Weather adaptation by U.S. railways and its externality*

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Abstract

Railway operation is affected by the weather. We quantify these effects using U.S. railway accident and delay data spanning 1997–2022. Exposure to temperature over 86°F leads to a 9.5% increase in accidents and a 57% increase in deaths. Operators, though, adapt to the local climate (with warmer places exhibiting lower damage from heat), learn from prior accidents, and change train speed and throughput in response to weather. Due to the fixed, network nature of railways, local responses to weather result in a negative externality of propagating delays. Our findings suggest a role for public funding to upgrade critical infrastructure.

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1 Introduction

Environmental conditions can present risks to economic systems (Hsiang et al., 2023; Aguilar-Gomez et al., 2022). Individuals facing these risks often engage in potentially costly behavioral changes to adapt to and attenuate these risks (Barreca et al., 2016; Kahn, 2016; Park et al., 2020; Randazzo et al., 2023; Zivin and Neidell, 2009; Deschenes et al., 2017; Zhang and Mu, 2018). These adaptations can be individually rational, but also have the potential to generate social costs, such as in the case of an individual operating an air conditioner in response to heat exposure. In cases where the costs and benefits of adaptation decisions are not solely private, the optimal overall level of adaptation, from the perspective of society, may be relatively higher or lower than the sum of individually optimal adaptation choices; this dynamic can also affect the preferred form of adaptation policy.

In this paper, we focus on adaptation to weather risks by the U.S. railway system. 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 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. We also test whether train operators learn from earlier accidents, possibly by adopting precautionary measures which lead to later reductions in accident rates, and whether operators change train speeds and throughput in response to weather shocks. Finally, we explore whether the networked structure of rail leads local adaptation decisions to propagate through space—an negative externality of adaptation.

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 industrialization and the western expansion of trade networks. Following a period of strict regulation from the 1880s to 1980, railroads have been largely deregulated. 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; similarly, intercity passenger rail service is almost entirely provided by a single company, often on track shared with freight service. Still, by 2017, the U.S. rail system comprised over 140,000 miles of track that supported the annual 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 is a key concern of remaining 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 affects rail operations. We are motivated by four observations: operators understand that weather affects rail safety, weather is predictable on short horizons, operators are able to mitigate weather risks in response to these predictions, and decisions of one rail operator—due to the fixed, network structure of the rail system—may affect other operators. 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). Ex-

[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 (Bru, 2014).

treme 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, if the U.S. torts and regulatory systems do not lead railroads to fully internalize the social costs of rail safety incidents, economic intuition suggests that operators would mitigate weather-related risks less intensively than the social optimum because 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 and legal liability, rail operators would choose a level of weather risk mitigation that weighs these predictable costs against multiple risk mitigation options: canceling or slowing 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.

Finally, the fixed, network structure of the rail system means that individual operator's choices affect not only the operation of their train but also the operation of nearby trains. As a result, a system of regulation and torts liability that leads operators to fully internalize the social cost of accidents would nonetheless lead operators to engage in too much risk mitigation from the perspective of society: individually rational decisions to slow trains in response to weather risks have knock-on effects on nearby trains, leading to more delays in aggregate than if each train operator was affected only by their own choices.

Our results contribute to our understanding of weather risks and adaptation in three ways. First, we provide a plausibly causal quantification of the effect of weather exposure on rail-

[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.

way 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 a setting in which local, private weather adaptation decisions have nonlocal, external effects. Adaptation is a necessary response to climate change and other environmental risks, and can often be justified on the basis of its private benefits, though these privately rational decisions are not often considered to entail external costs. When private adaptation results in external costs, arguments for the collective mitigation of risks gain force, though these external costs are often unobservable. Our setting, which is characterized by a fixed, known network structure, provides a unique opportunity to observe these dynamics.

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, deaths, speed, and delays

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.

Delay and speed information are unavailable for freight rail, though we are able to obtain this data for passenger rail service. The Amtrak Track-A-Train service[3] displays real-time data on train speed, which is scraped and aggregated by Intercity Rail Map[4]. For each train, these data contain train number, coordinates, heading direction, and speed at a minimum period of 10 minutes for 689 different Amtrak routes, not each of which operates each day. We summarize speed at the county–day level to match our temperature observations. We also obtain data

[3]Data is available at https://www.amtrak.com/track-your-train.html
[4]Data is available at https://asm.transitdocs.com/

on passenger rail delays by scraping the Amtrak Timetable Archives[5], which we summarize as average delay in minutes at the station–day level for all train stations ($N = 547$) over the period 2014 to 2022 (a total of 11.3 million departure records). The locations of all train stations are presented in Figure S7.

2.3 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

[5]Data is available at www.juckins.net/amtrak_timetables/archive/home.php

the number of injuries per car-mile).

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

3 Weather and railway incidents

3.1 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:

$$y_{it} = \exp(\sum_{m=1}^{M} \beta_m temp_bin_{it}^m + \sum_{n=1}^{N} \beta_n precip_bin_{it}^n + \gamma_{it})\varepsilon_{it} \tag{1}$$

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.

The outcome of interest is y_{it}, 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 state level, which accounts for potential auto-correlation over time and across counties within a state.

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).

Our identification relies on the assumption that percent deviations from average risk in a county–month when the temperature is different from the local mean are uncorrelated with un-

observed factors. Temperature fluctuations relative to a seasonal mean are random, and train schedules are decided in advance. Under the assumption of zero behavioral change, β is then the causal effect of temperature on railway events—namely, the percent deviation from average accident risk resulting temperature and precipitation exposure. In Section 4.5, we present evidence that the quantity of rail cars traversing a county is related to weather, introducing a downward bias into our main results.

3.2 Results

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 Eq. (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.

3.2.1 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 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 S3). We attribute the largely similar point estimates to two offsetting effects: the winsorization procedure we describe above likely reduces the magnitude of our estimates, but accounting for the operational changes we document in Figure S5 likely increases them. We also find that our rate-based model exhibits larger standard errors. We attribute this to 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.

3.3 Heterogeneity by train type

In Table S4, 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.

3.4 Heterogeneity by accident type

We separately estimate the temperature impact on different types of equipment incidents in Table S5. 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.

3.5 Heterogeneity by climate

We separately estimate Eq. 1 for counties with different climates.[6] 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

[6]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.

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:

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

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 Eq. 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.

In Table S7, 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 potential behavioral response lies in train delays. Railway operators may take extra time before train departure and arrival to avoid accident risks.[7] 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 2022. Locations, temperature, and daily number of trains are shown in Figure S8. We merge train delays with departing airports' daily temperature and precipitation and estimate Eq. 1.

In Table S8, 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 S9 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. The fixed, networked nature of railways motivates an interest in the impact of nonlocal weather: in rigid networks, disruptions can propagate, such that local delays caused by random weather variation can be outweighed by the effects of nonlocal random weather variation. In Section 5, we investigate the extent to which delays are caused by non-local weather.

[7] 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.

In Figure S6, 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. We model the tradeoff faced by railway operators between safety and speed, and the corresponding principal-agent problem in Section 6.

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.

On the right-hand side, $Tempbin_{it}^{k}$, $Prec_{it}$, γ_{it} and λ_t are the same variables as those in Eq. 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 S6 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.

4.5 Reduced throughput

In Figure S5, we demonstrate that temperature fluctuations affect the quantity of rail cars transiting a county on a given day. This may be evidence of a behavioral channel (on hot and cold days, rail operators choose to lower network speeds or shorten trains, leading to a reduction

in shipment volume), a productivity channel (on hot and cold days, fewer shipments are contracted), or may reflect knock-on effects of safety incidents or equipment failures on the rail network. These effects may also reflect reallocation of shipments in response to weather forecasts. We cannot differentiate between these channels, but nonetheless note that any sensitivity of county–day throughput to ambient temperature likely leads to a downward bias in our main estimates (our use of a Poisson model for Eq. 1 implicitly assumes that exposure intensity, conditional on fixed effects, is constant across county–days, yet we have shown here that it is systematically lower on hot and cold days).

5 Network externality of adaptation

Rail operations rely on a fixed, known network and thus are particularly well suited to studying how the effects of weather shocks propagate through space. In this section, we study how weather at distant but network-connected stations affects departure delays.

We construct a panel of train on-time performance by generalizing the spatial first difference approach of Druckenmiller and Hsiang (2018) and Taylor and Schlenker (2021) to a networked setting with spillovers. We begin by deriving anomalies by factoring out county station–year fixed effects for outcomes and weather information to account for station-level unobservables varying across years:

$$v_{it} = \alpha_{it} + \epsilon_{it}$$

Here, $v_{it} \in \{y_{it}, \mathbf{T}_{it}, \mathbf{P}_{it}\}$, where y_{it} is the delay in minutes, $\mathbf{T}_{it}$ a matrix of the basis functions for a natural cubic spline in temperature with two internal knots at the 25^{th} and 75^{th} percentiles, and $\mathbf{P}_{it}$ is a matrix of indicator variables for levels of daily precipitation with breaks at 1, 2, 5, 10, 20, 50, 100 mm. We focus on anomalies $\epsilon_{it}^{(v)}$. By the Frisch-Waugh-Lovell theorem, a regression of $\epsilon_{it}^{(y)}$ on $\epsilon_{it}^{(\mathbf{T})}$ and $\epsilon_{it}^{(\mathbf{P})}$ is equivalent to a fixed effects regression of y_{it} on $\{\mathbf{T}_{it}, \mathbf{P}_{it}, \alpha_{it}\}$.

We then determine the maximum number of non-repetitive 25-station paths (p) originating at each station and take the difference between $\epsilon_{ipt}^{(v)}$ and $\epsilon_{i-1,pt}^{(v)}$, which we label $\Delta_{ipt}^{(v)}$. We also take differences in $\epsilon_{ipt}^{(\mathbf{T})}$ and $\epsilon_{ipt}^{(\mathbf{P})}$ between all neighbor pairs along each path and include these in our estimation to account for potential spatial spillovers. To aid presentation, we introduce a spatial lag operator $L_{ip}(\cdot)$, which is a function defined relative to a position i and path p that

outputs a matrix of the input covariate at adjacent points, $[i-1, i-25]$, along path p. Our empirical approach is then:

$$\Delta_{ipt}^{(y)} = \Delta_{ipt}^{(\mathbf{T})}\beta + \Delta_{ipt}^{(L(\mathbf{T}))}\gamma + \Delta_{ipt}^{(\mathbf{P})}\delta + \Delta_{ipt}^{(L(\mathbf{P}))}\zeta + \eta_{ipt}$$

where the parameter of interest, β, is a vector of coefficients describing nonlinear spline relationship between a quasi-random temperature shock at station i and the outcome y_{it}. This is shown in Figure 4. The cumulative effect of that shock as it propagates through the rail network is shown in Figure 5.

Comparing results for same-station effects and cumulative network effects reveals that when the entire rail network experiences a day with average temperatures of 30°C, local conditions result in local delays of 2.65 minutes, but nonlocal conditions result in an additional 14.18 minutes of local delay. In other words, the networked structure of the rail network increases the effect of local adaptation on overall delays by 535%. Comparing these results to the network-naive model in Section 4.4, we find that the estimated effect of a local 30°C temperature shock on local delays is smaller, but its total propagated effect across the network is larger.

6 Stylized model

In this section, we propose a conceptual framework to show railway operators' tradeoff between speed and safety by choosing an optimal speed. Slow speeds lead to more cautious driving and accident avoidance but result in poorer on-time performance and thus potential revenue loss. An externality arises if operators do not consider the accident costs borne by surrounding residents due to injuries or pollutants released from damaged trains. This results in operators choosing a speed higher than that which would lead to a socially optimal level of safety.

Weather shocks affect both privately and socially optimal speeds. Railway operators privately bear at least some costs of accidents and thus rationally have a lower private optimal speed when weather—which we call, heuristically, "heat"—is risky. Weather-dependent speed regulations, such as slow orders, can lead to a closer match between privately and socially optimal speeds.

In a connected railway network, local adaptation can also result in non-local externalities, slowing down trains in nearby areas. We show that in this context, the socially optimal speed—considering both externalities and the entire country—is higher than the socially optimal speed

that only considers only the externality of accidents themselves. In Appendix Section S1, we present another externality between railway operators and drivers using a principal-agent model.

6.1 Model setup

We start with a local train operator's profit-maximizing problem. The market for providing passenger or freight service is competitive with homogeneous firms. Each company is operating at the production frontier, and the technology of production and safety is fixed in the short run.

A company's profit includes several parts. Revenue R is a function of speed s, with penalties for delays, possibly due to passengers' dissatisfaction or the late arrival of time-sensitive goods. The cost of operation is assumed to be exogenous, as fuel costs vary little with speed given the same running distance. Additional costs arise if accidents lead to extra expenditures and penalties, as companies may have to pay for repairs and compensation for employees' injuries. Railway operators' profit maximization problem can be specified as:

$$\max_{0 \le s \le \bar{s}} \pi = R(s) - C - P^A(s) \cdot C^A$$

where s is bounded between zero and the highest possible speed $\bar{s}$; revenue $R(s)$ is an increasing function of s due to late penalties; C represents the operational cost; C^A refers to the expenditure for each accident event; and P^A is the probability of experiencing an accident, which increases with s since higher speeds typically result in greater stopping distances and thus higher risks. We further assume P^A is a convex function of s, as the marginal safety loss due to high speed increases more sharply at higher speeds. The privately optimal speed s_1^* chosen by railway operators is given by taking first-order condition:

$$s_1^* : \quad \frac{\partial R(s)}{\partial s} - C^A \cdot \frac{\partial P^A(s)}{\partial s} = 0$$

Railway safety has a positive externality on surrounding residents near railways, whose welfare we specify as:

$$V \cdot [1 - P^A(s)]$$

where V is the value of statistical life. This welfare captures the value gained by avoiding an

accident. With these two parties, social welfare and social optimal speed s_2^* could be shown as:

$$W = R(s) - C - P^A(s) \cdot C^A + V \cdot [1 - P^A(s)]$$

$$s_2^* : \quad \frac{\partial R(s)}{\partial s} - (C^A + V) \cdot \frac{\partial P^A(s)}{\partial s} = 0$$

If we assume a linear late penalty (i.e., $R(s)$ is a linear function of s), the socially optimal speed s_2^* is smaller than the private optimum s_1^*. This is consistent with the observed fact that rail companies may prioritize economic revenue over safety, resulting in more accidents than the socially optimal level. We could specify functional forms for $R(s)$ and $P^A(s)$, and solve for optimal speeds s_1^* and s_2^* to better illustrate their differences:

$$R(s) = R_0 - A \cdot (\bar{s} - s); \quad P^A(s) = P_0 + \frac{1}{2} a \cdot s^2$$

$$s_1^* = \frac{A}{C^A \cdot a}$$

$$s_2^* = \frac{A}{(C^A + V) \cdot a}$$

6.2 Weather shocks

We detect an increase in accident risks due to hot and cold weather even with the same level of speed, with larger effects for heat exposure. This suggests an increase in parameter a during heat stress (i.e., $a^H > a$). Optimal speed levels should therefore be slower than before:

$$s_1^{*H} = \frac{A}{C^A \cdot a^H} < s_1^*$$

$$s_2^{*H} = \frac{A}{(C^A + V) \cdot a^H} < s_2^*$$

This aligns with our empirical findings. Railway companies adjust to hot weather by choosing slower speeds. Additionally, railway management departments issue slow orders to regulate speeds and prevent additional accidents on hot days.

6.3 Network externality

One unique aspect of railways is their networked nature. Local adaptation to hot weather leads to network delays in non-local areas. This negative externality results in revenue loss for non-

local railway operators. The socially optimal speed s_2^* may no longer be optimal and is too low due to the network spillovers. To incorporate this second externality, we instead assume a connected railway network with J counties. Each company's profit depends not only on its own speed but also on the speeds of the connected counties' rail operators. The new profit maximization problem is as follows:

$$\max_{0\leq s_i\leq \bar{s}} \pi = R(s_i) - \sum_{j=1}^{J} D_i(s_j)\cdot 1(j\neq i) - C - P^A(s)\cdot C^A$$

where s_i is the local speed, s_j is the non-local speed operated by railway companies in county j, $D_i(s_j)$ is i's delay affected by s_j and is a decreasing function (i.e., $\frac{D_i(s_j)}{s_j}<0$). The local effect $D_i(s_i)$ is incorporated in the revenue function $R(s_i)$. The newly added network externality does not affect the private optimal speed (i.e., $\frac{D_i(s_j)}{s_i}=0$), and the company still chooses s_1^*.

The updated social welfare function taking residents and railway operators in all counties together is shown as:

$$W = \sum_{i=1}^{J}[R(s_i) - \sum_{j=1}^{J\setminus i} D_i(s_j) - C - P^A(s)\cdot C^A]$$

The socially optimal speed s_3^* should satisfy:

$$s_3^*: \quad \frac{\partial R(s_i)}{\partial s_i} - \sum_{j\neq i}\frac{\partial D_j(s_i)}{\partial s_i} - (C^A+V)\cdot\frac{\partial P^A(s_i)}{\partial s_i} = 0$$

The second term incorporates all non-local externalities generated by local speed s_i. As D decreases with s, the new social optimum s_3^* should be higher than s_2^*, namely:

$$s_3^* = \frac{A - \sum_{j\neq i}\frac{\partial D_j(s_i)}{\partial s_i}}{(C^A+V)\cdot a} > s_2^* = \frac{A}{(C^A+V)\cdot a}$$

This suggests that speed regulation to s_2 to avoid accidents may result in a speed that is too low if we ignore the network externality. Moreover, depending on the parameter values, the equilibrium outcome without government intervention s_1 may be closer to the social optimum s_3^* compared with the regulated scenario.

One alternative policy is infrastructure upgrades and better coordination among counties. This will lead to a smaller absolute value of $\frac{D_i(s_j)}{s_j}$. As a result, s_3^* and s_2^* would be closer, allowing the first-best accident regulation to reach the social optimum. Forcing operators to fully internalize accident costs may result in too much delay relative to a social optimum.

7 Discussion and 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. 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. From the perspective of society, then, rail operations may be underresponding to weather risks.

At the same time, local adaptation decisions appear to have external costs via the propagation of network delays. Depending on the value of time and resources affected by these delays, railroads may in fact be over-responding to weather risks from the perspective of society, even despite the fact that they may not be paying the full social cost of accidents. The tension between the negative local externalities of specific safety incidents and the negative nonlocal externalities of behavioral changes to adapt to weather risks suggests a role for publicly coordinated risk reduction: by mitigating risks—through, for example, investment in rail infrastructure upgrades that reduce system vulnerability to weather shocks—both categories of social harm can be reduced. This argument gains force in the context of climate change, which will reallocate weather exposure, decreasing safety of the rail system due to the fixed nature of its embedded adaptation.

References

(2014). *Rail Temperature Prediction Model as a Tool to Issue Advance Heat Slow Orders*.

Aguilar-Gomez, S., H. Dwyer, J. Graff Zivin, and M. Neidell (2022). This is air: The "non-health" effects of air pollution. *Annual Review of Resource Economics 14*(1), 403–425.

Ashenfelter, O. and M. Greenstone (2004). Using mandated speed limits to measure the value of a statistical life. *Journal of Political Economy 112*(S1), S226–S267.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy 124*(1), 105–159.

Bureau of Transportation Statistics (2021a). Freight shipments by mode.

Bureau of Transportation Statistics (2021b). U.S. passenger-kilometers.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, J. Rising, A. Rode, H. K. Seo, A. Viaene, J. Yuan, and A. T. Zhang (2022, 04). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits*. *The Quarterly Journal of Economics 137*(4), 2037–2105.

Chen, J. and J. Roth (2022). Logs with zeros? Some problems and solutions. Publisher: arXiv Version Number: 7.

Chinowsky, P., J. Helman, S. Gulati, J. Neumann, and J. Martinich (2019, March). Impacts of climate change on operation of the US rail network. *Transport Policy 75*, 183–191.

Department of Transportation (2015). Hazardous materials: Enhanced tank car standards and operational controls for high-hazard flammable trains.

Deryugina, T. and S. M. Hsiang (2014, December). Does the environment still matter? daily temperature and income in the united states. (20750).

Deschenes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics 3*(4), 152–185.

Deschenes, O., M. Greenstone, and J. S. Shapiro (2017). Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review 107*(10), 2958–2989.

Druckenmiller, H. and S. Hsiang (2018). Accounting for unobservable heterogeneity in cross section using spatial first differences. Technical report, National Bureau of Economic Research.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics 8*, 43–75.

Hsiang, S., S. Greenhill, J. Martinich, M. Grasso, R. M. Schuster, L. Barrage, D. B. Diaz, H. Hong, C. Kousky, T. Phan, M. C. Sarofim, W. Schlenker, B. Simon, and S. E. Sneeringer (2023). *Economics*, Book section 19. Washington, DC, USA: U.S. Global Change Research Program.

Kahn, M. E. (2016). The climate change adaptation literature. *Review of Environmental Economics and Policy 10*(1), 166–178.

Kyriakidis, M., R. Hirsch, and A. Majumdar (2012). Metro railway safety: An analysis of accident precursors. *Safety Science 50*(7), 1535–1548.

Leard, B. and K. Roth (2015). Weather, traffic accidents, and climate change. *Resources For the Future Discussion Paper* (15-19).

Leon, G. and E. Miguel (2017, January). Risky transportation choices and the value of a statistical life. *American Economic Journal: Applied Economics 9*(1), 202–28.

Liu, X., M. R. Saat, and C. P. L. Barkan (2012, January). Analysis of Causes of Major Train Derailment and Their Effect on Accident Rates. *Transportation Research Record: Journal of the Transportation Research Board 2289*(1), 154–163.

Murphy, J. (2018, January). Lac-Megantic: The runaway train that destroyed a town. *BBC News*.

Neumann, J. E., P. Chinowsky, J. Helman, M. Black, C. Fant, K. Strzepek, and J. Martinich (2021, August). Climate effects on US infrastructure: the economics of adaptation for rail, roads, and coastal development. *Climatic Change 167*(3-4), 44.

Office of the Federal Register (2018). Removal of electronically controlled pneumatic brake system requirements for high hazard flammable unit trains.

Palmer, C. S., B. J. Gabbe, and P. A. Cameron (2016, January). Defining major trauma using the 2008 Abbreviated Injury Scale. *Injury 47*(1), 109–115.

Park, R. J., J. Goodman, M. Hurwitz, and J. Smith (2020). Heat and learning. *American Economic Journal: Economic Policy 12*(2), 306–39.

Randazzo, T., F. Pavanello, and E. De Cian (2023). Adaptation to climate change: Air-conditioning and the role of remittances. *Journal of Environmental Economics and Management 120*, 102818.

Rossetti, M. A. (2003). Potential Impacts of Climate Change on Railroads. Washington, D.C.

Rossetti, M. A. (2007). Analysis of Weather Events on U.S. Railroads.

Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management 98*, 102250.

Spicer, R. M. and T. R. Miller (2010). Final Report to the National Highway Traffic Safety Administration: Uncertainty Analysis of Quality Adjusted Life Years Lost.

Taylor, C. A. and W. Schlenker (2021). Environmental drivers of agricultural productivity growth: Co2 fertilization of us field crops. Technical report, National Bureau of Economic Research.

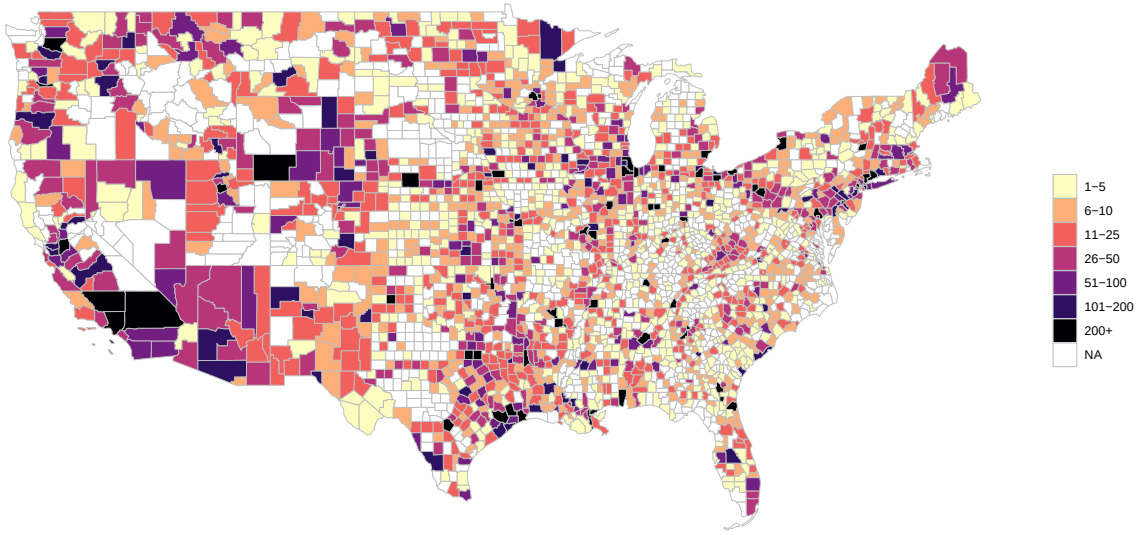
U.S. Railroad Retirement Board (2021). Railroad retirement survivor benefits.

Xia, Y., J. N. V. Ommeren, P. Rietveld, and W. Verhagen (2013). Railway infrastructure disturbances and train operator performance: The role of weather. *Transportation Research Part D 18*, 97–102.

Zhang, J. and Q. Mu (2018). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management 92*, 517–536.

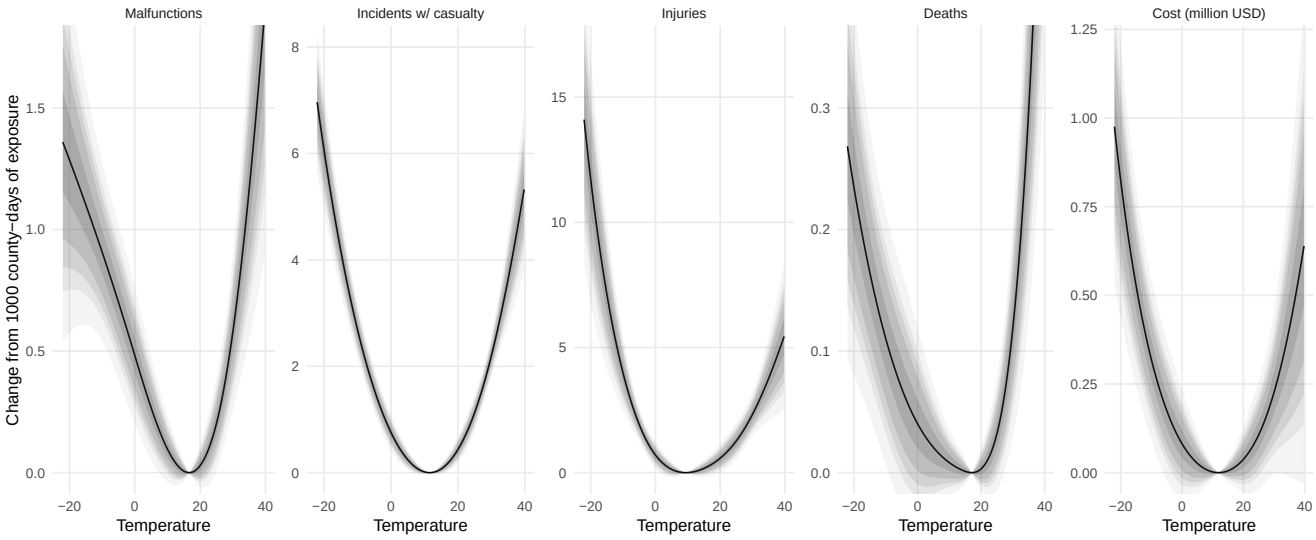
Zivin, J. G. and M. Neidell (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management 58*(2), 119–128.

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



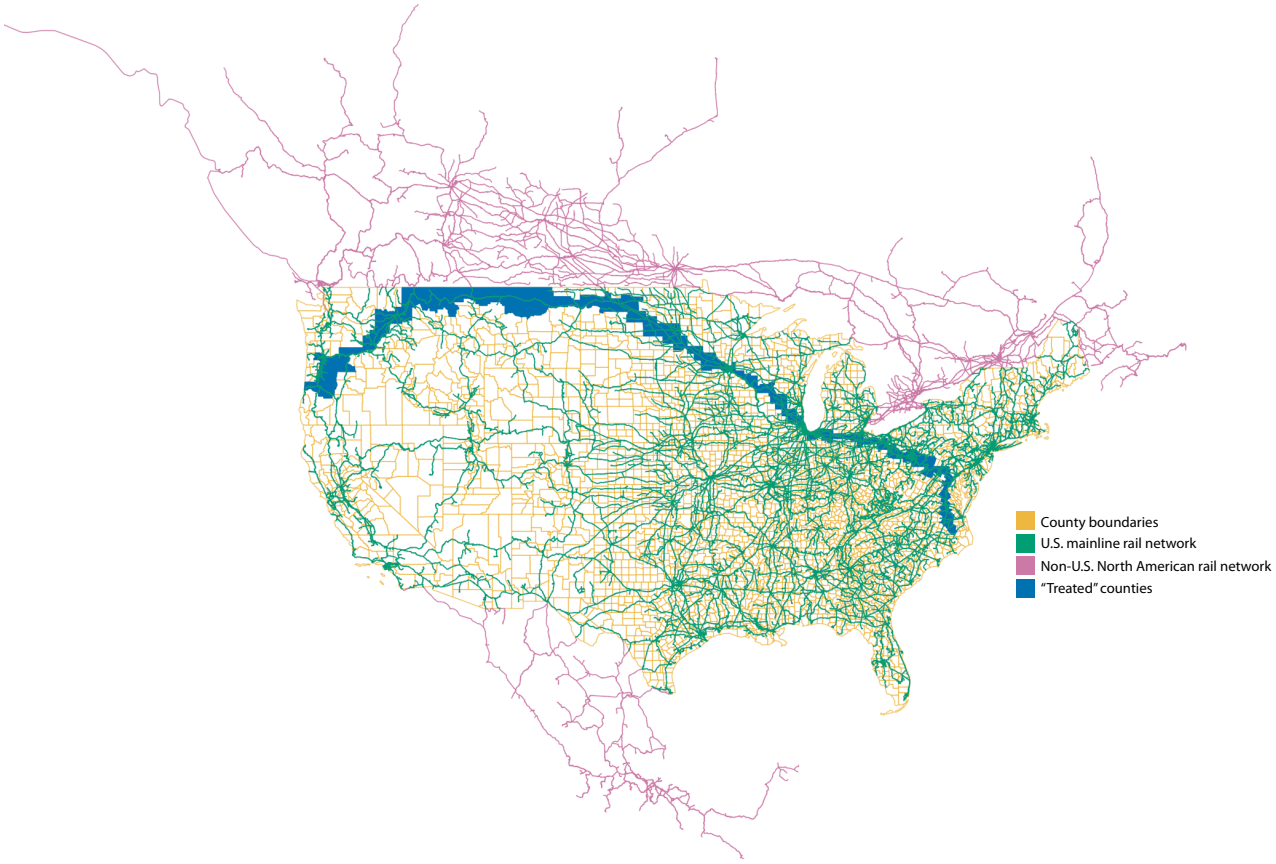
Notes: This figure depicts the total number of rail accidents at the county level between 1997 and 2019. Counties with no recorded accidents are shown in white.

Figure 2: Temperature and railway accidents



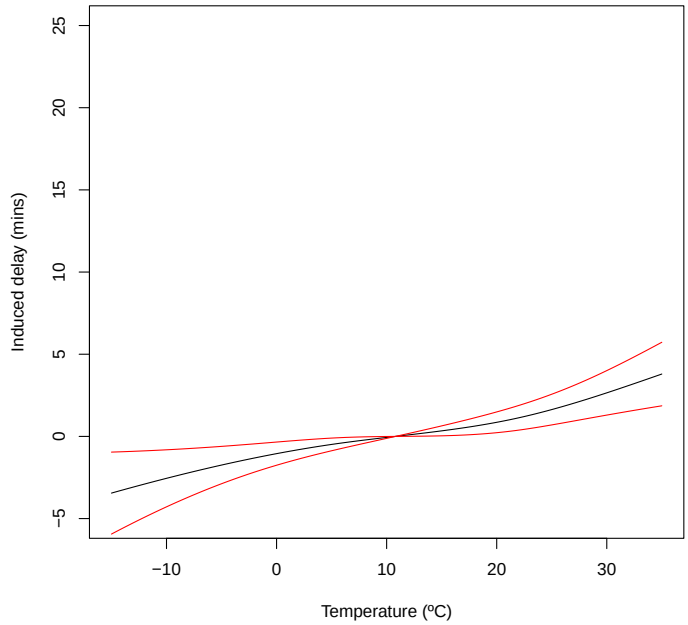
Notes: The estimated relationships between daily average temperature four outcomes: the number of incidents/accidents, the number of incidents/accidents leading to a casualty, the number of injuries, and the number of deaths. Note that the y-axis scales differ and that the values shown are for 1000 county–days 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 Eq. 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



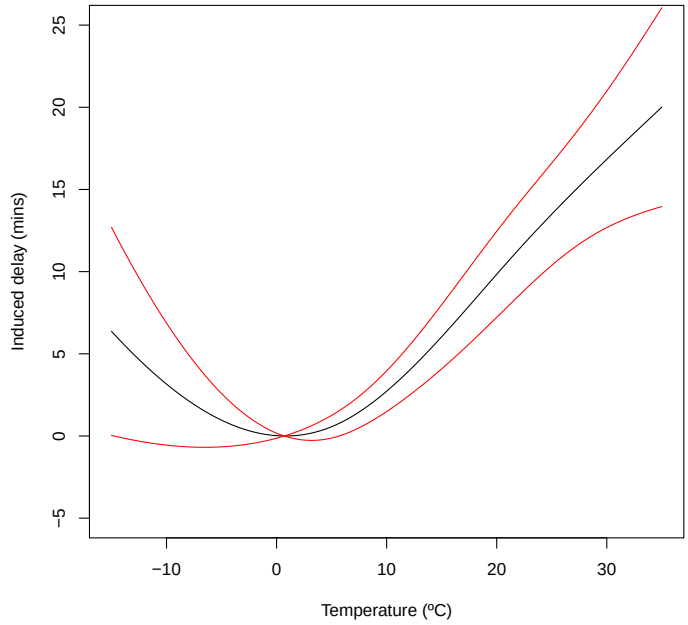
Notes: This diagram depicts the North American rail network used to route waybills for the portion of our analysis that relies on an imputed measure of train exposure intensity. The U.S. portion of the North American rail network used for waybill routing is depicted in green. A sample route as determined 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.

Figure 4: Same-station delay, spatial first differences approach



Notes: The effect of a single-station temperature shock on the delay of trains at that station alone. The relationship is estimated using a spatial first differences research design and is net of annual, station-specific disturbances.

Figure 5: Cumulative network delay, spatial first differences approach



Notes: The cumulative, nonlinear effect of a single-station temperature shock on the delay of trains at 25 adjacent stations. The relationship is estimated using a spatial first differences research design and is net of annual, station-specific disturbances.

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

Dep. variable:	Incident count	Casualty occurrence	Injuries	Deaths
precip $\in$ (1,2] mm	0.0413*	0.0288**	0.0347	0.0088
	(0.0210)	(0.0107)	(0.0233)	(0.0639)
precip $\in$ (2,5] mm	0.0731***	0.0477***	0.0355***	-0.0053
	(0.0166)	(0.0108)	(0.0119)	(0.0587)
precip $\in$ (5,10] mm	0.1305***	0.0744***	0.0761***	-0.0926
	(0.0209)	(0.0111)	(0.0124)	(0.0608)
precip $\in$ (10,20] mm	0.1567***	0.0708***	0.0691***	-0.1226
	(0.0207)	(0.0154)	(0.0203)	(0.0767)
precip $\in$ (20,50] mm	0.2363***	0.0852***	0.0727***	-0.1627
	(0.0251)	(0.0222)	(0.0262)	(0.1089)
precip $\in$ (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 $\in$ (-15,-12]°C	0.2375***	0.3205***	0.2967***	0.4489*
	(0.0550)	(0.0463)	(0.0564)	(0.2477)
temp $\in$ (-12,-9]°C	0.1650***	0.2707***	0.2419***	0.3595
	(0.0478)	(0.0335)	(0.0649)	(0.2561)
temp $\in$ (-9,-6]°C	0.1635***	0.1864***	0.1662***	0.3979**
	(0.0438)	(0.0251)	(0.0402)	(0.1650)
temp $\in$ (-6,-3]°C	0.1548***	0.1710***	0.1611***	0.2568
	(0.0322)	(0.0182)	(0.0371)	(0.1649)
temp $\in$ (-3,0]°C	0.1433***	0.1113***	0.1183***	0.1446
	(0.0255)	(0.0195)	(0.0393)	(0.1655)
temp $\in$ (0,3]°C	0.1059***	0.0208	0.0094	0.1857
	(0.0282)	(0.0158)	(0.0223)	(0.1342)
temp $\in$ (3,6]°C	0.1183***	-0.0106	-0.0011	0.3228***
	(0.0258)	(0.0154)	(0.0316)	(0.1006)
temp $\in$ (6,9]°C	0.0238	-0.0294	-0.0457*	0.1533
	(0.0201)	(0.0178)	(0.0237)	(0.1122)
temp $\in$ (9,12]°C	0.0108	0.0072	-0.0026	0.0840
	(0.0211)	(0.0105)	(0.0148)	(0.1079)
temp $\in$ (15,18]°C	-0.0054	0.0178	0.0504*	0.1473**
	(0.0178)	(0.0120)	(0.0287)	(0.0619)
temp $\in$ (18,21]°C	0.0006	0.0355***	0.0278	0.0017
	(0.0260)	(0.0129)	(0.0195)	(0.0706)
temp $\in$ (21,24]°C	0.0211	0.0569***	0.0658***	0.1727**
	(0.0253)	(0.0142)	(0.0241)	(0.0820)
temp $\in$ (24,27]°C	0.0582*	0.0864***	0.0831***	0.2602**
	(0.0326)	(0.0144)	(0.0237)	(0.1048)
temp $\in$ (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.

For Online Publication

S1 Principal-agent model

In this section, we propose a principal-agent model to show the tradeoff between speed and safety. Train operators care about economic revenue that decreases with delays. They design employment contracts and penalize drivers' delays. Though drivers care about safety, due to the income loss, their optimal efforts of safe driving are low. Then we introduce temperature as an exogenous shock to increase accident risk and delay and show heat stress makes safety efforts even lower.

S1.1 Model setup

A principal – railway company operator – employs an agent to drive the train. Each freight train carries products that generate economic revenue. Train delays decrease revenue due to the production disruption of downstream producers or negative feelings of product consumers. The agent's actions are to choose the efforts of safe driving. Efforts determine the probability of delay. Specifically, more efforts are allocated to safety, speeds are lower, and trains are more likely to delay. More efforts decrease accident risks and increase the agent's expected utility due to the survival of driving. The agent's efforts are not observable, but the delay outcomes are. The principal designs the wage contract and penalizes delay.

The principal's problem is to design an employment contract $w(d)$ so as to maximize his profit:

$$\max_{w(d)} \ \pi = R(d) - w(d) - P^A(e) \times C^A$$

where $w(d)$ is the employment contract that penalizes delay, i.e. $\frac{\partial w(d)}{\partial d} < 0$. Revenue of freight transport, $R(d)$, also decreases with d. $P^A(e)$ denotes the probability of having a railway accident and decreases with drivers' safety efforts e. C^A is the company's penalty for having an accident. In the U.S., the average death compensation is \$2,333 per month for the beneficiaries due to the lost income (U.S. Railroad Retirement Board, 2021).

The agent's problem is to choose an optimal level of safe-driving efforts to maximize his utility:

$$\max_{e} \; U = \max\{w(d) + [1 - P^A(e)] \times V, \bar{u}\}$$

where V is the agent's value of statistical life (VSL). Existing evidence shows the VSL is around \$1-2 million (Ashenfelter and Greenstone, 2004; Leon and Miguel, 2017). $\bar{u}$ is the agent's outside option. In summary, the principal's optimization problem is to choose an incentive scheme $w(d)$ so as to maximize his profit subject to the agent's incentive constraint and participation constraint.

S1.2 Optimal contract

We specify the functional forms as follows:

$$R(d) = \bar{R} - L \cdot d; \quad w(d) = \beta_1 - \beta_2 \cdot d;$$

$$d(e) = \alpha \cdot e; \quad P^A(e) = \theta - \sqrt{e}$$

The agent's utility maximization problem is to choose e under a given contract β_1 and β_2. It could be solved using the first-order approach:

$$\max_{e} \; U = \max\{w(d) + [1 - P^A(e)] \times V, \bar{u}\}$$

$$= \max\{\beta_1 - \beta_2 \cdot \alpha \cdot e + (1 - \theta + \sqrt{e}) \times V, \bar{u}\}$$

$$\frac{\partial}{\partial e}[\beta_1 - \beta_2 \cdot \alpha \cdot e + (1 - \theta + \sqrt{e}) \times V] = -\alpha\beta_2 + \frac{V}{2\sqrt{e}}$$

$$\Rightarrow e^* = \frac{V^2}{4\alpha^2\beta_2^2}$$

The optimal level of efforts increases with V if the agent care more about his life. It decreases with α, the production function of delay as safety efforts increase, and decreases with β_2 due to the wage penalization for delays.

The principal's optimization is to choose contract (β_1, β_2) given the agent's optimal effort (e^*):

$$\max_{\beta_1, \beta_2} \; \pi = R[d(e^*)] - w[d(e^*)] - P^A(e^*) \times C^A$$

$$= \bar{R} - L \cdot \frac{V^2}{4\alpha\beta_2^2} - \beta_1 + \beta_2 \cdot \frac{V^2}{4\alpha\beta_2^2} - \theta \cdot C^A + \frac{V \cdot C^A}{2\alpha\beta_2}$$

$$\frac{\partial}{\partial\beta_2}[\bar{R} - L\cdot\frac{V^2}{4\alpha\beta_2^2} - \beta_1 + \beta_2\cdot\frac{V^2}{4\alpha\beta_2^2} - \theta\cdot C^A + \frac{V\cdot C^A}{2\alpha\beta_2}]$$

$$= \frac{\partial}{\partial\beta_2}[-\frac{VL}{\beta_2^2} + \frac{V}{\beta_2} + \frac{2C^A}{\beta_2}]$$

$$\Rightarrow \beta_2^* = \frac{2VL}{V+2C^A}$$

$$\beta_1^* \geq \bar{u} - (1-\theta)\cdot V - \frac{V(V+2C)}{8\alpha L}$$

Under this contract, other parameters could be solved as follows:

$$e^* = \frac{(V+2C^A)^2}{16\alpha^2L^2};\quad P^{A*} = \theta - \frac{V+2C^A}{4\alpha L};\quad d^* = \frac{(V+2C^A)^2}{16\alpha L^2}$$

Consistent with intuition, wage penalization β_2 increases with L – railway companies' revenue loss due to delay – and decreases with C^A – accident penalty. In the U.S., C^A is small due to insufficient safety regulation and low employee protection. This results in a big β_2^*. Companies tend to design a contract to encourage high speed. The contract further incentivizes small e^* and risky driving behaviors. Besides, C^A also ignores external costs of accidents, like the cost on surrounding residents due to hazardous materials' release. This further leads to an even higher β_2^* and smaller e^*.

S1.3 Heat stress

Hot weather worsens accident risks and delays. It serves as an exogenous shock that increases α and θ. As a result, there are more accidents, delays, and lower safety efforts:

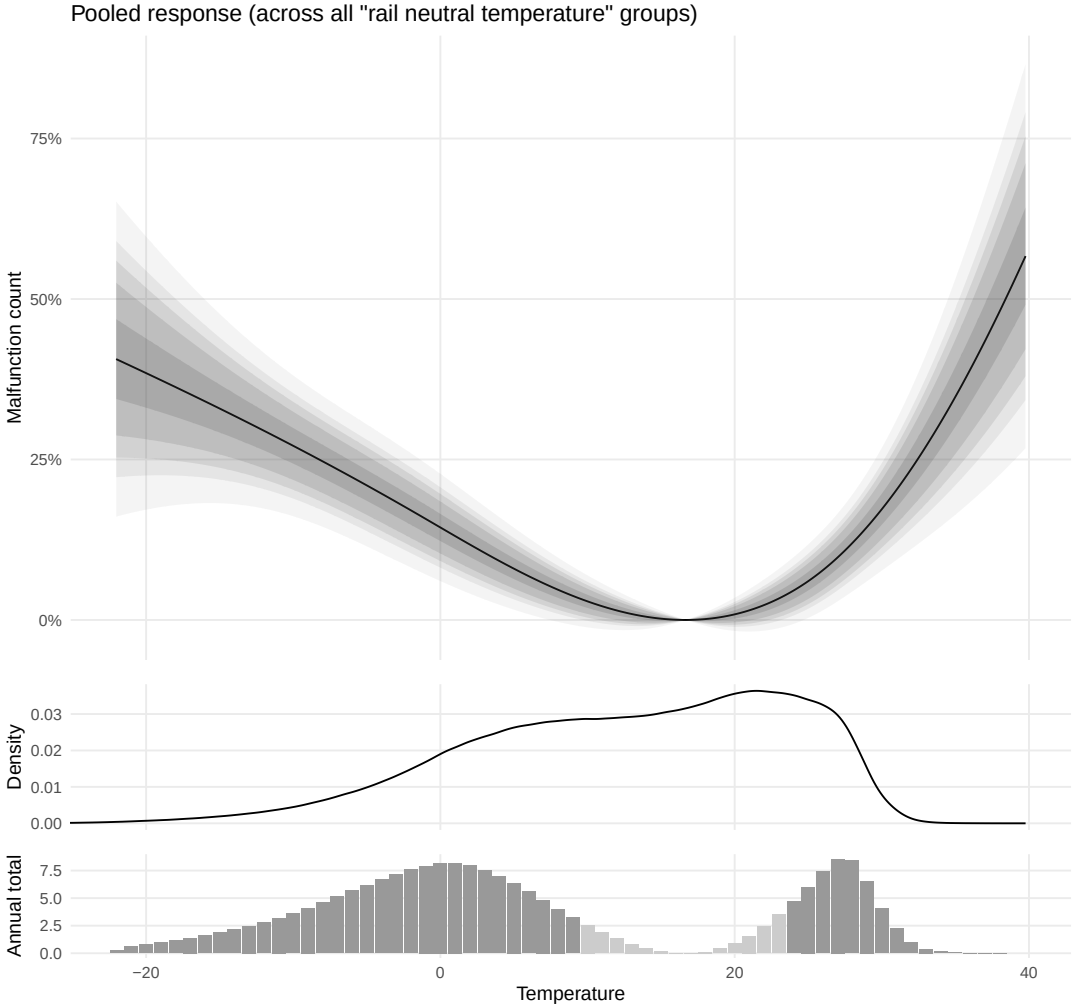
$$d(e) = \alpha\cdot e;\quad P^A(e) = \theta - \sqrt{e}$$

$$e^* = \frac{(V+2C^A)^2}{16\alpha^2L^2};\quad P^{A*} = \theta - \frac{V+2C^A}{4\alpha L};\quad d^* = \frac{(V+2C^A)^2}{16\alpha L^2}$$

The increase in accidents comes from two channels: the direct level increase due to hot weather, and the indirect increase due to lower safety efforts chosen by the driver. However, the optimal contract and β_2 are not affected by weather. Even observing more heat-induced accidents, companies would not automatically correct wage contracts. Therefore, government interventions are needed to internalize accident externality, correct C^A, incentivize firms' contracts and drivers' safe driving, so as to lower railway accidents.

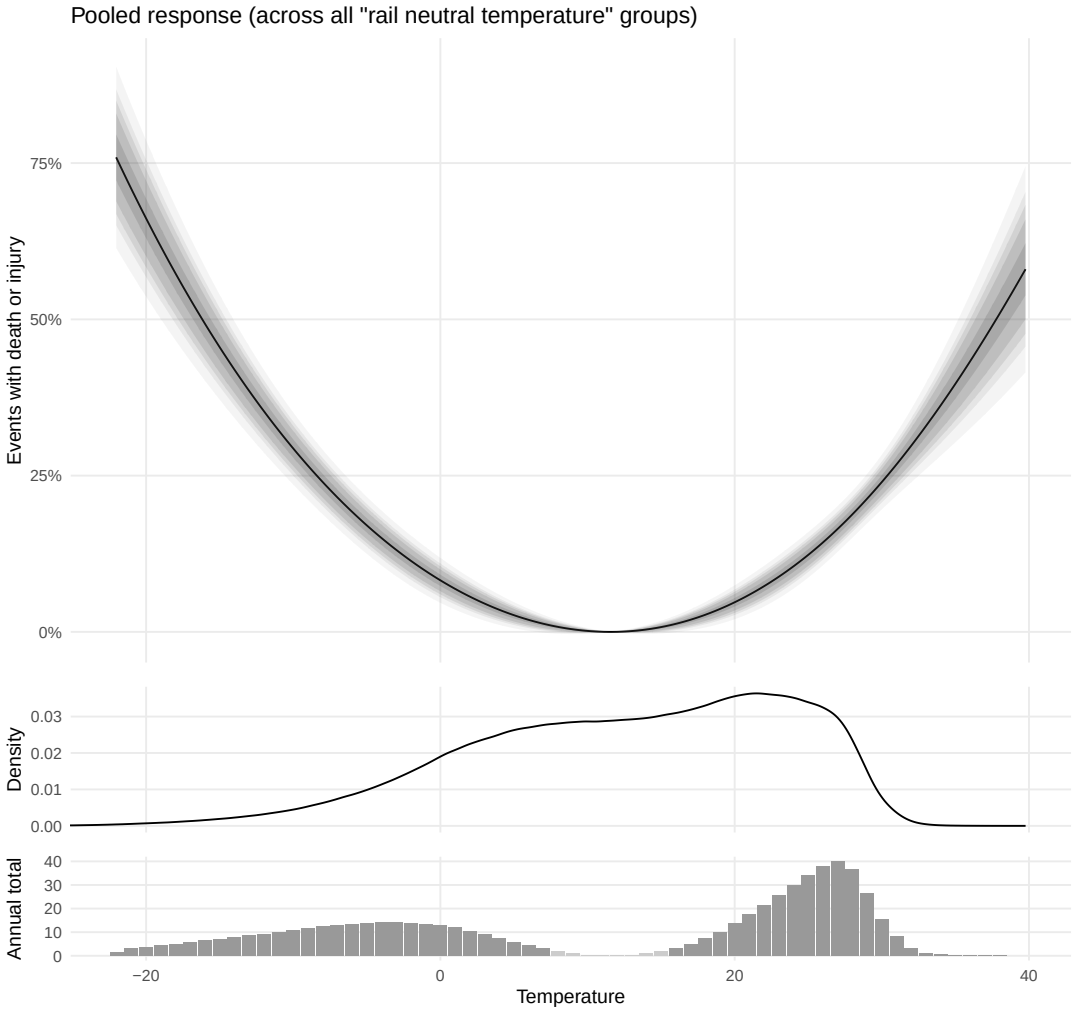
S2 Additional Figures

Figure S1: Temperature and railway accidents, malfunction



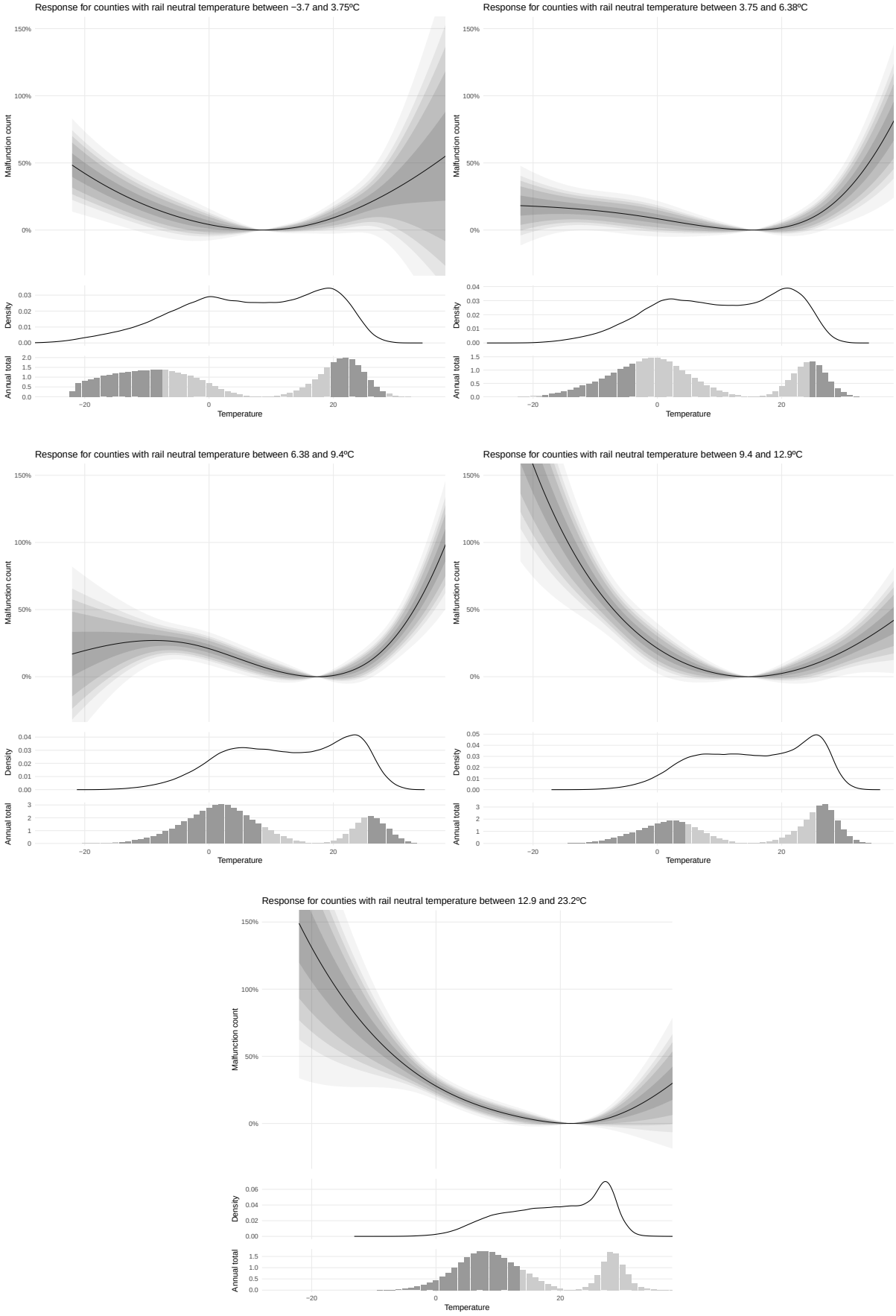
Notes: The top panel depicts the estimated relationship between daily average temperature and the count of safety incidents (one incident may lead to multiple casualties, deaths, etc.). The middle panel depicts the distribution of historical temperatures across all county–days. The bottom panel bins 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 Eq. 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



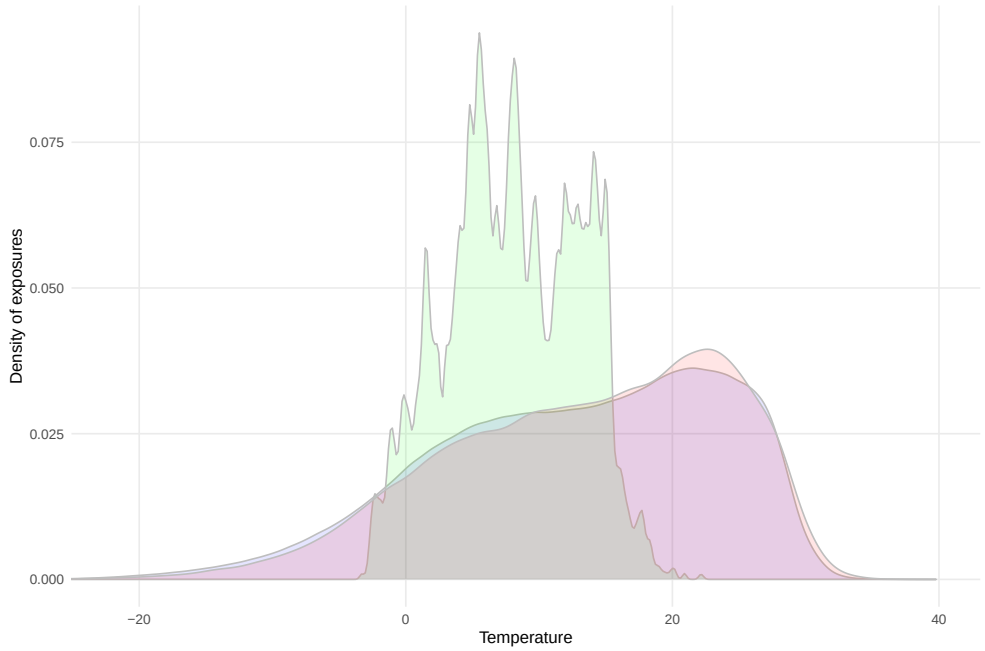
Notes: The top panel depicts the estimated relationship between daily average temperature and the count of casualties. The middle panel depicts the distribution of historical temperatures across all county–days. The bottom panel bins the middle panel by year and multiplies it by the top panel, resulting 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 Eq. 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



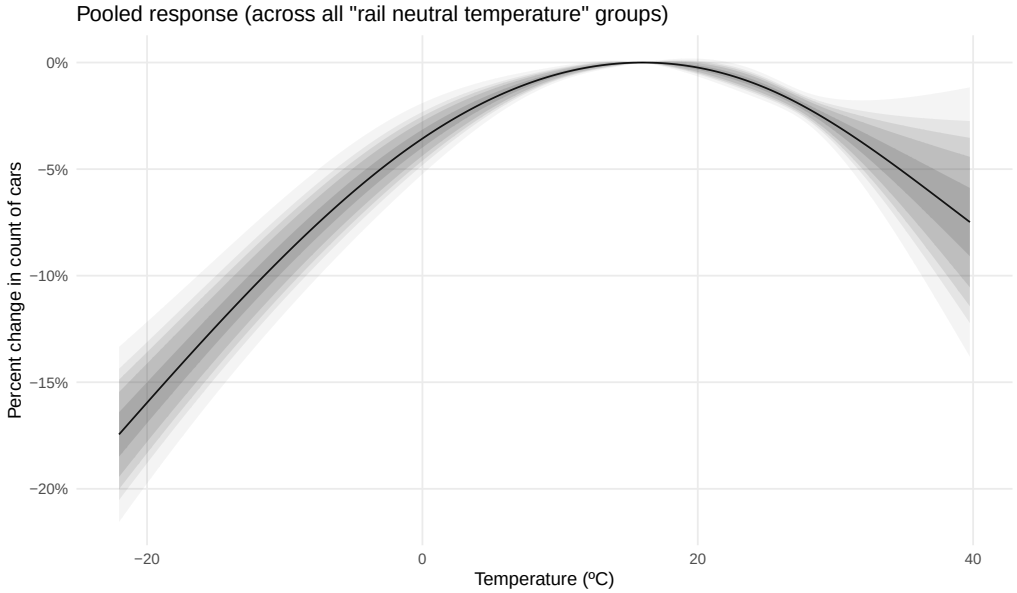
Notes: Rail neutral temperature is defined as the mean of a county's 1^{st} and 99^{th} percentile temperatures.

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



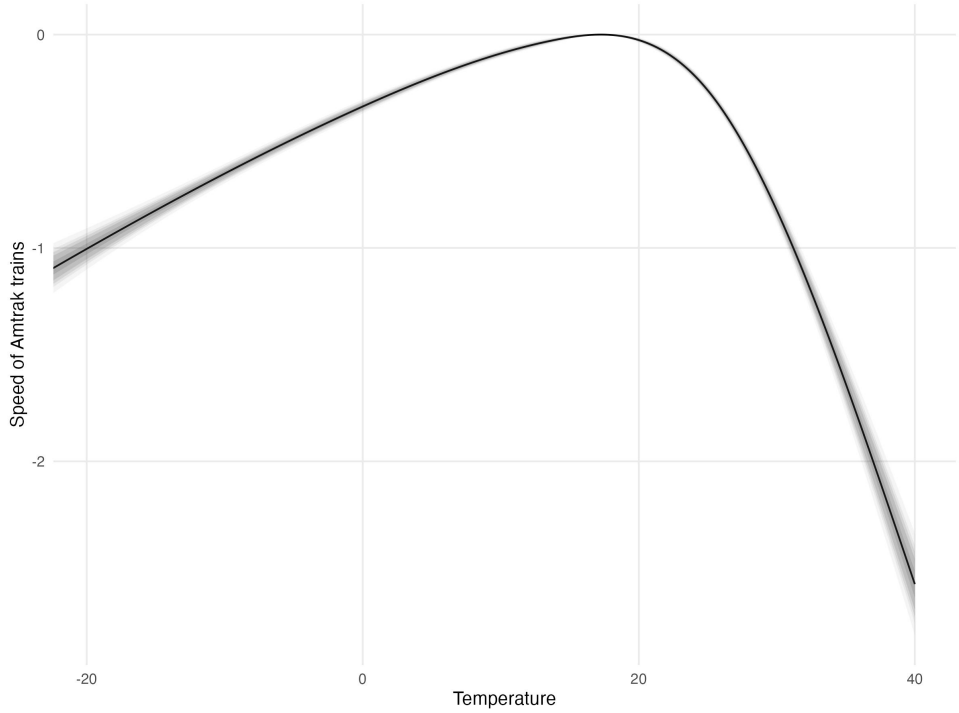
Notes: The density of historical temperature exposures. The blue kernel density estimate depicts the historical density of daily average temperature exposures. The green kernel density estimate depicts the distribution of annual rail neutral temperatures by county (the mean of annual maximum and minimum 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: Rail car count and ambient temperature



Notes: The estimated relationship between the inferred number of rail cars transiting a county on a given day and the county's average temperature on that day. 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 S6: 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 S7: Locations of all Amtrak train stations in the U.S.

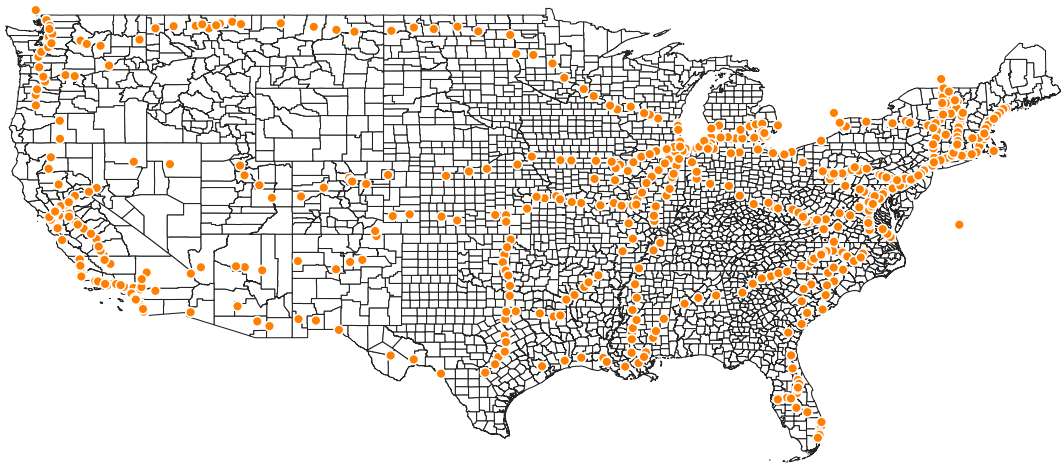
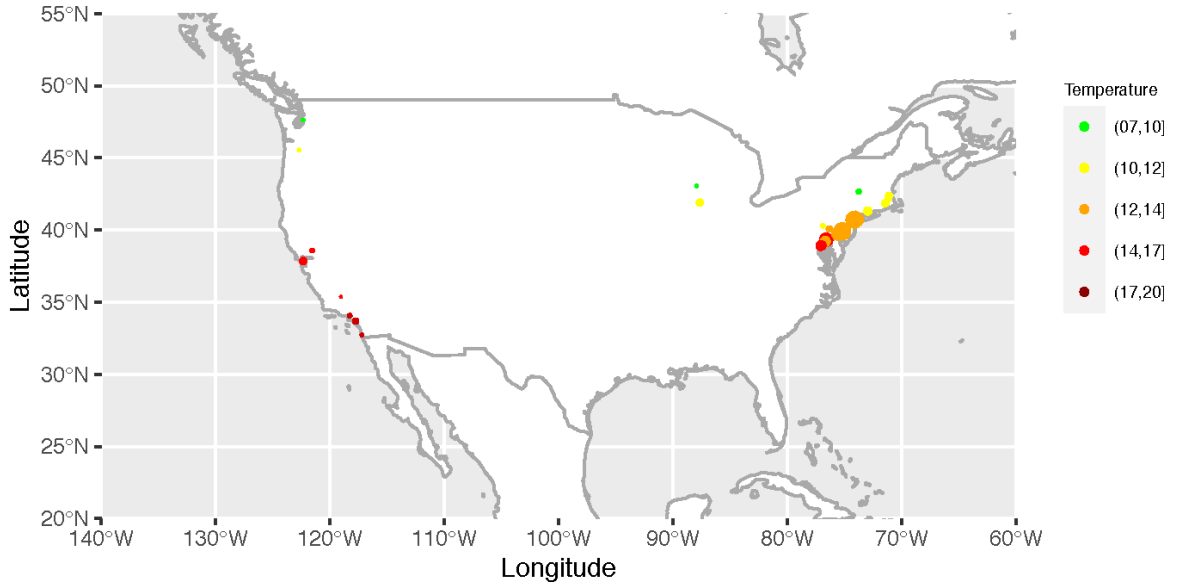
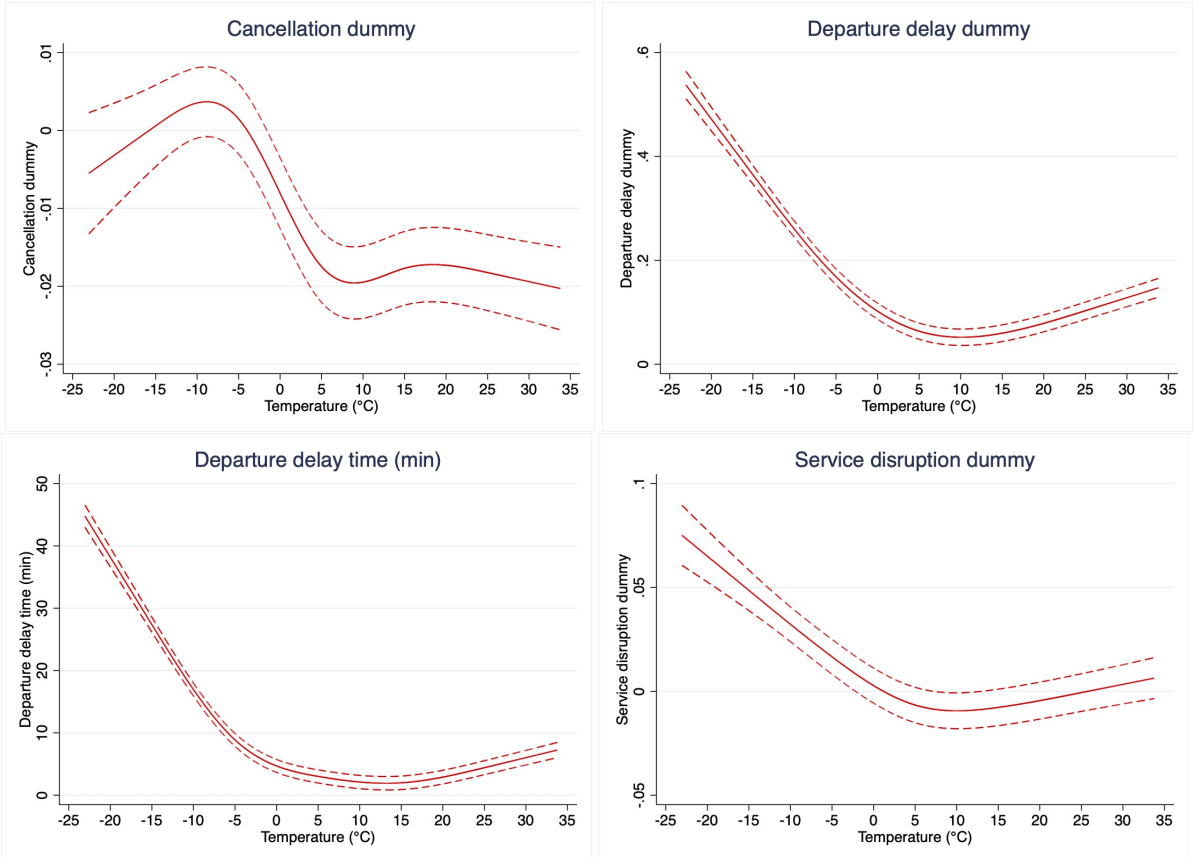


Figure S8: Locations of 25 large train stations in the U.S.



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 S9: 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.

S3 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	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: 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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (-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 ∈ (-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 ∈ (-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 ∈ (-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 ∈ (-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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 ∈ (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 S4: 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.

Table S5: 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 S6: Railway safety incidents at the company-county-day level

	Incident count					
temp $< -15°$C	0.044	0.044	0.007	0.007	0.003	0.003
	(0.029)	(0.029)	(0.014)	(0.014)	(0.010)	(0.010)
temp $\in$ [-15,-12)°C	0.037	0.037	0.019	0.019	0.009	0.009
	(0.027)	(0.027)	(0.015)	(0.015)	(0.010)	(0.010)
temp $\in$ [-12,-9)°C	0.061***	0.061***	0.028**	0.028**	0.012	0.012
	(0.023)	(0.023)	(0.013)	(0.013)	(0.008)	(0.008)
temp $\in$ [-9,-6)°C	0.010	0.010	0.001	0.001	0.002	0.002
	(0.018)	(0.018)	(0.008)	(0.008)	(0.007)	(0.007)
temp $\in$ [-6,-3)°C	.00572	.00572	-.00648	-.00648	-.00154	-.00154
	(.0144)	(.0144)	(.00711)	(.00711)	(.00593)	(.00593)
temp $\in$ [-3,0)°C	.00853	.00853	-.000314	-.000313	.0000871	.000088
	(.0125)	(.0125)	(.00646)	(.00646)	(.00537)	(.00537)
temp $\in$ [0,3)°C	.019*	.019*	.00562	.00562	.00276	.00276
	(.0108)	(.0108)	(.00521)	(.00521)	(.00447)	(.00447)
temp $\in$ [3,6)°C	.00804	.00804	.000719	.000719	.001	.001
	(.00949)	(.00949)	(.00517)	(.00517)	(.00393)	(.00393)
temp $\in$ [6,9)°C	.0133	.0133	.00439	.00439	.0026	.0026
	(.00902)	(.00902)	(.00458)	(.00458)	(.0035)	(.0035)
temp $\in$ [9,12)°C	.00293	.00293	.000312	.000312	-.000835	-.000835
	(.00775)	(.00775)	(.00419)	(.00419)	(.0031)	(.0031)
temp $\in$ [15,18)°C	.00836	.00836	-.00314	-.00314	-.000815	-.000814
	(.0084)	(.0084)	(.00432)	(.00432)	(.00299)	(.00299)
temp $\in$ [18,21)°C	.013	.013	.00181	.00181	.000638	.000638
	(.00873)	(.00873)	(.00428)	(.00428)	(.00325)	(.00325)
temp $\in$ [21,24)°C	.0197**	.0197**	-.0038	-.00379	-.00273	-.00273
	(.00994)	(.00994)	(.00485)	(.00485)	(.00377)	(.00377)
temp $\in$ [24,27)°C	.0246**	.0246**	-.00553	-.00553	-.00338	-.00338
	(.0115)	(.0115)	(.00538)	(.00538)	(.0047)	(.0047)
temp $\in$ [27,30)°C	.0497***	.0497***	.00344	.00344	.00201	.00201
	(.0147)	(.0147)	(.00684)	(.00684)	(.00585)	(.00585)
temp $\geq 30°$C	.0669*	.0669*	.0321	.0321	.0125	.0126
	(.035)	(.035)	(.022)	(.022)	(.0195)	(.0195)
precip	.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 $\times$ temp $< -15°$C					.387	.386
					(.802)	(.802)
#Freight $\times$ temp $\in$ [-15,-12)°C				1.14	1.14	
					(.965)	(.964)
#Freight $\times$ temp $\in$ [-12,-9)°C					1.67*	1.67*
					(.924)	(.924)
#Freight $\times$ temp $\in$ [-9,-6)°C					-.178	-.179
					(.562)	(.562)
#Freight $\times$ temp $\in$ [-6,-3)°C					-.578	-.578
					(.492)	(.492)
#Freight $\times$ temp $\in$ [-3,0)°C					-.0389	-.0389
					(.444)	(.444)

#Freight × temp ∈ [0,3)°C					.368	.368
					(.447)	(.447)
#Freight × temp ∈ [3,6)°C					-.0269	-.027
					(.427)	(.427)
#Freight × temp ∈ [6,9)°C					.237	.237
					(.44)	(.44)
#Freight × temp ∈ [9,12)°C					.159	.159
					(.404)	(.404)
#Freight × temp ∈ [15,18)°C					-.273	-.273
					(.409)	(.409)
#Freight × temp ∈ [18,21)°C					.152	.152
					(.359)	(.359)
#Freight × temp ∈ [21,24)°C					-.109	-.109
					(.421)	(.421)
#Freight × temp ∈ [24,27)°C					-.216	-.216
					(.387)	(.387)
#Freight × temp ∈ [27,30)°C					.204	.204
					(.432)	(.432)
#Freight × temp ≥ 30°C					1.74	1.74
					(1.1)	(1.1)
FEs	State-year, county-month, day-of-week					
Company FEs		Y		Y		Y
Dep. variable mean	0.123	0.123	0.123	0.123	0.123	0.123
Fit statistics						
Observations	40,038,705	40,038,705	40,038,705	40,038,705	40,038,705	40,038,705
Squared Correlation	0.001	0.001	0.748	0.748	0.749	0.749

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

Table S7: 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 S8: Nonlinear impact of temperature on on-time performance (°C)

	Cancellation dummy	Depart delay dummy	Depart delay time (min)	Service disruption dummy
temp < -20°C	16.934***	462.942***	51.185***	159.485***
	(3.436)	(72.577)	(6.791)	(38.968)
temp $\in$ [-20,-15)°C	10.517***	291.334***	29.767***	48.343***
	(2.568)	(48.037)	(5.358)	(10.956)
temp $\in$ [-15,-10)°C	16.479***	229.234***	17.444***	44.299***
	(3.659)	(25.913)	(1.530)	(4.256)
temp $\in$ [-10,-5)°C	23.588***	145.230***	9.398***	30.887***
	(4.153)	(18.241)	(0.981)	(3.038)
temp $\in$ [-5,0)°C	12.5***	67.8***	4.37***	16.9***
	(2.72)	(11.7)	(.643)	(2.33)
temp $\in$ [0,5)°C	4.42***	13.9***	1.3***	2.24
	(1.35)	(4.62)	(.319)	(2.11)
temp $\in$ [5,10)°C	.648	1.14	.595*	1.09
	(.401)	(3.32)	(.3)	(1.25)
temp $\in$ [15,20)°C	.83*	6.58**	.199	.823
	(.442)	(2.6)	(.15)	(1.04)
temp $\in$ [20,25)°C	1.6	22.1***	1.05***	4.39***
	(.98)	(3.47)	(.252)	(1.51)
temp $\in$ [25,30)°C	-.115	48***	2.43***	6.98***
	(.895)	(5.5)	(.421)	(1.6)
temp ≥ 30°C	1.17	114***	7.3***	28.2***
	(.754)	(22.4)	(1.69)	(6.93)
precip	.346***	2.86***	.137***	1.46***
	(.0453)	(.167)	(.012)	(.174)
FEs	Year, station-month, day-of-week			
Dep. variable mean	6.089	179.392	8.192	23.285
Fit statistics				
Observations	88,827	88,827	88,511	88,827
Squared Correlation	0.066	0.421	0.219	0.060

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

Note: Cancellation dummy, departure delay dummy and service disruption dummy are multiplied by 1000.