Analyzing the Risk of Transporting Crude Oil by Rail*

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December 27, 2019

Abstract

In this paper, I combine data on incidents associated with rail transportation of crude oil and detailed data on rail shipments to appraise the relation between increased use of rail to transport crude oil and the risk of safety incidents associated with those shipments. I find a positive link between the accumulation of minor incidents and the frequency of serious incidents, and a positive relation between increased rail shipments of crude oil and the occurrence of minor incidents. I also find that increased shipments are associated with a rightward shift in the distribution of economic damages associated with these shipments; the implied marginal impact of an additional 1,000 rail cars carrying oil between two states in a given month is $1,927. In addition, I find larger average effects associated with states that represent the greatest source of tight oil production.

JEL Codes: L71, L92, Q35, C14

Keywords: crude oil, railroad, accidents, economic damages

*Thanks are due Byeong-hak Choe, Thomas van Eaton and Ben White for their excellent research assistance, participants at the 2017 ASSA meetings, the Workshop on Energy Transitions held at the University of Southern Denmark in March 2017 as well as seminar participants at Washington State University and the University of Wyoming for lively discussion. Particular thanks are due to Ben Gilbert, Max Maelstrom, Lucy Qiu, two anonymous referees and Wes Wilson for their constructive feedback. Any remaining errors are solely my responsibility.

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1 Introduction

Within the past ten years, widespread use of new extractive technologies, such as 3-D imaging, horizontal drilling and hydraulic fracturing, has greatly expanded US oil production. What was fairly recently regarded as a sunset industry has witnessed a renaissance, with production levels approaching historic highs in 2014. While this increase in production created substantial net benefits in the form of increased domestic producer surplus, it also presented logistical challenges (Transportation Research Board, 2017). Much of the new production has occured in new regions; as a consequence, these production basins are not well serviced by existing oil pipelines; consequently, to deliver their product to market firms have increasingly turned to rail as a mode of transport.[1] In turn, this has lead to concerns related to safety: the concern is that the increased shipments of oil by rail may lead to a greater risk of accidents, with related concerns for damages. These concerns are underscored by the tragic derailment on 6 July, 2013 of a freight train carrying crude oil in the Quebec town of Lac-Mégantic. The derailment killed 47 people, spilled over one million gallons of crude oil, and caused widespread destruction; estimated damages exceeded $100,000,000.

Horrific as this event was, it was not singular, nor was 2013 a unique year: statistics compiled by the U.S. Department of transportation point to a steady stream of train derailments in the U.S. between 2009 and 2014, with corresponding increases in damages. These patterns are particularly noteworthy in light of recent trends in U.S. tight oil production, particularly from the Bakken play (which was the source of the crude on the train that derailed in Quebec).

Figure 1 offers a feel for recent trends in serious rail incidents.[2] The figure compares all serious events for each quarter between 2009 and 2014 related to all shipments (depicted as

[1] While building new pipelines is a potential resolution to the issue of insufficient takeaway capacity, there are important cost considerations: new pipelines are costly, and there are important regulatory obstacles to be overcome. In addition, the uncertainty associated with the evolution of crude prices induces an option value associated with delaying investment (Covert and Kellogg, 2017).

[2] Publicly available data on rail incidents is provided by the Pipeline and Hazardous Materials Safety Administration, the US governmental authority responsible for regulating rail shipments of crude oil. A subset of these incidents are referred to as "serious;" this category is reserved for events where substantial costs are incurred as a result of the event, or where there are serious injuries or fatalities.

circles) against shipments of crude oil (depicted as diamonds, and connected by the dashed line). Two patterns emerge. First, the general pattern of serious incidents did not rise over this six year horizon. Second, there was an increasing tendency for serious incidents associated with crude oil shipments: There was only one serious incident prior to the middle of 2011, while serious incidents occurred in every quarter but one after the middle of 2013 – with three quarters exhibiting multiple serious incidents.

Indeed, in response to the apparent heightened risk of shipping oil by rail, the US Department of Transportation (DOT) adopted a new rule governing rail shipments of oil; this rule took effect in July 2015. Trains with a continuous block of at least 20 cars loaded with a flammable liquid, or trains with at least 35 such cars, are defined as "high-hazard flammable trains" (HHFT); any tank cars constructed after September 2015 that are used in HHFTs must now meet a tougher standard.[3] Trains with 70 or more cars carrying flammable liquids are required to have in a functioning two-way end-of-train device or a distributed power braking system. In addition, a maximum speed of 50 miles per hour is now imposed on all HHFT; if such a train includes any cars that fail to meet the 117 standard, the speed limit is 40 miles per hour. The above observations, as well as the policy response they engendered, point to the importance of understanding the risks associated with rail shipments.

Such an empirical undertaking is complicated by the relative rarity of large scale events. Similar considerations apply in other situations, where high-consequence events are uncommon.[4] Examples include meltdowns at nuclear power plants (David et al., 1996; Escobar Rangel and Lévêque, 2014) or maritime disasters (Edwards and Kauffman, 2016). One promising approach in these settings is to focus on lesser events that can be thought of as precursors to disasters.[5] I adopt

[3] This new standard, referred to as DOT 117, requires rail cars include a 9/16 inch tank shell, 11 gauge jacket, 1/2 inch full-height head shield, thermal protection, and improved pressure relief valves and bottom outlet valves.

[4] An additional issue that can arise in such situations is the difficulty of framing a suitable model to predict the rare event. Indeed, Ord et al. (2010, p. 203) note that "any scientific risk assessment is only able to give us the the probability of a hazard occurring conditioned on the correctness of [the risk assessment's] main argument." The approach I propose below is subject to this qualification. But the authors also suggest that it may be sufficient to consider an "adequate" model, as opposed to a correct one, which I believe is a reasonable interpretation of my approach.

[5] Examples include unplanned outages, or "scrams," at nuclear power plants (David et al., 1996; Hausman, 2014) or deficiencies during maritime safety inspections (Edwards and Kauffman, 2016). Taking such an approach

similar two-pronged approach in this paper. The first step is to establish an empirical link between the prevalence of lesser incidents and the probability of a more serious incident occurring.[6] I then establish a link between various measures of rail activity and the prevalence of minor incidents. My empirical model uses data from the Surface Transportation Board (STB), under the Department of Transportation (DOT). This data includes observations on trail traffic between January 1, 2009 and December 31, 2014 (including the number of carloads of various commodities shipped, associated weight of those shipments, and miles the shipments traveled) as well as information on safety incidents associated with these shipments.[7]

I find a statistically important link between the number of cars containing crude oil shipped by rail in a given month and the distribution of incidents; in particular, increases in shipments are associated with a rightward-sift in the distribution. I also find a statistically important link between the occurrence of minor incidents on shipments between a given state pair in the preceding three months and the likelihood of a serious incident occurring on a shipment between that state pair in a particular month. Combining these two results yields the conclusion that crude by rail deliveries are linked to the prevalence of serious incidents. I then consider a variety of alternative interpretations, including the total volume of shipments and multiple measures of rail activity; the central theme that emerges is the importance of crude deliveries. In addition, I find that increased crude deliveries between a given state pair in a given month imply a rightward shift in the distribution of dollar damages from spills. The implied marginal impact of an additional 1,000 rail cars carrying oil between two states in a given month is estimated as $1,927; *i.e.*, less than $2 per car. These various effects are noticeably more important in states where recent increases in oil production – mainly

to appraising safety at nuclear power plants, David et al. (1996) identify a precautionary affect that followed in the aftermath of the Three Mile Island incident, while Hausman (2014) identifies the role played by deregulation of electricity markets. Gallagher (2014) demonstrates a link between TV coverage of flooding that impacts nearby areas upon homeowner uptake of insurance; because the floods in question have small or no direct impact on the homeowners in question, the media coverage is akin to a more common but less impactful signals.

6 Transportation Research Board (2017, p. 69) argue that lesser incidents may "be an indicator of safety risks not being properly managed."

7 The STB data reflects a sampling of all waybills filed by rail shippers, with sampling rates varying from 1 in 40 rail cars to 1 in 2 cars. For many shipments, the sampling rate is commonly 1 in 40; indeed, for the full sample this sampling frequency obtains for over 88% of records provided. However, the distribution of sampling rates is far more comprehensive for crude oil shipments: the sampling rate of 1 in 40 obtains for less than 29% of records, while more than 50% of records use a sampling rate of 1 in 2 or 1 in 3.

associated with the deployment of unconventional techniques – has been most pronounced.

The remainder of the paper is organized as follows. In section 2, I discuss the data used in my analysis. I describe my empirical strategy in section 3. In section 4, I discuss the results. I offer concluding remarks in Section 5.

2 Data

The data I use in this endeavor comes from two divisions in the Department of Transportation.

2.1 Incident Data

Information on rail incidents are drawn from the Pipeline and Hazardous Material Safety Administration (PHMSA) website. These data list the date, location and shipping source of each incident, along with information on the amount of materials released and costs associated with the incident, for all shipments over the selected time frame. I use information on incidents occurring between 1 January 2009 and 31 December 2014. Incidents can reflect minor occurrences, such as small leaks, or major events such as train derailments. In addition to the information described above, there is an indicator variable that identifies "serious incidents."[8] From this database, I extracted all records of incidents involving crude oil shipments.

Table 1 provides a summary overview of this data. The table is split into two parts. Part A, the top panel, summarizes the data on serious incidents involving crude oil shipments, while part B, the bottom panel, summarizes the data on minor incidents involving crude oil shipments. For each part, I show the fraction of weeks between 2009 and 2015 in which an event was observed; minor events were about 7 times as common – happening in roughly 50% of the weeks, while serious incidents occurred in about 7% of the weeks. For serious incidents, I present information on the

[8] PHMSA defines a serious incident as involving "a fatality or major injury caused by the release of a hazardous material, the evacuation of 25 or more persons as a result of release of a hazardous material or exposure to fire, a release or exposure to fire which results in the closure of a major transportation artery, the alteration of an aircraft flight plan or operation, the release of radioactive materials from Type B packaging, the release of over 11.9 gallons or 88.2 pounds of a severe marine pollutant, or the release of a bulk quantity (over 119 gallons or 882 pounds) of a hazardous material." See http://www.phmsa.dot.gov/resources/glossary#S.

period of time between events; as minor incidents were substantially more common I focus on the number of events in those weeks where an incident did occur. For each panel, I show the average value, the standard deviation of that value, the median value, and the skewness of the sample. On average, just over 13 weeks passed between serious incidents. This data is sharply asymmetric, with a large standard deviation and a skewness value well above 0 (the level associated with a symmetrically distributed sample). The median time between serious incidents is much smaller than the mean value, again indicating a distribution skewed towards larger values. For minor incidents, the data are a bit less skewed, with a median value that is much closer to the mean. In those weeks where an incident occurred, there were typically about two incidents. Combined with the information on the frequency of weeks with events, this indicates the number of minor incidents was similar to the number of weeks in the sample.

A visualization of the incident data is conveyed in Figure 2. The left panel of the figure depicts serious incidents involving crude oil shipments; here I plot the week in which the incident occurred against the number of weeks between major incidents (shown on the y-axis). The take-away message here is that serious incidents became more common over time thru the first half of 2014, with the time between such incidents falling from several months to less than one month. In the right panel, I plot the number of minor incidents per week. Here too, the frequency of incidents also rose through the middle of 2014. Put together, this graphic points towards a negative relation between the number of minor incidents and the time between serious incidents; it also suggests a link between accumulating minor incidents and the prevalence of serious events.[9]

2.2 Rail Traffic

I combine the data on incidents with information on rail shipments, taken from DOT "waybill" data. For any rail shipment, the waybill lists nearly 200 pieces of information. Included in this list are the following: state,]zip code and Federal Information Processing Standard (FIPS) – es-

[9] One way to interpret this last point is that minor incidents are harbingers of more serious events (Transportation Research Board, 2017). This feature occurs in other situations involving potential catastrophes, such as major adverse events at nuclear power plants (Escobar Rangel and Lévêque, 2014).

sentially, the relevant county – of shipment origin and destination; shipment contents (listed as a commodity, identified both by name and numeric code); number of cars containing the commodity, actual weight of the material shipped, and distance the shipment traveled; date of shipment; and the waybill number. I have data on all rail shipments in the US between 1 January 2009 and 31 December 2014.[10] Out of this very large dataset I identified all records involving crude oil shipments.

Most crude oil shipments originate in "PADD 2", which includes North Dakota, and "PADD 3," which includes Texas.[11] These are large oil producing states where important basins of production are located in remote areas, commonly poorly served by existing pipeline infrastructure. Figure 3 highlights the relative isolation of these oil fields. It is apparent that several oil producing areas (indicated as cross-hatched areas) are not proximate to the existing pipeline infrastructure; of particular importance here is the isolation of two major oil producing basins: the Bakken, in North Dakota, and the Permian, in West Texas. By contrast, these regions are reasonably close to a number of rail lines. This observation underscores the emerging significance of the rail mode of transportation for crude oil. As a result, shipments of crude oil by rail expanded relatively rapidly between 2010 and 2012, and the prevalence of incidents involving rail shipments of crude oil also increased sharply – as illustrated in Figure 4. At the same time, oil by rail shipments started taking up greater percentages of the cars carried in a given train, travelled longer distances, and went through an increasing number of US counties (Transportation Research Board, 2017). One implication of these trends was that an increasing number of people felt exposed to risks associated with serious incidents, which in turn lead to increased political pressure to raise regulatory oversight of rail shipments of oil (Molinski, 2015).

Table 2 provides summary information on crude oil shipments by rail from this sample period. I offer evidence using three measures of activity: the number of rail cars carrying crude

[10] This data is confidential and proprietary; it was provided to the NBER working group on oil infrastructure. A non-confidential subset of the waybill records is available from the Surface Transportation Board (see https://www.stb.gov/STB/industry/econ_waybill.html); this subset comprises roughly 2% of all waybills.

[11] The acronym PADD stands for "Petroleum Administration for Defense District"; its use originated during World War II. The US Energy Information Administration provides data on oil movements by various modes from each PADD; see `https://www.eia.gov/dnav/pet/PET_MOVE_RAIL_A_EPC0_RAIL_MBBL_M.htm`.

oil, the number of miles oil is transported and the weight of product in cars carrying crude oil. The third measure is not a simple transformation of the first, as some cars dedicated to transporting crude are likely to be empty (a rail car carrying crude from the oil patch to a refinery will typically be empty on the return run back to the oil patch). As such, these measures provide information on different pathways for oil shipments to lead to potential incidents. One notion is that oil shipments contribute to incidents by increasing congestion on rail lines; this idea would be related to the number of cars transported during a given period of time, perhaps combined with the distance traveled. Alternatively, oil shipments could increase wear and tear on the rail lines; this effect would be related to the combined weight of the shipment.[12] Evidently the role of rail as a mode for transporting oil increased dramatically in importance during the sample period, with the number of annual shipments increasing by a factor of roughly 15 between 2009 and 2014. Also, each of the three measures of activity increasing over the six year period: both the number of rail cars carrying crude oil and the miles travelled increased by a factor of roughly 20. The weight of crude oil shipments increased even more dramatically during this period; the combined weight of crude oil conveyed by rail increased by a factor of over 150, while the average weight per shipment increased by roughly ten-fold.

Figure 5 fleshes out the relation between rail activity and the prevalence of serious incidents; Figure 6 provides complementary information for minor incidents. In these figures, all variables are shown as percentage of total shipments associated with crude oil shipments; both figures display the quarterly average of all rail shipments associated with crude deliveries, using three measures of rail activity (number of cars shipped, miles travelled, and weight conveyed). Onto these plots, Figure 5 overlays the fraction of serious events associated with crude shipments, while Figure 6 overlays the fraction of minor incidents associated with crude shipments. A correlation between the three measures of rail activity and the frequency of incidents is apparent, particularly for mileage traveled and weight conveyed; this relation is particularly clear for minor incidents.

[12] Vartabedian (2015) notes that "[t]rack problems were blamed on 59% of the crashes, more than double the overall rate for freight train accidents." Similarly, Brown (2017) notes that government inspectors found thousands of safety defects on rail lines used to haul volatile crude oil, including worn rails; broken, loose; and cracked steel bars.

These figures anticipate results from a more formal analysis, which I turn to next.

3 Empirical Strategy

My empirical approach is to trace out a connection between rail shipments of crude oil and incidents. Because there are relatively few major incidents involving crude oil shipments, I undertake this analysis in two steps. In the first step, I tie the occurrence of serious incidents to the preponderance of lesser incidents that precede the major event. In the second step, I connect the number of rail cars shipped to the number of minor incidents.

3.1 Step 1: Modeling Serious Incidents

To model the frequency of serious events, I treat each shipment as an independent observation, where there is a risk of a major incident occurring. I model this risk using a Logit framework, where I conjecture that the risk of a serious incident is related to the accumulation of minor incidents in the recent past. I investigate various notions of "recent past", including the past 3 months, the past 6 months, the past 9 months and the past 12 months.

3.2 Step 2: Modeling Minor Incidents

The goal in the second step of my analysis is to explain the number of minor events associated with a particular combination of originating and terminating states, during a particular month. The key explanatory variable here is the number of rail car shipments between that state pair in that month. There are likely to be geographically idiosyncratic features at play, for example, because the potential pathways for shipments are exogenously fixed in advance of the sample period. Accordingly, I use a fixed effects approach, where the state pairs form the basis for these fixed effects.

The left-side variable in this step is strongly skewed, which suggests that ordinary least squares is ill-advised. Accordingly, I base this part of the analysis on models emanating from the literature on count data. Two models have received considerable attention in this vein: the Poisson and Negative Binomial models (Cameron and Trivedi, 2005). While I discuss results using each approach, I mainly focus on the Negative Binomial regression model. Related to this line of inquiry, I also explore the relation between the number of rail cars shipped between a given pair of states in a given month and the magnitude of harm arising from an event, as measured by the dollar harm associated with the event.[13]

This second line of investigation requires combining the two datasources described in the previous section. To this end, the data was first aggregated by month, for each pair of originating and destination states. I then merged information over space and time. Thus, an individual observation represents for each month and originating-destination state pairs: the number of cars in which oil is shipped, the number of incidents that occurred, the amount of oil spilled in any incidents that occurred, and the dollar damages associated with any incidents. For many months in the sample, oil is shipped with out incident (so that the last three variables are identically equal to zero). Because not all states are associated with oil shipments in any particular month, the panel is unbalanced; addressing this imbalance is an important motivation for including state-level fixed effects.

4 Results

I now turn to a discussion of the results.

4.1 The Role of Minor Incidents in Explaining Serious Incidents

The first part of my analysis evaluates the link between minor incidents and serious incidents. The hypothesis of interest is that the accumulation of minor incidents can explain the tendency for serious incidents to occur. I evaluate this possibility by using a Logit framework.

[13] This harm can come from five sources: the value of spilled oil, the cost associated with damaged capital (such as rail cars), the damages borne by property owners near the event location, the costs associated with any emergency responders, and any costs associated with remediation.

The results from the Logit analysis are collected in Table 3. I report results from four regressions, based on the various interpretations of recent past. Regression (1), reported in the second column, includes the past 3, 6, 9 and 12 months; regression (2) includes the past 3, 6 and 9 months; regression (3) includes the past 3 and 6 months; and regression four only includes the past 3 months. For each of these notions, I tabulated the number of minor incidents during the period in question for each state pair, and used that variable as a regressor. The left-side variable is an indicator taking the value 1 if a serious incident is observed in the particular state pair in the particular month, and zero otherwise. The results consistently point to the preceding 3 months as having explanatory value: increases in the number of minor incidents in that period exert a statistically important effect on the probability of a serious incident; in ballpark terms, each additional 3 minor incidents doubles the chance of a serious incident. None of the other time frames appear to exert an important effect.

One criticism of this approach is that I use the pair of origin and destination states as the geographical point of interest. An alternative is to base the analysis on the combination of origin and destination Federal Information Processing Standard (FIPS) code – essentially, the relevant county.[14] This approach provides a more granular geographic picture of the location of origin and destination for the shipment – though there will be far fewer shipments from any FIPS pair than from the associated state pair; this has the effect of increasing collinearity between explanatory variables. With this data, I am able to assess the role of preceding minor incidents in a similar manor to the preceding results. These results are collected in Table 4.

The first regression in Table 4 uses the number of minor incidents observed for the FIPS pair in n months prior to the observed serious incident, $n = 1, ..., 12$. In part because of the increased collinearity, STATA dropped several of the potential regressors from this regression, retaining only observations for $n = 3, 4, 8, 11$. That noted, I observe that each of the retained variables exerts a statistically significant and positive effect on the left-side variable. That is, observing additional minor incidents for a given pair of origin and destination FIPS in the recent past implies an in-

[14] An attractive approach would be to direct attention to the route used in the shipment. For the STB data set I am using, the FIPS pair identifies the route used for all but a handful of crude oil shipments.

creased probability of observing a serious incident in the current month. The second regression combines the observed number of minor incidents for the preceding $q = 1,2,3$ and 4 quarter. While the results here are less compelling than those in the first regression, I still observe a statistically important effect (albeit for incidents 3 quarters previous to the current month).

Based on these results, I conclude there is empirical evidence that minor events can predict the potential for serious incidents.

4.2 *The Role of Rail Traffic in Explaining Minor Incidents*

I now turn to an appraisal of the impact of the volume of rail traffic upon the occurrence of minor incidents, which the results from the preceding sub-section suggest is a marker for increased risk of serious incidents. Table 5 lists results from six regressions tying the volume of rail traffic in crude oil shipments to minor incidents. These results are based on two models of count data – the Poisson model and the Negative Binomial model.[15] For each count model, I present results from three regressions that allow for originating and terminating state-pair fixed effects. The first regression only includes a variable measuring rail traffic (thousands of cars carrying crude oil). The second regression for each model also allows for seasonal fixed effects, including an indicator variable taking the value 1 during the months of November, December, January and February. The third regression allows for idiosyncratic monthly effects, as reflected in the indicator variables Dmn, where $n = 1$ refers to January, $n = 2$ refers to February, and so on. These two variations are designed to control for possible weather-related effects. Including these controls is motivated by concerns that rail shipments might be exposed to greater risk during cold months, for example because of contraction in steel wheels or rail lines (Lowy, 2015). Alternatively, cargo contents might be subject to contraction during colder months, which might facilitate "sloshing," the concern being that if the rail car starts to rock from side to side this energy might induce a pattern of waves within the container, with the momentum associated with these waves then exacerbating the

[15] All regressions were run in STATA, using the fixed effects option in the XT package. Robust standard errors were computed using the "oim" (information matrix) option in the Poisson regressions, and the 'r' (robust) option in the Negative Binomial regressions.

tendency for the car to rock, potentially leading to derailment.

In each regression, the key parameter of interest is the coefficient on the number of cars carrying crude oil between a particular pair of states in a particular month, measured in thousands of cars. I note that the estimated coefficient on this variable is positive and statistically significant in each of the regressions, with broadly similar values (ranging from 0.228 to 0.322). In general, the Negative Binomial model points to a more substantial effect associated with rail traffic. I also note that allowing for temporal effects has little effect upon the estimated role of rail traffic: none of the time-related indicator variables exerts a significant effect.

In the results reported in this Table, the estimates indicate that an additional serious incident is likely to occur for each additional 3 to 4,000 rail cars shipping oil between a particular pair of states in a particular month. Referring back to Table 2, the number of rail cars carrying oil increased by roughly 40,000 between 2013 and 2014, which suggests this estimated impact is non-trivial.

Parallel to the analysis of the role minor incidents play in predicting serious incidents, one might object to the geographical unit of focus. Again, I revisit the analysis using the pair of origin and destination FIPS as the geographic focus. I report results for two sets of analyses. Table 6 reports results from Logit regressions, while Table 7 reports results from count regressions (using the Poisson model).

Table 6 presents results from four regressions. The first two of these regressions are based on a fixed-effects Logit analysis, where the left-side variable takes the value 1 if a minor incident occurred on a shipment between a particular FIPS pair in a given month. The third and fourth regressions are based on a random effects Logit model.[16] In this set of regressions, I include four variables of potential interest for crude oil shipments: tons of crude oil shipped between a particular FIPS pair in a given month, miles traveled along the shipping route, the interaction of tons shipped and miles traversed (*i.e.*, ton-miles) and the number of cars carrying crude. In the second and fourth regressions reported, I also include the interaction of tons shipped and miles traveled for

[16] The fixed effects regressions required the removal of any FIPS pairs with only one crude shipment during the sample period, which reduced the number of observations. That restriction did not apply to the random effects model, which therefore has a larger number of observations.

all shipments. In every regression, the distance traveled by crude shipments exerts a statistically significant and positive effect on the probability of observing an incident. The evidence on the implication of including total ton-miles for a shipment is mixed: in the fixed effects analysis, adding total ton-miles does not influence the sign and magnitude of the coefficients on distance traveled and number of cars carrying crude – both of which are positive. For the random effects model, including total shipments does not influence the sign and magnitude of the coefficient on distance traveled, but sharply reduces the sign of the coefficient on the ton-miles associated with cars carrying crude, and renders that coefficient insignificant. In addition, the coefficient on tons of crude shipped is negative in both regressions 3 and 4. While initially counter-intuitive, this sign may reflect an effect that has been conjectured for crude shipments – that part of the problem is associated with "sloshing" of material within a rail car. All else equal (including the capacity of the cars used and the number of cars carrying crude, adding more material will simultaneously raise the weight shipped and lower the ability of the material to slosh within the rail car.

Table 7 presents results from two regressions. For these regressions, the left side variable is a count measure admitting three possible values: '0' if there was no incident, '1' if there was a single incident, or '2' if there were multiple incidents.[17] Both regressions use the fixed effects Poisson model, and use the same regressors employed in regressions 1 and 3 from Table **??**. The second regression regression adds in ton-miles for all shipments. While this regressor is statistically important, its inclusion does not change the sign and magnitude of the two regressors that are statistically important in the first regression (miles crude is shipped, and number of cars carrying crude). Again, while the evidence is somewhat mixed, one message is consistent: increasing the distance a shipment carries crude exerts a positive and statistically important effect on the probability of an incident.

Before proceeding to a discussion of the consequences of spills, I pause briefly to consider the fixed effects. Upon retrieving the estimated residuals from a regression from Table 5, it is

[17] most of these observations had 2 incidents; for a small number of FIPS pairs in a given month there were more than 2 incidents, but these only occurred once in the whole sample – motivating the combining of these observations into category '2'.

straightforward to back out the state-pair fixed effects. Doing so, one finds that the largest five fixed effects are all associated with crude oil shipments out of North Dakota. In light of the importance of this state as a source of rail shipments of crude oil, this result suggests an intriguing possibility: that increased rail traffic might accelerate depreciation of certain rail routes, increasing the risk of worrisome incidents. I discuss this idea in greater detail below.

4.3 Consequences

I now turn to an evaluation of the relation between rail traffic and the consequences of spills. Table 8 contains the relevant results. Here, I list results from five regressions. The first of these is a fixed effects regressions of the relation between rail traffic and the economic damages resulting from an incident, using a Negative Binomial mode; this regression model allows me to identify the marginal impact of an increase in rail traffic on expected damages. The second set of results are based on a quantile regression approach; this approach allows me to ascertain the impact of additional rail traffic on the largest likely damages.

Negative Binomial Analysis

As above, the key parameter of interest is the coefficient on the number of cars carrying crude oil between a particular pair of states in a particular month, measured in thousands of cars. Again, this coefficient is positive and statistically significant, indicating that increased rail traffic shifts the distribution governing damages to the right – thereby increasing expected harm.[18]

These results can be used to infer the expected impact of a one unit increase in rail traffic. The expected value of total economic damages is

$$\mathcal{E}(D) = \exp(\hat{\beta}\,\bar{x}),$$

where $\mathcal{E}(D)$ is expectations operator applied to total economic damages, $\bar{x}$ is average rail traffic,

[18] I note that the sample included a small number of observations for which there was no information relating to dollar damages. Accordingly, these observations were dropped from the regression, resulting in a slightly smaller sample. I also considered the potential role for monthly fixed effects; these results were not substantially different from those reported in Table 8.

and $\hat{\beta}$ is the estimated coefficient on rail traffic. Thus, a one-unit increase in rail traffic will raise expected damages by $\beta\mathcal{E}(D)$. In the sub-sample used for the results reported in Table 8, the average value of dollar damages is $3,375; the estimated coefficient on thousand cars carrying crude is 0.571. Accordingly, the predicted marginal impact of an additional thousand cars carrying crude, starting from the average value, is $1,927 – less than $2 per car.

It is worth noting that the approach I employ in this part of the analysis implies a focus on expected effects, which is to say it implicitly assumes risk neutrality on the part of the relevant decision-maker. There are reasons to be skeptical of such an assumption. One might well argue that society exhibits some risk aversion, particularly in the face of low-risk, high-consequence events (Laes et al., 2011). Indeed, Krupnick et al. (1993, p. 1275) that the tendency for an implicit assumption of risk neutrality to mis-assess the *ex ante* damages society might place on environmental catastrophes the smaller is the probability of the event, or the larger are the consequences of such an event; both these attributes seem apropos to the problem at hand. Likewise, Sunstein and Zeckhauser (2011) argue that agents are likely to overweight low probability events, particularly when large externalities result – as is plainly the case with serious rail events such as derailments. And the implicit assumption that one can view decision-makers as making choices consisted with an expected utility framework is far from innocuous, particularly in the context of low-probability, high-consequence events (Machina, 1982). Altogether, these points suggest that the analysis I presented above might underestimate the true expected social cost associated with the risk of a serious incident associated with shipping oil by rail.[19]

Quantile Regression Analysis

The second set of results are based on a quantile regression approach. Here, I evaluated the relation between total economic costs and rail traffic (in thousands of cars) along with an indicator variable for winter months, for four percentiles: 80%, 85%, 90% and 95%.[20] These results give

[19] When these large consequence, low probability events lead to spatial correlated externalities, as seems likely with train derailments, inefficiently low levels of private insurance are likely to be undertaken (Gollier, 2005). On the other hand, Sunstein and Zeckhauser (2011) note that such an environment can readily lead society to overreact to the potential for large consequence, low probability events, for example by enacting overly burdensome regulations.

[20] I use these percentiles because positive damages only appear above the 75^{th} percentile. The total number of observations are 1497, as each of the bins has 5% of the observations, each contains 75 observations.

a feel for the impact of rail traffic upon costs as one moves into the tail of the distribution over costs. The key points to be gleaned from these regressions are that rail traffic becomes ever more important, in magnitude, as one moves from left to right in the distribution; these effects are also statistically at the 5% level in the 85^{th}, 90^{th} and 95^{th} percentiles, and at the 10% level in the 80^{th} percentile. Altogether, these results paint a picture wherein increased rail traffic pushes the distribution of costs to the right, with the most substantial impacts arising in the tail of the distribution; on balance, these results are qualitatively consistent with the Poissonregression results reported in the second column.

4.4 Robustness Checks and Extensions

In this subsection, I discuss a variety of robustness checks and extensions.

The preceding analysis supposed that the volume of rail traffic associated with crude oil shipments was directly related to the preponderance of minor incidents. Much of this rail traffic emanates from North Dakota, so an alternative interpretation might be that it is the flow of traffic from North Dakota that is at issue. If so, other commodities that are important sources of rail traffic would also be correlated with the preponderance of minor incidents. An obvious example here would be wheat (Bushnell et al., 2017). An alternative argument might be that it is the total volume of rail traffic that influences minor incidents. To evaluate these alternative conjectures, I revisit the Negative Binomial regression analysis from Table 5, now including the number of cars shipping wheat in a given month between a particular state pair (measured in thousands)along with the temporal dummy variables.

These results are contained in Table 9. There are three takeaway messages here. First, both the volume of wheat shipments and the total volume of traffic are irrelevant in explaining the prevalence of minor incidents. Second, as before there is no indication of monthly effects, nor does the dummy variable for winter months exert much influence. Third, in all specifications the statistical importance of crude oil shipments remains (although the significance level in each of regressions 2, 3, 5 and 6 – which include all rail traffic as an explanatory variable – do not quite reach the 5% level).[21] I conclude that the relation identified in Table **??** is not an artifact of using crude shipments rather than wheat or all shipments.

The second set of robustness results use different measures of rail activity as explanatory variables to explain the prevalence of minor incidents. These results are collected in Table 5. Here I investigate the potential role played by distance traveled (measured in million miles) and the weight of the product transported (measured in million tons). For each of these variables I analyze three specifications: one including the variable allocated to crude shipments and all shipments (regression 1 for miles and 4 for weight); one including the variable allocated to crude shipments and all shipments along with an indicator variable taking the value 1 for winter months and 0 otherwise (regression 2 for miles and 5 for weight); and one including the variable allocated to crude shipments and all shipments along with 11 indicator variables – one for each month from January to November (regression 3 for miles and 6 for weight). The key results here are: (i) there is no indication that time of year influences the prevalence of minor incidents; (ii) total miles travelled does seem to explain minor incidents, but weight of all commodities does not – suggesting that combined congestion might matter, but aggregate wear and tear is less important; (iii) in all specifications, the variable related to crude shipments is statistically important and consistent across specifications. Altogether, these results indicate that the that the relation identified in Table **??** is not an artifact of using the number of rail cars carrying crude, rather than distance travelled or weight transported.

I next consider the robustness of the two-step linkage I utilized in the discussion above. The empirical strategy I laid out is necessitated by the paucity of serious events associated with crude oil shipment. But there are many serious incidents involving other commodities; perhaps one might be able to identify a more direct linkage between measures of activity and the tendency for serious events to occur. I get at this idea with two sets of extensions.

The first set of extensions, reported in Table 10, focus on the possible role played by all shipments and crude shipments in determining the probability of a serious event. The left side

[21] In the regressions with the dummy variable for winter, the confidence levels are 5.2%; in the regressions with dummies for each month, the confidence levels are 6.4%.

variable in this set of regressions is an indicator variable taking the value 1 for all month–state pair observations in which a serious event took place, and 0 otherwise; here I use a Logit approach. The right-side variables blend together number of cars and miles travelled by defining a variable, "Million CarMiles", that is the multiple of cars and million miles traveled. I investigate two variations, one where the current values of Million CarMiles for both all shipments and crude shipments is used, and one where both current and lagged values are used (here I allow for values from once-, twice- and thrice-lagged months to exert an effect). For both of these frameworks I present two regressions, one focusing on the variables described above, and one where these variables are augmented by an indicator variable for winter months. The pattern of results here mimic earlier results: there is no indication that serious events are more likely to occur in winter months, and the role of crude shipments is of paramount importance. The second of these observations takes on added significance here: crude shipments raise the chance of serious events of *all* shipments, suggesting a spillover effect. One plausible explanation for such a spillover relates to crowding – if crude shipments raise the volume of traffic, they could make rail lines more congested, thereby elevating the chance of a serious event. That the various lagged variables do not seem to influence the chance of a serious event is consistent with such an interpretation. Finally, the fifth regression in this table combines the two contemporary measures of CarMiles with the number of minor incidents for the relevant month – state pair. In light of the results in Table 3, I investigate the impact of the number of minor incidents in each of the three preceding months. Parallel to the other results in the Table, I allow for differential effects associated with crude oil shipments and all shipments. The key point here is that the only statistically important variable in this regression is the number of minor incidents associated with crude shipments, in the current month.

Results from the second set of extensions in this line of inquiry are presented in Table 11. As in the last regression of the preceding table, I include the number of rail cars (for both crude shipments and all shipments) with the number of minor incidents for the relevant month – state pair as well as each of the three preceding months. Parallel to the results from the earlier tables, I include the three measures of rail activity (cars, miles, weight); as above, I allow for differential effects associated with crude oil shipments and all shipments. I present results from five permutations in this analysis. Regression 1 include current and previous counts of minor incidents for all shipments shipments, while regression 2 includes current and previous counts of minor incidents for all shipments and crude shipments. Regression 3 excludes the count variables, focusing on a comparison of the three measures of rail activity. Regressions 4 and 5 adapt regressions 1 and 2, respectively, by including the three measures of activity.

Regressions 1 and 2 each reveal a role played by the number of minor incidents in predicting serious events, though only crude incidents are statistically significant when minor incidents for both all and crude shipments are included. This pattern persists in regressions 4 and 5: again it is crude incidents that provide explanatory power. Perhaps the most intriguing results in the table have to do with a comparison of the three measures of activity. First, I note that the distance a commodity is shipped appears to not predict the likelihood of a serious event; this holds true in each of regression 3, 4 and 5. By contrast, in the two regressions where the current and past numbers of minor crude incidents are excluded (regressions 3 and 4), the number of cars carrying crude plays a statistically important role. In each of regressions 3, 4 and 5, the weight of crude shipped (but not weight of all shipments) is statistically important. Interestingly, this role is *negative*, suggest that heavier cars are less risky than lighter cars. While this results seems counter-intuitive at first blush, there is an explanation. Because crude is shipped as a liquid, it is prone to "sloshing" – if the car starts to rock from side to side this energy might induce a pattern of waves within the container. One conjecture is that the momentum associated with these waves can amplify the tendency for the car to rock, leading to derailment. To the extent that such an explanation holds true, it would require that there be sufficient free space within the container, which would translate in to less material – and hence less weight. The negative coefficients on weight of crude shipped might be evidence in support of this conjecture. By contrast, the variable measuring weight associated with all shipments combines both liquid and non-liquid material, and so is less likely to be consistent with the sloshing hypothesis.

The third set of extensions represents a first pass at the potential for depreciation of rail lines. Here, I add a new explanatory variable – the interaction of origin-destination state pair with the amount of weight shipped in the particular month, aggregated across all shipments. This variable provides information on the amount of wear and tear for the particular combination of space and time. I add this variable to the explanatory variables considered above, namely number of cars (measured in thousands, for both crude shipments and all shipments), distance travelled (measured in millions of miles, for both crude shipments and all shipments), and the number of minor incidents (for both crude shipments and all shipments). The dependent variable is the indicator variable taking the value 1 when a serious incident occurred in a given month for a shipment between a particular state pair. As in the earlier analyses, I allow for state-pair fixed effects. I also include interaction terms between weight and an indicator variable that takes the value 1 for shipments originating in an area where tight oil production occurs (which I denote as Dtight), or from the state of Texas (which I denote as Dtight_TX); these interaction terms allow for the possibility that specific deterioration effects can be ascribed to shipments from tight oil provinces, as some have conjectured might have occurred (Vartabedian, 2015; Brown, 2017). This exercise is complicated by the fact that there are a large number of potential state pairs, many of which have limited traffic; I deal with this complication by focusing on those state pairs with sufficient volume to facilitate successful conversion of the estimation package.[22]

I report results from four regressions in Table 12. Regressions 1 and 3 include contemporaneous effects only, while regressions 2 and 4 allow for lagged effects from the accumulated number of minor incidents (for both crude shipments and all shipments). All four regressions include the variable capturing the interaction between shipped weight and the indicator for states with tight oil, while regressions 3 and 4 also include the interaction between weight and shipments from Texas. Four key points emerge. The first three reflect those explanatory variables that are statistically important in explaining the prevalence of serious incidents, each with a positive effect.

[22] These regressions were conducted using the STATA package xtlogit. The procedure I followed was to first use the logit package, identify which of the over 2100 state pairs were retained in the logit regression (*i.e.*, those state pairs that were not dropped because of insufficient variation), and then use these retained state pairs in the xtlogit regressions. This yielded 28 state pairs, with roughly one-fourth of these corresponding to shipments from the two tight oil producing states.

These variables are the volume of crude shipped between a particular state pair in a given month, the distance travelled by all rail shipments between a particular state pair in a given month, and the number of minor incidents associated with crude shipments between a particular state pair in a given month. All other variables are statistically unimportant. The final key point is that the interaction terms relating weight of shipments from the tight oil basins are consistently unimportant. I conclude from this last point that there is little evidence to support the hypothesis that increased rail traffic, associated with the increased production tied to the increasing importance of tight oil plays, has exacerbated depreciation of rail lines.

5 Conclusion

My goal in this paper was to assess the relation between crude oil shipments by rail and safety incidents related to those shipments. Using a two-step procedure, I first confirm a link between the accumulation of minor incidents and the frequency of serious incidents, with a greater number of accumulated minor incidents associated with a shorter time between serious incidents; I then confirm a positive relation between increased rail shipments of crude oil and the occurrence of minor incidents. The preferred specification in the second step allows for state-level fixed effects; in this context, I find that the largest fixed effects are associated with states that represent the greatest source of tight oil production in the continental U.S.

These results offer some support for the perception that increased rail deliveries of crude oil, particularly from locations often associated with the fracking boom, carry an increased risk of accidents. Indeed, my analysis reveals a positive relation between increased rail deliveries and economic damages associated with safety incidents. My results imply an expected marginal impact of slightly less than $2,000, which can be interpreted as a blend of private costs and some external costs.[23] These costs do not include the social costs associated with environmental damages from

[23] The values for reported damages in the dataset reflect the damages from lost product and damaged capital, both of which are private costs; along with any damages borne by nearby property owners, any costs associated with emergency responders, and any remediation costs, which are externalities.

oil spills, property damages from major incidents (*e.g.*, resulting from spill-induced fires) and any loss of life. These aspects arguably comprise the most important external costs associated with any rail incidents.[24]

Whether the increase in safety related external costs arising form increased rail traffic is sufficient to rationalize the extra costs associated with building rail cars to a more exacting safety standard is a separate issue. This point ties into the broader question of determining appropriate public policies to deal with potential catastrophes – a thorny question in its own right. For that matter, it is not clear that the extra external costs associated with increased rail transport exceed the extra costs associated with other forms of delivery (Molinski, 2015). Indeed, the risk associated with pipeline delivery was a prominent feature of the recent protests against the Dakota Access Pipeline, which would offer an alternative means of transporting crude oil from the Bakken play.[25] Determining the optimal role of rail transport within the portfolio of crude oil transportation options remains an important focus for future research.

A key element related to the broader policy debate regarding rail standards is the likely future trajectory of crude oil production in the U.S., particularly in relatively remote areas. While domestic crude production softened during 2015, it rebounded in 2017, particularly in the Permian basin of West Texas; indeed, there are indications that domestic crude production will increase steadily during the foreseeable future.[26] An important effect that could impact this prospective growth is the scope of crude oil delivery infrastructure. Indeed, Agerton and Upton Jr. (2017) argue that pipeline delivery constraints played a particularly important role in domestic crude markets in the period near the end of my sample. As such, there are reasons to expect strong demand for rail delivery going forward, pointing to the likely future relevance of the analysis in this paper.

[24] The costs I have in mind here do not include pollution-related externalities. While these other externalities can be quite large (Clay et al., 2017), they do not have any bearing on the economic efficiency of the increased rail safety standards.

[25] Herrnstadt and Sweeney (2017) provides evidence that the perceived risk associated with pipelines may be relatively small.

[26] The U.S. Energy Administration projects annual growth of 4-5% over the next few years (see `https://www.eia.gov/outlooks/steo/`). The International Energy Administration is similarly bullish, opining that "U.S. shale oil producers will boost their output by 8 million barrels a day between 2010 and 2025" (Ivana Kottasová, 2017). Part of the push for this increased production comes from the decision to lift the 40-year old ban on exporting crude oil, which took effect in late 2015 (Brown et al., 2014).

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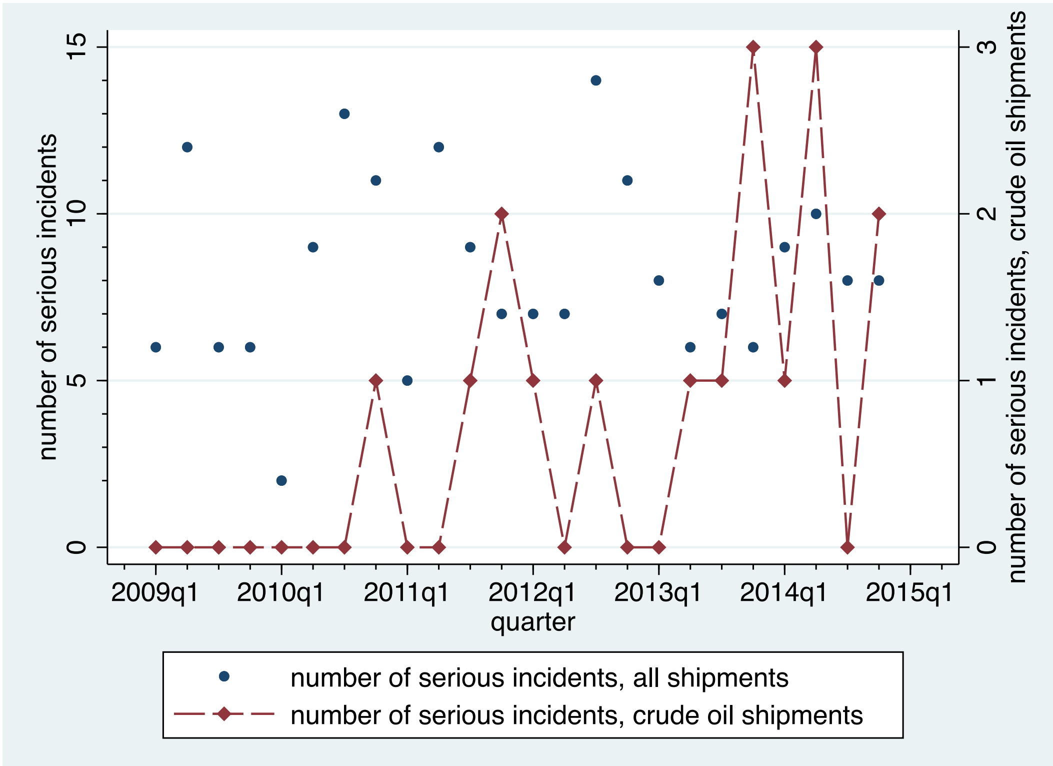
Figure 1: Serious Incidents, All Shipments vs. Crude Oil Shipments

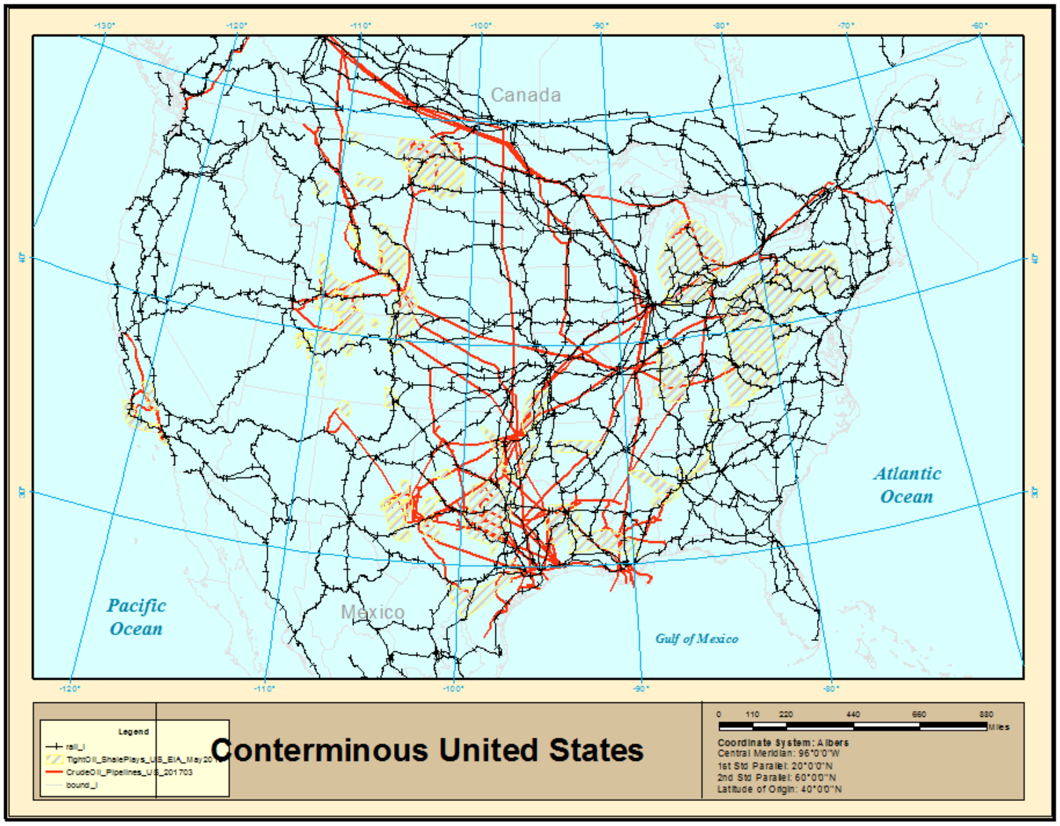


Source: Pipeline and Hazardous Materials Safety Administration

Figure 2: Minor Incidents and Time Between Serious Incidents

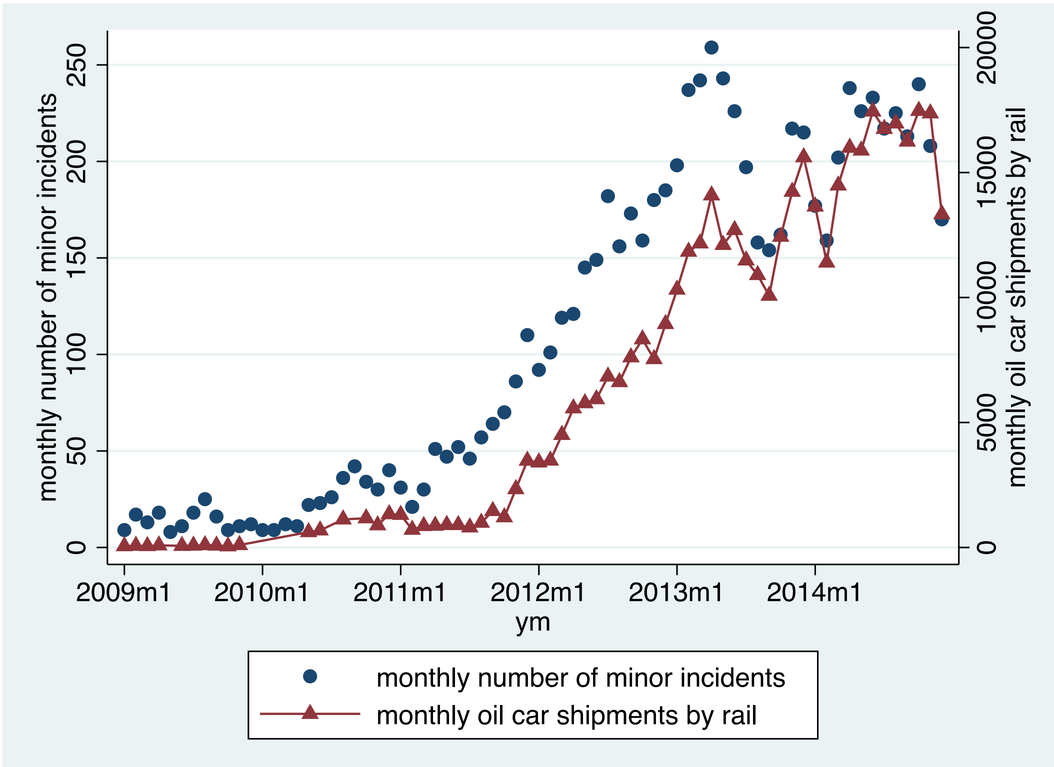
Source: Pipeline and Hazardous Materials Safety Administration

Figure 3: Rail and pipeline location, in relation to major oil producing areas



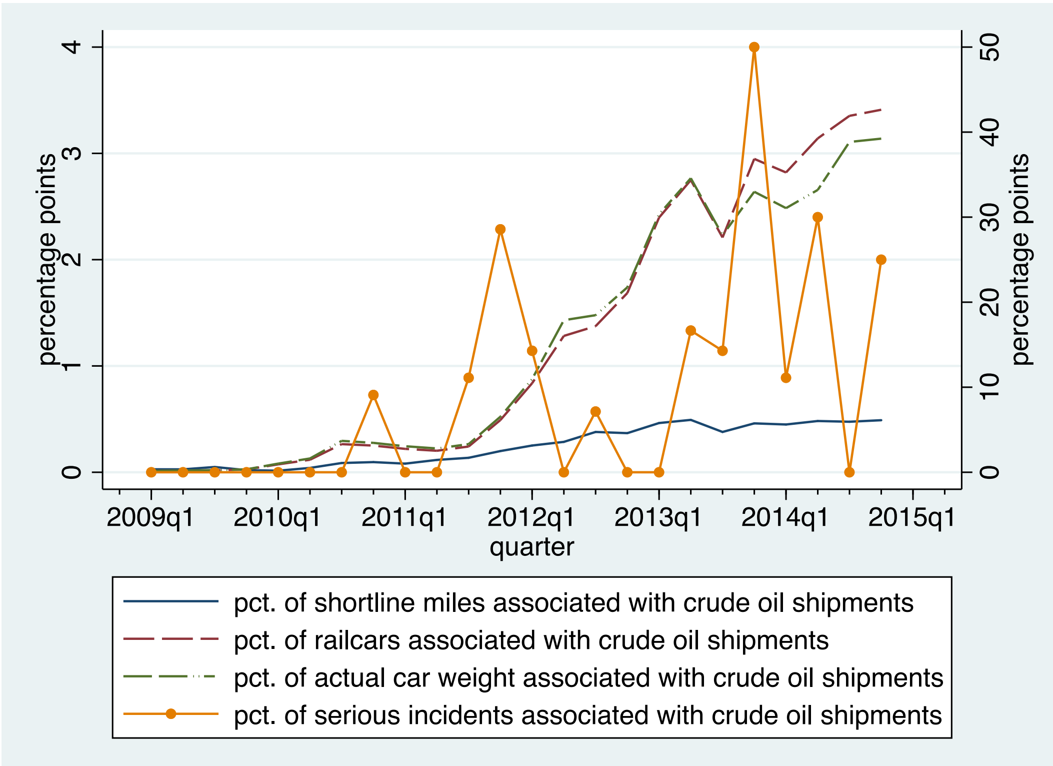
Source: Department of Transportation; Energy Information Administration

Figure 4: Minor Rail Incidents vs. Number of Railcars Shipping Oil, 2009-2014



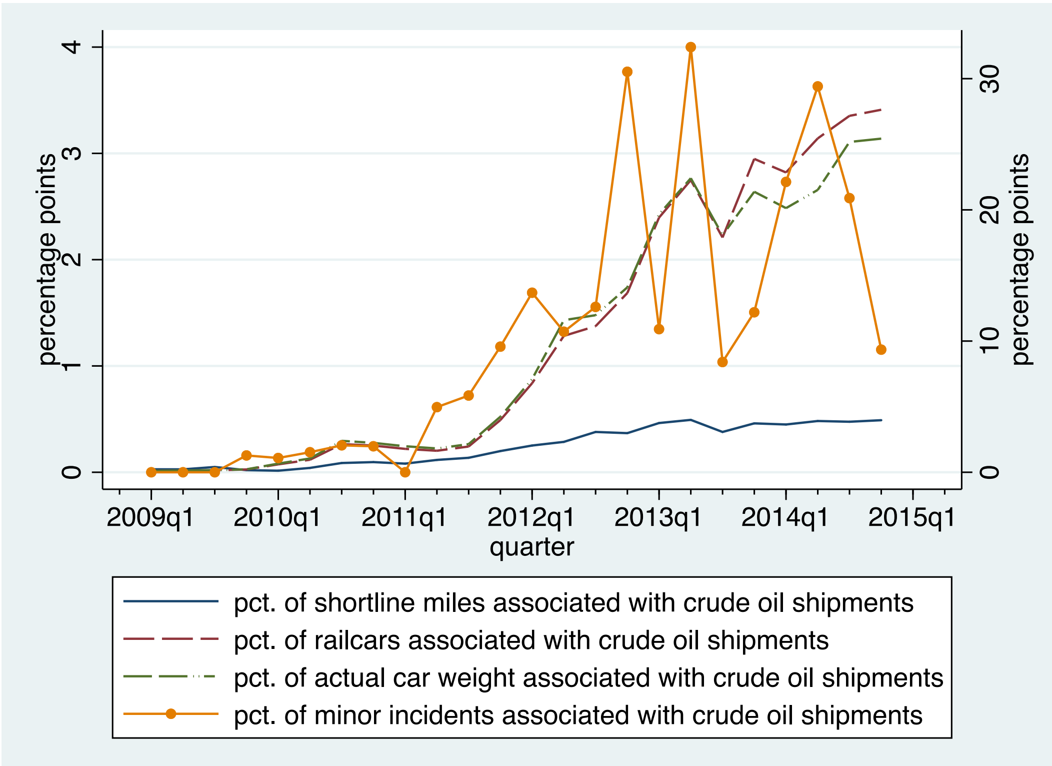
Source: Department of Transportation – Surface Transportation Board

Figure 5: Fraction of Crude Shipments, Serious Rail Incidents vs. Rail Activity, 2009-2014



Source: Department of Transportation – Surface Transportation Board;
Pipeline and Hazardous Materials Safety Administration

Figure 6: Fraction of Crude Shipments, Minor Rail Incidents vs. Rail Activity, 2009-2014



Source: Department of Transportation – Surface Transportation Board;
Pipeline and Hazardous Materials Safety Administration

Table 1: Crude Oil Rail Incidents

A. Serious Incidents

Fraction of weeks with an event	Number of weeks between events: Mean	Std. Dev.	Median	Skewness
0.07	13.23	20.34	6.50	3.18

B. Minor Incidents

Fraction of weeks with an event	Number of events per week: Mean	Std. Dev.	Median	Skewness
0.50	2.27	1.72	2.00	2.08

Table 2: Annual Crude Oil Shipments

		rail cars carrying oil		distance (thousand miles)		weight (thousand tons)	
year	oil shipments	total	per shipment	total	per shipment	total	per shipment
2009	167	942	5.6	170.8	1.023	1738.1	10.408
2010	294	9554	32.5	375.2	1.276	18613.8	63.312
2011	665	15818	23.8	843.9	1.269	29473.1	44.320
2012	1762	74525	42.3	2096.8	1.190	124203.0	70.490
2013	2508	147940	59	3001.8	1.197	223371.0	89.063
2014	2508	186954	74.5	3242.2	1.293	266733.1	106.353
Total	7904	435708	55.1	9730.7	1.231	664132.1	84.025

Table 3: Logit Analysis of Serious Incidents

	(1)	(2)	(3)	(4)
# minor incidents, past 3 mos.	0.363**	0.363**	0.305*	0.310***
	(0.168)	(0.165)	(0.166)	(0.052)
# minor incidents, past 6 mos.	-0.218	-0.219	0.003	
	(0.197)	(0.192)	(0.092)	
# minor incidents, past 9 mos.	0.134	0.141		
	(0.204)	(0.104)		
# minor incidents, past 12 mos.	0.005			
	(0.133)			
constant	-4.190***	-4.190***	-4.117***	-4.116***
	(0.318)	(0.314)	(0.296)	(0.296)

Regressions based on state pairs using Logit model, with 504 observations. Dependent variable: indicator for serious incident. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Logit Analysis of Serious Incidents, 2

	(1)	(2)
# minor incidents, 3 months lagged	1.336***	
	(0.432)	
# minor incidents, 4 months lagged	1.196**	
	(0.599)	
# minor incidents, 8 months lagged	1.559***	
	(0.384)	
# minor incidents, 11 months lagged	1.255**	
	(0.530)	
# minor incidents, 1-3 months lagged		0.378
		(0.254)
# minor incidents, 4-6 months lagged		0.226
		(0.469)
# minor incidents, 7-9 months lagged		0.422**
		(0.199)
# minor incidents, 10-12 months lagged		0.284
		(0.391)
constant	-8.129***	-7.944***
	(0.549)	(0.484)
N	10477	11736

Regressions based on FIPS pairs using Logit model. Dependent variable: indicator for serious incident. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regression Analysis of Minor Incidents Related to Miles (1, 2, 3) and Weight (4, 5, 6)

	(1)	(2)	(3)	(4)	(5)	(6)
Million Miles, Crude Shipments	9.842**	10.004**	11.559**			
	(4.563)	(4.427)	(4.857)			
Million Miles, All Shipments	12.380**	11.510**	10.566*			
	(5.743)	(5.594)	(5.617)			
Million Tons, Crude Shipments				0.119*	0.124*	0.117*
				(0.070)	(0.068)	(0.071)
Million Tons, All Shipments				0.031	0.024	0.028
				(0.053)	(0.051)	(0.054)
Winter dummy		-0.223			-0.269	
		(0.186)			(0.186)	
Dm1			-0.068			-0.052
			(0.455)			(0.461)
Dm2			0.105			0.034
			(0.447)			(0.453)
Dm3			0.325			0.375
			(0.405)			(0.404)
Dm4			0.436			0.476
			(0.393)			(0.392)
Dm5			0.453			0.529
			(0.392)			(0.391)
Dm6			-0.061			-0.068
			(0.424)			(0.425)
Dm7			-0.126			0.022
			(0.426)			(0.420)
Dm8			0.158			0.194
			(0.399)			(0.398)
Dm9			0.135			0.133
			(0.405)			(0.409)
Dm10			0.447			0.453
			(0.383)			(0.387)
Dm11			-0.023			0.014
			(0.415)			(0.414)
constant	-1.060***	-0.965***	-1.137**	-0.587*	-0.489	-0.705*
	(0.327)	(0.334)	(0.442)	(0.303)	(0.310)	(0.429)
χ^2	27.041	29.243	33.659	8.959	11.104	16.233

All regressions include fixed effects for origination-destination state pairs

Robust standard errors in parentheses

913 observations

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Logit Analysis of Minor Incidents using FIPS pairs

	(1)	(2)	(3)	(4)
Thousand Tons, Crude Shipments	-02.19	-2.24	-8.56*	-8.55*
	(0.00770)	(0.00770)	(4.52)	(4.48)
Thousand Miles, Crude Shipments	0.149**	0.149**	0.0971*	0.0972*
	(0.0648)	(0.0649)	(0.0542)	(0.0543)
Million Ton-Miles, Crude Shipments	2.05	-1.36	4.42*	0.530
	(4.02)	(6.23)	(2.37)	(0.281)
Thousand Cars, Crude Shipments	-4.34**	-4.33**	-1.09	-1.07
	(1.79)	(1.79)	(1.40)	(1.41)
Million Ton-Miles, All Shipments		3.43		3.87**
		(4.79)		(1.57)
constant			4.21***	4.22***
			(0.29)	(0.29)
N	873	873	2977	2977

Regressions based on origination-destination FIPS pairs using Logit model.
Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Count Analysis of Minor Incidents using FIPS pairs

	(1)	(2)
Thousand Tons, Crude Shipments	-3.05	-3.09
	(7.36)	(7.34)
Thousand Miles, Crude Shipments	0.135**	0.135**
	(0.0597)	(0.0598)
Million Ton-Miles, Crude Shipments	2.56	-0.486
	(3.89)	(3.83)
Thousand Cars, Crude Shipments	-4.20***	-4.20***
	(1.43)	(1.44)
Million Ton-Miles, All Shipments		3.07***
		(0.292)

Regressions based on origination-destination FIPS pairs using fixed effects Poisson model.
Number of observations = 875. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Analysis of total damages

	Negative Binomial	Percentile regressions 80%	85%	90%	95%
Thousand crude cars	0.571***	480.885*	1017.17**	2109.15***	3321.45**
	(0.080)	(274.03)	(446.95)	(393.99)	(1567.7)
Winter dummy	-0.272	0.481	0.000	0.000	-1183.39*
	(0.204)	(1.563)	(2.550)	(19.935)	(681.27)
constant	-4.848***	-0.962	-1.017	-2.109	1180.07**
	(0.142)	(1.830)	(2.985)	(21.073)	(505.647)
N	1003	75	75	75	75
χ^2	52.66				

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regression Analysis of Minor Incidents Including Wheat shipments

	(1)	(2)	(3)	(4)	(5)	(6)
Thousand crude cars	0.322***	0.244*	0.244*	0.312***	0.242*	0.242*
	(0.082)	(0.132)	(0.132)	(0.078)	(0.124)	(0.124)
Thousand wheat cars	0.020		-0.080	0.114		-0.001
	(0.831)		(0.843)	(0.818)		(0.834)
Thousand all cars		0.087	0.088		0.078	0.078
		(0.113)	(0.112)		(0.105)	(0.106)
Dm1	-0.062	-0.058	-0.058			
	(0.458)	(0.459)	(0.459)			
Dm2	0.031	0.053	0.053			
	(0.453)	(0.452)	(0.452)			
Dm3	0.363	0.356	0.355			
	(0.404)	(0.404)	(0.404)			
Dm4	0.489	0.477	0.479			
	(0.391)	(0.392)	(0.392)			
Dm5	0.533	0.507	0.510			
	(0.391)	(0.393)	(0.394)			
Dm6	-0.045	-0.058	-0.058			
	(0.424)	(0.425)	(0.425)			
Dm7	-0.041	-0.055	-0.055			
	(0.418)	(0.419)	(0.419)			
Dm8	0.225	0.211	0.210			
	(0.397)	(0.398)	(0.398)			
Dm9	0.156	0.146	0.147			
	(0.408)	(0.408)	(0.408)			
Dm10	0.446	0.458	0.457			
	(0.387)	(0.386)	(0.386)			
Dm11	-0.002	-0.000	-0.002			
	(0.414)	(0.414)	(0.414)			
Winter dummy				-0.275	-0.262	-0.262
				(0.186)	(0.187)	(0.187)
constant	-0.756*	-0.853**	-0.850**	-0.535*	-0.626**	-0.626**
	(0.417)	(0.424)	(0.425)	(0.293)	(0.307)	(0.309)
χ^2	22.976	23.649	23.671	18.985	19.668	19.668

All regressions include fixed effects for origination-destination state pairs

Robust standard errors in parentheses

913 observations

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Logit Analysis of Serious Incidents, 3

	(1)	(2)	(3)	(4)	(5)
Millon Crude CarMiles	0.359*	0.359*	0.848**	0.851**	0.168
	(0.195)	(0.195)	(0.408)	(0.410)	(0.197)
Millon All CarMiles	-0.039	-0.039	0.181	0.182	-0.023
	(0.177)	(0.177)	(0.206)	(0.206)	(0.180)
Millon Crude CarMiles, L1			-0.484	-0.483	
			(0.608)	(0.608)	
Millon Crude CarMiles, L2			0.091	0.088	
			(0.323)	(0.325)	
Millon Crude CarMiles, L3			-0.702	-0.705	
			(0.525)	(0.527)	
Millon All CarMiles, L1			0.109	0.110	
			(0.168)	(0.169)	
Millon All CarMiles, L2			0.101	0.102	
			(0.171)	(0.171)	
Millon All CarMiles, L3			0.103	0.103	
			(0.160)	(0.160)	
Count (Crude)					0.717**
					(0.314)
Count (Crude), L1					-0.051
					(0.426)
Count (Crude), L2					0.391
					(0.288)
Count (Crude), L3					0.077
					(0.349)
Count (All)					-0.191
					(0.216)
Count (All), L1					0.033
					(0.189)
Count (All), L2					0.170
					(0.183)
Count (All), L3					0.093
					(0.180)
Winter dummy		0.013		-0.033	0.058
		(0.271)		(0.282)	(0.288)
N	2558	2558	2454	2454	2454
χ^2	5.357	5.360	15.214	15.227	15.805

All regressions include fixed effects for origination-destination state pairs

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Logit Analysis of Serious Incidents, 4

	(1)	(2)	(3)	(4)	(5)
Count (All)	0.175	-0.190		0.029	-0.174
	(0.135)	(0.216)		(0.180)	(0.221)
Count (All), L1	0.060	0.027		0.152	0.031
	(0.140)	(0.189)		(0.169)	(0.192)
Count (All), L2	0.288**	0.175		0.323**	0.180
	(0.121)	(0.183)		(0.157)	(0.188)
Count (All), L3	0.195	0.095		0.189	0.127
	(0.127)	(0.180)		(0.161)	(0.187)
Count (Crude)		0.775**			0.938**
		(0.311)			(0.431)
Count (Crude), L1		-0.078			0.251
		(0.440)			(0.464)
Count (Crude), L2		0.450			0.773**
		(0.290)			(0.380)
Count (Crude), L3		0.077			0.086
		(0.355)			(0.473)
Thousand Cars, Crude Shipments			2.008**	2.011**	1.696
			(0.973)	(0.957)	(1.091)
Million Miles, Crude Shipments			-0.992	-1.098	-2.489
			(4.224)	(4.669)	(16.655)
Million Tons, Crude Shipments			-1.043**	-1.342**	-1.339**
			(0.521)	(0.553)	(0.605)
Thousand Cars, All Shipments			0.169	0.136	0.099
			(0.123)	(0.106)	(0.092)
Million Miles, All Shipments			1.178	0.857	0.929
			(1.125)	(1.187)	(1.186)
Million Tons, All Shipments			-0.014	0.086	0.084
			(0.113)	(0.117)	(0.115)
Winter dummy	0.013	0.046	0.073	0.110	0.084
	(0.170)	(0.288)	(0.277)	(0.293)	(0.297)
N	7687	2247	2486	2178	2178
χ^2	9.937	14.745	16.560	23.157	31.985

All regressions include fixed effects for origination-destination state pairs

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Logit Analysis of Serious Incidents, 5

	(1)	(2)	(3)	(4)
Thousand Cars (Crude)	1.500**	1.414*	1.500**	1.414*
	(0.755)	(0.842)	(0.755)	(0.842)
Thousand cars (All)	-0.419	-0.581	-0.419	-0.581
	(0.536)	(0.589)	(0.536)	(0.589)
Million Miles (Crude)	-0.970	-1.089	-0.970	-1.089
	(3.273)	(3.654)	(3.273)	(3.654)
Million Miles (All)	3.536**	3.506*	3.536**	3.506*
	(1.728)	(1.848)	(1.728)	(1.848)
Count (Crude)	1.057**	1.166**	1.057**	1.166**
	(0.440)	(0.474)	(0.440)	(0.474)
Count (Crude) L1		0.554		0.554
		(0.541)		(0.541)
Count (Crude) L2		0.781		0.781
		(0.513)		(0.513)
Count (Crude) L3		-0.337		-0.337
		(0.727)		(0.727)
Count (All)	-0.066	-0.033	-0.066	-0.033
	(0.247)	(0.245)	(0.247)	(0.245)
Count (All) L1		-0.038		-0.038
		(0.244)		(0.244)
Count (All) L2		0.197		0.197
		(0.224)		(0.224)
Count (All) L3		-0.056		-0.056
		(0.264)		(0.264)
Dtight x Weight	3.088	3.817	-0.130	-0.038
	(4.291)	(4.303)	(0.308)	(0.326)
Dtight_TX x Weight			3.217	3.855
			(4.292)	(4.301)
N	2111	2025	2111	2025
χ^2	49.938	57.548	49.938	57.548

All regressions include state-pair fixed effects and interactions between weight and state pairs
Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$