing and supply chain services to shippers and arrange transportation of cargo.

The various types of carriers and their drivers work in several different ways. Each for-hire TL carrier transports a single shipper's cargo between two locations in a single trip, while a less-than-truckload (LTL) carrier transports cargo for multiple shippers in a single trip that may require loading and unloading at multiple locations. Length of haul also varies. Some carriers provide primarily long-distance service (more than 500 miles per trip), while others provide regional (100 to 500 miles per trip) or local (less than 100 miles per trip) service. Finally, carriers use a variety of different trailer types, including dry trailers, refrigerated trailers, flat beds, and tank trailers.

Dwell time refers to the total amount of time spent at a shippers' or receivers' facility, including time spent loading and unloading. In addition to loading and unloading, other tasks associated with stops must be performed. For example, bills of lading[10] must be prepared, the load and vehicle may need inspection, and, depending on the type of cargo and method of carriage, the load may need to be secured. Detention, on the other hand, is any time spent waiting at a shipper or receiver's facility that is not spent performing these tasks.

Accurate and Complete Industrywide Data on Motor Carrier Loading and Unloading Delays Are Not Available

Accurate data on driver detention are not available because motor carriers and drivers do not collect data on the time spent actually loading and unloading and delays. Motor carriers and commercial vehicle drivers track only dwell time that is greater than the time allowed by their contracts for loading and unloading.

[10] A bill of lading is a document that must contain, at minimum, the names of the shipper and receiver, origin and destination points, number of packages, description of freight, and the weight, volume, or measurement of the cargo.

Electronic data, which are less prone to human error, are unavailable for a large portion of the industry because most small carriers and independent drivers rely on paper records.

Motor carriers and drivers refer to time spent at shipping and receiving facilities beyond that which is legitimately needed for loading and unloading—for example, waiting in a queue—as detention time. Eleven of 12 industry stakeholders we interviewed stated there is an informal industry consensus that 2 hours is generally a reasonable estimate of time required for loading and unloading. According to FMCSA representatives, factors such as motor carrier size, load size, type of cargo, and the sophistication of the shipper facility all influence the amount of time needed to load and unload cargo. For example, officials at one industry association told us that owner-operators typically experience more detention than drivers who work for larger carriers. Furthermore, factors such as cargo type and the way it is packaged for shipment can influence the amount of time required to load or unload.

Contracts between shippers, receivers, and motor carriers generally define limits on time to load or unload, and may entitle carriers to fees for any additional time spent at facilities, typically 2 hours.[11] As a result, carriers and drivers typically only track the amount of time spent at facilities that exceeds contractual thresholds rather than documenting actual detention time. For example, a driver could arrive at a shipping facility, wait for one hour, but require only one additional hour to load. If the shipping contract allowed 2 hours for loading, it is unlikely that the driver would document the hour spent waiting as detention time.

We found that studies of the frequency and length of detention time used data that were likely unrepresentative of the industry. For example, a 2011 Government Accountability Office (GAO) study[12] relied primarily on interviews with a non-statistical sample of 302 truck drivers and a variety of industry stakeholders, and did not include objective measures of the amount of time drivers spent waiting at facilities, such as systematically recorded detention times. Other studies[13] relied primarily on literature reviews, interviews, and focus groups for data, but did not attempt to quantify the frequency, length, or effects of detention time. As a result, any research on the frequency, length, or effects of

[11] Not all shipping contracts include detention pay clauses.

[12] GAO, *More Could Be Done to Determine Impact of Excessive Loading and Unloading Wait Times on Hours of Service Violations* (GAO-11-198), January 2011.

[13] We reviewed a variety of research conducted over the past 16 years, including: FMCSA, *Effects of Loading and Unloading Cargo on Commercial Truck Driver Alertness and Performance*, May 2001; FMCSA, *The Motor Carrier Efficiency Study 2007 Annual Report to Congress*, March 2009; Ann Williamson, Samantha Sadural, Ann-Marie Feyer, and Rena Friswell, *Driver Fatigue: A Survey of Long Distance Heavy Vehicle Drivers in Australia*, September 2001. Ann-Marie Feyer, Ann Williamson, Rena Friswell, and Samantha Sadural, *Driver Fatigue: A Survey of Long Distance Transport Companies in Australia*, September 2001; Transportation Research Board, *Potential Safety Benefits of Motor Carrier Operational Efficiencies: A Synthesis of Safety Practice*, 2011.

detention time will require approximation because accurate data on detention time do not exist.

In 2014, FMCSA published a study that used dwell time data and defined detention time as all time spent at a stop in excess of 2 hours. The study found that drivers experience detention at approximately 1 in 10 stops for an average duration of 1.4 hours. Medium-sized carriers experienced detention about twice as often as large carriers, and for-hire TL carriers experienced detention more frequently than for-hire LTL and private carriers. Trailer type also influenced length and frequency of detention, with refrigerated trailer drivers experiencing longer and more frequent detention than other drivers. However, this study also included several limitations. Specifically, the data:

- Covered a relatively small number of carriers that may not be an accurate representation of the trucking industry;
- Included little information from small carriers, with only two such carriers included among those sampled and no traditional owner-operators;[14] and
- Covered only 7 months of stops made in 2013

In 2015, FMCSA initiated a study to evaluate the safety and operational impact of driver detention on work hours, HOS violations, and crashes. The planned study would have measured detention time by recording times that a sample of truck trailers' rear doors are open and closed to measure the amount of time spent loading and unloading. This recording would give the Agency a better estimate of the amount of detention time and delays by disaggregating legitimate loading and unloading from the total time a driver spends at a facility. However, the Agency cancelled the study because the selected technology vendor discontinued its support of the work.

Industry associations, such as the American Transportation Research Institute (ATRI) and the Owner Operator Independent Drivers Association (OOIDA), have conducted surveys of their membership regarding the frequency and length of the detention time that drivers experience. These surveys used large sample sizes, and therefore may be representative of the industry sectors they sampled. However, the surveys were limited to certain sectors of the trucking industry and also relied on drivers' recollections rather than objective measures of detention time.

ATRI and several private CMV data vendors that we interviewed collect and maintain global positioning satellite (GPS) data that can be used to measure

[14] Owner-operators are individuals that own and operate their own trucking business. They may contract with larger carriers to provide freight-hauling service, or operate under their own authority. Those that operate under their own authority register with the DOT as carriers.

dwell time. Researchers have used dwell time as a proxy for detention time, but these data measure only approximately the frequency or lengths of detention time across the industry. According to trucking industry stakeholders we interviewed, large and medium sized carriers generally use GPS data to track dwell time because contracts allow them to charge fees for dwell time that exceeds the thresholds defined in contracts, but they do not distinguish between detention time and legitimate loading and unloading times. Furthermore, owner-operators and smaller carriers tend to collect data manually when they do not have detention pay clauses in their contracts. For example, they may note times of arrival and departure on bills of lading. They may then request shippers' representatives to confirm the times by signing the bills, but representatives do not always sign.

Detention Is Estimated To Increase Expected Truck Crash Rates and May Reduce Driver and Carrier Income by About $1 Billion Annually

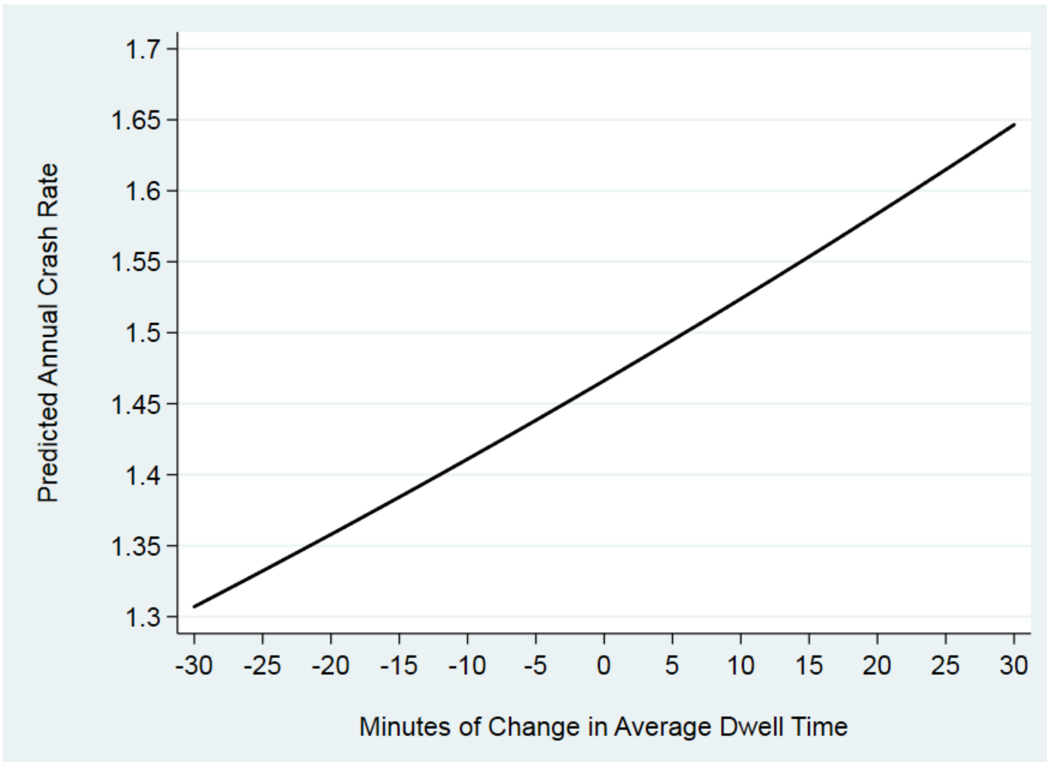
Our analysis estimates that an increase in average dwell time or in the probability of detention results in an increase in the expected rate of truck crashes. We also estimate that drivers and motor carriers may earn less when they experience detention.

Our Analysis of Available Data Estimates That an Increase in Average Dwell Time or the Probability of Detention Increases the Expected Rate of Truck Crashes

Our analysis of FMCSA safety data, along with vehicle dwell-time data, estimates that detention increases the likelihood of truck crashes involving fatalities, significant injuries or vehicle towing. We determined this by employing statistical methods that allow estimation given limited information and measurement error, using the 2013 dwell time data collected for the 2014 FMCSA study and the assumption that dwell time in excess of 2 hours represented detention.

We found that a 15-minute increase in average dwell time increases expected average crash rates by 6.2 percent. In MCMIS, the national crash rate per 100 power units of freight-hauling motor vehicles in 2013 was 1.56, so a 6.2 percent increase over this baseline would raise the crash rate to 1.66, implying one additional crash per 1,000 power units per year (see Figure 1). In 2013, freight-hauling motor carriers recorded a total of 104,318 crashes.[15] A 6.2 percent increase over this baseline would represent 6,509 additional crashes. We also found that, on average, every 5 percentage point increase in the share of loading and unloading stops that experience detention results in a 4.7 percent increase in expected crash rates. See exhibit B for additional detail on our methodology, results, and references to relevant scientific literature for our analysis of the safety effects of driver detention.

Figure 1. Predicted Crash Rates for Changes in Average Dwell Time



Note: The average dwell time in the dataset we used was 113 minutes in 2013.
Source: OIG analysis.

According to both FMCSA's 2014 study and our own analysis of the 2013 dwell time data, carrier size, operation type, and truck freight type all influence dwell time. Smaller and for-hire motor carriers experience longer average dwell time than larger and private motor carriers.

[15] Here, we report the number of crashes for 2013 because it is for the same time period as the dwell time data that informed this analysis. In the introduction to this report, we reported the number of crashes for 2015—the most recent available.

According to a Transportation Research Board report,[16] detention affects safety because drivers generally cannot use delays for sleep or other restorative rest. As a result, detention uses up drivers' available waking hours, contributing to fatigue when they drive. In addition, delays cause frustration and reduced income and may contribute to dangerous behaviors such as speeding and violations of HOS requirements.

Detention May Reduce the Income of Drivers and Motor Carriers by Over $1 Billion

We estimated that detention may be associated with reductions in annual earnings of between $1.1 billion and $1.3 billion for drivers collectively, and between $1,281 and $1,534 per individual driver—a reduction of between 3.0 and 3.6 percent in a driver's average annual income. However, this income loss may be at least partially off-set. Some carriers charge shippers detention fees and pay their drivers portions of those fees. About 60 percent of carriers responding to a 2015 ATRI survey[17] reported passing some portion of these fees to their drivers. Representatives of one large carrier told us that their company pays an hourly rate to drivers for time spent in detention.

On the other hand, our estimates rely on the distribution of dwell time identified in FMCSA's 2014 study, which included few small carriers within its scope. As a result, our estimates may understate the loss of income faced by drivers and carriers because small carriers report experiencing detention more frequently than larger carriers and receiving compensation from shippers less frequently.

For carriers, we estimated that detention is associated with reductions in net income of between $250.6 million and $302.9 million annually. Carriers may mitigate these costs by charging shippers detention fees, but according to ATRI's survey, a significant portion of smaller carriers do not charge these fees. Similarly, 37 percent of respondents to a 2014 OOIDA[18] survey of members—mostly small carriers—reported that they received no compensation for time spent in detention. Furthermore, six of eight motor carriers and owner-operators we interviewed informed us that shippers sometimes do not pay the detention fees that they charge. They stated that shippers refuse to pay for a variety of reasons, such as a truck's arrival a minute later than its scheduled appointment time or

[16] Transportation Research Board, *Potential Safety Benefits of Motor Carrier Operational Efficiencies: A Synthesis of Safety Practice*, 2011.
[17] ATRI, *An Analysis of the Operational Costs of Trucking: 2015 Update*, 2015.
[18] OOIDA, *2014 OOIDA Owner-Operator Member Profile Survey*, 2014.

shipper representatives' refusal to sign bills of lading noting trucks' arrival and departure times.

In addition to charging fees to compensate for delays, motor carriers may adjust their rates for shippers and receivers with records of delays. One study we reviewed[19] used statistical modeling to show that motor carriers typically charge higher freight rates to certain customers when they experience longer dwell times at those customers' facilities. In addition, 20 percent of respondents to OOIDA's survey reported that they negotiated higher rates with shippers to compensate for detention.

Because quantifying the effects of detention on the economy and on the transportation industry as a whole would require a number of major assumptions, we did not estimate a dollar value of these effects. However a 2009 FMCSA-sponsored study[20] estimated that society as a whole would gain $6.6 billion annually if detention time were reduced by 30 minutes at one third of all stops. The benefits cited in the study were attributed to environmental, safety, and congestion issues associated with detention delays. See exhibit C for additional detail on our methodology, results, and references to relevant scientific literature for our analysis of the driver income and carrier revenue effects of driver detention.

FMCSA's Planned Method for Data Collection Will Not Accurately Measure Detention and Its Effects

FMCSA has begun planning to respond to the FAST Act's mandate that the Agency collect data on driver detention. However, according to FMCSA officials, the Agency cannot ensure representativeness, verify data, or conduct detailed analyses.

According to an Agency official, FMCSA plans to establish a reporting form on its public website that drivers and carriers can use to voluntarily submit data on detention. The FMCSA official also stated that instead of verifying the data with information from motor carriers and drivers, the Agency plans to interpret the data as anecdotal. In addition, the FMCSA official told us that:

- If submitted data does not include sufficient details on the drivers and the detention time they experience, the Agency will not conduct detailed analyses of the data and will likely report summary-level statistics;

[19] C.H. Robinson, *Do "Favored Shippers" Really Receive Better Pricing and Service?*, 2015.
[20] FMCSA, *Motor Carrier Efficiency Study Annual Report to Congress*, March 2009.

- FMCSA wants to try to balance descriptive and detailed questions on the reporting form—which would allow for detailed analyses of truck and driver characteristics and trends—with ease of form use for respondents;

- The costs of collecting, validating, and analyzing robust data likely outweigh the benefits; for example, to conduct a representative survey of truckers would require clearance by the Office of Management and Budget (OMB) and would likely be costly; and

- The Agency's position on driver detention is that shippers and carriers should address the issue among themselves without Government intervention because detention is primarily a market efficiency problem.

GAO's *Standards for Internal Control in the Federal Government* (Federal Control Standards) direct managers to identify data sources that accurately represent the information they are seeking to collect and evaluate these data sources for reliability. The Federal Control Standards also state that managers should process data into accurate and accessible information for use by decision makers. Furthermore, the RAND Corporation's *Standards for High Quality Research and Analysis* (RAND Standards), which FMCSA uses for its own research, states that researchers should use the best available data and information and discuss the accuracy of the data presented. The RAND Standards also state that researchers should advance knowledge on policy issues.

Because data submissions will be voluntary, FMCSA will not be able to gauge the representativeness of the data until a sufficiently large data set exists, and as a result, cannot ensure that any data collected will be representative of the trucking industry.

Because FMCSA lacks a plan to ensure the representativeness and accuracy of any driver detention data it collects, its data may not accurately describe how the diverse trucking industry experiences driver detention. Unrepresentative data may fail to meet OMB's requirements for statistical significance, preventing FMCSA from using that data in support of any future detention time-related activities. Furthermore, since FMCSA may only report summary statistics of this self-reported driver data, the Agency's efforts may not advance knowledge of the frequency, length, and effects of driver detention beyond what industry surveys of drivers already report. Without such increased knowledge, the industry will have limited information as it seeks to balance efficiency against other factors, such as safety. FMCSA has no current plan to execute any alternative strategy that might better advance knowledge of driver detention.

Conclusion

Commercial motor carriers play an essential role in the Nation's economy. However, accurate, representative data on detention time are currently extremely limited and FMCSA does not plan to standardize, validate, or analyze the data it intends to collect beyond publication of basic summary statistics. Consequently, FMCSA's efforts are unlikely to advance understanding of the scope and effects of driver detention. Our estimates of the effects of increases in dwell time relied on dwell time data from 2013. Still, the magnitude of our estimates indicates that detention time is costly and increases safety risks.

Recommendations

To expand the knowledge of the frequency, severity, and effects of delays in loading and unloading commercial motor carriers' trucks, we recommend that the Federal Motor Carrier Safety Administrator:

1. Collaborate with industry stakeholders to develop and implement a plan to collect and analyze reliable, accurate, and representative data on the frequency and severity of driver detention times.

Agency Comments and OIG Response

We provided FMCSA with our draft report on November 30, 2017 and received its management response on January 12, 2018, which is included as an appendix to this report. FMCSA concurred with our recommendation and provided appropriate actions and a completion date.

FMCSA's comments on our draft report state that it is premature to draw empirical conclusions about the impact of driver detention times on crash rates or driver incomes given the limitations of current data sources. Our analysis and findings make note of these limitations but represent, in our view, the best estimates based on available data. We underscore the need for FMCSA to address the limitations of available data as it works to address our recommendation.

Actions Required

We consider our recommendation resolved but open pending completion of planned actions.

Exhibit A. Scope and Methodology

We conducted this performance audit between July 2016 and October 2017 in accordance with generally accepted Government auditing standards as prescribed by the Comptroller General of the United States. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives. To assess available data on motor carrier loading and unloading delays, we reviewed scientific literature published between 2001 and 2014 related to CMV delays. We also reviewed the results of CMV industry association surveys, and interviewed representatives of FMCSA, CMV industry associations, carriers and drivers, and academic experts.

To assess the possible effects of loading and unloading delays, we used statistical techniques and simulations to estimate the safety and income effects of detention. We chose our methods for estimating safety impacts based on the need to address data limitations. Specifically, available data are limited because: (1) there is no dataset that reports on both carrier safety and detention; (2) larger carriers are overrepresented in the available data on truck stops; and (3) measurement error is a concern.

We addressed the absence of a dataset for both safety and detention by using statistical techniques that enable estimation based on two independent datasets. Specifically, we used safety data reported in MCMIS, and the data on the lengths of stops by individual trucks assembled for the 2014 FMCSA-sponsored study of detention. Both datasets included information on carrier characteristics that could be used to link them. We used the truck stops data to estimate the parameters of the distribution of dwell time given carrier characteristics. Because this estimation should be unaffected by unrepresentative sampling, the overrepresentation of larger carriers did not arise as a limitation in our analysis. Because we had to use estimated measures of average dwell time and detention probability in the impact estimation, we also had to address the resulting measurement error. We did this by using differences between the truck stop data and our estimated values to remove it. Because we defined detention time as dwell time in excess of 2 hours, we introduced additional measurement error into the detention probability measure, and consequently into the impacts estimated for increases in the probability of detention. However, the data do not exist to address this.

To assure the quality of our safety impact estimates, we provided detailed documentation of our work to experts in the techniques we used who reviewed our work and determined our methods were sound. The expert reviewers were: Yingyao Hu, Professor of Economics, Johns Hopkins University; Arthur Lewbel, Barbara A. and Patrick E. Roche Professor of Economics, Boston College; and Elie Tamer, Professor of Economics, Harvard University.

To provide information on detention's effects on the incomes and net revenues of drivers and motor carriers, respectively, we adapted an FMCSA model—originally created to assess the effects of HOS regulations—to simulate driver behavior under varying lengths of delays. We also automated the model to allow us to run sufficient numbers of simulations to generate results within reasonable confidence intervals. This work also used data assembled for FMCSA's 2014 study of detention. We did not estimate the effects of delays on the overall economy because doing so would have required a number of major assumptions and therefore would not have yielded useful information.

To assess FMCSA's plans for collection of data related to delays, we interviewed FMCSA officials and reviewed standards for data collection, validation, and analysis, such as the Federal Control Standards, FMCSA's Research Standards,[21] and OMB's Information Quality Standards and Guidance for Administrative Data.[22]

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[21] FMCSA, *Source Standards and Guidelines for Conducting and Managing FMCSA Transportation Research Projects*, March, 2016.

[22] OMB, *Guidelines for Ensuring and Maximizing the Quality, Objectivity, Utility, and Integrity of Information Disseminated by Federal Agencies*, February 2002.

Exhibit B. Safety Impacts of Detention: Technical Appendix

This exhibit describes the scope and methodology of our analysis of the impact of detention time on CMV crash rates. First, we provide an overview of our methodology. Second, we discuss the data used in our analysis. Third, we detail our empirical models. Fourth, we present our results, including our checks on their robustness. References, tables, and figures discussed in the aforementioned sections are included at the end of the exhibit.

Our Approach

Our source of data on carrier safety performance is FMCSA's Motor Carrier Management Information System (MCMIS), which does not contain information on time spent waiting to load or unload cargo. However, we had a complementary dataset reporting dwell time information. First, we used this complementary dataset to estimate the distribution of dwell time given carrier characteristics. Second, we used the monthly information on motor carrier characteristics that MCMIS has in common with the dwell time dataset to calculate two measures of detention likelihood in each month for each carrier in our MCMIS dataset. The two measures are: (1) detention probability—the probability of dwell time in excess of 2 hours, and (2) average dwell time. Third, we estimated the impact of detention likelihood on monthly crash rates using a nonlinear regression model for each measure.

We expected that the dwell time that truck drivers experience depends on both the type of cargo they transport and the characteristics of the carrier they work for. In particular, based on the results in FMCSA (2014a), we expected that factors such as freight type, carrier operation type, and carrier size affect dwell time. Consequently, we modeled the distribution of dwell time by assuming a statistical distribution whose parameters depend on these factors. Based on a dwell time histogram (see figure 1) and the evidence in FMCSA (2014a), we assumed that dwell time follows a truncated lognormal distribution. We further followed FMCSA (2014a) in assuming minimum and maximum loading/unloading times of 30 minutes and 10 hours, respectively.

The estimated dwell time distribution allowed us to quantify both the probability of detention and average dwell time given carrier characteristics for each time period. However, estimates of those quantities may deviate from the actual detention probability and average dwell time experienced in each period. We used the truck stops data to obtain measurement errors by subtracting estimates from actual values for both detention probability and average dwell time. The measurement errors provide an empirical error distribution that we used to remove measurement error from the crash rate regression. Specifically, we removed measurement error by first converting the regression equation to moment conditions and then integrating with respect to the measurement error distribution. Consequently, we propose a regression model for crash rates that is estimable using simulated Generalized Method of Moments (GMM).

In addition to developing a model which uses estimates of detention time rather than actual values, we faced three primary challenges in designing a regression model for carrier monthly crash rates. First, the dependent variable is not continuous, as crash counts consist of nonnegative integers. Ignoring this fact could result in negative predicted crash outcomes (Wooldridge 2010, p. 723). Second, it is unlikely that all carriers are equally exposed to crash incidence In particular, the more power units a carrier operates the higher the number of possible crashes. Third, we had endogeneity concerns about one of the covariates in the regression. We followed the count data models literature by proposing a nonlinear regression model with exposure variable estimable using GMM. The resulting model is consistent with specifications in which the dependent variable is assumed to follow common distributions for count data, such as Poisson or Negative Binomial.[23] The GMM framework allows adjustment for endogenous covariates using instrumental variables and for measurement error using the approach discussed above. We estimated a separate regression model for each detention measure.

We based our approach on the considerable body of statistical research addressing how to estimate models incorporating mismeasured variables with as little information as possible (for example, Chen, Hu and Lewbel 2009; Schennach and Hu 2013). Specifically informing our approach to estimating detention effects, Chen, Hong and Nekipelov (2011) includes a survey of statistical methods applicable when at least one covariate used in a nonlinear regression model is unobserved – such as detention frequency – but where auxiliary information about this covariate is available. Our approach further follows the method in which researchers (Chen, Hong and Tamer 2006; Chen, Hong and Nekipelov 2011; Newey 2001; Lee and Sepanski 1995; Wang 2004; Hu 2017) formed moment conditions using a regression equation and then removed measurement error using the unobserved or estimated variable’s distribution.

[23] A popular alternative to estimate count data models when the researcher assumes a distribution such as Poisson or Negative Binomial is maximum likelihood estimation (MLE). We do not follow this approach for two reasons. First, GMM allows us to recover consistent estimates in the presence of endogenous covariates under weaker conditions than MLE (Greene 2012, pp 495, 529). Second, even if endogeneity concerns were not present, the computational burden arising from the need to integrate out measurement error for each observation in the MLE objective function would be quite substantial give the size of our MCMIS sample.

Data Description

We used two independent datasets in this study. The first consisted of a commercial vendor-supplied panel of recorded stops by individual trucks. The second consisted of a panel of carriers drawn from MCMIS. In this section, we describe them both.

Truck Stop Data

These data were originally acquired for an FMCSA-commissioned study on driver detention times in CMV operations (FMCSA 2014a). In that study, researchers collected data from two third-party vendors on truck stopping times and the associated carriers' characteristics—freight type, carrier operation type and carrier operation size. One vendor provided the bulk of the study data, and was also the only one to provide the information on freight type needed for our analysis. We only used data from that vendor.

The dataset used includes 2,984,340 observations, where each observation corresponds to a stop where a truck arrived between January 1, 2013 and June 30, 2013.[24] It contains the following variables: four IDs (for carrier, truck driver, power unit and the stop itself); the type of freight the truck is transporting; the carrier's specific type of operation—private, for-hire TL, and for hire LTL; two timestamps—one for the truck's arrival at the shipper's or receiver's facility and another for its departure; the difference between timestamps (measured in seconds) and the carrier size, represented by the number of power units it operates.[25]

When defining which observations represent loading/unloading activity, our analysis followed FMCSA (2014a) in specifying the lower and upper dwell time thresholds as 30 minutes and 10 hours, respectively. The number of truck stop observations remaining after the implementation of this restriction was 1,052,727. While only 0.76 percent of the initial sample was dropped due to a recorded dwell time over 10 hours, nearly 65 percent of observations were dropped because they fell below the 30 minute threshold. FMCSA (2014a) specified this threshold as a relatively conservative lower bound, and we retain this threshold throughout our work. However, according to industry experts, it is possible to safely perform a "Drop and Hook" unload and load in 15 to

[24] The data also include stops at which the truck driver arrived at the end of June and departed at the beginning of July. In our analysis, we assumed that the relevant month is the departure month, so our data contain some stops from early July.

[25] To preserve anonymity, carrier size was reported within ranges, such as 1 to 50 power units.

20 minutes.[26] If the lower threshold were set at 15 minutes rather than 30 minutes, only 36 percent of observations would be dropped.

The truncated data which uses only stops between 30 minutes and 10 hours is fit well by a truncated log-normal distribution. Figure 1 overlays the histogram of dwell times with a truncated log-normal distribution with parameters derived using Maximum Likelihood Estimation (MLE) on dwell time observations. The close match between the histogram shape and the truncated log-normal curve even without controlling for carrier characteristics justifies our choice of this distribution as the dwell time distribution model.

The truncated lognormal distribution also provides a reasonable fit when only stops under 15 minutes are dropped. Figure 2 plots a histogram of all dwell time observations in our truck stops data with a recorded dwell time under 5 hours. Greater than twenty percent of truck stops which last under 5 hours have a recorded time under 5 minutes, and a significant share of these observations have a recorded dwell time under one minute. We cannot identify what caused such low dwell time observations to be recorded. Consultations with industry experts lead us to believe that these observations do not represent loading or unloading activity. Figure 3 plots a histogram of all dwell time observations which have a recorded dwell time between 15 minutes and 2 hours.[27]

There is considerable variation in the dwell time distributions across the characteristics we observe in the truck stops data. Figure 4 presents the kernel density estimates of the truncated dwell time distribution for private and for-hire carriers. This illustrates that unconditional on any variables other than operation type, private carriers incur significantly lower dwell times than for-hire carriers. Similarly, figure 5 presents the kernel density estimates of the truncated dwell time distribution across carrier size groups. This figure illustrates that the largest carrier size group in our data records significantly lower average dwell times prior to conditioning on other variables than the two smaller size groups presented in the figure. In addition, these figures illustrate that after stratification across either of the specified characteristics the truncated dwell time distributions can be reasonably fit with a truncated log-normal distribution.

While the carriers in the dataset vary on all the characteristics observed in the truck stops data, these data have clear limitations. Most notably, only 28 carriers were included in the dataset. In addition, only 2 of the 28 were small carriers, a proportion which does not represent the carrier population. The majority of carriers in the population operate five or fewer power units—even though large

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[26] This is one of the fastest possible ways to unload cargo. The driver drops the trailer attached to her vehicle and attaches a new trailer.

[27] The upper threshold in these histograms is chosen entirely for illustrative purposes, as retaining the 10-hour threshold in these images would obscure the shape of the distribution.

carriers operate a disproportionate number of CMVs.[28] Table B-1 provides summary statistics on this dataset.

MCMIS Data

Our dataset for estimating our crash rate model came from MCMIS, which consists of a collection of data tables grouped into three files: a crash file, a census file, and an inspection file.

The crash file contains information on crashes involving drivers and vehicles of commercial motor carriers operating in the United States based on State police reports. Notably, only crashes resulting in vehicle towing, fatalities, or transportation of injured persons for medical assistance are reported in the crash file. The census file contains records on commercial motor carriers and other CMV-related entities such as shippers and vehicle registrants. It provides each carrier's US Department of Transportation (USDOT) number and other information that describes the carrier, such as number of power units operated, types of cargo transported, operation type, name and address. The inspection file contains data on State and Federal inspections involving CMVs of commercial motor carriers and of shippers and transporters of hazardous materials operating in the United States.

FMCSA combines information from all three files to create carrier safety scores as part of its Compliance, Safety and Accountability (CSA) program. On a monthly basis, CSA generates seven categories of motor carrier safety scores known as Behavior Analysis Safety Improvement Categories (BASIC)—safe driving; HOS violations; controlled substances/alcohol; vehicle maintenance; hazardous materials compliance; driver fitness; and crash indicator. MCMIS reports these scores.

The unit of observation in our MCMIS dataset was carrier-month. Our dataset covered each commercial motor carrier that reported its USDOT number, the number of power units it operated, its operation type, the type of cargo it usually transports, and whether 70 percent or more of its power units are made up of separable tractor and trailer combinations.[29] It also was limited to carriers that were active during our observation period.[30] Our dataset included observations from July 2012 through July 2013. We used the 2012 data observations only to

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[28] During the sample period, our MCMIS dataset has the following breakdown of carrier numbers by size: 99.2 percent small (1-50 power units); 0.7 percent small/medium (51-250 power units); 0.1 percent medium/large (251-500 power units); and 0.1 percent large (500+ power units). The percentage of the population of power units operated by these different size carriers is as follows: 54.0 percent small; 13.1 percent small/medium; 4.4 percent medium/large; and 28.5 percent large (500+ power units).

[29] The alternative to a combination tractor and trailer is a single unit vehicle, called a "straight" truck. The 70 percent cut-off is primitive to the MCMIS database.

[30] The Volpe National Transportation Systems Center identified the active carriers.

form lags of variables to use as instruments. To be consistent with the truck stop data, we used only observations from January 2013 through July 2013 in estimation. Our final estimation data set from MCMIS contained 861,340 motor carriers, and 5,863,573 monthly observations.[31] Table B-2 reports summary statistics on this dataset.

Empirical Models

We constructed two models, one for the dwell time distribution and another for crash rate estimation.

Dwell Time Distribution

Similar to other situations in which the dependent variable assumes values in an interval, we used truncation regression analysis to estimate the distribution of dwell time as a function of covariates. The structure of our regression model is

$$\log(Dwell\_time_i) = X_i\beta + \varepsilon_i^D \qquad (1)$$

where i indexes truck stop. The dependent variable $\log(Dwell\_time_i)$ represents the natural logarithm of the total duration of stop i. The vector X_i contains explanatory variables discussed below and a constant, while β is a vector of coefficients. ε_i^D represents the idiosyncratic error which is assumed to be independent of X_i and follow a zero-mean normal distribution with standard deviation σ.[32] Letting a and b be the lower and upper limit of $Dwell\_time$, the (truncated) probability density function for this variable for stop i is

$$f(Dwell\_time_i) = \frac{g(Dwell\_time_i)}{\mathrm{G}(b) - \mathrm{G}(a)} \qquad (2)$$

where $g(.)$ and $\mathrm{G}(.)$ represent the log-normal probability density function (PDF) and cumulative distribution function (CDF), respectively. [33] The lower and upper truncation limits were set to 30 minutes and 10 hours, respectively, based on expert opinion, as in FMCSA (2014a).[34]

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31 Our data set was not a balanced panel in the sense that the number of observations divided by the number of motor carriers did not equal exactly 7 months. Data could have been missing for several reasons, including carriers entering or leaving the market during the sample period and occasional misreporting. Our estimation methods did not require a balanced panel for implementation.

32 If the dependent variable $\log(Dwell\_time_i)$ is measured with error, then the error term ϵ_i^D will also include that measurement error, denoted v_i^D. Thus, the normality assumption on ϵ_i^D also implicitly assumes that if $\log(Dwell\_time_i)$ is measured with error, then v_i^D is also independent of X_i and is normally distributed.

33 Specifically, $g(y) = \phi((\log(y) - \mu)/\sigma)/(y\sigma)$ and $G(y) = \Phi((\log(y) - \mu)/\sigma)$, where $\phi(.)$ and $\Phi(.)$ represent the standard Normal distribution PDF and CDF, respectively, and $\mu = X\beta$.

34 We also estimated the model with the lower limit set to 25 minutes, but did not find significant differences in the results.

We estimated the dwell time PDF in (2) using MLE. This estimation method finds the values for β and σ that solve the conditions for maximizing the likelihood function of our truncated dwell time data. In cases in which the dataset does not reflect the population proportions of the covariates in X but the researcher is modeling the distribution of the dependent variable given X, both weighted and unweighted MLE yield consistent estimates (Wooldridge 2001). Our primary specification for (2) is unweighted MLE.[35] In addition to drawing inferences about the factors affecting dwell time, we used the estimated dwell time distribution to compute model predictions of both expected dwell time and detention probability given motor carrier characteristics. Specifically, let $f(Dwell\_time|X,\theta_D^*)$ and $F(Dwell\_time|X,\theta_D^*)$ denote the estimated dwell time PDF and CDF given carrier covariates X, respectively. The estimated probability of detention and expected dwell time given covariates X_{jt} are, respectively,

$$Prob\_Detention_{jt} = 1 - F(2|X_{jt},\theta_D^*) \quad (3)$$

$$E\_Dwell\_time_{jt} = \int_{0.5}^{10} tf(t|X_{jt},\theta_D^*)dt \quad (4)$$

where we classify dwell times in excess of 2 hours to be detention and where dwell time is assumed to lie between one half-hour and ten hours. We quantified (3) and (4) using the formulas derived in Jawitz (2004) for the truncated lognormal distribution.

We regressed the actual average dwell time observed in the data on the model's predicted average dwell time to recover the measurement error distribution and to assess fit quality. We proceeded analogously for the case of detention probability, which we defined as the fraction of stops with dwell time in excess of 2 hours. Notably, we aggregated the variables in both regressions up to the

[35] As a robustness check, we also estimate a weighted specification of (2). In the weighted estimation, we specify each observation weight as $w_i = Q_j/H_j$, where Q_j is the probability that a randomly drawn truck from MCMIS falls into stratum B_j and H_j is the fraction of observed truck stops in stratum B_j. We define stratum B_j as a combination of carrier size, operation type, and freight type (for example, $B_1 = \{Large\ carrier\} \cap \{Private\} \cap \{Reefer\}$). There are a total of 56 possible strata and we denote this set by $\Xi = \{B_1, B_2, \dots, B_{56}\}$. Thus, for each $j = 1, 2, \dots, 56, Q_j$ and H_j are computed as the frequency of B_j in MCMIS and truck stops data, respectively. We also considered a weighting extension that incorporated MCMIS information not present in the truck stops data, specifically carrier combination/straight status. We constructed the weights for this extension as follows. For each combination/straight status (denoted *A*) and each possible stratum $B \in \Xi$, we calculated the proportion of trucks in the population that are in $A \cap B$ using the MCMIS database. Since we observed *B* but not *A* in the truck stop data, we took expectations of these proportions given *B*. The best prediction of $\Pr(A \cap B)$ given *B* minimizing the squared prediction error is the conditional expectation $\mathrm{E}[\Pr(\mathrm{A} \cap \mathrm{B})\,|\mathrm{B}] = \Pr(\mathrm{C} \cap \mathrm{B})\Pr(\mathrm{C}|\mathrm{B}) + \Pr(\mathrm{S} \cap \mathrm{B})\Pr(\mathrm{S}|\mathrm{B})$, where *C* represents combination carrier and *S* represents straight carrier. We quantify each probability in this formula using the MCMIS data. For example, for $B = \{Large\ carrier\} \cap \{Private\} \cap \{Reefer\}$ we calculated $\Pr(C \cap B)$ as the fraction of trucks in the population that are operated by large, private, reefer combination carriers. For the same stratum *B*, $\Pr(C|B)$ was calculated as the fraction of combination carrier trucks within the pool of trucks operated by *B*-type carriers.

carrier-month level to provide compatibility with the MCMIS data. For both detention likelihood measures, the linear regression model is

$$D_{jt} = \rho_0 + D_{jt}^* \rho_1 + \varepsilon_{jt}^Q \quad (5)$$

where D_{jt} is actual average dwell time for carrier j in month t, D_{jt}^* is its prediction based on estimation of (2), and the subscript i is dropped due to the aggregation.

In regressions such as (5) in which the dependent variable is a group average (such as average dwell time by carrier-month) and the number of observations is not large, it is important to assess the need for weighting the regression by the within-group observation count in the interest of precision. As discussed in Solon *et al.* (2015), if the number of observations (in this instance, truck stops) by group varies widely and is small in some groups, then estimating a linear regression such as (5) using within-group weights could improve precision substantially. We tested for the necessity of weighting by following the procedure described in Solon *et al.* (2015). Formally, we first estimated (5) using ordinary least squares, and then we regressed the squared estimates of ε_{jt}^Q on a constant and $1/J_{jt}$, where J_{jt} is the number of truck stops for carrier j in month t. A statistically significant t-ratio for the coefficient on the variable $1/J_{jt}$ would indicate regression (5) should be weighted. We obtained t-ratios of 3.68 and 3.79 when D_{jt} represents average dwell time and detention probability, respectively, which are significant at the 1 percent level. So we estimated (5) weighting each carrier-month observation by the number of stops observed for that carrier in that month. We expected that the estimated values for ρ_0 and $\rho_1$would be very close to zero and one, respectively, or that D_{jt}^* is an unbiased predictor of D_{jt}. In this framework, the regression residuals represent measurement errors.

Crash Rate Regression Model

Similar to other situations in which the dependent variable takes on nonnegative integer values, we followed the count models literature by proposing a regression model adapted to fitting count data. The basic structure of our regression model prior to adjusting for count data specifics was

$$Monthly\_Crashes_{jt} = \alpha_0 + W_{jt}\alpha + D_{jt}\lambda + \varepsilon_{jt}^C \quad (6)$$

where j indexes motor carrier and t indexes time. The vector W_{jt} contains explanatory variables that may vary by carrier and time. It includes a vector of time (monthly) dummies, which in part serves to absorb shifts in conditions potentially affecting delays at shippers, such as demand for freight service or weather conditions. D_{jt} is a detention likelihood measure that also varies by carrier and time. ε_{jt}^C represents the idiosyncratic error, where the sequence $\{\varepsilon_{jt}^C: t = 1, \ldots, T\}$ is allowed to be serially correlated. The idiosyncratic errors are assumed to cluster over time within each carrier but be independent across carriers.

Estimation of model (6) using linear regression is problematic because its estimates could result in negative predictions for monthly crash counts (Wooldridge 2010, p. 723). Moreover, model (6) does not control for differences in crash exposure across carriers—the more power units a carrier operates, the higher the number of possible crashes in a month. The adjusted version of our model is

$$Monthly\_Crashes_{jt} = PU_{jt} * \exp(\alpha_0 + W_{jt}\alpha + D_{jt}\lambda) + \varepsilon_{jt}^{C} \quad (7)$$

where $\exp(.)$ is the exponential function and PU_{jt} represents carrier j's exposure to crashes in period t, as measured by the number of power units it operates.[36] The errors are assumed to cluster as described above. Equation (7) is consistent with other models for count data, such as Poisson Regression and the Negative Binomial Model under common specifications. [37]

Since one of the covariates is not observed, but its prediction is available, we estimate (7) by integrating out prediction errors after forming appropriate moment conditions, as in the statistics literature (Lee and Sepanski 1995; Newey 2001; Chen, Hong and Tamer 2006; Chen, Hong and Nekipelov 2011; Wang 2004). We accomplished this by forming moment conditions based on interacting ε_{jt}^{C} with covariates and then integrating out measurement error using ε_{jt}^{Q} from (5). Specifically, we define the residual function

$$\varepsilon_{jt}^{C}\left(PU_{jt}, W_{jt}, D_{jt}^{*}; \Theta\right) = Monthly\_Crashes_{jt} - E\left[PU_{jt} * \exp(\alpha_0 + W_{jt}\alpha + D_{jt}\lambda)\middle|PU_{jt}, W_{jt}, D_{jt}^{*}\right]$$

$$= Monthly\_Crashes_{jt} - \int PU_{jt} * \exp(\alpha_0 + W_{jt}\alpha + D_{jt}\lambda) f_{D|D^*}\left(D\middle|D_{jt}^{*}\right) dD \quad (8)$$

where $f_{D|D^*}(D|D_{jt}^{*})$ is the distribution of D_{jt} conditional on D_{jt}^{*}. Based on the results of Train (2009), we performed the integration in (8) numerically using Halton draws by generating pseudo-random draws of D_{jt} and then averaging the integrand in (8) across draws. We formed a GMM estimator where moments are defined as averages of the product of the residual function defined in (8) with a set of variables exogenous to that residual. In our estimation, the exogenous

[36] An alternative measure of exposure to crashes would be miles driven reported by the carrier. We preferred number of power units as exposure instead, as the quality of vehicle miles traveled is low due to misresponse and nonresponse.

[37] A common specification for either the Poisson, Negative Binomial I, or Negative Binomial II regression models specifies the conditional mean as $E[Y_i|x_i] = e_i * \exp(x_i'\beta)$, where e_i represents a measure of exposure, x_i represents a $k \times 1$ vector of explanatory variables, and β represents a $1 \times k$ vector of parameters (Ismail and Jermain 2007).

variables are a constant (vector of ones), all the variables in W_{jt} except for the intervention dummy for the crash indicator, the detention measure predictor D^*_{jt}, and a lag of the crash indicator intervention dummy. We provide details on these variables in the next subsection.

Variable Construction

All variables used to estimate the dwell time distribution (2) and equation (5) were constructed from the truck stop dataset. All variables in the crash rate model (7)—apart from the detention likelihood measures—used MCMIS data. Tables B-1 and B-2 report summary statistics for all variables constructed.

Our choice of control variables for estimating the dwell time distribution built on the results of FMCSA (2014a). Accordingly, our control variables consisted of dummy variables falling into three groups—carrier size, truck freight and carrier operation type.

We labeled a carrier small, small-medium, medium-large or large if the number of power units it operates lies between 1 and 50, 51 and 250, or 251 to 500, or 501 and up, respectively. We defined three dummy variables for each of the latter three size groups so that small carriers were in the reference group. For example, $large_i$ is set to one if the truck in stop i is operated by a large carrier, and zero otherwise. We expected truck drivers working for larger carriers to experience lower average dwell times than those operating for smaller carriers. As discussed in FMCSA (2014a), larger carriers tend to benefit from factors that could mitigate loading/unloading delays, such as detention fee clauses in contracts with shippers, familiarity with loading/unloading procedures at frequently visited shippers, and past experience in handling delay-prone situations.

Six dummy variables controlled for truck freight types. The following freight types were in the truck stop data: (1) *dry bulk*—dry materials in bulk, such as flour and phosphates; (2) *liquid bulk/tank*—liquid materials transported in a tank-like container, such as oils or gas; (3) *mixed*—diverse freight with at least three different cargo types; (4) *reefer*—temperature controlled goods, such as meat, dairy products or produce, transported in refrigerated trucks called "reefers;" (5) *van*—a dry van truck not equipped with temperature control; (6) *van/flatbed*—a truck transporting either dry goods or capital goods, such as metal fabrication or cars; and (7) *van/reefer*—a truck that can transport either dry or refrigerated goods. *Mixed* was our reference group when forming the six dummies for the remainder freight categories. For example, $Reefer_i$ is set to one if the truck in stop i is a reefer, and zero otherwise. Based on the descriptive statistics in FMCSA (2014a), we expected that reefers tend to experience longer dwell time than other freight types.

We recorded carrier operation type by forming a dummy variable for private carriers. That is, $Private_i$ is set to one if the carrier operating the truck involved in stop i is a private carrier, and zero otherwise—that is, if it is a for-hire carrier, either TL or LTL.[38] We expected drivers working for private carriers to experience lower dwell times compared to drivers working for for-hire carriers because in a private operation both the carrier and the shipper work for the same entity, and therefore have incentive to cooperate on mitigating loading/unloading delays. We also considered interactions of the private carrier dummy variable with carrier size dummies, allowing the effect of private operations on dwell times to vary by carrier size.

Five dummy variables represented the months January through May, based on the departure timestamp.[39] For example, $March_i$ is set to one if, for stop i, the truck departed from the shipper in March, and zero otherwise.

Our data on motor carrier crashes comes from MCMIS's crash file. The dependent variable in regression model (7), $Monthly\_Crashes_{jt}$, measures the number of crashes carrier j has in month t. We constructed it by counting the number of crashes in the crash file for each carrier USDOT number for each month. Our carrier-specific covariates included combination carrier status, carrier operation type, freight type, and safety performance measures.

Carriers whose operating units were at least 70 percent separable tractors combined with separable trailers we named combination carriers. Carriers whose operating power units consisted of over 30 percent single unit trucks or other non-combination vehicles we named straight carriers. The dummy variable CUT_{jt} is set to one if carrier j is a combination carrier and zero otherwise. We expected combination carriers to have a higher crash risk than straight carriers due to differences in maneuverability and evidence reported in the literature (Medina *et al.* 2013).

Similar to the dwell time covariate discussed above, the dummy variable $Private_{jt}$ is set to one if carrier j is a private carrier and zero otherwise. We allowed for crash risk differences between for-hire and private carriers because of the different role transportation plays in the two types of business.

We controlled for the impact on crash rates of different freight types by controlling for the freight type reported by each carrier to MCMIS. We converted the cargo categories used in MCMIS into the same freight categories as in the

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[38] We did not form additional dummy variables to allow for TL/LTL differentiation because that information cannot be used for data combination because it is unavailable in MCMIS.
[39] We left out June to avoid collinearity in estimating the dwell time model. Because few stops date from early July, we did not include a dummy for that month either.

truck stops data (see table B-3 for this conversion). We then formed variables in the same fashion as for the dwell time estimation, except that each observation represented a carrier rather than a truck. For example, $Reefer_{jt}$ is set to one if carrier j reports operating reefer trucks in period t, and is zero otherwise. $Mixed_{jt}$ is our reference group.

BASIC scores, FMCSA's safety performance measures, are available for only a minority of the motor carrier population. However, information on whether a carrier has been flagged for intervention under each BASIC category is available for all carriers in our data. When a carrier's BASIC score is poor enough to cross a given threshold, FMCSA flags the carrier for intervention with a warning letter, a notice of violation, or an investigation. We controlled for differences in carrier safety risks by using intervention dummy variables for each BASIC score category. For example $Unsafe\_flagged_{jt}$ is set to one if carrier j has been flagged for intervention in month t because of its unsafe driving BASIC score and zero otherwise. Intervention dummy variables for the remaining six BASICs are defined analogously.[40] We expected carriers that have been flagged for intervention to have higher crash rates than carriers that are not flagged.

We share concerns about the endogeneity of BASIC crash indicator scores with other empirical models for motor carrier crashes (Mitra 2017). A carrier with a poor BASIC crash indicator score is more likely to crash again, but further crash incidence worsens its BASIC crash indicator score. Analogous feedback mechanisms suggest that FMCSA intervention with carriers with BASIC crash indicator scores above a given threshold is also endogenous in crash rate models. Exploiting the fact that BASIC crash indicator scores are computed using a 24-month time window, we used lagged FMCSA intervention based on BASIC crash indicator, $Crash\_flagged_{j,t-1}$, to instrument for FMCSA intervention based on BASIC crash indicator scores in the current period, $Crash\_flagged_{j,t}$.

Our time-specific variables for the crash rate model consisted of dummy variables defined in similar fashion as with the truck stop data for the months January through June. For example, $March_{jt}$ is set to one if month t is March, and zero otherwise. July is the reference month.

Results

We found that large and medium-large carriers experience lower dwell times than small carriers. Private carriers experience lower dwell times relative to for-

[40] We did not need a reference group for this set of dummies because a value of one in one dummy variable does not imply a zero for the remaining dummies. For example, carriers not flagged for intervention have a value of zero for all seven dummy variables.

hire carriers, whereas trucks that transport specific freight types—reefers in particular—experience higher dwell times relative to mixed freight trucks.

We also found that detention substantially increases carrier crash rates. This pattern appeared consistently in the results for both the detention likelihood measures we considered—average dwell time and percentage of dwell times in excess of 2 hours. Furthermore, these results are robust to a variety of model specifications.

Dwell Time Distribution Results

Table B-4 details the results for the dwell time distribution estimated using MLE on equation (1). The estimated coefficients on the carrier size dummies are negative, indicating that small carriers experience longer dwell times than larger carriers. While only some of those coefficients are significant at the 5 percent level, the estimated coefficients on the interaction between the private carrier dummy variable and the three carrier size dummies are all negative and statistically significant at the 1 percent level. Therefore, privately operated carriers experience lower dwell times than for-hire carriers by a considerable margin.

The estimates on all freight type coefficients are positive and statistically significant at the 1 percent level. Therefore, compared to mixed freight truckers, those hauling specialized freight on average experience longer dwell times at shippers and receivers. Consistent with the evidence in FMCSA (2014a), reefers experience on average longer dwell times at shippers/receivers than other truck types.

Estimated coefficients attached to monthly dummies from January through May are all small and statistically insignificant at the 10 percent level. Therefore, we did not find evidence that the dwell time distribution differs significantly by month.

Table B-5 reports the results of regressing the detention likelihood measures by carrier-month on their model predictions – that is, estimating equation (5). In both cases, the intercept value is very close to zero (and not statistically significant at the 10 percent level) while the slope coefficient estimate is close to one (the difference is not statistically significant at the 10 percent level), as expected.[41] Moreover, the R^2 statistic for both regressions exceeds 80 percent, indicating that our model predicts well both average dwell time and average detention probability.

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[41] If the dependent variable $\log(Dwell\_time_i)$ is measured with error, denoted v_i^D, then the estimate of ρ_1 could depend on the standard deviation of v_i^D. The fact that the estimate of ρ_1 is very close to one indicates that measurement error in $\log(Dwell\_time_i)$ is not a significant concern.

Crash Rate Model Results

Tables B-6 and B-7 present the results estimated using equation (7) for our two candidate measures of detention likelihood—average dwell time and detention probability. We present both coefficient estimates and their associated marginal effects, where the latter refers to the effect of a one-unit change in the measure of detention likelihood. The estimated coefficient on the detention likelihood measure is positive and significant at the 1 percent level in both specifications. The coefficient on average dwell time indicates that if the average dwell time experienced by a carrier's drivers in a month increases by 15 minutes, the expected crash rate of that carrier increases by 6.2 percent. The estimated coefficient on detention frequency implies that if the probability of detention increases by five percentage points, the expected crash rate of that carrier increases by 4.7 percent. Given the relative rarity of motor carrier crashes—particularly of the more severe crash types captured in MCMIS and our estimates—it is informative to consider the scale of our results. The national crash rate in MCMIS per 100 power units per year for freight-hauling vehicle types from January 2013 through December 2013 was 1.56, so a 6.2 percent increase over this baseline would raise this crash rate to 1.66. This suggests one additional crash per 1,000 power units per year. In 2013, freight-hauling motor carriers in MCMIS recorded a total of 104,318 crashes. A 6.2 percent increase over a baseline of 104,318 crashes would represent 6,509 additional crashes.

Most control variable coefficients had the expected effect on crash rates. We found that combined carriers have higher average crash rates than straight carriers while private carriers have lower average crash rates compared to for-hire carriers. Four of the dummy variables indicating a carrier has been flagged for FMCSA intervention (unsafe driving, hours of service, vehicle maintenance, and crash indicator) had statistically significant coefficients at the 1 percent level. Furthermore, the marginal effects attached to each of these four coefficients are large. For example, carriers who are flagged for intervention under the HOS BASIC score are estimated to have an average crash rate 64 percent higher than those that are not flagged, holding other variables constant.

Several coefficients were not statistically significant, such as the coefficients on some monthly dummies and the intervention dummies for BASICs for hazard materials compliance, controlled substances and driver fitness. However, the lack of significance and the small magnitude of the coefficients for these dummies agrees with the available evidence on the correlation of these BASICs with crash rates (GAO 2014; FMCSA 2014b; USDOT Office of Inspector General 2014).

Robustness Analysis

Our robustness analysis consists of two classes of alternate specifications. First, we estimated the model under a specification which estimates a weighted dwell time distribution to address the unrepresentative nature of the truck stops dataset. Second, we estimated the model with three alternative specifications using the unweighted dwell time distribution. We found that our estimates of the dwell time distribution are robust to estimating the model with population weights. Both weighted and unweighted estimators result in comparable coefficient estimates and similar estimates of our detention measures. We also found that our estimates of the impact of detention measures on average crash rates are robust to alternative instruments for the safety-intervention flag on crash indicator BASIC. Additionally, we estimated a specification where we assumed carriers missing freight information represented mixed freight carriers. In this specification, estimates of detention's impact on average crash rates are essentially unchanged from the baseline specification.

Tables B-8 and B-9 present the robustness analysis results for the simulated GMM estimates. Table B-10 presents marginal effects for a 15-minute increase in average dwell time as well as a 5 percentage-point increase in detention probability for the baseline specification and the robustness checks. The range of marginal effects for the former across models is 5.0 percent to 7.1 percent, whereas the range of marginal effects for the latter across models is 3.8 percent to 5.3 percent. Our baseline estimates of 6.2 percent and 4.7 percent for average dwell time and detention probability, respectively, fall within this range.

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Table B-1. Summary Statistics: Truck Stop Data (N = 1,052,727)

Variable	Mean	Std. Dev	Min	Max	Carrier Count
Dwell time in hours	1.110	0.995	0.5	9.999	28
January	0.156	0.363	0	1	25
February	0.152	0.359	0	1	28
March	0.166	0.372	0	1	28
April	0.170	0.375	0	1	27
May	0.187	0.390	0	1	27
June	0.169	0.375	0	1	27
July	0.001	0.031	0	1	18
Small carrier	0.0003	0.016	0	1	2
Small-medium carrier	0.171	0.376	0	1	19
Medium-large carrier	0.093	0.290	0	1	4
Large carrier	0.736	0.441	0	1	3
Private carrier	0.747	0.435	0	1	7
Small private carrier	0.000	0.000	0	1	0
Small-medium private carrier	0.036	0.186	0	1	3
Medium-large private carrier	0.031	0.173	0	1	2
Large private carrier	0.680	0.467	0	1	2
Bulk freight	0.022	0.147	0	1	2
Bulk/Tank freight	0.060	0.237	0	1	3
Mixed freight	0.000	0.008	0	1	1
Reefer freight	0.049	0.216	0	1	6
Van freight	0.230	0.421	0	1	8
Van/Flatbed freight	0.029	0.168	0	1	3
Van/Reefer freight	0.610	0.488	0	1	5

Note: All variables except dwell time are dummy variables set to 1 if the relevant condition is satisfied. All dummy variables except for months are constant across observations for each carrier.
Source: OIG analysis.

Table B-2. Summary Statistics: MCMIS Data (N = 5,863,573)

Variable	Mean	Std. Dev.	Min	Max
Monthly crashes	0.007	0.185	0	85
Number of power units	5.382	194.649	1	106053
Estimated probability of detention	0.305	0.120	0.004	0.595
Estimated average dwell time	1.886	0.475	0.688	3.110
Combination carrier	0.341	0.474	0	1
January	0.141	0.348	0	1
February	0.142	0.349	0	1
March	0.143	0.350	0	1
April	0.143	0.350	0	1
May	0.143	0.350	0	1
June	0.144	0.351	0	1
July	0.144	0.352	0	1
Small carrier	0.991	0.093	0	1
Small-medium carrier	0.007	0.086	0	1
Medium-large carrier	0.001	0.027	0	1
Large carrier	0.001	0.025	0	1
Private carrier	0.603	0.489	0	1
Small private carrier	0.598	0.490	0	1
Small-medium private carrier	0.004	0.060	0	1
Medium-large private carrier	0.0003	0.019	0	1
Large private carrier	0.0003	0.017	0	1
Bulk freight	0.005	0.067	0	1
Bulk/Tank freight	0.112	0.315	0	1
Mixed freight	0.003	0.057	0	1
Reefer freight	0.061	0.239	0	1
Van freight	0.230	0.421	0	1
Van/Flatbed freight	0.582	0.493	0	1
Van/Reefer freight	0.007	0.084	0	1
Intervention flags:				
Controlled substance/alcohol	0.004	0.059	0	1
Crash indicator	0.006	0.076	0	1
Driver fitness	0.007	0.081	0	1

Variable	Mean	Std. Dev.	Min	Max
Hazardous material	0.001	0.025	0	1
Hours-of-service compliance	0.023	0.151	0	1
Unsafe driving	0.009	0.096	0	1
Vehicle maintenance	0.024	0.154	0	1

Note: Unit of observation is carrier-month.
Source: OIG analysis.

Table B-3. Freight Classification Conversion

MCMIS Cargo Classification	Truck stop data freight types
General Freight (GENFREIGHT)	Van
Household Goods (HOUSEHOLD)	Van
Metal: Sheets, Coils, Rolls (METALSHEET)	Van/Flatbed
Motor Vehicles (MOTORVEH)	Van/Flatbed
Driveaway/Towaway (DRIVETOW)	Van/Flatbed
Logs, Poles, Beams, Lumber (LOGPOLE)	Van/Flatbed
Building Materials (BLDGMAT)	Van/Flatbed
Mobile Homes (MOBILEHOME)	Van/Flatbed
Machinery, Large Objects (MACHLRG)	Van/Flatbed
Fresh Produce (PRODUCE)	Reefer
Liquids/Gases (LIQGAS)	Bulk/Tank
Intermodal Containers (INTERMODAL)	Van
Oilfield Equipment (OILFIELD)	Van/Flatbed
Livestock (LIVESTOCK)	Van
Grain, Feed, Hay (GRAINFEED)	Van/Flatbed
Meat (MEAT)	Reefer
U.S. Mail (USMAIL)	Van
Chemicals (CHEM)	Bulk/Tank
Commodities Dry Bulk (DRYBULK)	Bulk
Refrigerated Food (COLDFOOD)	Reefer
Beverages (BEVERAGES)	Van/Reefer
Paper Products (PAPERPROD)	Van
Utility (UTILITY)	Van/Flatbed
Farm Supplies (FARMSUPP)	Van/Flatbed
Construction (CONSTRUCT)	Van/Flatbed
Water - Well (WATERWELL)	Bulk/Tank
Other (CARGOOTHR)	Mixed

Source: OIG crosswalk of freight categorizations.

Table B-4. Dwell Time Distribution Estimates

Variables	Unweighted Truck Stops Data
January dummy	-0.0821
	(0.0504)
February dummy	-0.0495
	(0.0346)
March dummy	-0.0568
	(0.0450)
April dummy	-0.0440
	(0.0426)
May dummy	0.00423
	(0.0220)
Small-medium carrier dummy	-0.524
	(0.357)
Medium-large carrier dummy	-0.664***
	(0.243)
Large carrier dummy	-0.378**
	(0.187)
Small-medium private carrier dummy	-0.988***
	(0.255)
Medium-large private carrier dummy	-1.305***
	(0.402)
Large private carrier dummy	-0.403***
	(0.152)
Bulk freight dummy	2.080***
	(0.619)
Bulk/Tank freight dummy	2.013***
	(0.470)
Reefer freight dummy	2.430***
	(0.593)
Van freight dummy	1.859***
	(0.426)
Van/flatbed freight dummy	1.179***
	(0.456)
Van/reefer freight dummy	0.0868***
	(0.0324)

Variables	Unweighted Truck Stops Data
Constant	-1.497***
	(0.506)
Sigma	0.971***
	(0.141)
Observations	1,052,727

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

Table B-5. Weighted OLS Regression of Actual Detention Measure on Model Prediction

Variables	Observed Average Dwell Time	Observed Detention Probability
Average Dwell Time	1.022***	
	(0.0338)	
Detention Probability		1.038***
		(0.0358)
Constant	-0.0200	-0.0052
	(0.0397)	(0.0052)
Observations	180	180
R-Squared	0.837	0.825

Note: Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Source: OIG analysis.

Table B-6. Crash Model GMM Estimates Using Average Dwell Time

Variables	Coefficient	Marginal Effect
Average Dwell Time	0.242***	0.274***
	(0.0649)	(0.083)
Private dummy	-0.367***	-0.307***
	(0.0632)	(0.044)
Bulk freight dummy	0.243	0.275
	(0.274)	(0.349)
Bulk/Tank freight dummy	0.324	0.383
	(0.266)	(0.368)
Reefer freight dummy	0.424*	0.528
	(0.256)	(0.391)
Van freight dummy	0.335	0.398
	(0.241)	(0.337)
Van/flatbed freight dummy	0.477**	0.611*
	(0.227)	(0.366)
Van/reefer freight dummy	0.570**	0.768*
	(0.233)	(0.412)
January dummy	0.117***	0.124***
	(0.0185)	(0.021)
February dummy	-0.00152	-0.002
	(0.0196)	(0.020)
March dummy	0.0398**	0.041**
	(0.0188)	(0.020)
April dummy	-0.0197	-0.020
	(0.0188)	(0.018)
May dummy	0.0152	0.015
	(0.0184)	(0.019)
June dummy	-0.0252	-0.025
	(0.0182)	(0.018)
Combination dummy	0.804***	1.234***
	(0.0642)	(0.144)
Unsafe driving flag	0.497***	0.644***
	(0.0362)	(0.060)
Hours of service flag	0.395***	0.484***
	(0.0336)	(0.050)
Drug/Alcohol flag	0.0276	0.028
	(0.0937)	(0.096)
Maintenance flag	0.311***	0.365***

Variables	Coefficient	Marginal Effect
	(0.0349)	(0.048)
HM compliance flag	0.0915	0.096
	(0.0726)	(0.080)
Crash indicator flag	0.796***	1.217***
	(0.0514)	(0.114)
Driver fitness flag	-0.0314	-0.031
	(0.0469)	(0.045)
Constant	-7.922***	NA
	(0.235)	NA
Observations	5,855,153	

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

Table B-7. Crash Model GMM Estimates Using Detention Probability

Variables	Coefficient	Marginal Effect
Detention Probability	0.921***	1.512**
	(0.249)	(0.625)
Private dummy	-0.365***	-0.306***
	(0.0532)	(0.037)
Bulk freight dummy	0.234	0.264
	(0.232)	(0.293)
Bulk/Tank freight dummy	0.314	0.369
	(0.226)	(0.309)
Reefer freight dummy	0.427**	0.533
	(0.216)	(0.331)
Van freight dummy	0.324	0.383
	(0.205)	(0.283)
Van/flatbed freight dummy	0.471**	0.602*
	(0.193)	(0.309)
Van/reefer freight dummy	0.569***	0.766**
	(0.197)	(0.348)
January dummy	0.117***	0.124***
	(0.0156)	(0.018)
February dummy	-0.00160	-0.002
	(0.0166)	(0.017)
March dummy	0.0398**	0.041**
	(0.0159)	(0.017)
April dummy	-0.0198	-0.020
	(0.0159)	(0.016)
May dummy	0.0153	0.015
	(0.0156)	(0.016)
June dummy	-0.0252	-0.025*
	(0.0154)	(0.015)
Combination dummy	0.805***	1.237***
	(0.0542)	(0.121)
Unsafe driving flag	0.496***	0.642***
	(0.0306)	(0.050)
Hours of service flag	0.396***	0.486***
	(0.0285)	(0.042)
Drug/Alcohol flag	0.0274	0.028
	(0.0793)	(0.082)
Maintenance flag	0.312***	0.366***

Variables	Coefficient	Marginal Effect
	(0.0295)	(0.040)
HM compliance flag	0.0918	0.096
	(0.0615)	(0.067)
Crash indicator flag	0.796***	1.217***
	(0.0435)	(0.096)
Driver fitness flag	-0.0313	-0.031
	(0.0397)	(0.038)
Constant	-7.740***	NA
	(0.194)	NA
Observations	5,855,153	

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

Table B-8. Weighted Dwell Time Distribution Estimates

Variables	Weighted Truck Stops Data
January dummy	-0.00929
	(0.0148)
February dummy	-0.00646
	(0.0202)
March dummy	0.0279**
	(0.0122)
April dummy	0.0309*
	(0.0179)
May dummy	0.0607***
	(0.0224)
Small-medium carrier dummy	-0.934*
	(0.505)
Medium-large carrier dummy	-1.099***
	(0.414)
Large carrier dummy	-0.523
	(0.385)
Small-medium private carrier dummy	-1.133***
	(0.217)
Medium-large private carrier dummy	-2.715***
	(0.513)
Large private carrier dummy	-0.455***
	(0.0748)
Bulk freight dummy	2.321***
	(0.642)
Bulk/Tank freight dummy	3.390***
	(0.684)
Reefer freight dummy	3.599***
	(0.753)
Van freight dummy	2.711***
	(0.571)
Van/flatbed freight dummy	1.909***
	(0.621)
Van/reefer freight dummy	0.144***
	(0.0155)
Constant	-2.651***

Variables	Weighted Truck Stops Data
	(0.551)
Sigma	1.249***
	(0.125)
Observations	1,052,727

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

Table B-9. Alternative Crash Model Estimates Using Average Dwell Time

Variables	Unweighted Distribution IV: Lag 1 Missing coded as mixed	Unweighted Distribution IV: Lag 3 Missing freight dropped	Unweighted Distribution IV: Lag 6 Missing freight dropped	Weighted Distribution IV: Lag 1 Missing freight dropped
Average Dwell Time	0.242***	0.258***	0.273***	0.196***
	(0.0637)	(0.0653)	(0.0657)	(0.0529)
Private dummy	-0.345***	-0.359***	-0.351***	-0.375***
	(0.0517)	(0.0622)	(0.0614)	(0.0645)
Bulk freight dummy	-0.306*	0.217	0.194	0.419
	(0.161)	(0.274)	(0.275)	(0.263)
Bulk/Tank freight dummy	-0.226	0.301	0.280	0.315
	(0.145)	(0.266)	(0.266)	(0.269)
Reefer freight dummy	-0.130	0.392	0.362	0.514**
	(0.125)	(0.257)	(0.258)	(0.245)
Van freight dummy	-0.213**	0.318	0.301	0.391*
	(0.0946)	(0.242)	(0.243)	(0.236)
Van/flatbed freight dummy	-0.0750	0.468**	0.460**	0.486**
	(0.0561)	(0.228)	(0.229)	(0.227)
Van/reefer freight dummy	0.0231	0.568**	0.566**	0.570**
	(0.0829)	(0.233)	(0.234)	(0.234)
January dummy	0.110***	0.120***	0.123***	0.100***
	(0.0172)	(0.0186)	(0.0188)	(0.0181)
February dummy	-0.0127	-0.000132	0.00248	-0.0120
	(0.0182)	(0.0197)	(0.0199)	(0.0196)
March dummy	0.0309*	0.0402**	0.0418**	0.0235
	(0.0169)	(0.0190)	(0.0192)	(0.0187)
April dummy	-0.0294*	-0.0192	-0.0176	-0.0337*
	(0.0168)	(0.0189)	(0.0190)	(0.0188)
May dummy	0.0164	0.0143	0.0146	0.00843
	(0.0165)	(0.0185)	(0.0186)	(0.0187)
June dummy	-0.0254	-0.0253	-0.0246	-0.0252
	(0.0165)	(0.0183)	(0.0184)	(0.0183)
Combination dummy	0.831***	0.796***	0.787***	0.804***
	(0.0531)	(0.0637)	(0.0635)	(0.0654)
Unsafe driving flag	0.521***	0.458***	0.422***	0.495***
	(0.0333)	(0.0371)	(0.0404)	(0.0366)
Hours of service flag	0.418***	0.392***	0.390***	0.398***
	(0.0299)	(0.0336)	(0.0338)	(0.0343)
Drug/Alcohol flag	0.0638	0.0214	0.0130	0.0288

Variables	Unweighted Distribution IV: Lag 1 Missing coded as mixed	Unweighted Distribution IV: Lag 3 Missing freight dropped	Unweighted Distribution IV: Lag 6 Missing freight dropped	Weighted Distribution IV: Lag 1 Missing freight dropped
	(0.0803)	(0.0917)	(0.0899)	(0.0956)
Maintenance flag	0.315***	0.304***	0.297***	0.315***
	(0.0322)	(0.0352)	(0.0356)	(0.0356)
HM compliance flag	0.130*	0.0707	0.0510	0.0815
	(0.0694)	(0.0693)	(0.0681)	(0.0726)
Crash indicator flag	0.765***	0.909***	1.013***	0.793***
	(0.0501)	(0.0593)	(0.0695)	(0.0515)
Driver fitness flag	-0.0656	-0.0329	-0.0342	-0.0375
	(0.0468)	(0.0466)	(0.0465)	(0.0472)
Constant	-7.394***	-7.943***	-7.962***	-7.865***
	(0.0786)	(0.236)	(0.236)	(0.233)
Observations	7,638,064	5,828,101	5,769,528	5,855,153

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

Table B-10. Alternative Crash Model Estimates Using Detention Probability

Variables	Unweighted Distribution IV: Lag 1 Missing coded as mixed	Unweighted Distribution IV: Lag 3 Missing freight dropped	Unweighted Distribution IV: Lag 6 Missing freight dropped	Weighted Distribution IV: Lag 1 Missing freight dropped
Detention Probability	0.933***	0.982***	1.037***	0.749***
	(0.246)	(0.251)	(0.252)	(0.202)
Private dummy	-0.344***	-0.357***	-0.349***	-0.375***
	(0.0432)	(0.0511)	(0.0492)	(0.0577)
Bulk freight dummy	-0.320**	0.207	0.184	0.411*
	(0.137)	(0.227)	(0.222)	(0.236)
Bulk/Tank freight dummy	-0.241*	0.290	0.268	0.315
	(0.124)	(0.221)	(0.215)	(0.239)
Reefer freight dummy	-0.133	0.396*	0.367*	0.522**
	(0.105)	(0.212)	(0.207)	(0.219)
Van freight dummy	-0.229***	0.306	0.287	0.383*
	(0.0827)	(0.201)	(0.197)	(0.212)
Van/flatbed freight dummy	-0.0825*	0.463**	0.454**	0.480**
	(0.0488)	(0.188)	(0.184)	(0.204)
Van/reefer freight dummy	0.0217	0.567***	0.565***	0.570***
	(0.0695)	(0.193)	(0.188)	(0.209)
January dummy	0.110***	0.120***	0.123***	0.100***
	(0.0145)	(0.0154)	(0.0151)	(0.0162)
February dummy	-0.0127	-0.000218	0.00240	-0.0120
	(0.0153)	(0.0163)	(0.0160)	(0.0175)
March dummy	0.0309**	0.0401**	0.0417***	0.0237
	(0.0142)	(0.0156)	(0.0154)	(0.0167)
April dummy	-0.0294**	-0.0193	-0.0177	-0.0335**
	(0.0141)	(0.0156)	(0.0153)	(0.0168)
May dummy	0.0164	0.0143	0.0147	0.00873
	(0.0138)	(0.0152)	(0.0150)	(0.0167)
June dummy	-0.0254*	-0.0253*	-0.0246*	-0.0252
	(0.0139)	(0.0151)	(0.0148)	(0.0164)
Combination dummy	0.832***	0.797***	0.787***	0.804***
	(0.0445)	(0.0524)	(0.0509)	(0.0586)
Unsafe driving flag	0.520***	0.457***	0.421***	0.495***
	(0.0280)	(0.0306)	(0.0326)	(0.0329)
Hours of service flag	0.419***	0.394***	0.392***	0.398***

Variables	Unweighted Distribution IV: Lag 1 Missing coded as mixed	Unweighted Distribution IV: Lag 3 Missing freight dropped	Unweighted Distribution IV: Lag 6 Missing freight dropped	Weighted Distribution IV: Lag 1 Missing freight dropped
	(0.0252)	(0.0279)	(0.0273)	(0.0309)
Drug/Alcohol flag	0.0637	0.0211	0.0128	0.0290
	(0.0675)	(0.0757)	(0.0724)	(0.0856)
Maintenance flag	0.315***	0.305***	0.298***	0.316***
	(0.0271)	(0.0290)	(0.0286)	(0.0319)
HM compliance flag	0.131**	0.0710	0.0513	0.0804
	(0.0584)	(0.0573)	(0.0550)	(0.0650)
Crash indicator flag	0.765***	0.909***	1.013***	0.792***
	(0.0421)	(0.0490)	(0.0561)	(0.0460)
Driver fitness flag	-0.0653*	-0.0329	-0.0342	-0.0384
	(0.0394)	(0.0385)	(0.0375)	(0.0423)
Constant	-7.212***	-7.748***	-7.757***	-7.718***
	(0.0484)	(0.190)	(0.186)	(0.206)
Observations	7,638,064	5,828,101	5,769,528	5,855,153

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

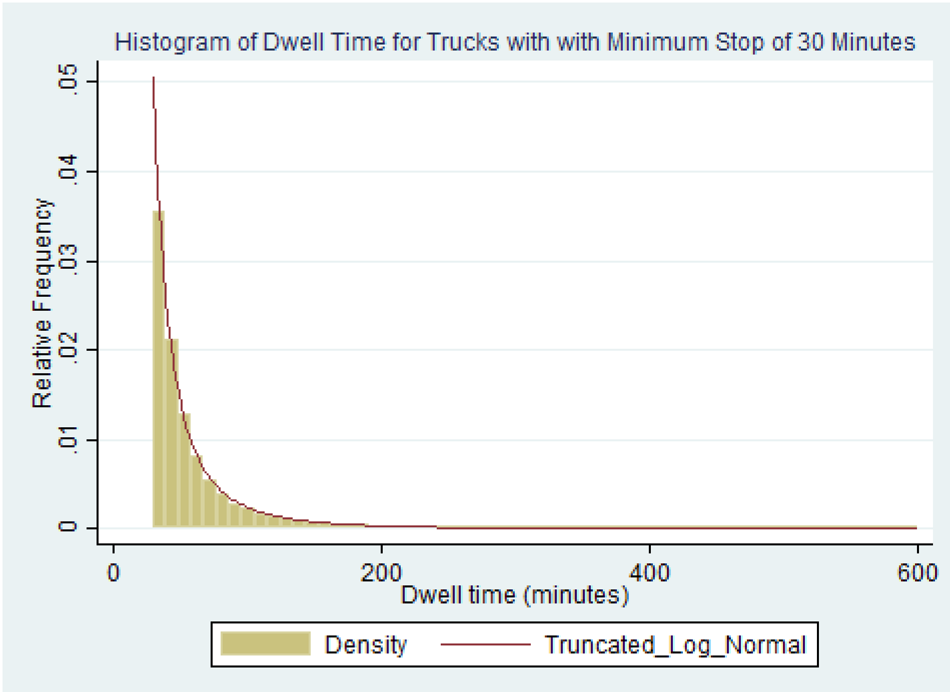
Table B-11. Marginal Effects of Detention for All Specifications

Specification	15 Minute Increase: Average Dwell	5 Percentage Point Increase: Detention Probability
Unweighted Distribution IV: Lag 1 Missing freight dropped	0.062*** (0.017)	0.047*** (0.013)
Unweighted Distribution IV: Lag 1 Missing coded as mixed	0.062*** (0.017)	0.048*** (0.013)
Unweighted Distribution IV: Lag 3 Missing freight dropped	0.067*** (0.017)	0.050*** (0.013)
Unweighted Distribution IV: Lag 6 Missing freight dropped	0.071*** (0.018)	0.053*** (0.013)
Weighted Distribution IV: Lag 1 Missing freight dropped	0.050*** (0.014)	0.038*** (0.010)

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.
Source: OIG analysis.

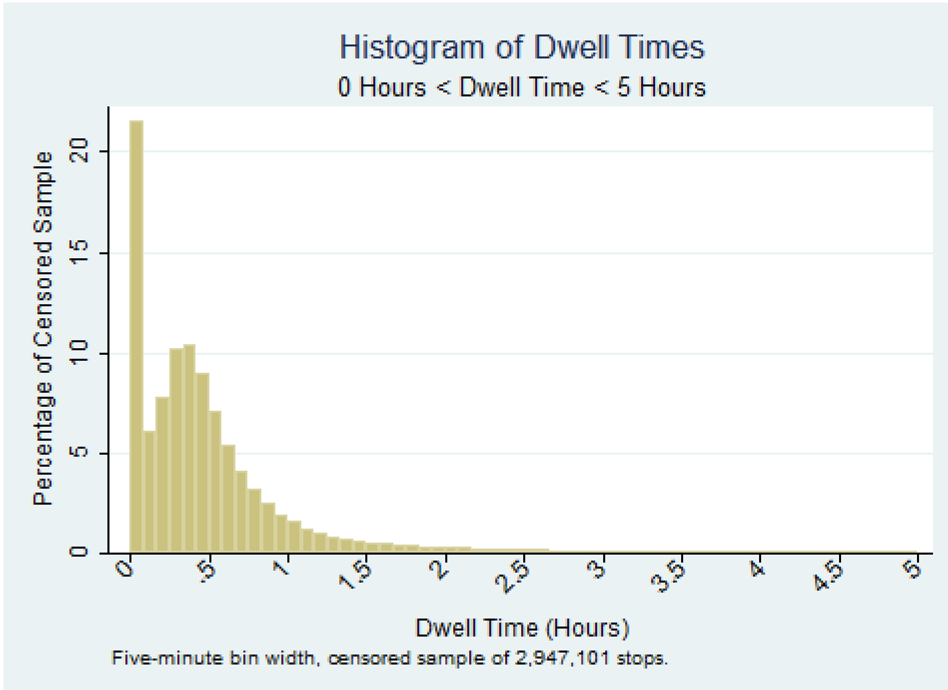
Figures

Figure B-1. Dwell Time Histogram and Truncated Log-Normal Curve



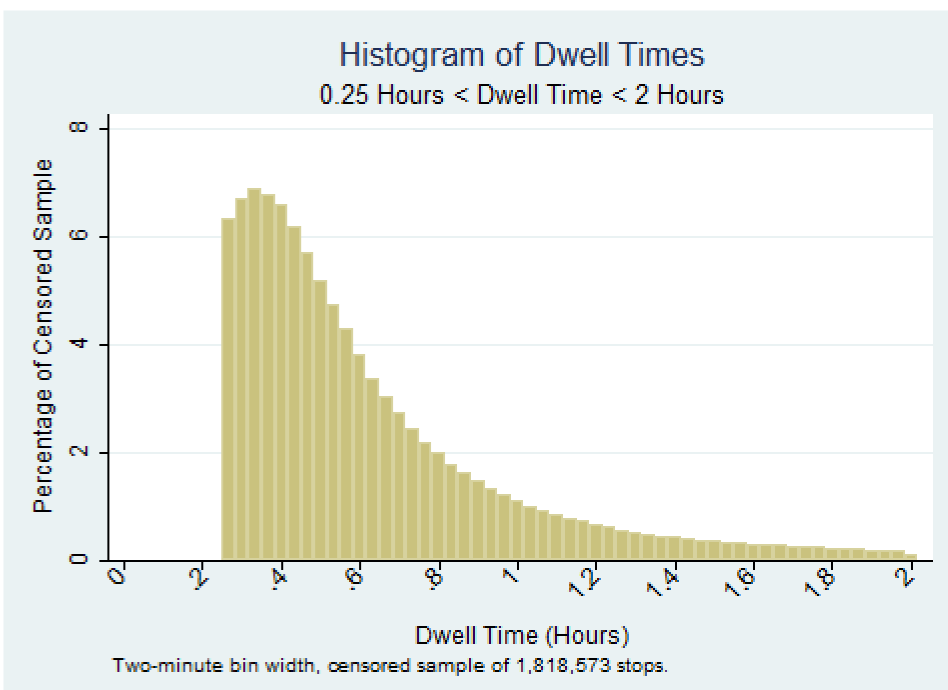
Source: OIG analysis.

Figure B-2. Dwell Time Histogram for All Stops Under 5 Hours



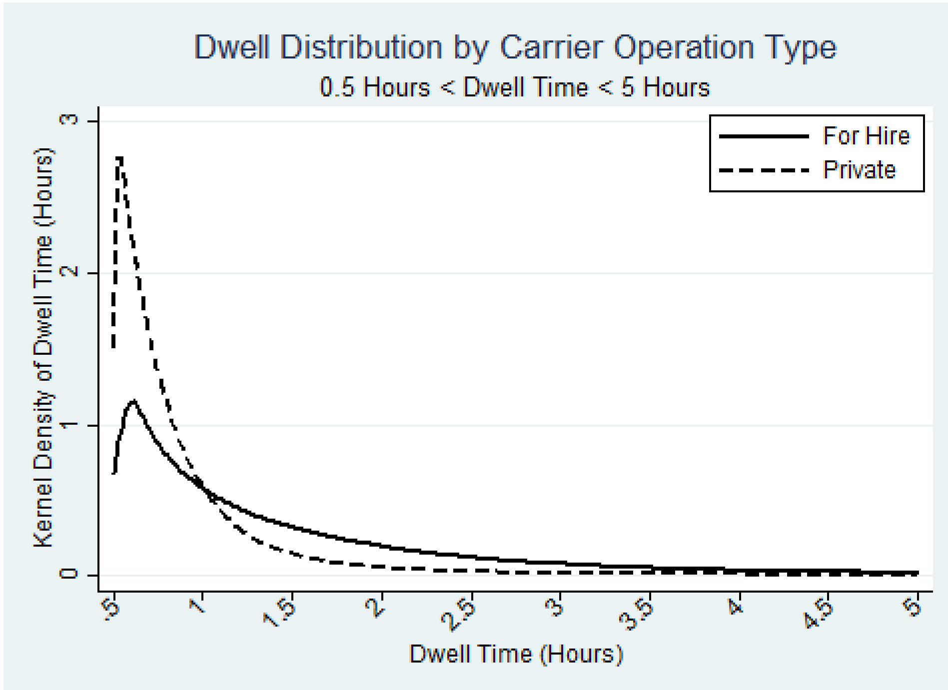
Source: OIG analysis.

Figure B-3. Dwell Time Histogram for Stops between 15 Minutes and 2 Hours



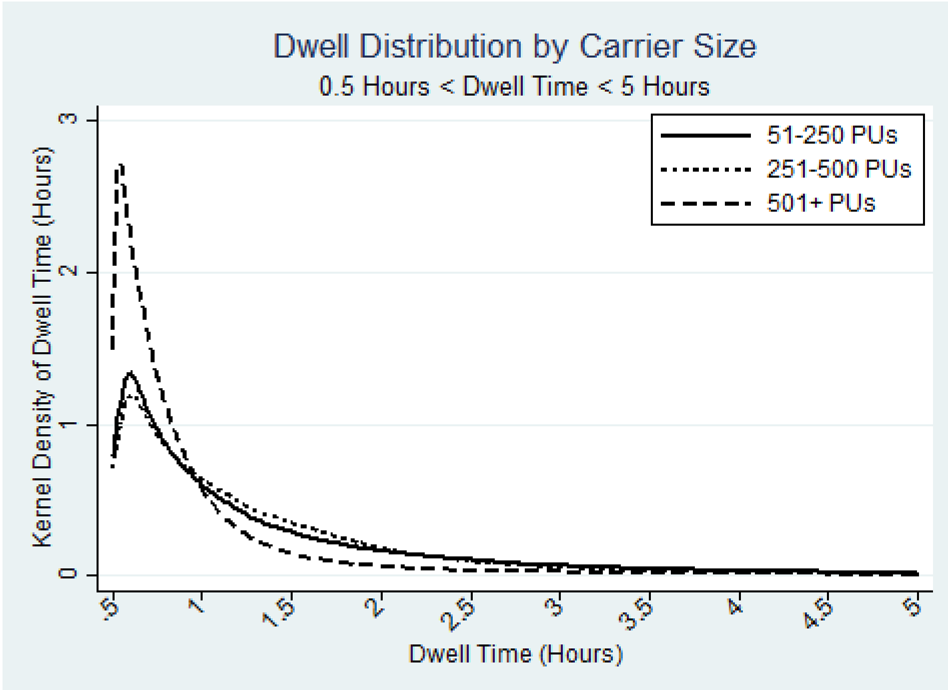
Source: OIG analysis.

Figure B-4: Dwell Time Distribution by Carrier Operation Type



Source: OIG analysis.

Figure B-5: Dwell Time Distribution by Carrier Size



Source: OIG analysis.

Exhibit C. Economic Impacts of Detention: Technical Appendix

The goal of our economic analysis was to quantify the impact of detention on commercial motor carriers' and drivers' incomes. This exhibit provides our detailed scope and methodology for estimating those economic impacts. Specifically, it presents (1) our analytical approach using a FMCSA simulation model (2) data inputs (3) impact calculations, and (4) model assessment.

OIG Approach

The key basis for the measures of impact is the difference between expected miles traveled with and without detention. Our approach begins by modeling the effects of changes in dwell time on mileage for over-the-road[42] (OTR) trucking fleets operating in North America. We do this by using discrete event simulation combined with data from a 2014 FMCSA-commissioned study and industry data. FMCSA initially validated the discrete event simulation model for its 2007 regulatory impact analysis that assessed the impact of changing hours of service (HOS) regulations.[43] We repurposed that model for this project because it provides itineraries of scheduled driving and on-duty hours under a variety of assumptions. The model assumes economic impacts on drivers and motor carriers to be directly related to the number of driving or on-duty hours. In order to translate dwell time impacts into detention impacts, we assumed that dwell times exceeding 2 hours represents detention.

The FMCSA Model

The FMCSA model, developed by ICF International in 2006, simulates how a commercial motor vehicle (CMV) operator would behave on a trip that starts at his home terminal, includes stops to pick up and deliver shipments, and incorporates required rest periods. The model tracks the operator as he moves

[42] According to FMCSA (2011), an OTR trucking fleet is any company and driver that operates beyond a 100-mile radius. One hundred miles is compatible with the minimum length-of-haul class in the 2007 commodity flow survey conducted by DOT's Bureau of Transportation Statistics,' Research and Innovative Technology Administration and U.S. Census Bureau. FMCSA defines "local" as less than 100 miles.

[43] Hours of Service Computer Simulation Program: A complex computer model simulating the movements of a single vehicle (with one or two drivers in different scenarios) operated in compliance with FMCSA HOS regulations. http://www.regulations.gov/#!documentDetail;D=FMCSA-2004-19608-3488 This model was used in the 2007 Regulatory Impact Analysis in Docket Item FMCSA-2004-19608-2529.

between origin and destination points, choosing new loads at the end of each run from a set of loads randomly selected from a database representative of inter-county shipment patterns.

The simulation starts at a user-defined home terminal and selects the next shipment to be carried from an array of 20 randomly generated, origin-destination pairs. Specifically, the origin terminals are randomly drawn from the set of terminals that are within 100 miles of the operator's current location. The destination terminal for each origin is then randomly drawn based on the probabilities of various origin-destination pairs in the inter-county shipment patterns. In addition to an origin and destination, each shipment has the following randomly drawn characteristics:

- Pick-up and delivery days of the week;
- Pick-up and delivery terminals' hours of operation; and
- Time windows for scheduled pick-up and delivery.

The model simulates carrying a shipment between each origin-destination pair and yields schedule output for each. The schedule output shows how the operator would behave in each 15- or 30-minute time increment—whether the operator drives, rests, loads, or unloads—until the vehicle arrives at the destination. By listing the operator's action in each time increment, the model can analyze whether the operator is able to meet the pick-up and delivery windows and how efficiently the operator is moving to the destination. If the simulation model finds that the operator cannot meet the pick-up or delivery time window, the model assigns a zero value to that particular origin-destination pair and moves on to simulate the next pair. When the simulations for the feasible[44] pairs are done, the model selects the origin-destination pair offering the highest utility[45] to the operator. Once the simulation has the operator arrive at the destination, the process begins again. The simulation ends when the user-determined trip duration—e.g., 90 days—is reached.

FMCSA model documentation is available online.[46] However, we found that the model ICF and FMCSA implemented in Visual Basic differs from the one they originally outlined. Some of the differences appear in how the simulation

[44] The operator's feasible options are determined by which loads can be picked up and delivered within specified time windows, given the limits imposed by HOS requirements. The operator is assumed to choose or be assigned the feasible load that most contributes to his utility.
[45] The operator's utility depends on vehicle operating costs, labor and labor-related costs, capital costs, revenue earned, penalties for the operator's time and distance away from his home, and the working hours remaining before hitting the 60- and 70-hour HOS limits.
[46] http://www.regulations.gov/#!documentDetail;D=FMCSA-2004-19608-3488.

randomly assigned breaks (either 30 minutes or an hour) and rests (restarting either after the minimum amount of off-duty hours or restarting in the morning after the minimum rest period), calculated the utility, and shifted potential pick-up and drop-off dates when none of the options were feasible. The breaks and rests were deterministic, and the utility did not account for the number of days away from home.

Our Adaptation of the FMCSA Model

For our analysis, we modified the FMCSA model originally developed to analyze the impact of changing HOS rules. By changing the assumption in the FMCSA model determining the length of time an operator spends at a shipper or receiver, we were able to use the model to simulate the impact of various detention times on truck use.[47] In adapting the FMCSA model for our purposes, we did the following to all stops:

- Assigned the same fixed load and unload time;
- Initialized the load/unload time at 1 hour and increased it by 1 hour increments up to 10 hours;[48]
- Accounted for different haul lengths by restricting the minimum and maximum distances between origin and destination;
- Accounted for region effects by restricting the geographic boundaries of which different origin and destination pairs are generated;
- Set the trip duration at 90 days; and
- Repeated each fixed load/unload time- distance group- region- 90-day simulation at least 100 times to obtain statistically meaningful results.

We developed our version of the model simulation (RSim) using the statistical software language R to automate and reduce process time. The automation enabled us to effectively execute 5,000 simulation runs and thereby to produce statistically meaningful results. The RSim implements similar deviations from the FMCSA model documentation as the ICF implementation in terms of break, rest, and utility definition. However, we differed in how we implemented the shifts when there were no feasible options. For example, we differed in how we added 1 or 2 days for shipment pick-ups or drop-offs when none of the initial options

[47] In J.B. Hunt Transport Inc. (2004), J.B. Hunt conducted a simulation analysis that showed that expected truck miles per day decreases as the average load/unload times increases. Subsequently, Hunt changed its policy from charging shippers for loading/unloading times that exceeded 2 hours to charging for loading/unloading times exceeding 1 hour.

[48] FMCSA (2014).

are feasible. Additionally, we deviated from the FMCSA model by taking the square root of the utility function; this was initially done to limit the share of simulated trip durations that take over a week to execute. This change effectively meant our model would more likely select shorter origin-destination pairs.

We did not validate if the industry has changed since FMCSA originally validated the model in 2006. Specifically, we assumed that the inter-county shipments patterns did not change, and factors entering the utility function did not change over time. The inter-county shipments patterns impact the likelihood of certain origin-destination pairs being randomly selected. Misspecification of the patterns is likely to impact the total miles traveled or loads delivered for each simulated run. Misspecification of the factors affecting the operator's utility, such as revenue and cost per mile, is likely to impact the magnitude of the utility, but not the relative differences in origin-destination pair options.

Data Inputs

We estimated wage and income effects using data from FMCSA studies,[49] trade association surveys, and industry data. Operator wage data come from American Transportation Research Institute's (ATRI) 2015 survey of operation costs of trucking. Industry data such as cost per mile come from DAT Solutions, LLC's DAT Trendlines. In addition, the FMCSA model drew upon multiple surveys of different industry segments with a concentration on truckload (TL) sectors to obtain information used to develop operator itineraries (see online documentation).

We obtained data on truck dwell times from the 2014 FMCSA-commissioned study on operator detention times in CMV operations. In that study, researchers collected from two third-party vendors data on truck dwell times and some characteristics—freight type, carrier operation type, and carrier operation size over a 6-month period. It includes information on nearly 3 million stops by individual trucks. However, it is not representative in terms of carrier size of operations, reporting on the truck stops made by 6 large carriers, 23 medium carriers, and 2 small carriers. Additionally, the data do not differentiate dwell times by load or unload time. Therefore, we do not assume they are different as is allowed in the original FMCSA model and as explicitly modeled in the J.B. Hunt 2004[50] paper.

Like FMCSA's 2014 report, we restricted the sample to dwell times that are 30 minutes or more but less than or equal to 10 hours. The resulting data

[49] FMCSA (2011) and FMCSA (2014).

[50] *Simulation Analysis of Truck Driver Scheduling Rules*, Proceedings of the 2004 Winter Simulation Conference, J.B. Hunt Transport, Inc. (2004).

displayed a log-normal distribution[51] as suggested by J.B. Hunt's paper. We calculated the likelihood of being in any particular stop as the number of observations in the hour bin (e.g., 1 hour to 2 hour) divided by the total number of observations. Most stops were less than or equal to an hour (46 percent), and approximately 21 percent exceeded 2 hours. The 21 percent of stops exceeding 2 hours is the same percentage as reported by the brokerage firm C.H. Robinson (2015) in its own detention analysis based on sampling of some of their clients.

Since the number of truckload carrier firms is unknown, we assumed that the number of operators is 842,380, a function of the number of tractors FMCSA estimated in 2007 (FMCSA (2011)) inflated by the growth rate of Gross Domestic Product from 2007 to 2013.

The distribution of operators for various haul lengths comes from the Owner-Operator Independent Drivers Association (OOIDA) and ATRI surveys, which recorded different percentages of operators in each haul length segment. We used the surveys to determine the likelihood of an operator being in different haul-length segments. Eighty-eight percent of OOIDA's members provide for-hire service for distances that exceeds 100 miles, whereas only 72 percent of ATRI responders reported that they did so (see table C-1).[52] The biggest difference between the OOIDA and ATRI segmentation comes in the 1000 miles plus group, 25 percent versus 11 percent respectively. Nearly 40 percent of ATRI (2015) responders' hauls fell in the 100 to 500 miles segment, compared to 35 percent for OOIDA (2014) responders. The likely impact of detention differs for the different market segments due to stop frequency, and shorter hauls mean more frequent stops and greater impacts from detention.

Impact Calculation Methods

Overview

We based our calculation of impact on the difference between expected miles traveled with and without excessive delays. We assumed that the livelihood and industry impacts are directly related to the number of hours driven or on-duty hours and, consequently, the total number of miles driven. We calculated the expected number of miles driven for each haul-length region and dwell times ranging from 1 to 10 hours, and the expected number of miles for dwell times

[51] A continuous distribution in which the logarithm of a variable has a normal distribution.

[52] According to FMCSA's model documentation, the ICF model is only useful for haul lengths that exceed 100 miles. In general, the revenue and cost for the less than 100 mile market is sufficiently different that FMCSA did not explicitly model the impact of changing HOS regulations on this segment.

strictly less than or equal to 2 hours. The difference between the two estimates is our measure of the impact conditioned on the following:

- We did not distinguish between miles trucks carried freight and miles where they did not, which impacts the actual revenue per mile;
- We assumed that all revenue is based on per mileage fees instead of a mix of per mileage, per load and portion of load;
- We did not account for an operator to potentially receive detention fees to offset lost wages or revenue;
- We assumed full compliance with HOS regulations; and
- We assumed that the same dwell time distribution applies to all operators, which likely understates the impact of detention on smaller carriers;

Calculation Methods

We used FMCSA's 2014 study data on the distribution of dwell times to assign likelihoods to the different dwell time durations (see table C-2). This allowed us to calculate the expected number of miles an operator would drive over a defined period of time. For simplicity, we assumed that the dwell time distribution was the same at both shippers and receivers.[53]

We calculated the expected number of miles driven for each haul-length region with dwell times ranging from 1 to 10 hours, with dwell times restricted to 1 and 2 hours, and the standard errors for each haul-length region combination. The expected miles are calculated as a weighted average, the sum of the average miles at each hour multiplied by the likelihood of a dwell time being in that hour. When we estimated the expected miles associated with no excessive delays, we assumed that the likelihood of 1 hour of dwell time is the same as when there are excessive delays (approximately 46 percent), and the likelihood of 2 hours of dwell time is approximately 54 percent instead of 33 percent when dwell times could exceed 2 hours (see table C-3).

To annualize our results, we multiplied each 90-day haul-length, region, and dwell time hour combination by 4. (see table C-4). To generate industry wide estimates, we multiplied the annualized results by the number of truck drivers (842,380). Our calculation of annual driver wage and carrier income losses is a function of the annualized mileage loss for each haul-length, region, driver wage per mile and carrier income per mile, and the likelihood that a driver would operate in a particular haul-length region. We assumed wages of $0.462 per mile

[53] Although according to FMCSA (2014), the distributions of load/unload times vary according to carrier fleet type, size, and operation type, we did not disaggregate along those dimensions.

for drivers and income of $0.11 per mile for carriers. We used two different distributions of the likelihood of operating within different haul lengths, based on the OOIDA and ATRI surveys.

To calculate the standard error, we had to choose between two generally accepted methods for calculating the standard deviation (a measure of spread or uncertainty) of a weighted mean. We chose the more conservative weighting method, which resulted in larger standard errors. [54] We reduced the estimated standard error by increasing the number of simulated runs for each hour-haul length, region combination; we ran each hour haul-length, region combination at least 100 times.

Results

We estimate the impact of detention on CMV drivers' wages is an annual loss of $1 billion to $1.3 billion and the annual impact on carriers' incomes is $250 million to $300 million. These estimated amounts represent an annual loss of 3.6 to 4.1 percent in wages or income (see table C-5). The range in losses results from differences in the combinations of haul-length distribution and region used.

The standard error of the impact estimates (wage or income loss), using the expected miles lost from the 100 to 500 Northeast and Midwest regions, is 26.9 percent for estimates using the OOIDA (2014) distribution of drivers across haul length markets or 28.8 percent for estimates using ATRI (2015). The 95-percent confidence interval for the estimated impact on drivers' wages is between $623 million and $1.962 billion, assuming the OOIDA (2014) distribution. The same confidence interval estimate assuming the ATRI (2015) distribution is between $463.4 million and $1.722 billion.

Model Assessment

Comparing Our Simulation to Survey Results

In order to determine the reasonableness of our model, we compared the expected annual miles estimated from our model to the average miles reported in the trucking association surveys. The comparison suggests that our simulations produce reasonable results. The average reported annual miles for OOIDA (2014) and ATRI (2015) operators were 101,192 and 97,566 respectively. Our model

[54] One that utilizes an "effective base", $b = \frac{(\sum_{i=1}^{n} w_i)^2}{\sum_{i=1}^{n} w_i^2}$, to divide the unweighted sample variance ($s^2 = \frac{\sum_{i=1}^{n}(xi-\bar{x})^2}{n-1}$), and another that uses a "weighted" variance, $s_w^2 = \frac{\sum_{i=1}^{n} w_i(x_i-\bar{x})^2}{\sum_{i=1}^{n} w_i - 1}$, as its estimate of variance divided by the sum of the weights. The latter is not an unbiased estimate of the variance of the weighted mean. We used the "weighted" variance and sum of weights to calculate the standard errors.

estimated that the simulated OOIDA and ATRI operators are expected to drive between 102,086 and 103,466 miles, and between 95,460 to 97,388 miles, respectively, see table C-5. The choice of region generates the range in expected miles for each trade association.

Comparing Our Simulation to FMCSA's Simulation

In order to determine the impact of the changes introduced in our adaption of the FMCSA model, and to determine whether our results are reasonably close to what would have come from the validated FMCSA model, we compared the expected miles from the west region of haul-lengths of 100 to 500 miles from the RSim and FMCSA simulation programs. We used 100 simulated runs per haul-length hour for the RSim model and 25 runs of the FMCSA model. The differences in impacts were not statistically significant.

The two models' results differ by 1,717 miles per 90 day-period with excessive delays, and 1,642 miles without excessive delays. The simulated RSim operator drives approximately 20,534 miles per period when there are excessive delays and the simulated FMCSA operator drives approximately 22,251. The simulated RSim and FMCSA operators drive approximately 21,526 and 23,168 miles without excessive delays. Where the RSim impacted operator loses 992 miles or 4.8 percent of his total mileage per period to excessive delays, the FMCSA simulated operator loses 917 miles or 4.1 percent of his total mileage. The 75-mile difference in estimated impacts of excessive delays between the two models is not statistically significant.

References

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ATRI (2015), American Transportation Research Institute. An Analysis of the Operational Costs of Trucking: 2015 Update

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Table C-1. Assumed Truckload Statistics by Trade Association

	OOIDA		ATRI	
Distribution of Drivers by Market Segment	Percentage of Drivers per Segment	Estimated Number of Drivers per Segment*	Percentage of Drivers per Segment	Estimated Number of Drivers per Segment*
100 to 500 miles	35%	294,833	40%	336,952
501 to 1000 miles	28%	235,866	21%	176,900
1000+ miles	25%	210,595	11%	92,662

Note: Based on* 842,380 Truckload Over-the-road drivers.
Source: OIG analysis of data from OOIDA (2014), ATRI (2015), and FMCSA (2011).

Table C-2. Distribution of Dwell Time

Dwell Time	Likelihood of Dwell Time
1	46.18%
2	32.84%
3	11.57%
4	4.50%
5	1.99%
6	1.05%
7	0.63%
8	0.45%
9	0.44%
10	0.39%

Source: OIG analysis of FMCSA 2014 data.

Table C-3. Quarterly Mileage Loss by Market Segmentation

Market Segments by Haul Length (miles) and Region	Expected Quarterly Miles with Dwell <= 10 hours	Expected Quarterly Miles with Dwell <= 2 Hours	Expected Difference	SE of the Difference
100 to 500 NE and MW	19666.9	20679.8	1012.9	461.9
100 to 500 West	20534.4	21525.9	991.5	434.1
100 to 500 Other	20258.4	21245.9	987.5	465.0
500 to 1000 National	28374.6	29384.0	1009.4	402.5
1000+ National	30522.1	31294.9	772.8	366.2

Source: OIG analysis.

Table C-4. Expected Miles Loss Due to Detention by Markets

Market Segments by Haul Length (miles) and Region	Expected Annual Miles with Dwell <= 10 hours	Expected Annual Miles with Dwell <= 2 Hours	Expected Annual Miles Loss Due to Excessive Delays	% Potential Loss of Miles (Loss/Expected)
100 to 500 NE and MW	78,668	82,719	4,051	5.2%
100 to 500 West	82,138	86,104	3,966	4.8%
100 to 500 Other	81,034	84,984	3,950	4.9%
500 to 1000 National	113,498	117,536	4,038	3.6%
1000+ National	122,088	125,180	3,091	2.5%

Source: OIG analysis.

Table C-5. Expected Losses Due to Detention by Trade Association

	OOIDA		ATRI	
	Minimum Expected Miles	Maximum Expected Miles	Minimum Expected Miles	Maximum Expected Miles
Expected Annual Miles per Driver	102,086	103,466	95,460	97,388
Expected Annual Miles w/o Excessive Delays per Driver	105,860	107,206	99,361	101,241
Expected Annual Loss of Miles	3,774	3,740	3,901	3,853
% Potential Loss of Miles (Loss/Expected) per Driver	3.7%	3.6%	4.1%	4.0%
Industry Total Miles Loss Due to Excessive Delays*	2,797,821,291.50	2,772,630,759.98	2,365,821,197.43	2,337,032,018.55
Expected Annual Driver Wage Loss Due to Excessive Delays ($)* ^^	$1,292,593,437	$1,280,955,411	$1,093,009,393	$1,079,708,793
Expected Annual Industry Loss Due to Excessive Delays ($)* ***	$307,760,342	$304,989,384	$260,240,332	$257,073,522

Note: Based on * 842,380 Truckload Over-the-road drivers, ^^ 46.2 cents per mile for driver wage [DAT Treadline], and *** 11 cents per mile for carrier [DAT Treadline].
Source: OIG analysis.

Exhibit D. Organizations Visited or Contacted

FMCSA Facilities

FMCSA Headquarters

Other Organizations

American Transportation Research Institute

National Industrial Transportation League

National Retail Federation

Owner Operator Independent Drivers' Association

Virginia Tech Transportation Institute

Selected Motor Carriers, Owner-Operators, and Motor Carrier Technology Vendors

Exhibit E. List of Acronyms

BASIC	behavior analysis safety improvement category
CDF	cumulative distribution function
CMV	commercial motor vehicle
CSA	Compliance, Safety, and Accountability Program
DOT	Department of Transportation
FAST Act	Fixing America's Surface Transportation Act of 2015
FMCSA	Federal Motor Carrier Safety Administration
GAO	Government Accountability Office
GMM	generalized method of moments
GPS	global positioning system
HOS	hours of service
LTL	less-than truckload
OIG	Office of Inspector General
OMB	Office of Management and Budget
OOIDA	Owner Operator Independent Drivers' Association
TL	truckload

Exhibit F. Major Contributors to This Report

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Appendix. Agency Comments

Memorandum

U.S. Department of
Transportation
Federal Motor Carrier Safety Administration

Subject: INFORMATION: Management Response to the Office of Inspector General (OIG) Draft Report, Estimates Show Commercial Driver Detention Increases Crash Risks and Costs, but Current Data Limit Further Analysis

Date: JAN 12 2018

From: Cathy F. Gautreaux
Deputy Administrator
Federal Motor Carrier Safety Administration

To: Barry J. DeWeese
Assistant Inspector General
for Surface Transportation Audits

Safety is the top priority for the Federal Motor Carrier Safety Administration (FMCSA). We are committed to understanding factors that can affect roadway safety, such as the impact of detention times on drivers. Although there is currently no standard definition, the industry commonly defines detention time as "any time drivers have to wait beyond 2 hours, which is the average time it takes to load or unload their cargo."[1] As the OIG noted in its draft report, accurate and complete industry-wide data on motor carrier loading and unloading delays are not available. Although FMCSA collects data from roadside inspections, providing information about Hours of Service (HOS) violations, roadside inspectors do not collect information relating to how detention time may have contributed to these violations or other safety hazards.

We have completed several actions to further gauge the impacts of driver detention. For example, FMCSA has:

- Identified an average lost time of 1 to 1.7 hours during the December 2014 study on Driver Detention Times in Commercial Motor Vehicle Operations;
- Established the coercion final rule, 80 FR 74695 - Prohibiting Coercion of Commercial Motor Vehicle Drivers, to safeguard a motor carrier or its employees from being compelled to violate federal safety regulations, such as drivers' HOS limits, commercial driver's license regulations, drug and alcohol testing rules, and hazardous materials regulations. The rule provides FMCSA with the authority to take enforcement action and

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[1] U.S. Government Accountability Office (GAO), *Commercial Motor Carriers: More Could Be Done to Determine Impact of Excessive Loading and Unloading Wait Times on Hours of Service Violations,* GAO-11-198, January 2011

issue stiff fines against motor carriers, shippers, receivers, and transportation intermediaries. These enforcement actions will serve as an indicator of the size of the problem. Complaint data is maintained by the Agency, and this data, along with data on enforcement actions relating to coercion will be a useful indictor as to the scope of the problem, and allow FMCSA to address detention times immediately with the shipper through enforcement; and

- Requested the Motor Carrier Safety Advisory Committee (MCSAC) discuss the issue of Driver Detention time at its June 12, 2017 meeting. FMCSA presented its response to Section 5501 of the FAST Act requirements, which required FMCSA to establish by regulation a process to collect data on delays experienced by operators of commercial motor vehicles before the loading and unloading of such vehicles and at other points in the pick-up and delivery process. MSCAC members stated the underlying problem regarding detention time is that unlike workers in other transportation modes, drivers often are not paid during detention time, resulting in a lack of incentives for shippers and receivers to fix the detention problem. MCSAC's recommendations included the following: (1) improve the supply chain; (2) use the Australian model, where shippers and receivers are included in the safety regime; (3) gather data to better show the extent of the problem; and (4) ensure adequate enforcement and monitoring of where improvements are made. Notes from the MCSAC's discussion may be found at https://www.fmcsa.dot.gov/advisory-committees/mcsac/mcsac-driver-detention-time-discussion-notes.

Based on our review of the draft report, FMCSA concurs with the recommendation. FMCSA plans to address the OIG's data collection recommendation by engaging industry stakeholders to discuss potential methods to collect representative data on the frequency and severity of driver detention times. The Agency also plans to provide a reporting form on its public website that drivers and carriers can use to voluntarily submit data on detention. FMCSA plans to implement the recommendation by December 31, 2019.

FMCSA would also note that, given the limitations of current data sources identified by OIG, it would be premature to draw any empirical conclusions about the impact of driver detention times on crash rates or driver incomes at this time. Once sufficient, reliable, accurate, and representative data is collected, FMCSA will be in a better position to analyze and understand the potential implications of driver detention.

We appreciate the opportunity to review the OIG draft report. Please contact Steve Smith, Director, Office of Director, Analysis, Research, and Technology at 202-493-0145 with any questions.

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