Modelling the Number and Severity of Railroad Tank Car Spills for Use in Policy Making

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Increased transportation of oil by rail has increased the risk of derailments that result in spills. Most notably, the June 2013 derailment in Lac Mégantic resulted in substantial damages. Recent policy actions in response to this increased risk highlight the need for better tools to analyze the potential benefits of from these policy actions. In this paper, we model factors influencing both the annual number and severity of spills resulting from derailments of railroad tank cars. Doing so allows us to better forecast both the annual count and the severity of spills for use in analysis of proposed policy changes.

INTRODUCTION

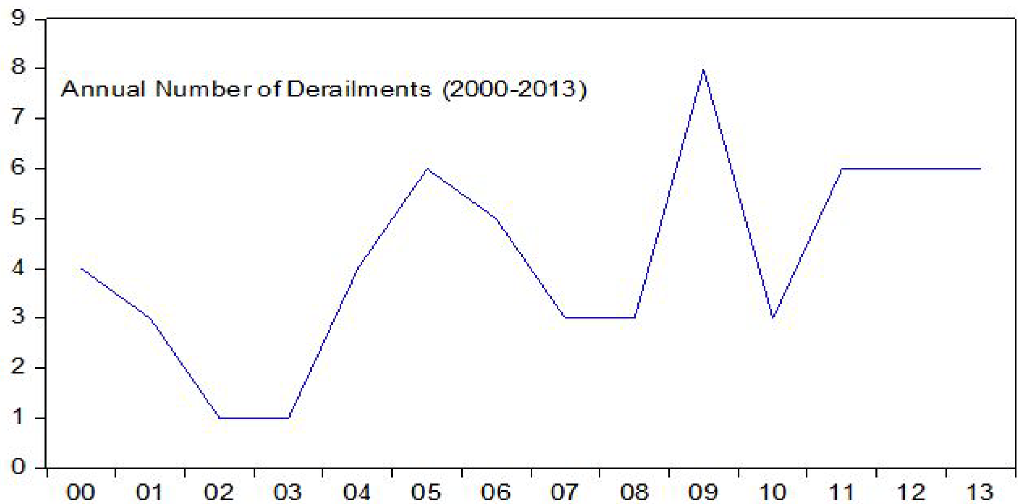
On June 6, 2013, unattended 74-car freight train carrying Bakken Formation crude oil derailed in the town of Lac Mégantic, Quebec, resulting in the fire and explosion of multiple tank cars. Forty-two people were confirmed dead, with five more missing and presumed dead. This event bolstered public concern about the risks and costs of transporting oil on rail cars. This resulted in changes to tank car design and other safety measures in North America. In particular, in May 2015 the U.S. Department of Transportation (DOT) promulgated regulations to that effect (https://www.federalregister.gov/articles/2015/05/08/2015-10670/hazardous-materials-enhanced-tank-car-standards-and-operational-controls-for-high-hazard-flammable).

The regulations provided for an enhanced tank car standard (9/16 inch shell thickness) and a risk-based retrofitting schedule for older tank cars carrying crude oil and ethanol. In particular, replacing or retrofitting legacy 7/16" thick DOT 111 tank cars which are currently the vast majority of the fleet. It also provided for new braking standards (electronic control) and operational protocols for trains transporting large volumes of flammable liquids. The final rule applied to any high-hazard flammable train (HHFT) operating in the U.S. comprised of 20 or more tank carloads of Class 3 flammable liquids in a continuous block or 35 or more tank carloads of a Class 3 flammable liquid across the entire train. Crude and ethanol are the only Class 3 flammable liquid shipped in HHFTs.

In examining the potential impact (e.g. benefits from prevented derailments) of policy actions like these, practitioners frequently analyze the annual number of incidents in an estimation period to determine how many incidents would be prevented in an event period had the policy action been in place.

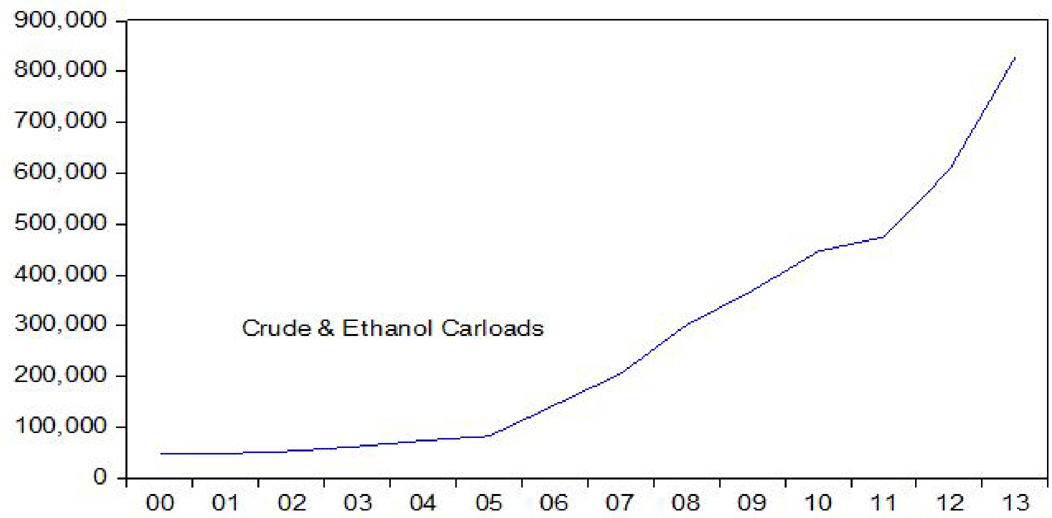
This approach is adequate when the number of annual incidents is fairly stable and where there has not been a "paradigm shift" in underlying conditions. However, this was not the case here. Not only was the scale of Lac Mégantic unprecedented, but the level of transportation of oil in rail cars increased drastically in recent years in response to "shale plays" in the Bakken and other recent developments (a 14 fold increase from 2000-2013). Arguably, the increased exposure has increased the risk of derailments resulting in oil spills. This is borne out if Figures 1 & 2 which show the number of derailments and carloads from 2000 to 2013. We include both crude & ethanol since the policy action in question applied equally to both and because they utilize the same types of rail cars. Hereafter, we refer to crude and ethanol carloads as hazmat carloads and derailments of crude and ethanol derailments as hazmat derailments.

FIGURE 1
DERAILMENTS INVOLVING SPILLS OF CRUDE & ETHANOL (HAZMAT)



This leads us to an important question. How do you estimate benefits from preventing spills from hazmat transported by rail when the historical number of annual cases is low? In this paper, we model both the factors influencing the annual number of oil spills from railroad tank car derailments as well as the severity of those spills (gallons released). As causal factors affecting both the number and the severity of spills change over time (e.g. due to increased carloads of crude transported in trains), both the number and severity of spills may be different than historical levels (e.g. they can be higher when amount of oil transported by rail is relatively high). By forecasting the causal factors, one can provide a more rigorous range of potential benefits from policy actions than from a point estimate based on the historical average.

FIGURE 2
CRUDE & ETHANOL CARLOADS (HAZMAT)



The organization of the paper is as follows. The next section provides a review of the literature and identifies causal factors that will drive the econometric models. The third section describes the methodology and models we use for estimating the annual number of derailments. The fourth section provides a description of the data sources, and the fifth section discusses the results for the annual number of derailments model. The sixth section describes the methods, additional data, and results for the severity model. The final section concludes the paper.

LITERATURE REVIEW

Many historical models of oil spills develop probabilistic estimates of oil spill occurrence. Frequently, researchers have modeled spill occurrence as a Poisson process (Anderson & Labelle, 1990, and Homan & Steiner, 2008). In these models, a stochastic process $N(t)$ is a counting process if $N(t)$ represents the total number of events that have occurred up to time t. These models generally model spills as a function of oil handled, or similar variables such as number of trips. Much of the literature on spills focuses on tank vessels. This is especially so for annual counts.

Sarin and Scherer (1976) suggest that tanker accident spillage increases with tanker size. This, of course, is a function that larger tankers can handle more oil. For trains, this would be analogous to a higher number of rail cars carrying oil. Talley and Anderson (1995, 1996) have modeled the determinants of accident oil spillage. In addition to investigating the link between increased vessel size and spills, they also investigated the price of oil. The rationale for the latter variable was that vessel owners would be more careful as the price of oil increased (more valuable cargo) and as such would tend to increase the cost of negligence. Homan and Steiner (2008) found that both the number of tank vessels and vessel size were positive factors contributing to the number of spills that the price of oil was a negative factor.

Instead of spills we are modelling derailments that can result in spills. Barkan et.al. (2011) postulated that traffic exposure is a critical factor in explaining derailment risk. Historical models of train derailment severity often model the mean number of cars derailed. Saccomanno and El-Hage (1989, 1991) estimate the mean number of cars derailed as a function of derailment speed, accident cause, and other factors such as train length. The model was more recently modified by Bagheri (2009). Broken rails are the most common cause of freight-train derailments on U.S. Class I mainlines (Barkan et.al., 2003; Liu et.al., 2012). However, this is not a variable we can use for modelling the annual count of derailments (e.g. an annual track quality index). Barkan et.al. (2003) also found that speed and the number of cars derailed were both highly correlated with hazardous materials releases. There are other factors that can lead to a derailment but would not show up in annualized patterns. For example, bad weather may be a factor but this is not a variable we can readily pick up in an annual index that would be useful in modelling an annual count of incidents. The same would be true of human error. A more pressing question for the purposes of this paper is not severity measured in derailed cars but rather the quantity of hazardous material released. Barkan and Saat (2005) develop a metric called "release risk" which they defined as the expected value of the quantity lost from a tank car given that it is in an accident. They model quantity lost as a function of tank thickness and found that release risk may be a useful means of assessing the relative benefits of different tank car safety design modifications. However, for hazmat tank cars during the study period (2000-2014) nearly all tank cars were legacy 7/16 inch thick DOT-111 cars. A new Casualty Prevention Circular (CPC) 1232 voluntary car standard was finalized in late 2011 (1/2" thick) but these cars did not come into production until later in 2012 and were not integrated into trains until after that. Consequently, thickness is not much of an issue in the study period.

METHODS AND MODEL FOR NUMBER OF DERAILMENT SPILLS

For modelling the number of spills in any given year, we employ a count model. We can use these models when the dependent variable (y) takes integer values that represent the number of events that occur. In these cases, the dependent variable assumes discrete values, but is not a categorical value. Classic examples include the number of accidents on a pipeline. In the pipeline case, an explanatory variable could be the amount of product shipped. In such a case, a Poisson regression model would be appropriate (Maddala, 1989). This, of course, is similar to what we are trying to model here.

With a Poisson model, the explanatory variables (Y_1, Y_2, …, Y_n) have independent Poisson distributions with parameters $\lambda_1, \lambda_2, \ldots, \lambda_n$, respectively.

$$\text{Prob}(Y_i = r) = exp(-\lambda_i)\,[(\lambda_i)^r / y_i] \tag{1}$$

$$\text{In } \lambda_i = \beta_0 + \sum \beta_j X_{ij} \tag{2}$$

With Poisson models, the conditional variance is equal to the mean. This is not always true in actual data so it can limit the usefulness somewhat. The usefulness may also be limited if process does not have independent increments (i.e., independence of past events). This violation would occur if a derailment event were not independent of a prior derailment; however, this does not appear to be the case here. To measure for over-dispersion between the variance and the mean, we use the Wooldridge test (Wooldridge, 1997). The test is a regression with the fitted values of y_i as the independent variable on es_i - 1 (the squared standardized residuals - 1). A significant t-statistic suggests over-dispersion and the value of the coefficient is an estimate of the necessary adjustment for it using an alternate Count Model framework (Negative Binomial). Otherwise, the Poisson specification is fine. We show the negative binomial specifications in equation (3).

$$\text{var}(y_i/x_i, \beta) = \text{m}(x_i, \beta)(1+\eta^2 m(x_i, \beta)) \tag{3}$$

We report whether the Wooldridge test is significant; however for space conservation purposes we report only the Poisson or the negative binomial estimates depending on whether the Wooldridge test was significant.

We express the annual number of derailments (HMDERAILMERNTS) involving a spill of hazmat carloads as a function of all carloads (ALL CARLOADS) on the network, the number of hazmat (HM CARLOADS), and the price of crude oil (PETROL).

HMDERAILMENTS = *f*(ALL CARLOADS, HM CARLOADS, PETROL)

HMDERAILMENTS are derailments of hazmat carloads that result in a spill. As previously noted, we include both crude and ethanol derailments/carloads for two reasons. First, crude and ethanol carloads utilize the same types of rail cars. Additionally, having both allows for a more robust count number in the dependent variable.

The expected relationship between HMDERAILMENTS and ALL CARLOADS is positive. As the amount of traffic on the rail network increases, the opportunity for a derailment increases all else held constant. The expected relationship between HMDERAILMENTS and HM CARLOADS is also positive. As the number of hazmat carloads increases we would expect the opportunity for derailments increases. This is a more direct commodity exposure relationship than with ALL CARLOADS. With tank vessels the expected sign between spills and PETROL is positive since as the price of petroleum increases (more valuable cargo) carriers would be more careful since the cost of negligence increases with the price. This makes sense when the amount transported is inelastic to changes in the price of petroleum. If the demand for transportation by rail for petroleum products was stable this would also be the case. However, the shipment of petroleum products by rail is positively linked to the price. Increased production in the Bakken and other "shale plays" has largely been driven by higher oil prices. The increased production, coupled with the lack of adequate access to pipelines, has been a driving factor in the increased use of rail to transport crude. Consequently, we'd expect that the relationship between PETROL and HM CARLOADS is not independent and the inclusion of both variables could result in a significant amount of multicollinearity.

DATA

We used actual historical data (2000-2014) from the Surface Transportation Board's (STB) Waybill Sample to derive total annual carloads and the total annual hazmat carloads (for more information on this data source see http://www.stb.dot.gov/stb/industry/econ_waybill.html). The STB collects cargo waybill data under the requirement that all U.S. railroads that terminate more than 4,500 revenue carloads submit a yearly sample of terminated waybills. This data provides an indication of the annual volume of freight rail traffic, as well as the annual volume of hazmat carloads.

We used available rail accident and incident reports from both Federal Railroad Administration (FRA) Form 6180.54 (Rail Equipment Accident/Incident Report) and Pipeline and Hazardous Materials Safety Administration (PHMSA) Form 5800.1 (Hazardous Materials Incident Report), to derive total annual derailments, car type, and spill size data (2000-2014). We used Form 6180.54 for speed data and Form 5800.1 for tank car type. For more information on data submitted by these forms see http://safetydata.fra.dot.gov/OfficeofSafety/publicsite/Forms.aspx and http://www.phmsa.dot.gov/hazmat/incident-report. Rail carriers are required to report accidents that occur on the following types of track: main, yard, siding and industry. We only used main and siding accidents and incidents involving hazmat given the scope of this research.

For the price of oil, we used the adjusted (real $2014) U.S. Crude Oil Domestic Acquisition Cost by Refiners (RAC) data series published by the US Energy Information Administration (EIA) [10]. http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=R1200____3&f=A

This series represents the cost of domestic crude oil to refiners and as such is a proxy for the cost of negligence.

RESULTS – COUNT MODEL

We first run the models on annual data. Due to data limitations in earlier years, we only have data available for derailments from 2000. We first run the models from 2000-2013. We then use quarterly data to have a more robust number of observations. We then re-do the process for 2000-2014 to add another year of data. However, starting in the latter half of 2013 there were several changes in industry oversight ranging from increased inspections to FRA emergency orders on unattended oil trains and speed restrictions in urban areas. Additionally, by 2014 both Canada and the United States were proposing regulatory action which at the margin would lead to operational changes by carriers in anticipation of the potential regulatory actions. Consequently, causal relationships may be somewhat weaker by adding the additional year. We ran the model using EVIEWS7 statistical software. Given potential issues of over dispersion, all models use GLM robust standard errors and covariance (McCullagh and Nelder, 1989).

We first ran the model where the annual number of hazmat derailment incidents. (HMDERAILMENTS) is a function of a constant, all carloads (ALL CARLOADS) and the total number of hazmat carloads in that year (HM CARLOADS). The results are below in Table 1 (middle of the table). The coefficient for HM CARLOADS was positive at nearly a 95 percent level of confidence indicating that derailments are an increasing function of the number of hazmat carloads. The coefficient for ALL CARLOADS was not significant which would imply that overall traffic is not a factor in the annual number of hazmat. We next add PETROL to see if it adds any explanatory power (shown first in Table 1). The inclusion to the equation was found not to be significant (i.e. we do not reject the null hypothesis that the coefficient for PETROL is equal to zero and as such does not belong in the equation). Additionally, the adjusted R^2 was lower with PETROL in the equation. As expected, PETROL's inclusion also resulted in multicollinearity. We next test the effect of excluding ALL CARLOADS and found that its exclusion was not significant (i.e. we do not reject the null that the coefficient was equal to zero). The resulting equation containing only a constant and HM CARLOADS had the best overall fit and the coefficient for HM CARLOADS was significant at a 95 percent level of confidence.

TABLE 1
ANNUAL MODEL 2000-2013

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2
Constant	2.16	.888 (.375)	.290	.077
All Carloads	-3.63E-08	-.487 (.626)		
HM Carloads	4.27E-07	.436 (.663)		
Petrol	.006	.609 (.542)		
Constant	.744	.325 (.746)	.242	.104
All Carloads	1.17E-08	.179 (.858)		
HM Carloads	9.67E-07	1.957 (.0503)*		
Constant	1.159	5.988 (.00)***	.257	.195
HM Carloads	9.42E-07	2.03 (.042)**		

* Significant at a 90% level of confidence
** Significant at a 95% level of confidence
*** Significant at a 99 % level of confidence

A concern with the annual model is having too few observations. Consequently, we also run the model with quarterly data (56 observations). We transform the annual data series into a quarterly data by either dividing by four quarters (e.g. carloads) or keeping the price constant for all quarters (PETROL). For derailment counts, we rounded to the closest integer while ensuring that the total for all quarters matched the annual total. As shown in Table 2 below, the quarterly model confirms the results of the annual one. As before, ALL CARLOADS is not significant and we found its exclusion not to be significant. Similarly, we found again that adding PETROL was not significant and that its inclusion introduced multicollinearity. The model with only a constant and HM CARLOADS again had the best overall fit and the coefficient for HM CARLOADS was significant at a 99 percent level of confidence.

TABLE 2
QUARTERLY MODEL 2000-2013

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2
Constant	.570	.40 (.69)	.163[a]	.115
All Carloads	-1.29E-07	-.728 (.467)		
HM Carloads	1.29E-06	.471 (.638)		
Petrol	.007	1.094 (.274)		
Constant	-.015	-.011 (.991)	.155[a]	.124
All Carloads	-2.57E-08	-.173 (.863)		
HM Carloads	3.89E-06	2.894 (.004)***		
Constant	-.240	-1.917 (.055)*	.151[a]	.135
HM Carloads	3.94E-06	3.000 (.003)***		

a. Wooldridge test significant & ran with negative binomial specification
* Significant at a 90% level of confidence
*** Significant at a 99 % level of confidence

As previously noted adding 2014 may create issues due to operational measures taken by carriers in response to federal directives. Nevertheless, we run the annual model through 2014 to add an additional observation. The results shown in Table 3 generally confirm the annual model using data from 2000-2013. However, both the R^2 and the significance level for the coefficient for HM CARLOADS were somewhat lower.

TABLE 3
ANNUAL MODEL 2000-2014

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2
Constant	1.685	.865 (.387)	.253[a]	.049
All Carloads	-2.69E-08	-.455 (.649)		
HM Carloads	1.61E-07	.221 (.825)		
Petrol	.009	1.010 (.312)		
Constant	1.310	.629 (.529)	.208	.076
All Carloads	-2.98E-09	-.049 (.961)		
HM Carloads	6.99E-07	1.817 (.069)*		
Constant	1.215	6.768 (.00)***	.204	.143
HM Carloads	6.85E-07	1.866 (.062)*		

a. Wooldridge test significant & ran with negative binomial specification
* Significant at a 90% level of confidence
*** Significant at a 99 % level of confidence

Using our first annual model as our benchmark (2000-2013), we also ran a comparison between the actual number of annual hazmat derailment incidents involving a spill and the forecast number from the model ("Fitted") during the estimation period (2000-2013). Table 4 below shows the results. With the exception of certain outlier years on both the high and the low end (e.g. 2002 and 2009) the model did a reasonable job of predicting the number of hazmat derailment incidents in the estimation period. The model also did not have a systematic bias in over or under predicting derailments as forecast errors residuals ("Residual") are fairly evenly split between positive residuals (under predict) or negative residuals (over predict). The biggest issue with the model is the limited sample size of 14 years followed by lack of additional explanatory variables; the latter which might be picked up in the constant term. With respect to the sample size, running the model with quarterly data (to increase the sample size) generally confirms the results from the annual model. The results are also consistent, and indeed with a much higher model R^2, if we run an annual model of crude only carloads on crude only derailments. However, this crude-only model reduces the count of derailments in the dependent variable and in some years would result in a count of zero derailments. While there are strong reasons for using the count framework (see Section 3), the results for carloads are robust to other methods. For example, the results for hazmat carloads are still positive and significant when running an ordinary least squares model.

TABLE 4
ACTUAL & FORECAST NUMBER OF DERAILMENTS

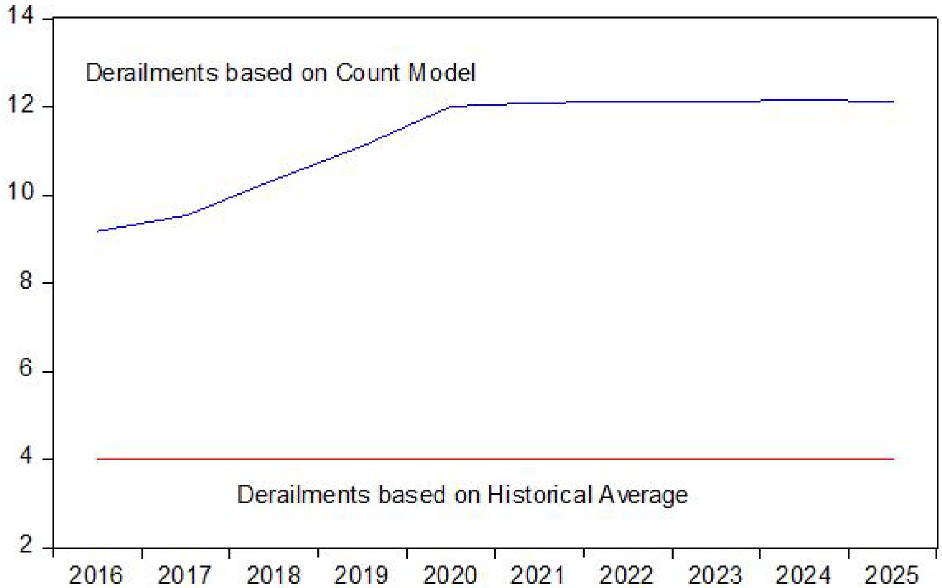
Obs	Actual	Fitted	Residual
2000	4.00000	3.34235	0.65765
2001	3.00000	3.33821	-0.33821
2002	1.00000	3.35401	-2.35401
2003	1.00000	3.38114	-2.38114
2004	4.00000	3.41878	0.58122
2005	6.00000	3.44825	2.55175
2006	5.00000	3.65176	1.34824
2007	3.00000	3.87245	-0.87245
2008	3.00000	4.23517	-1.23517
2009	8.00000	4.51326	3.48674
2010	3.00000	4.85479	-1.85479
2011	6.00000	4.98631	1.01369
2012	6.00000	5.64621	0.35379
2013	6.00000	6.95731	-0.95731

The average annual number of hazmat derailment incidents involving a spill over the sample was 4.2 (median equal to four). In forecasting the annual number of incidents for estimating benefits, practitioners often will take the average over a recent historical estimation period. However, this can underestimate the number of cases if there is a "paradigm shift". For example, increased demand for rail cars to transport crude would lead to more hazmat derailments than the historical average. We can use the results of the model to forecast future hazmat derailments with spills based higher levels of hazmat rail cars in the future. For this exercise, we use the forecast annual number of hazmat cars that the Department of Transportation used in its rulemaking (see pp. 81-83, Table EB3: Predicted Crude and Ethanol Derailments https://www.regulations.gov/#!documentDetail;D=PHMSA-2012-0082-3442).

We forecast the annual number of hazmat derailment incidents with spills for 10 years (2016-2025). The annual number range from between 9 and 12 hazmat derailments in absence of the rule. The graph below (Figure 3) shows the forecast number of derailments based on the historical average of about 4 and the forecasted number using the Count Model.

The forecast number using the count model is greater than using the forecast from the historical average. As such, the historical average would underestimate the annual number of hazmat derailment incidents and would lead to lower benefit pool than the Count Model forecast in periods of increased rail traffic. Actual traffic is a function of production which in turn would be a function price. If crude prices remain lower we'd expect less production and fewer carloads which would lead to fewer derailments. In either case, this approach is useful in providing different derailment scenarios based on different production possibilities. These different scenarios can help in a more robust description of potential benefits in analyzing similar types of policy actions.

FIGURE 3
FORECAST HAZMAT DERAILMENTS INVOLVING A SPILL



DERAILMENT SPILL SEVERITY

Historical models of train derailment severity often model the mean number of cars derailed. Unfortunately, this is not particularly tractable for estimating the potential future benefit pool of a policy action. However, cars derailed are highly correlated with hazardous materials releases (i.e. spills) and the severity of a spill is tractable for estimating benefits (e.g. clean-up costs).

In this paper, we attempt to estimate a model for the severity of a derailment involving a spill based on spill size (gallons). We do so using a sample of 46 derailments with spills from 2006 through 2014. Barkan and Saat (2005) found that the spillage was a function of tank thickness. However, this would not be a factor we could modify to adjust the average severity and hence the benefit pool of any policy action and would be held constant in a forecast period. More importantly, based on PHMSA data 45 of the 46 derailment involved spills where the tank cars were all legacy DOT-111 with the same thickness (.4375 of an inch). Only one incident was on a train where the spills were on hazmat cars that were all newer 1232 standard tank cars (1/2 of an inch) but it was a relatively small release of hazmat. However, it is challenging to make inferences from one event. For this paper, we express spill size as a function of hazmat carloads, speed, and hazmat cars derailed with spills. As the amount of hazmat shipped increases we'd expect a higher number of hazmat derailments leading to spills. For this variable we use the number of hazmat carloads on the train (HM CARLOADS). We'd also expect the risk of a derailment to increase at higher speeds (SPEED). We express SPEED in miles per hour at the time of the incident. The most obvious explanatory factor is the number of hazmat cars derailed with spills on the train that derailed (HMSPILLS). Indeed, when we run a regression with these variables, only HMSPILLS is significant and with the expected sign. HMSPILLS is significant at a 99 percent level of confidence. We found that the exclusion of SPEED and HM CARLOADS was not significant (i.e. we do not reject the null that the coefficients were jointly equal to zero). Table 5 shows the results with all the variables and only

HMSPILLS. Given the likelihood of a non-constant error variance (e.g. by HMSPILLS) we run all severity models using a White heteroscedasticity-consistent standard errors and covariance (White, 1980).

TABLE 5
SPILL SIZE & TANK CARS WITH SPILLS

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2	F-Stat (Probability)
Constant	5666.97	.395 (.695)	.921	.915	158.385 (.00)***
HM Carloads	-249.46	-.929 (.358)			
SPEED	-1063.31	-1.630 (.111)			
HMSPILLS	24037.05	9.425 (.00)***			
Constant	-24496.01	-3.259 (.002)	.914	.912	458.346 (.00)***
HMSPILLS	22583.05	10.420 (.00)***			

*** Significant at a 99 % level of confidence

The purpose of this exercise is to be able to better forecast range of potential benefits from policy actions. To do so requires an explanatory variable that we can vary in a plausible manner. It would be challenging to forecast the number of tank cars spilled per derailment (or to plausibly assign a higher number per spill in the forecast period) so we'd want a more tractable model. For example, HM CARLOADS in a train is reasonable proxy for HMSPILLS since given a derailment of hazmat cars it is likelier that you'll have more cars derailed with spills the greater the number of hazmat cars. Indeed, there is a significant relationship between HM CARLOADS and HMSPILLS. Table 6 shows these results.

TABLE 6
TANK CARS WITH SPILLS & ALL TANK CARS (CRUDE & ETHANOL)

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2	F-Stat (Probability)
Constant	.405	.474	.183	.164	9.84 (.003)***
HM CARLOADS	.097	2.730 (.009)***			

*** Significant at a 99 % level of confidence

With these relationships established, we next run a model where spill size is a function of the number of hazmat cars and speed (as a control variable). As can be seen below, both variables are significant and have the expected sign. The amount of a spill is a positive function of how many hazmat cars you have and how fast you are going. Table 7 shows these results.

TABLE 7
SPILL SIZE & TANK CARS (CRUDE & ETHANOL) MODEL IN LEVELS

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2	F-Stat (Probability)
Constant	-120651.50	-2.426 (.020)**	.303	.270	9.140 (.001)***
HM Carloads	2137.969	3.059 (.004)***			
SPEED	4445.342	2.168 (.036)**			

** Significant at a 95% level of confidence
*** Significant at a 99 % level of confidence

To focus on the impact of thickness, we also ran the model in Table 7 excluding the spill with 1232 cars. The results for the model coefficients and corresponding t-stats, as well as model diagnostics were not materially different. We also ran the model over all the observations including a variable for thickness. While the variable was significant, the results for the other coefficients as well as the diagnostics were not materially different.

We next ran the model in logs. Doing so allows us to interpret the coefficient for HM CARLOADS as a constant elasticity and we can easily use this to forecast changes in severity based on changes in the number of hazmat cars in a train. The coefficient for HM CARLOADS is still significant but the coefficient for SPEED is not. Table 8 shows these results.

TABLE 8
SPILL SIZE & TANK CARS (CRUDE & ETHANOL) LOG MODEL

Independent Variable	Coefficient	T-Stat (Probability)	R^2	Adjusted R^2	F-Stat (Probability)
Constant	-1.966	-.489	.145	.099	3.144 (.001) *
HM Carloads	1.494	2.032**			
SPEED	1.488	1.517			

* Significant at a 90% level of confidence
** Significant at a 95% level of confidence

What the constant elasticity for carloads implies is that for every one percent increase in the number of hazmat cars in a train you will get approximately a 1.5 percent increase in the severity of spills ($[(1.01)^{1.496} – 1] * 100 = 1.498$). While the Count Model allows for annual number of spills different than the historical average, the Severity Model allows for the severity of the spill to vary based changes in the forecasted number of hazmat cars per train. The average spill size in the sample was about 77,000 gallons and the average number of hazmat cars per train was about 42 cars. If expected market conditions call for a higher percentage of a train to be taken up by hazmat cars (e.g. increased use of unit trains carrying crude), then we'd expect the typical severity to increase. For example, if the average number of hazmat cars increases by 30 percent to about 55 cars, the spill size increases by about 45 percent to about 112,000 gallons per incident. This is another way to adjust the potential benefit pool and to provide alternate ranges to evaluate policy options.

CONCLUSION

The paper summarizes research modelling the causal factors causing both the annual number and severity of spills (spill size) resulting from derailments of railroad tank cars carrying crude and ethanol products (hazmat). We found that the annual number of spills is an increasing function of the amount of hazmat rail cars. Based on this relationship we can forecast future annual level of spills based on higher levels of hazmat rail traffic. For example, this would be the case if production of crude in the Bakken and other "shale plays" continues. This would lead to a higher annual number of spills than using historical averages when levels of hazmat rail traffic were lower. This has important implications for providing a more robust description of the likely benefit pool (potential benefits) in analyzing policy proposals designed to mitigate the risk of derailments and subsequent spills. Similarly, we find that the severity of any spill is an increasing function of the number of hazmat cars on the train and train speed. Holding speed constant, for every one percent increase in the number of hazmat cars in a train you will get approximately a 1.5 percent increase in the severity of the spill. Based on this constant elasticity, we can forecast the severity of future spills based on changes in the forecasted number of hazmat cars per train (e.g. from increased use of unit trains carrying crude). This also allows for an increased benefit pool for analyzing policy proposals.

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