Analyzing the Risk of Transporting Crude Oil by Rail*

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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. 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

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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 coming very lose to 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. Much of the new production occurs 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. 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 incidents related to rail shipments of crude oil. In this diagram, I focus on incidents termed "serious" by the Pipeline and Hazardous Materials Safety Administration, the US governmental authority responsible for regulating rail shipments of crude oil. The volume of crude oil released in a serious incident, in thousands of barrels, is indicate as a circle. The dollar cost associated with a serious incident, in millions of US dollars, is indicated by a diamond. The figure displays these variates for each major incident between 2009 and 2014. Three points are germane. First, serious incidents were relatively rare before the second half of 2011, and became far more between the latter part of 2011 and the end of 2014. Second, there are a handful of very costly incidents. Because total costs include material costs, capital costs and response costs, an incident that involves a derailment with little or no oil released could still be extremely costly, as with two incidents in 2014. That noted, a major incident that involves the release of a substantial amount of oil will generally be quite costly. This important trend, combined with the relative lack of pipeline capacity to ship oil from the Bakken play, strongly suggest an expanding role for rail in transporting American crude oil going forward.

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). The new rule requires any tank cars constructed after September 2015 that are used in HHFTs to meet the DOT 117 design standard: that the car includes 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. 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.

In this paper I provide a careful empirical assessment of the risks associated with shipping a given amount of crude by rail. Using data from the department of Transportation, I construct an empirical model that links rail incidents to the quantity of oil shipped by rail. This data includes monthly observations on the number of carloads of crude oil shipped between January 1, 2009 and December 31, 2014, as well as information on safety incidents associated with these shipments. 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 find similar effects relating shipments to the volume of oil spilled as well as the dollar damages from spills. These effects are noticeably more important in states where recent increases in oil production – mainly 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 (DOT). 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 total 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."[1] 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 half the weeks, while serious incidents occurred in about 7% of the weeks. For serious incidents, I present information on the period of

[1] 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.

time between events; as minor incidents were substantially more common I focus on the number of events in those weeks were 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, there were just over 13 weeks 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, and 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 major 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 major 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 thru 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.

Information on rail shipments is taken from DOT "waybill" data. Information on any rail shipment is conveyed through a waybill, which lists nearly 200 pieces of information. Included in this list are the following: state, FIPS and zip code of shipment source and destination; shipment contents (listed as a commodity, identified both by name and numeric code); number of cars containing the commodity; 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.[2] Out of this very large dataset I

[2] 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.

extracted all records involving crude oil shipments.

Most crude oil shipments originate in “PADD 2”, which includes North Dakota and Oklahoma.[3] These are large oil producing states where important basins of production are located in remote areas, and hence are 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. 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.

Table 2 provides summary information on crude oil shipments by rail from this sample period. 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. At the same time, the number of rail cars carrying crude oil increased by a factor of roughly 20. Combined, these observations imply the typical rail shipment entailed an increasing number of cars.

3 Empirical Strategy

My empirical approach is to trace out a connection between rail shipments and incidents. Because there are relatively few major incidents, 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.

I use two approaches in the first part of the analysis. The first of these approaches uses survival analysis, which makes use of “time to failure” model. Here, I focus on the number of weeks between serious incidents, regarding the occurrence of such an incident as the “failure.”

[3] 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`.

The explanatory variable in this model is the accumulated number of minor incidents during the period between the preceding serious event and the current serious event. Analysis of failure times proceeds by modeling the hazard rate as a function of a set of explanatory variables.

Survival models are comprised of two parts: a baseline hazard function $\lambda_0(t)$, which describes the way the risk an event occurs within a particular period of time (given baseline levels of the relevant covariates), and the effect of the covariates upon the hazard.[4] In the application at hand, the "event" corresponds to a serious incident, and the covariate of interest is the number of minor incidents that have occurred since the last event took place. Two alternative approaches to analyze failure times have commonly been utilized.

The first uses the Cox semi-parametric proportional hazards model. In this model, the probability that the number of periods between serious incidents equals some value t equals:

$$F(t) = 1 - exp\left(-\int_0^t \lambda_0(s)e^{\beta x}du\right),$$

where x is the accumulated number of minor incidents and β is the parameter of interest. The second approach assumed functional form for the baseline hazard function. I discuss two such models below: the Weibull proportional hazards model and the exponential proportional hazards model. Under the first, the distribution of failure times follows a Weibull density function, which implies the hazard rate changes monotonically over time. Under the second, the hazard rate is constant. This restriction may be tested by comparing the shape parameter p, discussed below, with 1.

An alternative approach is to treat each shipment as an independent observation, where there is a risk of a major incident occurring. Here I model the 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 four notions of "recent past", corresponding to three-month periods (*i.e.*, the past 3 months, the past 6 months, the past 9 months and the past 12 months).

The goal in the second step of my analysis is to explain the number of minor events as-

[4] For a discussion of survival time models, see Lawless (2003).

sociated 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 originating in that state pair in that month. Because there are likely to be geographically idiosyncratic features at play (in particular, since the potential pathways for shipments are exogenously fixed in advance of the sample period), 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; in particular, I employ a negative binomial regression (Cameron and Trivedi, 2005).

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 two variables that measure the magnitude of harm arising from an event: the volume of oil released, and the dollar harm associated with the event.[5]

This second line of investigation requires combining the two datasources. To this end, the data was first aggregated by month, for each originating state. I then merged information over space and time. Thus, an individual observation represents for each month and originating state: 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.

[5] This harm can come from four 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, and opportunity costs associated with any emergency responders or foreclosed major arteries.

4 RESULTS

I now turn to a discussion of the results.

4.1 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, as measured by the time that elapses between serious incidents. I evaluate this possibility by using three time to failure models.

The results from the time-to-failure analysis are collected in Table 3. The second column presents results based on the Cox proportional hazard model, the third column lists results from the exponential hazard model, and the fourth column gives results from the Weibull model. In each case, a negative estimated coefficient indicates that increases in the number of minor incidents shifts the hazard function governing the probability a serious incident will occur in the current period to the left (*i.e.*, it raises the probability of a serious incident in the near future). For each of the three survival time models, the estimated coefficient on the accumulated number of minor incidents is negative;this effect is significant at the 10% level for the two parametric models and at the 1% level in the Cox semi-parametric model.[6]

The results from the Logit analysis are collected in Table 4. I report results from four regressions, based on the various interpretations of "recent past". Regression (1), reported in the second column, includes all four candidates for recent past; regression (2) includes the three notions associated with the past 3, 6 and 9 months; regression (3) the two most proximate periods (3 and 6 months), and regression four the immediate past three 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 variate 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

[6] As I noted above, the empirical validity of the exponential model can be assessed by comparing the shape parameter p to 1 in the Weibull regression; here, the estimated parameter is 0.905, and not statistically different from 1.

results consistently point to the most recent period as having explanatory value: increases in the number of minor incidents in the preceding three months exert a statistically important effect on the probability of a serious incident; in ballpark terms, each extra 3 minor incidents doubles the chance of a serious incident. None of the other time frames appear to matter.

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*

I now turn to an appraisal of the impact of the volume of rail traffic upon incident occurrence and consequence. I discuss three sets of regression results, each detailing the effect of crude oil rail traffic upon a measure of adverse impact. The first batch of results relates to the impact on the frequency of minor incidents, which the results from the preceding sub-section suggest is a marker for increased risk of serious incidents, while the second and third describe the impact on more direct measures of adverse impact.

Table 5 lists results from four 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. For each model, I present results from two regressions that allow for originating and terminating state-pair fixed effects. The second regression for each model also allows for monthly fixed effects; here the idea is to control for possible weather-related effects.[7] In each regression, the key parameter of interest is the coefficient on the measure of rail traffic, here the number of cars carrying crude oil from a particular state 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 four regressions, with magnitudes ranging from 0.226 to 0.333. Moreover, allowing for temporal fixed effects has little effect upon the estimated role of rail traffic; more important is the probabilistic model: In general, the negative binomial model points

[7] Explanatory variables relating to the fixed effect for month n is denoted as Dmn, where $n = 1$ refers to January, $n = 2$ refers to February, and so on.

to a more substantial effect associated with rail traffic.[8]

In the results reported in this Table, the estimates indicate that an additional serious incident is likely to occur for each additional 3-4,000 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.

Before proceeding to a discussion of the second and third sets of regression results, I pause briefly to consider the fixed effects. Upon retrieving the estimated residuals from a regression from Table 5, it is 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 now turn to an evaluation of the relation between rail traffic and the consequences of spills. Table 6 contains the relevant results. Here, I list results from four regressions, organized by left-side variable. The first two of these regressions are fixed effects regressions of the relation between rail traffic and the quantity of oil spilled in an incident; as above, I provide information from a Poisson regression and from a Negative Binomial regression. The second pair of results describe the relation between rail traffic and the economic damages resulting from an incident. As above, the key parameter of interest is the coefficient on the number of cars carrying crude oil from a particular state in a particular month, measured in thousands of cars. Again, this coefficient is positive and statistically significant in each of the four regressions, indicating that increased rail traffic shifts the distributions governing quantity of oil spilled and resultant damages to the right – thereby increasing expected harm.[9]

These results can be used to infer the expected impact of a one unit increase in rail traffic.

[8] A test of the appropriateness of the Poisson model is available in a version of the negative binomial model without fixed effects. For these data, such a test points strongly to the preferability of the negative binomial model.

[9] 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 two regressions for economic damages, 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 6.

For example, 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, and $\hat{\beta}$ is the estimated coefficient on rail traffic. Thus, a one-unit increase in average rail traffic will raise expected damages by $\beta\mathcal{E}(D)$. In the sub-sample used for the second batch of results in Table 6 the average value of dollar damages is $3,375; accordingly, the predicted marginal impact of an increase in rail traffic, starting from the average value, is $1,731.

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 lower 48.

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 around 1700, which can be interpreted as a blend of private costs and some external costs.[10] These costs do not include the social costs associated with environmental damages from

[10] 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 response costs and the costs from closure of main transportation arteries, which

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.

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. 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.[11] 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. Determining the optimal role of rail transport within the portfolio of crude oil transportation options remains an important focus for future research.

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are social costs.

[11] As Molinski (2015) articulates, there are risks associated with any form of delivery.

References

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Figure 1: Major Incidents: Quantity of Oil Spilled and Economic Damages

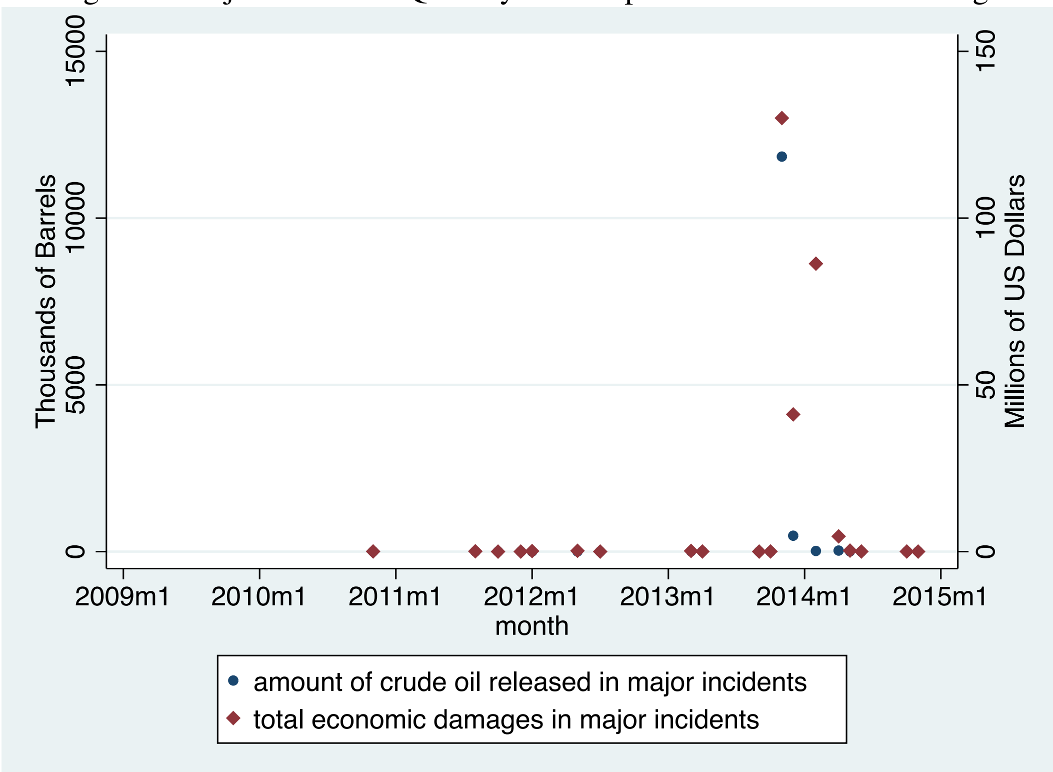

Figure 2: Minor Incidents and Time Between Major Incidents

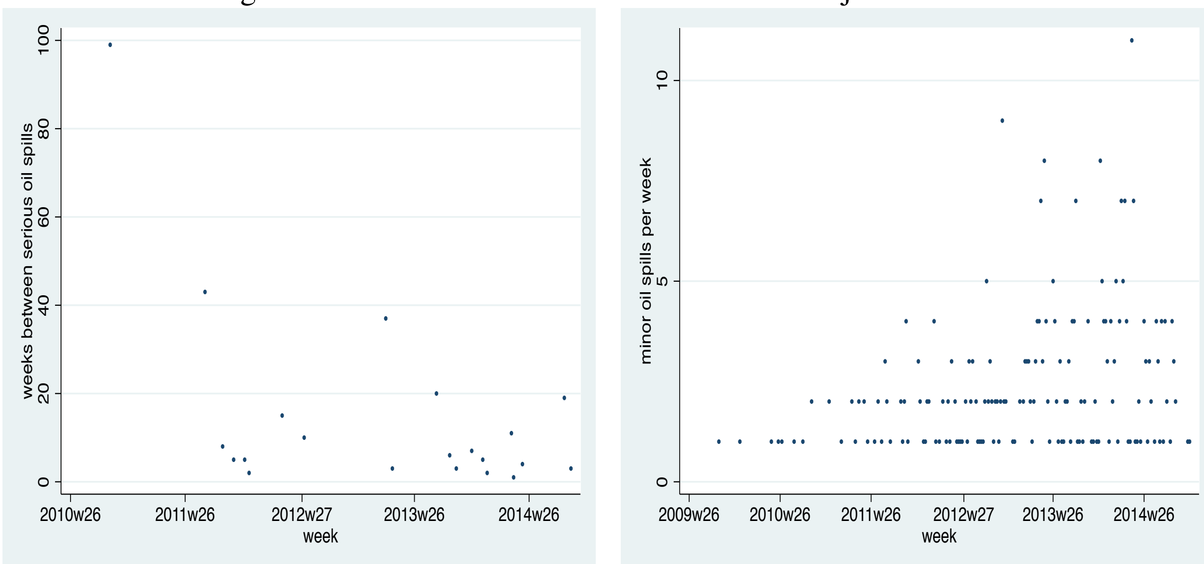

Figure 3: Rail and pipeline location, in relation to major oil producing areas

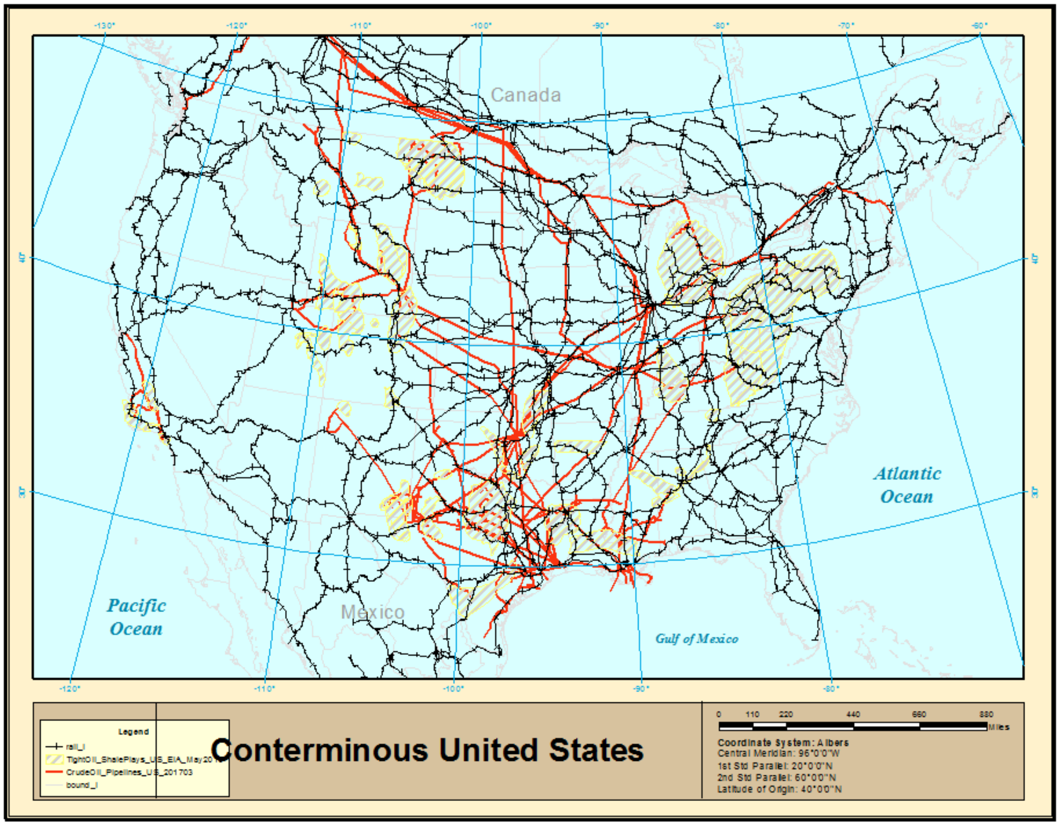

Figure 4: Minor Rail Incidents vs. Number of Railcars Shipping Oil, 2009-2014

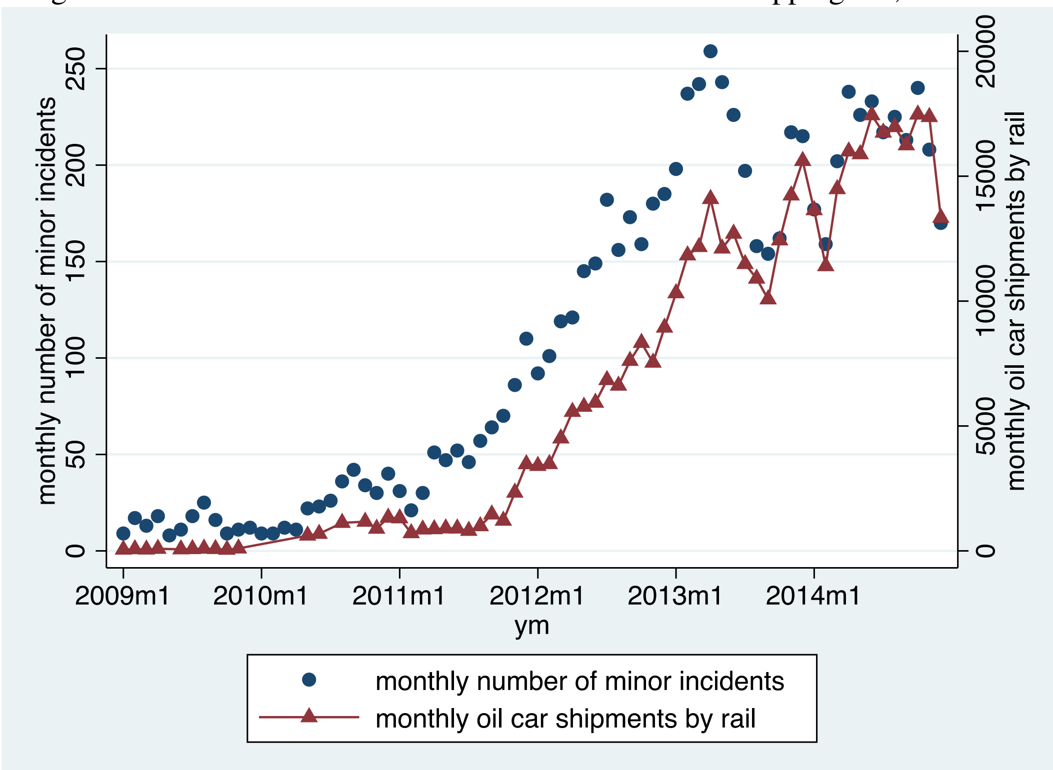

Table 1: Crude Oil Rail Incidents

A. Serious Incidents

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

B. Minor Incidents

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

Table 2: Annual Crude Oil Shipments

year	oil shipments	rail cars carrying oil	rail cars per shipment
2009	167	942	5.6
2010	294	9554	32.5
2011	665	15818	23.8
2012	1762	74525	42.3
2013	2508	147940	59
2014	2508	186954	74.5
Total	7904	435708	55.1

Table 3: Regression Analysis of Time Between Serious Incidents

	Regression model		
regressor	Cox	Exponential	Weibull
Cumulative number of minor incidents	-0.025*** (0.009)	-0.019* (0.011)	-0.019* (0.010)
constant		-2.255*** (0.504)	-1.956*** (0.272)
p			0.905 (0.146)
χ^2 statistic	7.644***	3.101*	3.599*

Standard errors in parentheses

*: significant at 10%; **: significant at 5%; ***: significant at 1%

Table 4: 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)
χ^2	37.390	36.512	35.834	35.731

Table 5: Regression Analysis of Relation Between Rail Car Shipments and Minor Incidents

	Poisson		Negative Binomial	
	(1)	(2)	(3)	(4)
Thousand cars	0.226***	0.226***	0.333***	0.319***
	(0.048)	(0.055)	(0.095)	(0.095)
Dm1		0.186		-1.085**
		(0.519)		(0.426)
Dm2		-0.053		-0.968**
		(0.418)		(0.443)
Dm3		0.169		-1.000**
		(0.386)		(0.459)
Dm4		0.495		-0.540
		(0.394)		(0.387)
Dm5		0.544		-0.483
		(0.334)		(0.377)
Dm6		0.739***		-0.383
		(0.284)		(0.380)
Dm7		0.075		-0.895**
		(0.461)		(0.395)
Dm8		0.018		-0.859**
		(0.407)		(0.389)
Dm9		0.278		-0.686*
		(0.375)		(0.378)
Dm10		0.247		-0.810**
		(0.285)		(0.397)
Dm11		0.482		-0.453
		(0.325)		(0.361)
Dm12				-0.905**
				(0.386)
constant			-0.783***	
			(0.272)	
N	872	872	872	872
χ^2	22.416	80.720	12.233	22.121

All regressions include fixed effects for origination-destination state pairs
Standard errors in parentheses
*: significant at 10%; **: significant at 5%; ***: significant at 1%

Table 6: Relation Between Rail Car Shipments and (a) Oil Spilled, (b) Total Damages

Dep. Vbl.:	(a) Quantity of Oil Spilled		(b) Total Economic Damages	
	Poisson	Negative Binomial	Poisson	Negative Binomial
	(1)	(2)	(3)	(4)
Thousand cars	-0.145***	0.412***	0.183***	0.513***
	(0.056)	(0.074)	(0.056)	(0.085)
constant		-2.876***		-4.830***
		(0.134)		(0.137)
N	872	872	863	863
χ^2	6.641	31.026	10.744	36.538

Standard errors in parentheses

*: significant at 10%; **: significant at 5%; ***: significant at 1%