Weather and the safety of U.S. railways*

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Abstract

Railway safety is affected by the weather. We quantify these effects by leveraging a comprehensive dataset on railway safety incidents in the United States spanning 1997–2019. Though weather conditions are noted as a primary or contributing factor to 2.2% of railway safety incidents during our data period, we find that weather causes closer to 8.5% of all rail safety incidents—four times the documented amount. Both heat and cold cause elevated incident counts, with effects especially strong for incidents leading to injuries or deaths. Exposure to a daily average temperature over 30°C (86°F) leads to a 9.5% increase in the number of rail safety incidents, a 27% increase in the number of incidents leading to a casualty, and 25% and 57% increases injuries and deaths—effects net of any operational adjustments made to mitigate these effects. Extreme cold and extreme precipitation also affect safety. We find that locations are adapted to their local climate, with, for example, warmer places exhibiting a weaker relationship between heat and incident count. Further, past exposure to hazardous weather leads to fewer accidents future accidents, perhaps demonstrating learning. The numbers of injuries and deaths associated with rail system weather exposure may suggest a role for enhanced rail safety regulations and adaptation funding to protect critical infrastructure.

Climate change, weather, railroads, climate adaptation

JEL Classification: Q54, R41

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1 Introduction

Railways are a critical component of many economies, serving as an efficient way to move people and goods. Rail is of particular importance in the United States, where it played a key role in U.S. industrialization and the western expansion of trade networks. The elaboration of the U.S. rail network in the 19th century connected communities across the country to domestic and international markets but led to the consolidation of market power. In 1887, the U.S. government responded by creating the Interstate Commerce Commission. By the 1970s, railroads were facing financial crisis due perhaps in part to excessive regulation by the Commission. In response, Congress largely deregulated the industry by removing rate controls, simplifying procedures for opening or closing rail lines, limiting the Commission's authority to intervene in markets dominated by a small number of participants, and circumscribing the administrative state's authority to prevent rail mergers and acquisitions. The number of active freight rail lines and operators shrunk dramatically; today, freight rail is dominated by a small set of "Class I" railroads that move most of their cargo on a set of non-redundant lines between major hubs. Still, by 2017, the U.S. rail system comprised over 140,000 miles of track that supported the movement of 1.7 billion tons ($690 billion) of domestic freight (Bureau of Transportation Statistics, 2021a) and handled over 6.6 billion passenger–miles of transportation (Bureau of Transportation Statistics, 2021b).

Given the industry's scope and scale, safety remains a key concern of rail regulation. For example, the passage of the Rail Safety Improvement Act of 2008 mandated regular equipment and track inspections and updated various technical standards applied to rail equipment. This and related regulations—as well as voluntary investment by rail operators—have led rail to be among the safest means of good and passenger transportation per service mile (Kyriakidis et al., 2012). Nonetheless, individual rail safety incidents can lead to large social costs, as trains can carry hazardous materials or large numbers of people and travel at high speeds through populated areas. A series of high-profile derailments around 2015—one of which destroyed an entire town (Murphy, 2018)—led to the promulgation of rules to require upgraded braking systems in trains carrying high-hazard flammable materials (Department of Transportation, 2015). These rules, however, were eventually rescinded on the basis of their high cost (Office of the Federal Register, 2018), a sign of the fraught nature of rail safety regulation made all the more complex by arcane tracking rules and interoperability challenges.

Here, we investigate the degree to which weather exposure is associated with rail safety incidents. We are motivated by three observations: operators understand that weather affects rail safety, weather is predictable on short horizons, and operators are able to mitigate weather risks in response to these predictions. We discuss each in turn.

First, weather is a known determinant of rail safety(Rossetti, 2003, 2007). In North America, rails are laid in long sections, typically 1500 feet (about 0.5 kilometers). These sections are brought to temperatures close to the annual average of extreme heat and cold experienced by rail at its installation location ("rail neutral temperature")[1] before being secured into place with a small amount of slack to allow for thermal expansion and contraction. However, slack is minimized to avoid undermining rail stability. As a result, if track temperatures rise too high, rail will buckle or warp, leading to derailments or other safety hazards(Liu et al., 2012). Extreme cold is also problematic for railways, and can lead to track fractures. However, whereas breaks caused by thermal contraction can be detected by resulting interruptions in rail signaling systems, buckling or warping due to heat cannot be detected in the same way.[2]

Second, weather is predictable over timescales that enable rail operators to modify their behavior to counteract its risks. Over hourly to daily timescales, rail operators have a number of strategies available for weather risk mitigation including cancelling or slowing routes or changing the number of cars they move per locomotive, which improves train control. Indeed, rail operators are routinely subject to "slow orders" (temporarily imposed speed limits) to give rail crew time to react to track bends caused by heat exposure and to reduce the stress caused to heated rails by trains transiting at a high speed (Xia et al., 2013).

Third, economic intuition suggests that operators may be mitigating weather-related risks less intensively than they would if they bore the full costs of rail safety incidents—some costs are borne by persons not directly connected to rail operators, such as those injured or killed in the event of a train derailment. Conversely, available adaptation strategies are often costly and produce benefits—such as an improved perception of rail safety in general—that do not accrue to any particular railroad. In the absence of regulation, rail operators must then choose a level of weather risk mitigation that weighs these predictable costs against multiple risk mitigation options: cancelling or slow shipments, which risks supply chain disruptions; moving fewer cars per locomotive, which increases costs; or making costly capital investments, such as improved braking equipment or track upgrades, which may be difficult given competitive pressures or liquidity constraints. In other words, absent appropriate regulation, economic intuition suggests that weather risk will be mitigated at a level too low from the perspective of society.

Motivated by these observations, we leverage detailed data on all railroad safety incidents (which includes all railroad equipment failures and incidents involving railroads resulting in at least one casualty—i.e., an injury or death) that occurred in the United States between January 1997 and December 2019. We summarize these events at the county–day level, which we then link to detailed weather information. We isolate plausibly random variation in temperature and precipitation conditional on a location's climate and determine an overall relationship between

[1]This range of temperatures may be quite large, as steel rails exposed to direct sunlight are routinely 20°C hotter than ambient air temperature (Bruzek et al., 2014).

[2]A notable implication of rail infrastructure design is that a change in average temperatures or temperature variability—changes currently underway as a result of climate change—may move installed rail, which typically has a life between 20 and 100 years, outside of its design specifications more frequently. Appropriate responses to such changes may include modifying installed rail or accelerating rail replacement schedules, both of which are expensive and disruptive.

random variations in weather and a range of outcomes, such as changes in the count of safety incidents or the number of resulting injuries and deaths (see Methods). We likewise evaluate whether certain types of accidents or rail service appear particularly vulnerable to weather variation. We then assess whether a location's climate affects the strength of these relationships, hypothesizing that, for example, warmer locations may exhibit lower vulnerability to a given level of extreme heat. Finally, we test whether train operators learn from earlier accidents, possibly by adopting precautionary measures which lead to later reductions in accident rates (see Methods).

We contribute to the existing literature in three ways. First, we provide a plausibly causal quantification of the effect of weather exposure on railway safety incidents. Closest to our paper, Xia et al. (2013) provides descriptive evidence on weather and railway disturbances in the Netherlands without controlling for potential confounding effects like seasonality. They find that exposure of rail to temperatures higher than 30°C increases service disruptions by 30%. Some related work has also demonstrated that air pollution and weather affect rates of road traffic accidents (Leard and Roth, 2015; Sager, 2019). Second, we contribute to the broader literature on the effects of weather on socioeconomic outcomes. We focus on railway systems, which are an important element of transportation systems but are less studied than other forms of transportation. Third, our study highlights tradeoffs between, on the one hand, speed and tonnage—which determine railroad profits—and, on the other hand, safety. We motivate this tradeoff with economic intuition that in turn leads us to a set of policy recommendations.

2 Data and methods

2.1 Weather

Weather data for the contiguous United States is calculated from the PRISM weather dataset is processed in a way that holds "fixed" the set of weather stations and harmonizes them into a complete panel (details of this process can be found here) before transforming observations—in this case, temperature and precipitation—into a gridded product with a 2.5×2.5 mile resolution. We calculate daily temperature as the average of daily maximum and minimum temperatures, a method often deployed in studies focused on daily mean temperature values (Deryugina and Hsiang, 2014). Figure S4 displays aspects of the distribution of temperatures between 1997 and 2019 across the contiguous United States.

2.2 Railway incidents, injuries, and deaths

Railway incident data comes from the Federal Railroad Administration (FRA). Our study uses two distinct FRA datasets: Rail Equipment Accident/Incident data (REA/I data, submitted by completing "Form 54") and Injury/Illness Summary - Casualty data (I/IS-CD data, submitted by completing "Form 55A"). Before collapsing to the county–day level, we collapse the REA/I data by incident (the unit for the raw data is a report, and single incidents can and often do generate multiple reports). The unit of the I/IS-CD data is a single illness or injury, so a preliminary collapse is not needed. Though the REA/I data reports counts of injuries and deaths, these counts are smaller than the number of injuries and deaths reported in the I/IS-CD data because REA/I uses a higher reporting threshold. For our analyses of injury and death counts, we rely on the I/IS-CD data.

We make a small but crucial adjustment to counts of injuries and deaths in the I/IS-CD data: we omit all events that are described as a suicide in the narrative included with each record.

For each incident in the REA/I data, the FRA reports one of 13 incident types, including derailments, collisions, incidents at grade crossings, explosions, and other events. FRA also documents the type of trains involved in each accident, including freight trains, passenger trains, commuter trains, and work trains. We redefine a passenger train as any of 'Commuter Train - Pulling,' 'Commuter Train - Pushing,' 'Passenger Train - Pulling,' or 'Passenger Train - Pushing.' Critically, all FRA data excludes incidents of mass transit operations in an urban area that are not connected with the national network of mainline rail.

Throughout, we compare overall results from our empirical approach with the tally of accidents actually attributed to weather by reporting entities. We define an incident as "weather attributed" if the primary cause code or contributing cause code is one of a set of weather related codes (codes M101–105, M199, M306, and T002) or if the accompanying narrative includes a weather-related word (such as "rain," "wind," "temperature," or "frostbite"). We manually verified 1000 records to ensure that this method correctly identifies weather-related incidents.

Figure 1 shows the total number of incidents for each county between 1997 and 2019.

2.3 Empirical framework

We estimate a flexible Poisson relationship between rail safety outcomes and weather, similar to Deschenes and Greenstone (2011) and Hsiang (2016), as follows:

$$y_{it} = \exp\Big(\sum_{m=1}^{M} \beta_m temp\_bin_{it}^m + \sum_{n=1}^{N} \beta_n precip\_bin_{it}^n + \gamma_{it}\Big)\varepsilon_{it} \tag{1}$$

where $temp\_bin_{it}^m$ is a dummy variable that measures whether mean temperature in county i on day t falls in the bin m. Mean daily temperature is calculated as the average between the daily maximum and daily minimum temperature. We group mean temperature into 17 bins ($M = 17$), with the hottest bin covering temperature above 30°C, the coldest bin covering temperature below −15°C, and 3°C temperature increments. The 12–15°C bin, which includes the mean temperature, is used as the reference bin; the coefficient β_m then captures the marginal effect of shifting a county-day from the 12–15°C bin to bin m. Similarly, $precip\_bin_{it}^n$ is binned total daily precipitation, in millimeters, in county i on day t, with the reference bin set to the

0–1 mm bin.

y_{it} is the outcome of interest, typically the count of accidents or the count of some subtype of accident that occurred in county i on day t. γ_{it} includes county-by-month fixed effects, which adjust for seasonal weather variation by county, and state-by-year fixed effects, which adjust for state-level annual conditions. We adopt a Poisson GLM approach due to the large number of zero-valued county–day observations in our sample (Chen and Roth, 2022). We cluster standard errors at the county level, which accounts for auto-correlation over time within a county.

To aid visualization, in Figure 2, we replace our binned approach with a continuous natural cubic spline in temperature (with knots placed at the 10^{th}, 50^{th}, and 90^{th} percentiles of the historical temperature distribution).

The identification assumption requires that percent deviations from average risk in a county–month when the temperature is different from the local mean are uncorrelated with unobserved factors. Temperature fluctuations relative to a seasonal mean are random, and train schedules are decided in advance. While it is possible that the quantity of people or goods moving on a given day can be related to weather, we believe these effects are likely to be small and to bias our results downward. Under the assumption of zero behavioral change, β is the causal effect of temperature on railway events, namely the percent deviation from average accident risk resulting temperature and precipitation exposure.

2.4 Waybills

Our main empirical approach assumes a Poisson relationship between our outcomes of interest and covariates. In supplementary analyses, we instead attempt to convert these count outcomes to rates. The incident data contain information only on incidents, without accompanying information about the degree of exposure (in terms of cars, car-miles, etc. per county-day). We use a separate dataset to impute values for this denominator: the Confidential Carload Waybill Sample (CCWS) from the U.S. Department of Transportation's Surface Transportation Board. The CCWS is a stratified sample of carload waybills for all U.S. rail traffic submitted by large rail carriers (those terminating 4500 or more revenue carloads annually). Waybills are a non-negotiable transport document nominating a rail carrier to transport a shipment. Waybills are generally issued at the point that a shipment is received by a rail carrier.

Individual CCWS records contain a substantial amount of information, including information related to billing, shipment characteristics, shipment routing, and all companies handling a shipment during transit. We use the waybill date (which we take as a proxy for shipment start date), origin and destination counties, and shipment carloads to approximate the movement of rail cars across the U.S. freight rail network.

Our procedure starts with the North American Rail Network Lines dataset maintained by the Bureau of Transportation Statistics. We link each county in the U.S. to a segment of the U.S. rail network by finding the segment closest to the county's center of population. We then use Dijkstra's algorithm to find the shortest path along rail main lines for each county pair. We assume that shipments follow these shortest paths at a constant speed (30 miles per hour) and start at midnight on the date the waybill is generated, which gives us a panel of the counties that each shipment traversed on each day of our sample. We aggregate these shipments as cars and car-miles per county–day, which we use alternatively as an offset in our main specification and as a denominator for our outcome variables (e.g., instead of estimating the relationship between covariates and percent changes in injuries, we estimate the relationship between covariates and the number of injuries per car-mile).

A diagram depicting the data setting for this routing exercise is shown in Figure 3.

3 Results

3.1 Weather and railway incidents

Figure S4 displays the distribution of daily mean temperatures across the 21.6 million county-days in our 23-year sample. Here, the green kernel density estimate depicts the distribution of annual "rail neutral" temperatures by county (the annual mean of location-specific 99th- and 1st-percentile daily average temperatures). The blue kernel density estimate depicts the density of historical daily average temperature exposures for county-days without recorded rail incidents leading to casualties; by contrast, the red kernel density estimate depicts the distribution of temperatures for county-days with recorded rail incidents leading to a casualty. As is suggested by this figure, the skewness of the overall temperature exposure distribution results in a large amount of probability mass warmer than the distribution of rail installation temperatures, suggesting that heat may cause relatively more stress to rail infrastructure. Notably, county-days with casualty incidents exhibit more probability mass on the hot side of overall historical temperatures, especially at the highest temperatures and for temperatures just above the distribution of rail-neutral temperatures– -around 20°C to 25°C. Specifications that use a binned approach to estimating temperature–accident relationships are noisier for the highest and lowest bins, as those bins contain substantially less data; for example, over our sample period, the portions of all county-days with average temperatures over 27°C and 30°C are 6.4% and 0.8%, respectively.

Figure 1 shows the total number of equipment incidents for each county 1997–2019. Counties with no recorded equipment incident during this period are shown in white and are excluded from our empirical analysis as we cannot distinguish counties without any rail service from those with rail service that experienced no accidents. Notably, metropolitan areas—such as Los Angeles, Chicago, New York, and Houston—experience more accidents than the average rural county. This may be unsurprising, as they also likely have more rail exposure, both in passenger counts and freight movement. That said, a number of low population states and counties, especially in the middle of the country, nonetheless experience a large number of accidents. For example, Nebraska, which has less than 0.6% of the U.S. population, is the site of 3.4% of accidents in our sample. As a result, the correlation between county population and historical accident count is less than 0.6. Together, county area and population only explain about 40% of the variation in historical accident counts. Overall, the states with the largest number of incidents during 1997–2019 are Texas (11.2% of the total), Illinois (9.4%), California (6.0%), Nebraska (3.4%), and Pennsylvania (3.3%).

Table 1 reports the impact of exposure to different temperature and precipitation bins on railway accidents by estimating equation (1). In Column (1), all the coefficients on temperature bins are significantly positive when the temperature is above 24°C or below 6°C. This confirms both hot weather and cold weather affect train safety. When the temperature is above 27°C, equipment failures increase by around 10% relative to the mean.

In Columns (2) to (4), we find similar nonlinear effects of temperature on casualty events, deaths and injuries. Point estimates increase as temperature bins move away from the mean. Single days at temperatures above 30°C are associated with a 27% increase in casualty events, a 25% increase in injuries, and a 57% increase in deaths. The magnitude of the effect is larger than that for incidents overall, suggesting that the subset of incidents caused by temperature tend to be more harmful to health than other accidents in the data. The opposite is true for rainfall, which appears to generate incidents that are less harmful to health (i.e., effects of rainfall on incident count are larger than effects on injuries and deaths).

Figure 2 highlights the nonlinearity of estimated temperature–accident relationships, but replaces our binned temperature approach with a continuous natural cubic spline with three internal knots at the 10th, 50th, and 90th percentile of historical temperature exposure. Across the four subplots of this figure, it is evident that both cold and heat lead to increased numbers of rail accidents, incidents leading to a casualty of any type, and injuries and deaths resulting from railway incidents. Counts of accidents overall are minimized around 18°C (or 64°F), and rise nearly symmetrically to an associated rate of around 1 accident per 1000 county-days of exposure at 5th and 95th percentile average daily temperatures (−5.8°C and 27.6°C, respectively), though the slope is steeper for exposure to heat. The count of incidents leading to a casualty are minimized at a somewhat lower temperature than accidents overall, leading the effect of exposure to 5th percentile (cold) temperatures on casualty incidents to be about 1/3 the effect size of exposure to 95th percentile (hot) temperatures. The third subplot depicts the relationship between temperature and counts of injuries; here, we find that 5th and 95th percentile temperature exposure leads to around 2 and 3 more injuries per 1000 county-days of exposure, respectively. The fourth subplot depicts the relationship between temperature and counts of deaths; here, we find that 5th and 95th percentile temperature exposure leads to around 0.2 and 0.3 more deaths per 1000 county-days of exposure, respectively. In other words, the exposure of 20% of U.S. counties to one week of average temperatures around 85°F would cause one additional death due to incidents on railroads.

3.1.1 Alternative model with imputed exposure estimate

As an alternative to main model, we reproduce our main results using two alternate specifications for our outcomes of interest. Both rely on our development of an imputed measure of exposure (i.e., cars traversing a county on a given day or car-miles traveled during on a county-day). In the first alternate specification, we add this imputed measure of exposure as an offset in our Poisson model. We find largely similar results (Table S2). In our second alternate specification, we use our imputed measure of exposure as a denominator, essentially converting, for example, the count of incidents on a county–day to the count of incidents per car–mile on a county day. We then re-estimate our main specification as a linear rather than Poisson model. To estimate this model, we must make two changes to the data: first, we drop county–days for which we impute that the number of car–miles is zero (this would result in dividing our outcome by zero); second, we winsorize the top 1% of nonzero county–day rates. Together, these two adjustments lead us to drop about 1.2% if the data. Using this alternate specification, we estimate roughly similar overall effects of weather on rail safety, but our point estimates are noisier (Table S4). We attribute these larger standard errors to the noise in our imputed exposure estimate, which relies on assumptions about shipment routing and transit speed. These assumptions likely result in nonclassical measurement error in the dependent variable (which is a ratio). We thus find it challenging to attach a clear interpretation to our results using this modeling approach.

3.2 Heterogeneity by train type (freight v. passenger)

In Table 2, we separate accidents for freight trains and passenger trains. We find suggestive evidence that freight trains—and especially trains carrying hazardous materials—are less sensitive to weather than passenger trains. For example, temperatures between -3 and -6°C are associated with a 53% increase in passenger train incidents, a 34% increase in freight train incidents, and a 19% increase in incidents involving freight trains transporting hazardous materials. When temperatures are above 30°C, passenger trains experience a 118% increase in incident count, whereas freight trains experience only a 23% increase and hazardous materials trains experience essentially no change. We believe some of this may be explained by a greater flexibility in freight schedules. An alternate explanation is that passenger trains on average travel at a much higher speed than freight trains, making them more vulnerable to equipment or track problems caused by the weather.

3.3 Heterogeneity by accident type

We separately estimate the temperature impact on different types of equipment incidents in Table S3. Derailments are much more frequent than the other accident types we study, accounting for 60.6% of all incidents. Our results in columns (1)–(4) suggest that derailments drive most of our results. Very hot weather (temperature higher than 30°C) increases derailments by about 16% relative to the mean, an effect size similar in magnitude to that found in prior work (Liu et al., 2012). Colder weather is also harmful, with temperatures below 3°C associated with at least a 20% increase in derailments. By contrast, we do not estimate statistically significant effects on collisions, accidents at grade crossings, or fires/explosions. Our specification including fixed effects, temperature, and precipitation also has a higher predictive power for derailments, as indicated by a larger R^2, than for other incident types.

3.4 Heterogeneity by climate

We separately estimate equation (1) for counties with different climates.[3] Figure S3 plots the marginal effect of a single county–day of a given temperature on the count of safety incidents. Following prior work (Barreca et al., 2016; Carleton et al., 2022), we hypothesize that effects of high temperatures on operations in the warmest U.S. counties will be higher than effects of similar temperatures on cold counties. This is indeed what we find. We also find that effects in warmer counties are minimized at a higher temperature (around 21°C), whereas the coldest counties experience the lowest number of safety incidents at colder temperatures (around 9°C). The coldest counties in the U.S., however, experience a wider range of temperatures throughout a typical year, which may explain why we also find that marginal effects at the 1^{st} and 99^{th} percentile temperatures for these counties are larger than effects at the 1^{st} and 99^{th} percentile temperatures for counties with the warmest climates.

4 Adaptation

We explore three possible dimensions along which rail operators may be adjusting behavior to reduce the harmful effects of weather: learning (a general concept possibly inclusive of other channels), delaying trains, slowing trains, and changing train length (longer and heavier trains are harder to control).

4.1 Learning from previous accidents

One behavioral response is learning from previous accidents. Train operators may be more cautious after experiencing a safety incident. We use a two-stage Poisson generalized linear model to test whether train operators learn from previous accidents by estimating the following equation:

$$y_{it} = \exp\left(\sum_{m=1}^{M} \beta_m temp\_bin_{it}^m + \sum_{n=1}^{N} \beta_n precip\_bin_{it}^n + \alpha \hat{y}_{s,t-1} + \gamma_{it}\right)\varepsilon_{it} \tag{2}$$

[3] We use the average between the top 1% and the bottom 1% temperature 1997–2019 to classify counties, which we believe approximates "rail neutral" temperature for a location.

where $\hat{y}_{s,t-1}$ is the total number of accidents in the state containing county i in the calendar year before day t. We estimate predicted events at the county–day level using equation (1). We the sum up predicted values to the state–year level to code $\hat{y}_{st}$. We assume a state is the correct geography for learning because we believe that matches the scale at which safety incidents are most salient. In our model, coefficient α captures the impact of last year's predicted number of statewide incidents (via exposure) on this year's number of incidents conditional on last year's temperature fluctuation. A negative sign, as seen in column (1) for overall incident count, would imply that prior incidents due to weather are resulting in a behavioral response that improves future safety. Despite some evidence that this is the case for the overall number of incidents, we see no evidence that operators are learning, year-over-year, how to reduce the more serious safety incidents—i.e., those leading to casualties or even death.

4.2 Train delays

Another behavioral response lies in train delays. Railway operators may take extra time before train departure and arrival to avoid accident risks. To study the relationship between temperature and delays, we obtain railway on-time performance data from Amtrak Timetable Archives.[4] To construct the sample, we scrape scheduled and actual departure time and the occurrence of cancellation for all trains departing from 25 large U.S. train stations from January 2009 to December 2018. Locations, temperature, and daily number of trains are shown in Figure S6. We merge train delays with departing airports' daily temperature and precipitation and estimate equation (1).

In Table S7, single days above 30°C lead to 7.3 minutes of departure delays—an 89% increase relative to the mean delay time—and temperatures below −20°C lead to an over 50 minute delay—a 625% increase relative to the mean. The total extra delay from weather exposure is 3.9 hours per day per station, taking all trains together. On days above 30°C, trains also experience 2.8 percentage points more likely to experience a service disruption; on days below −10°C, this value is at least 3%. Hot weather is not associated with significant changes in cancellations, though weather below freezing is strongly associated with at least a 1 percentage point increase in cancellations. Figure S7 plots the fitted restricted cubic spline using departure stations' daily temperature and train performances with 10 knots. There is a convex relationship between temperature and train delay, while we find no effect of hot weather on train cancellations.

These results suggest that our estimates for safety incidents do not capture the full social (or even private) cost of weather on train operations, as a nonzero portion of these costs come through the channel of delays and cancellations, which are costly.

[4]The data can be downloaded here: www.juckins.net/amtrak_timetables/archive/home.php. Note that this portion of our analysis focuses only on passenger services, omitting freight and intraurban services. Any claims made may also hold for other rail service types, though the exact magnitudes for other types of service are not observable.

4.3 Railway speed

We also assess the impact of hot weather on train speeds during transit, as departure and arrival delays may not fully capture changes in speed or temperature exposure. Since faster trains are associated with higher accident risks, railway dispatchers implement speed limits and slow orders in response to weather conditions. The relationship between temperature and speed is then a joint adaptation effort by both train drivers and railway operators.

We obtain train speed data from Amtrak Status Maps.[5] For each train, we observe train number, coordinates, heading direction, and speed every 10 minutes or more frequently. There are 689 different routes (train numbers) in total, with an average of 290 routes per day. We then merge temperature at the county-day level with train speed.

In Figure S5, we observe a similar nonlinear relationship between temperature and train speed. Both high and low temperatures lead to slower trains. The magnitude at 99^{th} percentile temperatures is twice as large as the magnitude at $1st$ percentile temperatures. A temperature range of 20–25°C results in a 1 mph decrease in train speed, equivalent to the speed decrease when the temperature is -20°C. When the temperature reaches above 40°C, the speed decrease is around 2.5 mph.

These results show that train operators are changing operations in response to temperature, suggesting adaptive behavior. In the absence of this adaptation, we expect that safety incidents would be more common.

4.4 Train lengths

The U.S. freight trains are mainly operated by private companies. They face a tradeoff between adding more freight cars and avoiding accident risks. With one train engine, an extra freight car generates high marginal revenue with low marginal costs. However, longer trains are on average heavier and are thus harder to control with the same number of locomotives.

To understand how freight train lengths affect accident risks, we perform a company-county-day level analysis to disentangle the role of train operators:

$$Y_{ict} = \sum_{k=1}^{K} \beta_k Tempbin_{it}^{k} + Prec_{it} + \phi Lengths_{ict} + \eta_c + \gamma_{it} + \lambda_t + \varepsilon_{ict} \tag{3}$$

where Y_{ict} is the number of freight train accidents in county i on day t that happen on trains owned by company c 1997–2000. We use all Class 1 Railroad companies to construct our sample. Company list and characteristics are reported in Table S1. Among these 10 Class 1 companies, the number of freight incidents over these four years ranges between 2 and 1582, with an average of 461.

[5]Real-time data is available from the Amtrak Track-A-Train service: https://www.amtrak.com/track-your-train.html. Historical data since December 2016 is scraped and made publicly available by Intercity Rail Map: https://asm.transitdocs.com/

On the right-hand side, $Tempbin^k_{it}$, $Prec_{it}$, γ_{it} and λ_t are the same variables as those in equation (1), including county-day level weather variables, local seasonality, annual differences in each state, and day of week fixed effects. $Lengths_{ict}$ is the average number of freight cars in each train with failure. We use the sum of loaded and unloaded freight cars to code total lengths. In our sample, the number of freight cars for each train varies between 29 and 95, and the mean is 70. Since we are not able to observe trains without accidents, ϕ captures the intensive margin of accident risks. We add company fixed effects in η_c to capture each company's time-invariant conditions.

Table S5 Column (1) shows similar nonlinear patterns as those in Table 1. Temperature bins above the average bin witness significant increases in freight equipment failures. When weather is hotter than 27°C and 30°C, the number of events increases by 0.05×10^{-3} and 0.07×10^{-3} at the company-county-day level, equivalent to 40.4% and 54.4% of the mean. The magnitude of results is more striking than that in the county-day level analysis, suggesting heat stress generates more severe damage on companies operating more freight trains. Column (2) adds company fixed effects and reports very similar estimates on hot bins, suggesting a robust nonlinear relationship between temperature and freight accidents. R^2 is small and has almost no change from .0007 to .0009. This indicates that companies have little predicting power of accident risks.

In Columns (3) and (4), the length of freight cars is associated with a higher risk of equipment failure. As the number of freight cars increases by 1 per train, the number of incidents increases by 0.014 per company-county-day. Column (5) and (6) show freight lengths also make heat stress more severe, captured by positive estimates on the interaction terms of freight length and temperature bins above 27°C. Estimates on interaction terms with cold bins are negative, suggesting cold-induced accidents are less severe on longer trains. Among all freight train companies, the average number of freight cars per train is 67, and the maximum is 204. Moving from the 75th quartile (98) to the 25th quartile (36) could decrease heat-induced accidents by 0.9 per company-county-year.

5 Conclusion

Railway systems play a vital role in economic activity—a role that is growing in importance over time. While it is known that weather affects rail safety, the overall magnitude of these effects is unknown. By leveraging methods from the climate impacts literature, we shown that the number of safety incidents attributed to weather undercount the number of incidents caused by weather by a factor of four. We demonstrate that this is true for a range of outcomes, including injuries and deaths from safety incidents. We also explore mechanisms through which train operators adapt to weather risk. Our results suggest that adaptation increases train safety, but that the external costs of accidents may not be fully internalized.

Prior work documenting the potential effects of climate change on the U.S. rail network, including Chinowsky et al. (2019) and Neumann et al. (2021), has not assessed the costs or damages associated with safety incidents. We find that these are , but these can be large. Over our sample period, railroads report \$507 million in damages to rail infrastructure per year due to accidents. Our results suggest that around \$48 million of those costs are caused by temperature exposure, with about half of expenses related to cold and half related to heat. A uniform 2°C shift in the historical temperature distribution, without corresponding adaptation, would increase overall temperature-related damages by around \$10 million annually. The sizes of these effects are much larger if one monetizes associated injuries and deaths.

We find that precipitation and temperature exposure cause around 8.5% of the 3000 reported annual safety incidents experienced on the U.S. rail network, as well as around 4.9% of casualties. Importantly, we find that reporting entities have attributed only 15 historical deaths (3735 injuries) to weather, while we find that weather was causative of around 108 historical deaths (7145 injuries). Applying a reasonable estimate for the value of a statistical life (\$10 million) approximately doubles our estimate of the annual costs of weather exposure on U.S. railroads. Assuming reported injuries fall evenly into Abbreviated Injury Codes(Palmer et al., 2016) 1 and 2 and applying a common U.S. government approach to valuing quality of life loss from injury (Spicer and Miller, 2010), our estimates increase to approximately \$175 million annually.

Railroads have long understood that weather affects the safety of their operations. We have shown that rail operators delay train departures, slow trains down, and learn from past weather exposure how to reduce future accidents. We have also shown that rail operations are adapted to their local climate. Nonetheless, weather exposure causes around 8.5% of annual rail safety incidents—four times greater than the count officially acknowledged by rail operators in incident reports. Overall, U.S. railroads report about 703 safety incidents per year involving hazardous materials, 49 of which lead to a hazardous materials release; rail accidents are also associated with 834 direct annual deaths and 9449 direct annual injuries—the latter leading to over 300,000 days of missed or restricted work. Even a modest valuation of the health consequences of rail accidents suggests that most costs are borne by employees and the communities in which railroads operate, which may suggest a role for enhanced safety regulations. Climate change will also reallocate weather risks, making existing rail system adaptations—which rely on particularly fixed assets—less effective, decreasing safety overall. This suggests a need for greater expenditure on adaptation.

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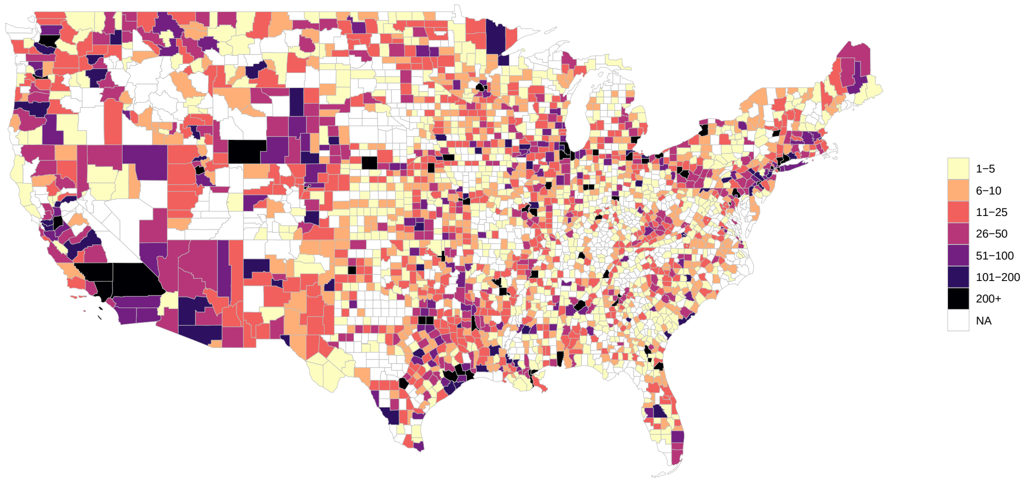
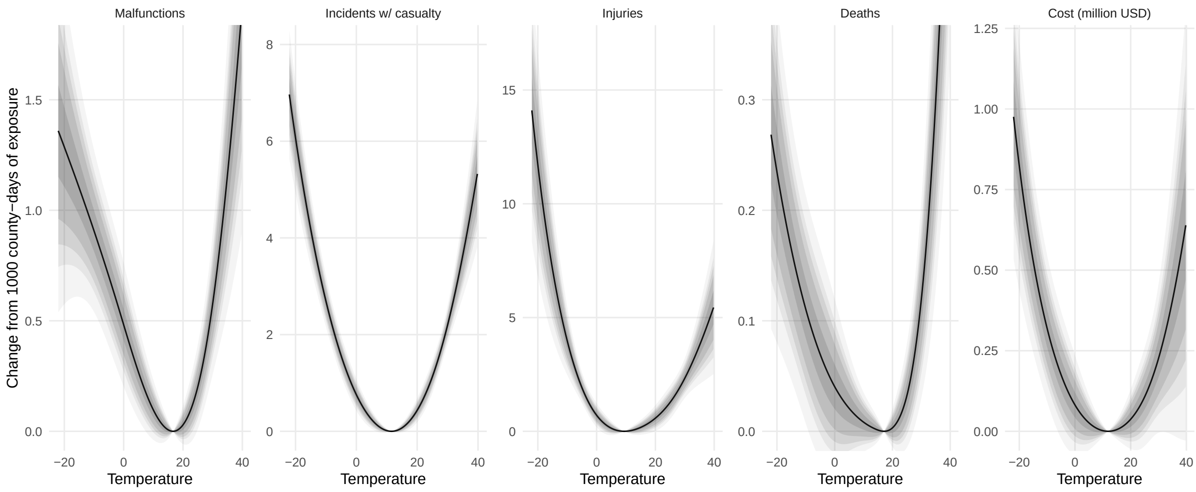
Figure 1: Rail safety incidents across the U.S.



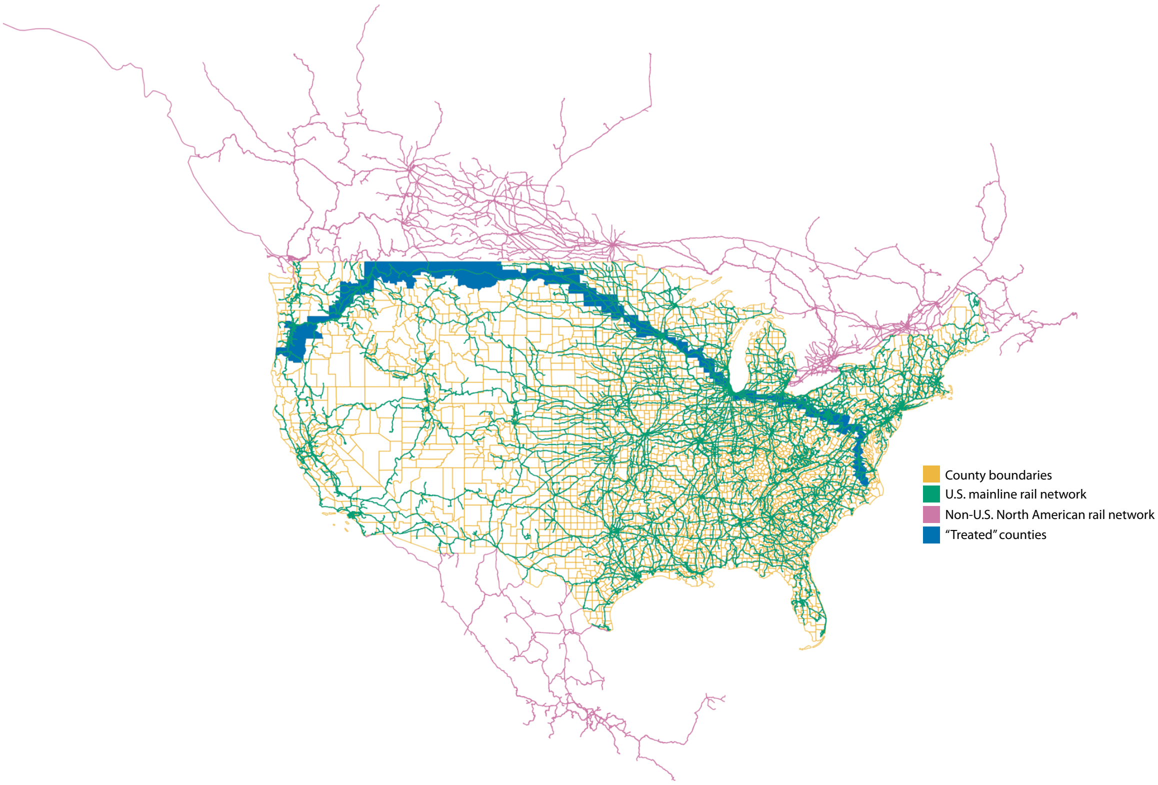
Notes: This figure depicts the total number of rail accidents at the county level between 1997 and 2019. Counties without no recorded accidents are shown in white.

Figure 2: Temperature and railway accidents



Notes: The estimated relationships between daily average temperature four outcomes: the number of incidents/accidents, the number of incidents/accidents leading to a casualty, the number of injuries, and the number of deaths. Note that the y-axis scales differ and that the values shown are for 1000 county–days of exposure at the indicated temperature. The x-axis is shown from the 1st percentile of historical cold exposure and up to the maximum of historical heat exposure to improve presentation while still exhibiting the portion of the relationship relevant for the changing climate. Due to the fixed effects specification, the level of each relationship is identified relative to minimum effect temperature, which we set to zero. The full empirical specification is as in 1, though we replace bins of temperature with basis functions for a natural cubic spline with knots at the 10th, 50th, and 90th percentile of historical temperature exposure. In each plot, the shaded areas represent 99%, 95%, 90%, 80%, and 50% simultaneous confidence intervals for each spline.

Figure 3: North American rail network, sample route, and estimated “treatment” counties



Notes: This diagram depicts the North American rail network used to route waybills for the portion of our analysis that relies on an imputed measure of train exposure intensity. The U.S. portion of the North American rail network used for waybill routing is depicted in green. A sample route as determined by our algorithm, from Bertie County, NC to Lane County, OR, is shown as the blue path. At an assumed transit speed of 30 mph, this path takes around 4.6 days to complete.

Table 1: Effects on main outcomes for all trains (Poisson model)

Dep. variable:	Incident count	Casualty occurrence	Injuries	Deaths
precip ∈ (1,2] mm	0.0413*	0.0288**	0.0347	0.0088
	(0.0210)	(0.0107)	(0.0233)	(0.0639)
precip ∈ (2,5] mm	0.0731***	0.0477***	0.0355***	-0.0053
	(0.0166)	(0.0108)	(0.0119)	(0.0587)
precip ∈ (5,10] mm	0.1305***	0.0744***	0.0761***	-0.0926
	(0.0209)	(0.0111)	(0.0124)	(0.0608)
precip ∈ (10,20] mm	0.1567***	0.0708***	0.0691***	-0.1226
	(0.0207)	(0.0154)	(0.0203)	(0.0767)
precip ∈ (20,50] mm	0.2363***	0.0852***	0.0727***	-0.1627
	(0.0251)	(0.0222)	(0.0262)	(0.1089)
precip ∈ (50,100] mm	0.6255***	0.1785***	0.1473***	0.3353*
	(0.1240)	(0.0466)	(0.0466)	(0.1962)
precip > 100 mm	0.3959	-0.0944	-0.0045	-9.098***
	(0.2753)	(0.2568)	(0.2636)	(0.0282)
temp < -15°C	0.3816***	0.3699***	1.022***	0.7965***
	(0.0663)	(0.0570)	(0.3799)	(0.2002)
temp ∈ (-15,-12]°C	0.2375***	0.3205***	0.2967***	0.4489*
	(0.0550)	(0.0463)	(0.0564)	(0.2477)
temp ∈ (-12,-9]°C	0.1650***	0.2707***	0.2419***	0.3595
	(0.0478)	(0.0335)	(0.0649)	(0.2561)
temp ∈ (-9,-6]°C	0.1635***	0.1864***	0.1662***	0.3979**
	(0.0438)	(0.0251)	(0.0402)	(0.1650)
temp ∈ (-6,-3]°C	0.1548***	0.1710***	0.1611***	0.2568
	(0.0322)	(0.0182)	(0.0371)	(0.1649)
temp ∈ (-3,0]°C	0.1433***	0.1113***	0.1183***	0.1446
	(0.0255)	(0.0195)	(0.0393)	(0.1655)
temp ∈ (0,3]°C	0.1059***	0.0208	0.0094	0.1857
	(0.0282)	(0.0158)	(0.0223)	(0.1342)
temp ∈ (3,6]°C	0.1183***	-0.0106	-0.0011	0.3228***
	(0.0258)	(0.0154)	(0.0316)	(0.1006)
temp ∈ (6,9]°C	0.0238	-0.0294	-0.0457*	0.1533
	(0.0201)	(0.0178)	(0.0237)	(0.1122)
temp ∈ (9,12]°C	0.0108	0.0072	-0.0026	0.0840
	(0.0211)	(0.0105)	(0.0148)	(0.1079)
temp ∈ (15,18]°C	-0.0054	0.0178	0.0504*	0.1473**
	(0.0178)	(0.0120)	(0.0287)	(0.0619)
temp ∈ (18,21]°C	0.0006	0.0355***	0.0278	0.0017
	(0.0260)	(0.0129)	(0.0195)	(0.0706)
temp ∈ (21,24]°C	0.0211	0.0569***	0.0658***	0.1727**
	(0.0253)	(0.0142)	(0.0241)	(0.0820)
temp ∈ (24,27]°C	0.0582*	0.0864***	0.0831***	0.2602**
	(0.0326)	(0.0144)	(0.0237)	(0.1048)
temp ∈ (27,30]°C	0.1041**	0.1677***	0.1575***	0.3478**
	(0.0417)	(0.0169)	(0.0250)	(0.1308)
temp > 30°C	0.0906**	0.2384***	0.2226***	0.4491**
	(0.0440)	(0.0210)	(0.0308)	(0.1944)
Dep. variable mean	0.0033	0.0092	0.0098	0.00026
Fit statistics				
Observations	20,580,000	20,580,000	20,580,000	20,580,000
Squared Correlation	0.03019	0.17618	0.05326	0.00212

Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Due to our use of a Poisson model, effects should be interpreted as $e^{\beta} - 1$ percent changes from the mean.

Table 2: Effects on incident count by train type (Poisson model)

Dep. variable:	Passenger trains	Freight trains	Hazmat trains
precip $\in$ (1,2] mm	0.0682	0.0467**	0.0307
	(0.0743)	(0.0223)	(0.0431)
precip $\in$ (2,5] mm	-0.0060	0.0811***	0.0226
	(0.0600)	(0.0171)	(0.0312)
precip $\in$ (5,10] mm	0.0580	0.1387***	0.1253***
	(0.0629)	(0.0252)	(0.0364)
precip $\in$ (10,20] mm	0.1692	0.1298***	0.2024***
	(0.1068)	(0.0279)	(0.0310)
precip $\in$ (20,50] mm	0.3774***	0.2269***	0.1482***
	(0.0849)	(0.0295)	(0.0501)
precip $\in$ (50,100] mm	1.017***	0.5898***	0.3487*
	(0.2022)	(0.1083)	(0.2058)
precip > 100 mm	-9.558***	1.049***	0.6257
	(0.0197)	(0.2546)	(0.5160)
temp < -15°C	0.9914**	0.5919***	0.4868***
	(0.4093)	(0.0866)	(0.0730)
temp $\in$ (-15,-12]°C	0.7859**	0.4623***	0.2607*
	(0.2946)	(0.0994)	(0.1361)
temp $\in$ (-12,-9]°C	0.6747***	0.3041***	0.1626*
	(0.1674)	(0.0801)	(0.0927)
temp $\in$ (-9,-6]°C	0.4447**	0.2691***	0.1752***
	(0.1680)	(0.0628)	(0.0619)
temp $\in$ (-6,-3]°C	0.4315***	0.2915***	0.1708***
	(0.1171)	(0.0475)	(0.0636)
temp $\in$ (-3,0]°C	0.1368	0.2719***	0.1993***
	(0.0989)	(0.0377)	(0.0471)
temp $\in$ (0,3]°C	-0.0693	0.2207***	0.1558***
	(0.1112)	(0.0348)	(0.0522)
temp $\in$ (3,6]°C	0.0744	0.1784***	0.1184**
	(0.1016)	(0.0297)	(0.0454)
temp $\in$ (6,9]°C	-0.0886	0.0790***	0.0241
	(0.0772)	(0.0260)	(0.0330)
temp $\in$ (9,12]°C	0.0968	0.0437*	0.0565
	(0.0792)	(0.0255)	(0.0363)
temp $\in$ (15,18]°C	0.0507	-0.0202	-0.0111
	(0.0988)	(0.0247)	(0.0476)
temp $\in$ (18,21]°C	0.2107**	-0.0189	-0.0215
	(0.1001)	(0.0446)	(0.0679)
temp $\in$ (21,24]°C	0.2211**	0.0055	0.0335
	(0.0922)	(0.0448)	(0.0655)
temp $\in$ (24,27]°C	0.3506***	0.0287	0.0779
	(0.1235)	(0.0486)	(0.0607)
temp $\in$ (27,30]°C	0.3850**	0.1300**	0.1249*
	(0.1533)	(0.0624)	(0.0626)
temp > 30°C	0.7815***	0.2055***	0.0342
	(0.2647)	(0.0622)	(0.0810)
Dep. variable mean	0.00018	0.0015	0.00072
Fit statistics			
Observations	20,580,000	20,580,000	20,580,000
Squared Correlation	0.00798	0.00647	0.00916

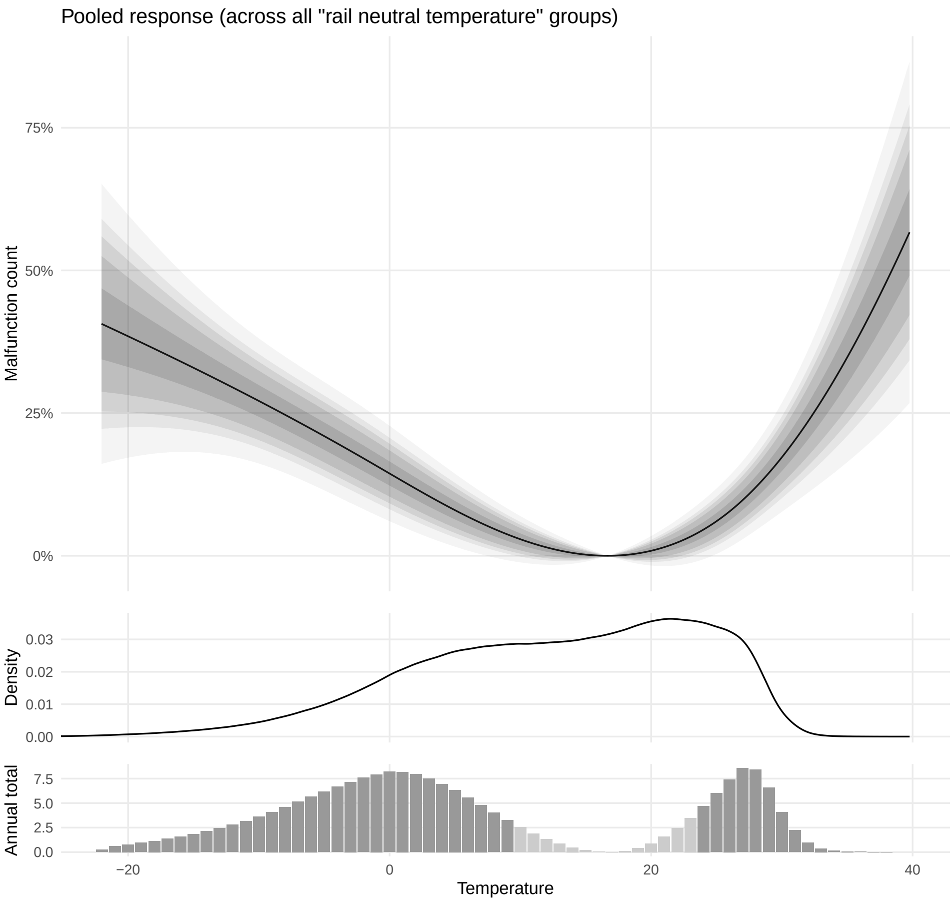
Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Due to our use of a Poisson model, effects should be interpreted as $e^{\beta} - 1$ percent changes from the mean.

Online Appendix

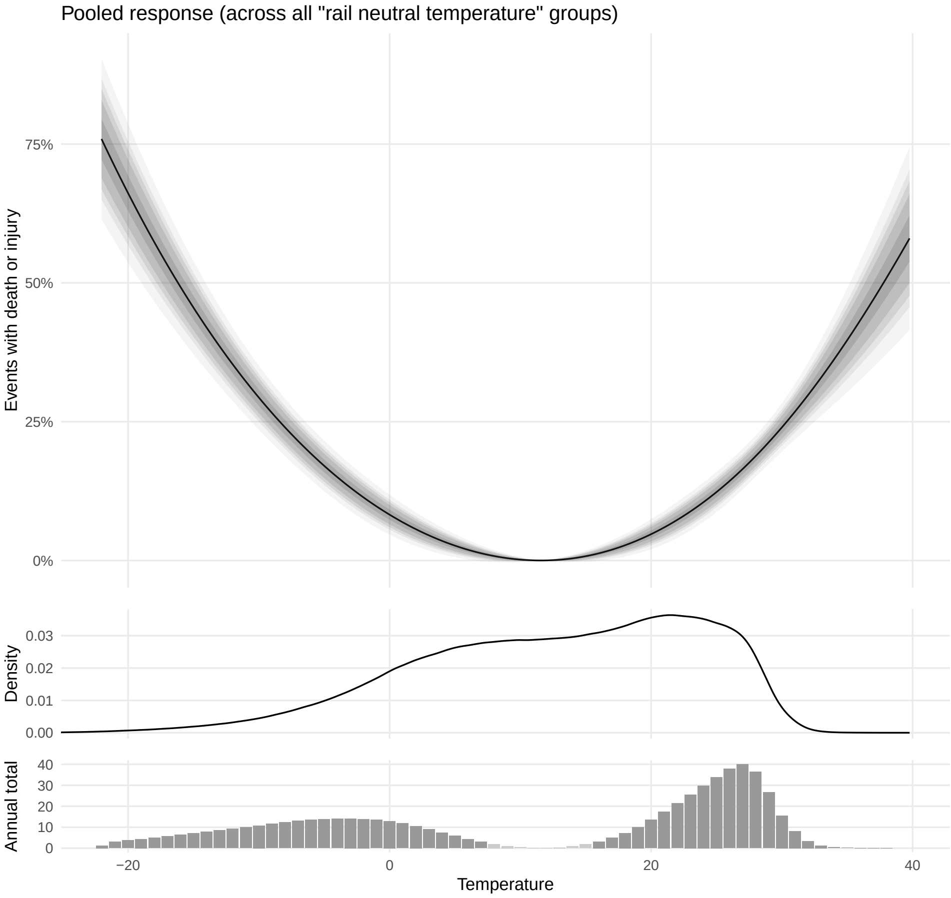
S1 Additional Figures

Figure S1: Temperature and railway accidents, malfunction



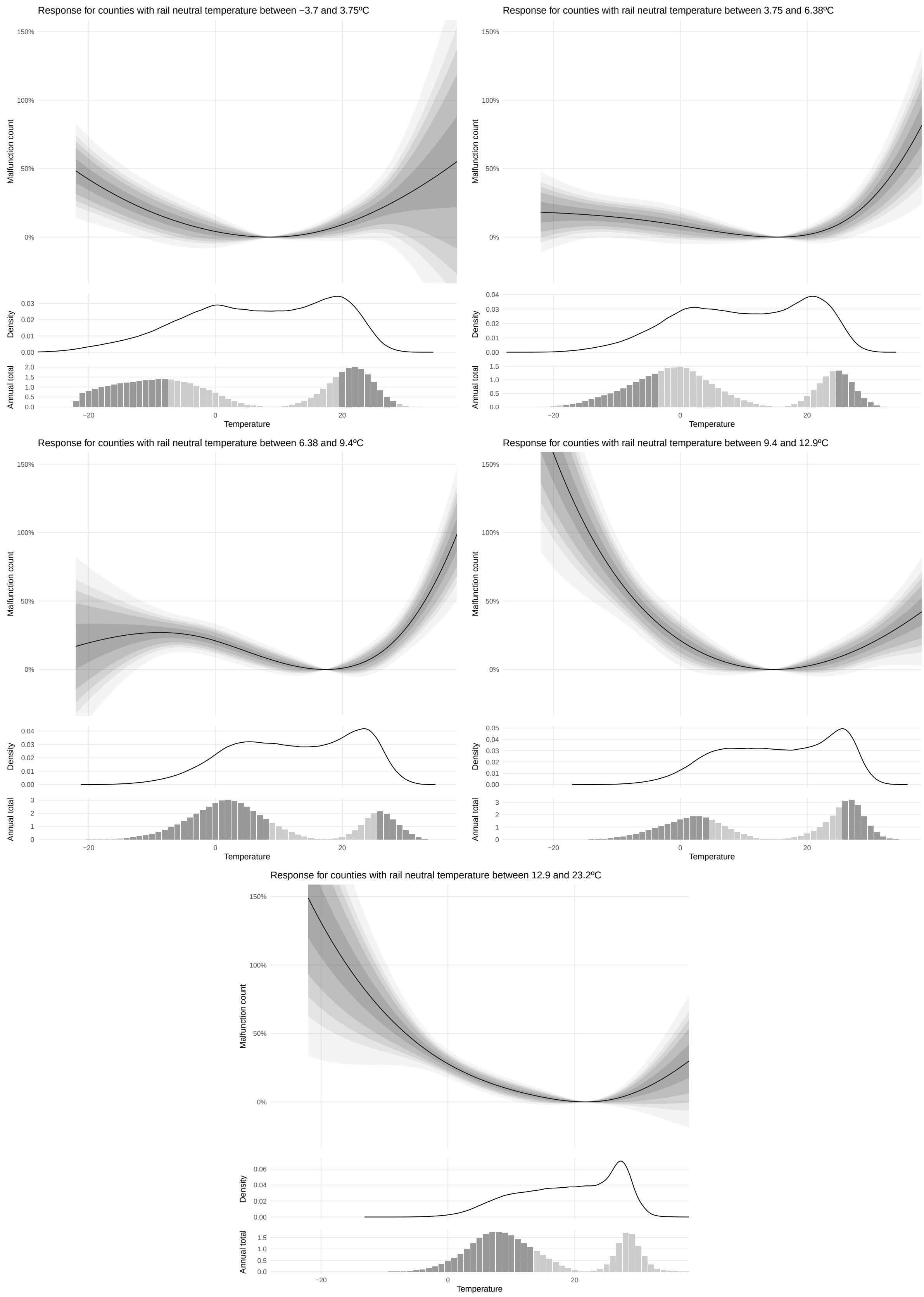
Notes: The top panel depicts the estimated relationship between daily average temperature and the count of safety incidents (one incident may lead to multiple casualties, deaths, etc.). The middle panel depicts the distribution of historical temperatures across all county–days. The bottom panel bins the middle panel by year and multiplies it by the top panel, resulting in the estimates number of safety incidents resulting from each bin of temperature exposure across the entire U.S. each year. The x-axis is shown from the 1st percentile of historical cold exposure and up to the maximum of historical heat exposure to improve presentation while still exhibiting the portion of the relationship relevant for the changing climate. Due to the fixed effects specification, the level of each relationship is identified relative to minimum effect temperature, which we set to zero. The full empirical specification is as in 1, though we replace bins of temperature with basis functions for a natural cubic spline with knots at the 10th, 50th, and 90th percentile of historical temperature exposure. In each plot, the shaded areas represent 99%, 95%, 90%, 80%, and 50% confidence intervals for each spline.

Figure S2: Temperature and railway accidents, events with death or injury



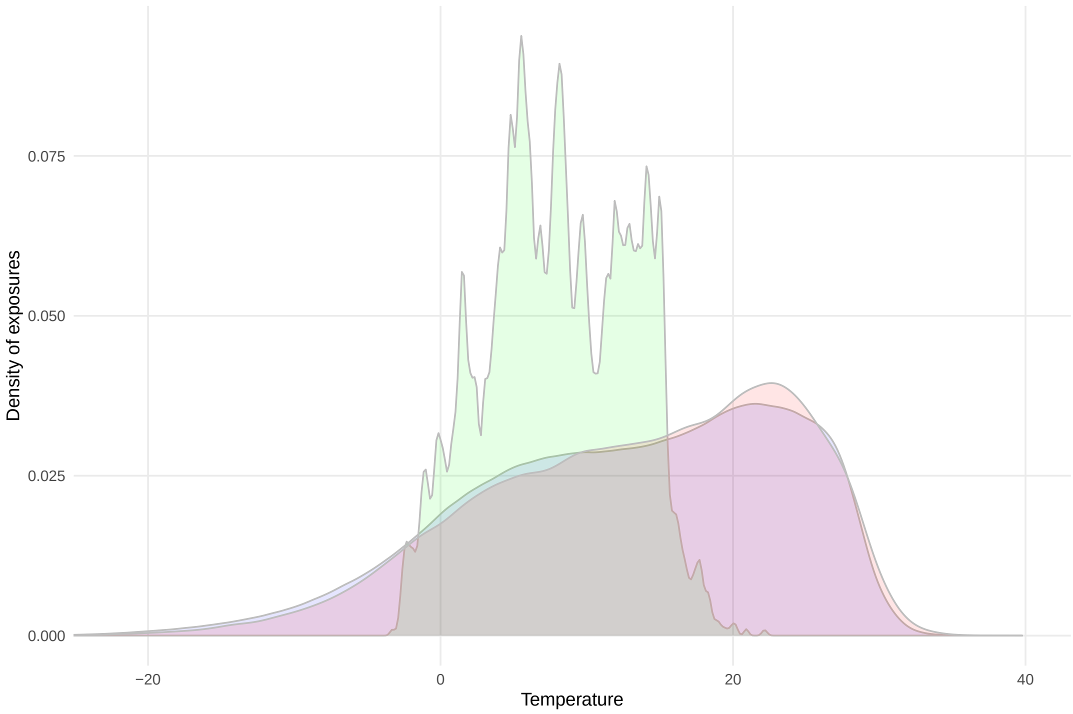
Notes: The top panel depicts the estimated relationship between daily average temperature and the count of casualties. The middle panel depicts the distribution of historical temperatures across all county–days. The bottom panel bins the middle panel by year and multiplies it by the top panel, resulting in the estimates number of casualties resulting from each bin of temperature exposure across the entire U.S. each year. The x-axis is shown from the 1st percentile of historical cold exposure and up to the maximum of historical heat exposure to improve presentation while still exhibiting the portion of the relationship relevant for the changing climate. Due to the fixed effects specification, the level of each relationship is identified relative to minimum effect temperature, which we set to zero. The full empirical specification is as in 1, though we replace bins of temperature with basis functions for a natural cubic spline with knots at the 10th, 50th, and 90th percentile of historical temperature exposure. In each plot, the shaded areas represent 99%, 95%, 90%, 80%, and 50% confidence intervals for each spline.

Figure S3: Heterogeneity across baseline temperature



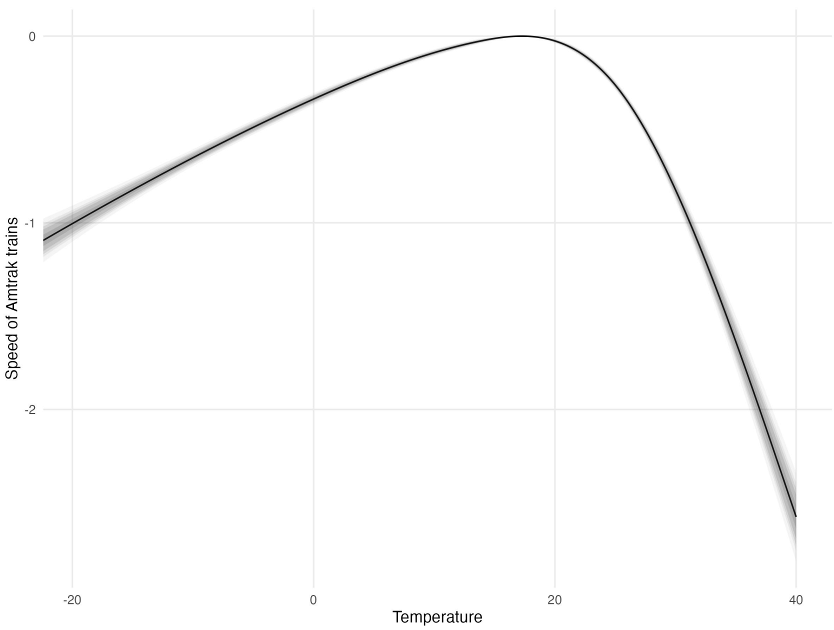
Notes: Rail neutral temperature is defined as the mean of a county's 1^{st} and 99^{th} percentile temperatures.

Figure S4: Distribution of daily mean temperature, 1997-2019 (°C)



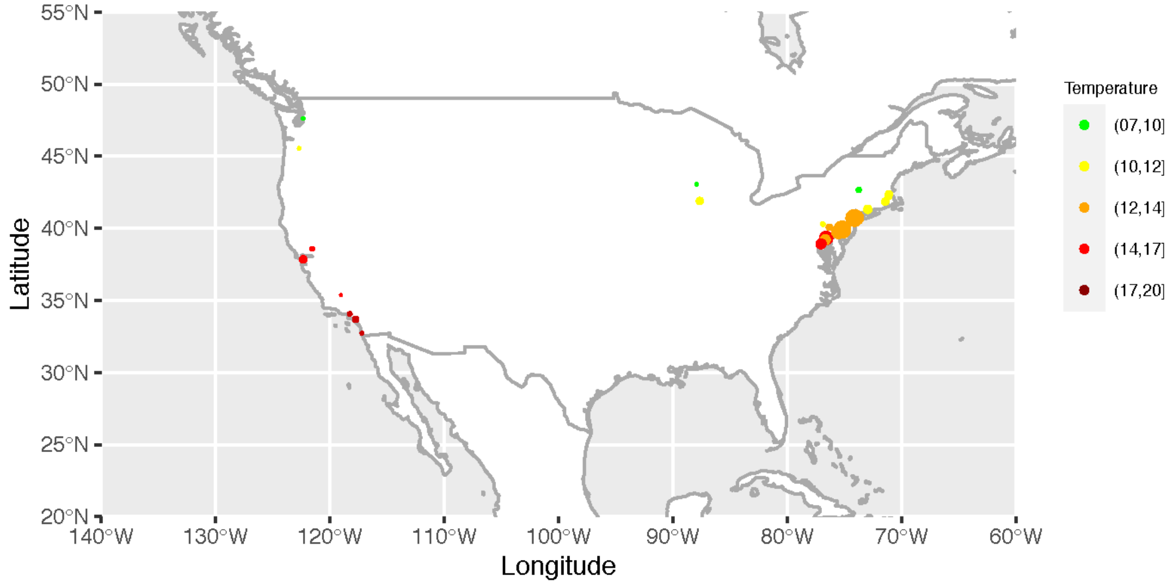
Notes: The density of historical temperature exposures. The blue kernel density estimate depicts the historical density of daily average temperature exposures. The green kernel density estimate depicts the distribution of annual rail neutral temperatures by county (the mean of annual maximum and minimum temperatures, which is ideally the temperature at which rail is installed). The red kernel density estimate depicts the distribution of temperatures for county-days on which rail accidents occurred.

Figure S5: Train speed and ambient temperature (Amtrak)



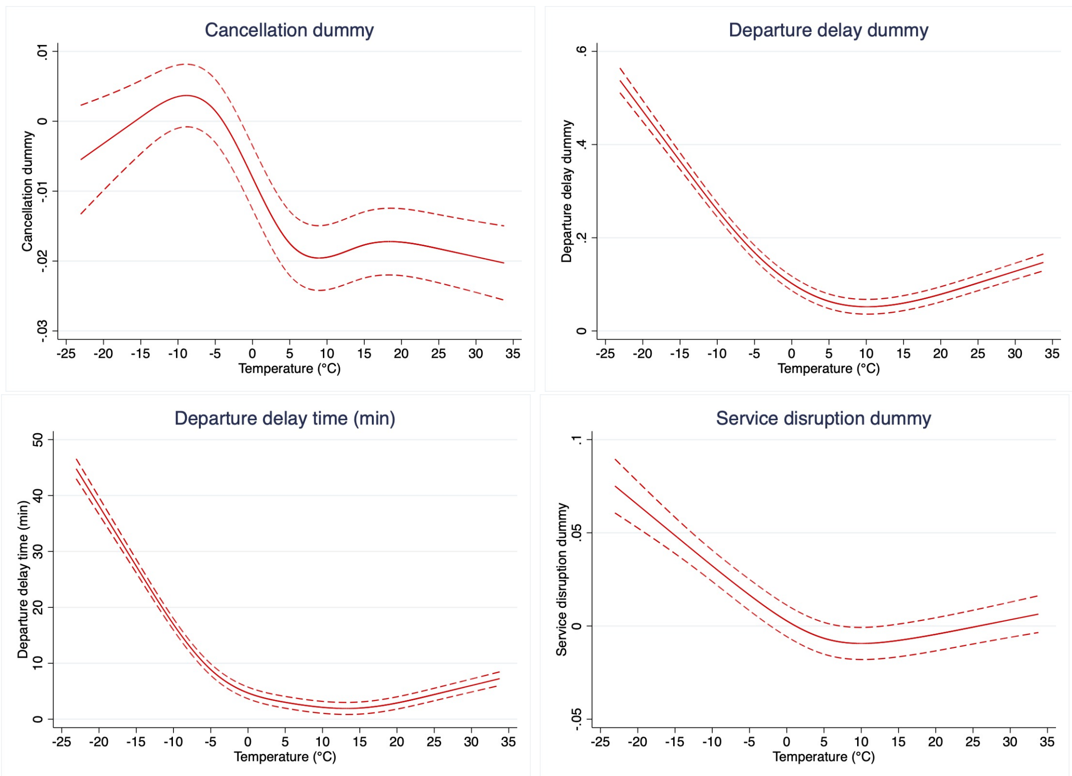
Notes: The estimated relationship between average temperature and the speed of Amtrak trains by county–day. The main relationship is modeled as a natural cubic spline with knots at the 10th, 50th, and 90th percentile of historical temperature exposure, with county-by-train route fixed effects. The shaded areas represent 99%, 95%, 90%, 80%, and 50% simultaneous confidence intervals for each spline.

Figure S6: Locations of 25 large train stations in the U.S.



Notes: Daily mean temperature averaged over 10 years is denoted by color. Daily average number of trains is denoted by size, 6 to 86 trains per day.

Figure S7: Nonlinear impact of temperature on on-time performances



Notes: This figure shows temperature and predicted performance using restricted cubic splines. The dash lines indicate the 95% confidence intervals.

S2 Additional Tables

Table S1: Class 1 railway companies

Railroad code	Company name	#Events 1997-2000	#Freight cars per train
UP	Union Pacific Railroad Company	1582	73.7
BNSF	BNSF Railway Company	1303	74.4
CSX	CSX Transportation	779	67.8
NS	Norfolk Southern Railway Company	518	68.6
KCS	Kansas City Southern Railway Company	178	63.8
IC	Illinois Central Railroad Company	124	78.3
SOO	SOO Line Railroad Company	75	72.9
GTW	GRAND TRUNK WESTERN RAILROAD INC.	43	72.7
CR	Conrail	4	94.5
CRSH	Consolidated Rail Corporation	2	29.0

Table S2: Effects on main outcomes for all trains (Poisson model, **car–miles offset**)

Dep. variable:	Incident count	Casualty occurrence$^{\beta}$	Injuries	Deaths
precip $\in$ (1,2]	0.0426**	0.0294***	0.0353	0.0120
	(0.0210)	(0.0105)	(0.0231)	(0.0639)
precip $\in$ (2,5]	0.0762***	0.0506***	0.0384***	-0.0037
	(0.0169)	(0.0107)	(0.0117)	(0.0593)
precip $\in$ (5,10]	0.1344***	0.0778***	0.0793***	-0.0911
	(0.0210)	(0.0108)	(0.0121)	(0.0609)
precip $\in$ (10,20]	0.1609***	0.0746***	0.0729***	-0.1199
	(0.0210)	(0.0154)	(0.0204)	(0.0772)
precip $\in$ (20,50]	0.2410***	0.0898***	0.0776***	-0.1661
	(0.0248)	(0.0222)	(0.0259)	(0.1105)
precip $\in$ (50,100]	0.6273***	0.1881***	0.1579***	0.3367*
	(0.1225)	(0.0463)	(0.0464)	(0.1949)
precip $>$ 100 mm	0.4282	-0.0784	0.0099	-8.959***
	(0.2646)	(0.2521)	(0.2594)	(0.0275)
temp < -15°C	0.3979***	0.3914***	1.043***	0.7855***
	(0.0679)	(0.0530)	(0.3794)	(0.1990)
temp $\in$ (-15,-12]°C	0.2379***	0.3366***	0.3108***	0.4775*
	(0.0526)	(0.0445)	(0.0538)	(0.2473)
temp $\in$ (-12,-9]°C	0.1733***	0.2905***	0.2597***	0.3850
	(0.0487)	(0.0291)	(0.0616)	(0.2559)
temp $\in$ (-9,-6]°C	0.1679***	0.1978***	0.1759***	0.4152**
	(0.0450)	(0.0255)	(0.0398)	(0.1633)
temp $\in$ (-6,-3]°C	0.1597***	0.1816***	0.1702***	0.2703
	(0.0338)	(0.0178)	(0.0340)	(0.1637)
temp $\in$ (-3,0]°C	0.1458***	0.1178***	0.1233***	0.1551
	(0.0258)	(0.0202)	(0.0384)	(0.1642)
temp $\in$ (0,3]°C	0.1055***	0.0234	0.0100	0.1846
	(0.0287)	(0.0164)	(0.0220)	(0.1344)
temp $\in$ (3,6]°C	0.1182***	-0.0104	-0.0022	0.3254***
	(0.0258)	(0.0156)	(0.0302)	(0.0995)
temp $\in$ (6,9]°C	0.0218	-0.0306*	-0.0472*	0.1571
	(0.0198)	(0.0178)	(0.0236)	(0.1109)
temp $\in$ (9,12]°C	0.0095	0.0044	-0.0050	0.0855
	(0.0211)	(0.0101)	(0.0146)	(0.1081)
temp $\in$ (15,18]°C	-0.0068	0.0141	0.0468	0.1482**
	(0.0175)	(0.0123)	(0.0289)	(0.0617)
temp $\in$ (18,21]°C	-0.0019	0.0315**	0.0240	0.0006
	(0.0254)	(0.0128)	(0.0196)	(0.0708)
temp $\in$ (21,24]°C	0.0177	0.0514***	0.0599**	0.1720**
	(0.0253)	(0.0147)	(0.0245)	(0.0832)
temp $\in$ (24,27]°C	0.0545	0.0814***	0.0775***	0.2586**
	(0.0331)	(0.0143)	(0.0234)	(0.1062)
temp $\in$ (27,30]°C	0.0998**	0.1638***	0.1537***	0.3477**
	(0.0419)	(0.0171)	(0.0258)	(0.1338)
temp $>$ 30°C	0.0810*	0.2283***	0.2122***	0.4429**
	(0.0426)	(0.0209)	(0.0318)	(0.1971)
Dep. variable mean	0.0033	0.0092	0.0098	0.00026
Fit statistics				
Observations	20,580,000	20,580,000	20,580,000	20,580,000
Squared Correlation	0.03019	0.17618	0.05326	0.00212

Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Due to our use of a Poisson model, effects should be interpreted as $e^{\beta} - 1$ percent changes from the mean.

Table S3: Effects on count of incidents by subtype (Poisson model)

Dep. variable:	Derailments	Collisions	Grade crossing incidents	Fires and explosions
precip $\in$ (1,2] mm	0.0804***	-0.0139	-0.0783	0.0494
	(0.0203)	(0.0653)	(0.0525)	(0.1575)
precip $\in$ (2,5] mm	0.1311***	-0.0493	-0.0115	-0.0703
	(0.0176)	(0.0490)	(0.0460)	(0.1337)
precip $\in$ (5,10] mm	0.1718***	0.0377	0.0452	-0.0120
	(0.0282)	(0.0580)	(0.0647)	(0.1452)
precip $\in$ (10,20] mm	0.1900***	0.1407	0.0587	0.0928
	(0.0232)	(0.0863)	(0.0778)	(0.1680)
precip $\in$ (20,50] mm	0.2672***	0.0019	0.2613***	-0.6011*
	(0.0301)	(0.1068)	(0.0913)	(0.3349)
precip $\in$ (50,100] mm	0.3582***	0.8151***	0.3297	0.6241
	(0.1076)	(0.2314)	(0.3326)	(0.5399)
precip $>$ 100 mm	0.7071***	-8.895***	0.6320	-12.15***
	(0.2443)	(0.0303)	(0.7040)	(0.0474)
temp < -15°C	0.4442***	-0.1095	0.5107*	-0.1849
	(0.1154)	(0.2834)	(0.2949)	(0.5109)
temp $\in$ (-15,-12]°C	0.3405***	0.3458	0.0376	-12.73***
	(0.0816)	(0.2185)	(0.2625)	(0.2153)
temp $\in$ (-12,-9]°C	0.3491***	-0.5842***	-0.0115	-0.3772
	(0.0684)	(0.1918)	(0.2286)	(0.5410)
temp $\in$ (-9,-6]°C	0.2489***	-0.1683	0.1597	-0.4166
	(0.0581)	(0.1645)	(0.1366)	(0.3828)
temp $\in$ (-6,-3]°C	0.2829***	-0.1902	0.2606**	0.1376
	(0.0491)	(0.1261)	(0.1206)	(0.3298)
temp $\in$ (-3,0]°C	0.2684***	0.0071	0.1318	-0.1654
	(0.0374)	(0.1094)	(0.1282)	(0.2817)
temp $\in$ (0,3]°C	0.2093***	-0.0941	0.0634	0.0681
	(0.0335)	(0.1172)	(0.0898)	(0.2331)
temp $\in$ (3,6]°C	0.1864***	0.0804	0.0390	0.2606
	(0.0312)	(0.1007)	(0.1024)	(0.2040)
temp $\in$ (6,9]°C	0.0727***	0.0756	-0.0851	0.3027
	(0.0248)	(0.0771)	(0.0769)	(0.1846)
temp $\in$ (9,12]°C	0.0521*	-0.0390	0.0758	0.0226
	(0.0262)	(0.0777)	(0.0611)	(0.1611)
temp $\in$ (15,18]°C	-0.0185	0.0037	0.0187	-0.0549
	(0.0217)	(0.0845)	(0.0669)	(0.1596)
temp $\in$ (18,21]°C	-0.0229	-0.0172	0.0332	0.0465
	(0.0304)	(0.0957)	(0.0715)	(0.1660)
temp $\in$ (21,24]°C	0.0194	0.0537	-0.0028	0.0880
	(0.0319)	(0.1103)	(0.0620)	(0.1968)
temp $\in$ (24,27]°C	0.0605	0.0843	0.0129	-0.0241
	(0.0406)	(0.1118)	(0.0800)	(0.2425)
temp $\in$ (27,30]°C	0.0534	0.1550	0.2123*	0.1336
	(0.0387)	(0.1631)	(0.1102)	(0.2949)
temp $>$ 30°C	0.1460**	-0.2485	0.0883	-0.3953
	(0.0583)	(0.2114)	(0.1343)	(0.4542)
Dep. variable mean	0.0020	0.00036	0.00031	0.000035
Fit statistics				
Observations	20,580,000	20,580,000	20,580,000	20,580,000
Squared Correlation	0.01772	0.00474	0.00175	0.00269

Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Due to our use of a Poisson model, effects should be interpreted as $e^{\beta} - 1$ percent changes from the mean.

Table S4: Change in outcomes per car-mile (linear model, imputed denominator)

Mean car-miles per county–day: 8184					
Dep. variable:	Incident count	Casualty occurrence	Injuries	Deaths	Cost of damage (2022 USD)
precip $\in$ (1,2]	6.58×10^{-8}	-2.18×10^{-9}	8.43×10^{-9}	7.45×10^{-8}	0.0055
	(4.82×10^{-8})	(9.32×10^{-8})	(1.83×10^{-8})	(8.58×10^{-8})	(0.0065)
precip $\in$ (2,5]	2.98×10^{-8}	2.78×10^{-7}	1.51×10^{-8}	3.09×10^{-7}	0.0134**
	(4.26×10^{-8})	(1.98×10^{-7})	(1.87×10^{-8})	(2×10^{-7})	(0.0065)
precip $\in$ (5,10]	$2.09 \times 10^{-7***}$	$8.29 \times 10^{-7**}$	$-2.15 \times 10^{-8**}$	$6.93 \times 10^{-7**}$	0.0160**
	(6.12×10^{-8})	(3.48×10^{-7})	(1.01×10^{-8})	(3.32×10^{-7})	(0.0067)
precip $\in$ (10,20]	$2.74 \times 10^{-7**}$	$7.42 \times 10^{-7*}$	-1.9×10^{-8}	7.19×10^{-7}	0.0271***
	(1.02×10^{-7})	(4.36×10^{-7})	(2.05×10^{-8})	(4.55×10^{-7})	(0.0085)
precip $\in$ (20,50]	$5.52 \times 10^{-7***}$	6.22×10^{-7}	-8.73×10^{-9}	5.42×10^{-7}	0.0617***
	(1.18×10^{-7})	(5.61×10^{-7})	(2.99×10^{-8})	(5.04×10^{-7})	(0.0127)
precip $\in$ (50,100]	$1.2 \times 10^{-6***}$	$2.59 \times 10^{-6*}$	2.29×10^{-9}	2.58×10^{-6}	0.2937***
	(3.87×10^{-7})	(1.54×10^{-6})	(5.91×10^{-8})	(1.61×10^{-6})	(0.0790)
precip > 100 mm	6.79×10^{-7}	2.04×10^{-6}	$-1.61 \times 10^{-7***}$	1.61×10^{-6}	0.6728
	(8.47×10^{-7})	(3×10^{-6})	(3.65×10^{-8})	(2.94×10^{-6})	(0.4081)
temp < -15°C	9.07×10^{-8}	$1.39 \times 10^{-6***}$	7.58×10^{-8}	$1.28 \times 10^{-6***}$	0.0553**
	(9.44×10^{-8})	(4.5×10^{-7})	(8.05×10^{-8})	(4.57×10^{-7})	(0.0233)
temp $\in$ (-15,-12]°C	-4.22×10^{-8}	$9.05 \times 10^{-7**}$	1.74×10^{-7}	$9.73 \times 10^{-7**}$	0.0492*
	(8.17×10^{-8})	(4.19×10^{-7})	(1.34×10^{-7})	(4.64×10^{-7})	(0.0250)
temp $\in$ (-12,-9]°C	1.32×10^{-7}	$1.24 \times 10^{-6***}$	1.14×10^{-8}	$1.19 \times 10^{-6**}$	0.0546***
	(1.1×10^{-7})	(4.07×10^{-7})	(3.13×10^{-8})	(4.51×10^{-7})	(0.0175)
temp $\in$ (-9,-6]°C	$2.54 \times 10^{-7*}$	7.09×10^{-7}	5.1×10^{-8}	7.67×10^{-7}	0.0428*
	(1.27×10^{-7})	(4.85×10^{-7})	(3.23×10^{-8})	(5.27×10^{-7})	(0.0216)
temp $\in$ (-6,-3]°C	$2.45 \times 10^{-7**}$	1.04×10^{-6}	7.98×10^{-9}	8.86×10^{-7}	0.0378***
	(9.53×10^{-8})	(7.02×10^{-7})	(2.85×10^{-8})	(6.67×10^{-7})	(0.0126)
temp $\in$ (-3,0]°C	$2.07 \times 10^{-7**}$	2.74×10^{-7}	1.2×10^{-8}	2.2×10^{-7}	0.0443***
	(8.43×10^{-8})	(3.66×10^{-7})	(2.68×10^{-8})	(4.24×10^{-7})	(0.0162)
temp $\in$ (0,3]°C	$1.83 \times 10^{-7**}$	2.38×10^{-7}	1.91×10^{-8}	2.58×10^{-7}	0.0374***
	(7.6×10^{-8})	(4.5×10^{-7})	(1.88×10^{-8})	(4.57×10^{-7})	(0.0131)
temp $\in$ (3,6]°C	9.76×10^{-8}	-3.13×10^{-7}	$5.66 \times 10^{-8*}$	-2.84×10^{-7}	0.0203*
	(9.4×10^{-8})	(2.8×10^{-7})	(2.85×10^{-8})	(2.37×10^{-7})	(0.0112)
temp $\in$ (6,9]°C	8.22×10^{-8}	-2.23×10^{-7}	2.22×10^{-8}	-2.37×10^{-7}	0.0112
	(7.87×10^{-8})	(2.49×10^{-7})	(2.24×10^{-8})	(2.54×10^{-7})	(0.0112)
temp $\in$ (9,12]°C	$1.67 \times 10^{-7**}$	$-5.01 \times 10^{-7**}$	1.3×10^{-8}	-4.59×10^{-7}	0.0083
	(6.59×10^{-8})	(2.44×10^{-7})	(2.11×10^{-8})	(2.76×10^{-7})	(0.0089)
temp $\in$ (15,18]°C	$1.66 \times 10^{-7**}$	-4.5×10^{-7}	2.32×10^{-8}	-4.3×10^{-7}	0.0061
	(7.34×10^{-8})	(3.33×10^{-7})	(2.25×10^{-8})	(3.04×10^{-7})	(0.0097)
temp $\in$ (18,21]°C	5.11×10^{-8}	-3.25×10^{-7}	-7.87×10^{-9}	-3.23×10^{-7}	0.0083
	(5.84×10^{-8})	(3.81×10^{-7})	(1.58×10^{-8})	(3.61×10^{-7})	(0.0092)
temp $\in$ (21,24]°C	7.4×10^{-8}	-1.77×10^{-7}	1.54×10^{-8}	-8.52×10^{-8}	0.0129
	(5.6×10^{-8})	(3.57×10^{-7})	(2.18×10^{-8})	(3.19×10^{-7})	(0.0086)
temp $\in$ (24,27]°C	$2.34 \times 10^{-7***}$	$5.07 \times 10^{-7*}$	1.2×10^{-8}	$5.56 \times 10^{-7**}$	0.0147
	(6.67×10^{-8})	(2.87×10^{-7})	(2.93×10^{-8})	(2.7×10^{-7})	(0.0106)
temp $\in$ (27,30]°C	$3.12 \times 10^{-7***}$	$1.06 \times 10^{-6**}$	8.2×10^{-8}	$1.08 \times 10^{-6**}$	0.0266
	(1.04×10^{-7})	(4.5×10^{-7})	(5.24×10^{-8})	(4.27×10^{-7})	(0.0189)
temp > 30°C	$5.04 \times 10^{-7***}$	$1.56 \times 10^{-6***}$	9.71×10^{-10}	$1.51 \times 10^{-6***}$	0.0319
	(1.82×10^{-7})	(5.37×10^{-7})	(4.28×10^{-8})	(5.22×10^{-7})	(0.0228)
Dep. variable mean	1.18×10^{-6}	6.29×10^{-6}	6.47×10^{-6}	1.12×10^{-7}	0.129
Fit statistics					
Observations	20,226,070	20,225,000	20,226,608	20,224,971	20,226,070
R^2	0.00405	0.08893	0.00165	0.09050	0.00248
Within R^2	5.26×10^{-6}	5.66×10^{-6}	1.53×10^{-6}	5.38×10^{-6}	6.18×10^{-6}

Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S5: Railway safety incidents at the company-county-day level

	Incidents					
	(1)	(2)	(3)	(4)	(5)	(6)
(,-15)	0.044	0.044	0.007	0.007	0.003	0.003
	(0.029)	(0.029)	(0.014)	(0.014)	(0.010)	(0.010)
[-15,-12)	0.037	0.037	0.019	0.019	0.009	0.009
	(0.027)	(0.027)	(0.015)	(0.015)	(0.010)	(0.010)
[-12,-9)	0.061***	0.061***	0.028**	0.028**	0.012	0.012
	(0.023)	(0.023)	(0.013)	(0.013)	(0.008)	(0.008)
[-9,-6)	0.010	0.010	0.001	0.001	0.002	0.002
	(0.018)	(0.018)	(0.008)	(0.008)	(0.007)	(0.007)
[-6,-3)	.00572	.00572	-.00648	-.00648	-.00154	-.00154
	(.0144)	(.0144)	(.00711)	(.00711)	(.00593)	(.00593)
[-3,0)	.00853	.00853	-.000314	-.000313	.0000871	.000088
	(.0125)	(.0125)	(.00646)	(.00646)	(.00537)	(.00537)
[0,3)	.019*	.019*	.00562	.00562	.00276	.00276
	(.0108)	(.0108)	(.00521)	(.00521)	(.00447)	(.00447)
[3,6)	.00804	.00804	.000719	.000719	.001	.001
	(.00949)	(.00949)	(.00517)	(.00517)	(.00393)	(.00393)
[6,9)	.0133	.0133	.00439	.00439	.0026	.0026
	(.00902)	(.00902)	(.00458)	(.00458)	(.0035)	(.0035)
[9,12)	.00293	.00293	.000312	.000312	-.000835	-.000835
	(.00775)	(.00775)	(.00419)	(.00419)	(.0031)	(.0031)
[15,18)	.00836	.00836	-.00314	-.00314	-.000815	-.000814
	(.0084)	(.0084)	(.00432)	(.00432)	(.00299)	(.00299)
[18,21)	.013	.013	.00181	.00181	.000638	.000638
	(.00873)	(.00873)	(.00428)	(.00428)	(.00325)	(.00325)
[21,24)	.0197**	.0197**	-.0038	-.00379	-.00273	-.00273
	(.00994)	(.00994)	(.00485)	(.00485)	(.00377)	(.00377)
[24,27)	.0246**	.0246**	-.00553	-.00553	-.00338	-.00338
	(.0115)	(.0115)	(.00538)	(.00538)	(.0047)	(.0047)
[27,30)	.0497***	.0497***	.00344	.00344	.00201	.00201
	(.0147)	(.0147)	(.00684)	(.00684)	(.00585)	(.00585)
[30,)	.0669*	.0669*	.0321	.0321	.0125	.0126
	(.035)	(.035)	(.022)	(.022)	(.0195)	(.0195)
Precipitation	.00127***	.00127***	.000307*	.000307*	.000312*	.000312*
	(.000328)	(.000328)	(.000168)	(.000168)	(.000167)	(.000167)
#Freight cars			11.6***	11.6***	11.6***	11.6***
			(.113)	(.113)	(.316)	(.316)
#Freight × (,-15)					.387	.386
					(.802)	(.802)
#Freight × [-15,-12)					1.14	1.14
					(.965)	(.964)
#Freight × [-12,-9)					1.67*	1.67*
					(.924)	(.924)
#Freight × [-9,-6)					-.178	-.179
					(.562)	(.562)
#Freight × [-6,-3)					-.578	-.578
					(.492)	(.492)
#Freight × [-3,0)					-.0389	-.0389
					(.444)	(.444)
#Freight × [0,3)					.368	.368
					(.447)	(.447)
#Freight × [3,6)					-.0269	-.027
					(.427)	(.427)
#Freight × [6,9)					.237	.237

					(.44)	(.44)
#Freight × [9,12)					.159	.159
					(.404)	(.404)
#Freight × [15,18)					-.273	-.273
					(.409)	(.409)
#Freight × [18,21)					.152	.152
					(.359)	(.359)
#Freight × [21,24)					-.109	-.109
					(.421)	(.421)
#Freight × [24,27)					-.216	-.216
					(.387)	(.387)
#Freight × [27,30)					.204	.204
					(.432)	(.432)
#Freight × [30,)					1.74	1.74
					(1.1)	(1.1)
Observations	40038705	40038705	40038705	40038705	40038705	40038705
R-square	0.001	0.001	0.748	0.748	0.749	0.749
Y-mean	0.123	0.123	0.123	0.123	0.123	0.123
Y-std.dev.	11.487	11.487	11.487	11.487	11.487	11.487
FEs	State-year, county-month, day of week					
Company FEs		Y		Y		Y

Notes: Outcome variables are multiplied by 1000. Robust standard errors are clustered at the county level and reported in parentheses.

Table S6: Learning from previous accidents

Dep. variable:	Incident count	Casualty events	Deaths
# incident type last year	-0.0001***	3.6×10^{-6}	0.0003
	(2.86×10^{-5})	(8.57×10^{-6})	(0.0031)
precip $\in$ (1,2] mm	0.0469**	0.0301**	0.0060
	(0.0205)	(0.0114)	(0.0643)
precip $\in$ (2,5] mm	0.0777***	0.0494***	-0.0300
	(0.0164)	(0.0112)	(0.0647)
precip $\in$ (5,10] mm	0.1383***	0.0771***	-0.0754
	(0.0211)	(0.0116)	(0.0637)
precip $\in$ (10,20] mm	0.1643***	0.0724***	-0.1448*
	(0.0207)	(0.0163)	(0.0805)
precip $\in$ (20,50] mm	0.2432***	0.0909***	-0.1963*
	(0.0258)	(0.0209)	(0.1060)
precip $\in$ (50,100] mm	0.6325***	0.1386***	0.0846
	(0.1255)	(0.0463)	(0.2576)
precip $>$ 100 mm	0.4238	-0.0960	-9.156***
	(0.2756)	(0.2642)	(0.0321)
temp < -15°C	0.3794***	0.3467***	0.8401***
	(0.0662)	(0.0562)	(0.2274)
temp $\in$ (-15,-12]°C	0.2645***	0.3016***	0.4874*
	(0.0596)	(0.0509)	(0.2624)
temp $\in$ (-12,-9]°C	0.1828***	0.2626***	0.2920
	(0.0494)	(0.0323)	(0.2758)
temp $\in$ (-9,-6]°C	0.1780***	0.1757***	0.3642**
	(0.0414)	(0.0246)	(0.1773)
temp $\in$ (-6,-3]°C	0.1552***	0.1633***	0.2469
	(0.0324)	(0.0184)	(0.1630)
temp $\in$ (-3,0]°C	0.1426***	0.1079***	0.1385
	(0.0267)	(0.0193)	(0.1784)
temp $\in$ (0,3]°C	0.1060***	0.0189	0.2164
	(0.0260)	(0.0140)	(0.1437)
temp $\in$ (3,6]°C	0.1188***	-0.0172	0.3527***
	(0.0260)	(0.0150)	(0.1019)
temp $\in$ (6,9]°C	0.0277	-0.0336*	0.1758
	(0.0220)	(0.0183)	(0.1165)
temp $\in$ (9,12]°C	0.0106	0.0056	0.1029
	(0.0210)	(0.0094)	(0.1120)
temp $\in$ (15,18]°C	-0.0070	0.0319***	0.1959***
	(0.0185)	(0.0112)	(0.0604)
temp $\in$ (18,21]°C	-0.0047	0.0475***	0.0180
	(0.0276)	(0.0139)	(0.0649)
temp $\in$ (21,24]°C	0.0175	0.0776***	0.2043**
	(0.0279)	(0.0137)	(0.0847)
temp $\in$ (24,27]°C	0.0518	0.1090***	0.3052***
	(0.0343)	(0.0142)	(0.0953)
temp $\in$ (27,30]°C	0.1047**	0.1956***	0.3955***
	(0.0427)	(0.0170)	(0.1204)
temp $>$ 30°C	0.0774*	0.2583***	0.3621
	(0.0458)	(0.0217)	(0.2169)
FEs	Year, county-month, day of week		
Fit statistics			
Observations	20,580,000	20,580,000	20,580,000
Squared Correlation	0.02928	0.16765	0.00095

Clustered (state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Due to our use of a Poisson model, effects should be interpreted as $e^{\beta} - 1$ percent changes from the mean.

Table S7: Nonlinear impact of temperature on on-time performance (°C)

	Cancellation dummy	Depart delay dummy	Depart delay time (min)	Service disruption dummy
(,-20)	16.934***	462.942***	51.185***	159.485***
	(3.436)	(72.577)	(6.791)	(38.968)
[-20,-15)	10.517***	291.334***	29.767***	48.343***
	(2.568)	(48.037)	(5.358)	(10.956)
[-15,-10)	16.479***	229.234***	17.444***	44.299***
	(3.659)	(25.913)	(1.530)	(4.256)
[-10,-5)	23.588***	145.230***	9.398***	30.887***
	(4.153)	(18.241)	(0.981)	(3.038)
[-5,0)	12.5***	67.8***	4.37***	16.9***
	(2.72)	(11.7)	(.643)	(2.33)
[0,5)	4.42***	13.9***	1.3***	2.24
	(1.35)	(4.62)	(.319)	(2.11)
[5,10)	.648	1.14	.595*	1.09
	(.401)	(3.32)	(.3)	(1.25)
[10,15)	0	0	0	0
	(.)	(.)	(.)	(.)
[15,20)	.83*	6.58**	.199	.823
	(.442)	(2.6)	(.15)	(1.04)
[20,25)	1.6	22.1***	1.05***	4.39***
	(.98)	(3.47)	(.252)	(1.51)
[25,30)	-.115	48***	2.43***	6.98***
	(.895)	(5.5)	(.421)	(1.6)
[30,)	1.17	114***	7.3***	28.2***
	(.754)	(22.4)	(1.69)	(6.93)
Precipitation	.346***	2.86***	.137***	1.46***
	(.0453)	(.167)	(.012)	(.174)
Observations	88827	88827	88511	88827
R-square	0.066	0.421	0.219	0.060
Y-mean	6.089	179.392	8.192	23.285
Y-std.dev.	40.171	173.844	10.082	74.306
DOW FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Station-month FEs	Y	Y	Y	Y

Notes: Cancellation dummy, departure delay dummy and service disruption dummy are multiplied by 1000. Standard errors are clustered at the train station level, reported in parentheses.