Paul Stainier has nothing to disclose.

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Worker Incentives and Occupational Safety in Trucking

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Abstract

We provide evidence that truck drivers' incentives moderate the relationship between extreme weather events and truck crashes. Using data on 1.4 million truck accidents across the continental United States, we first show that weather shocks increase crash risk. Cold and rainy weather is especially dangerous: icy conditions increase same day truck accident risk by 118 percent, an effect that is twice as large as that for all-vehicle accidents. We then test the effect of an electronic monitoring mandate, which increased the incentive for unsafe driving, on the ice-crash relationship. Leveraging the fact that several large trucking firms had implemented electronic monitoring prior to the mandate, we estimate a triple-difference model and find that the mandate resulted in a 22 percent higher impact of ice on truck crashes. These findings highlight the importance of considering workers' incentives in designing policies that intend to minimize occupational hazards.

Keywords: Workplace Safety, Worker Incentives, Trucking, Road Safety, Ice
JEL Codes: Q54, J28, R41

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1 Introduction

Occupational safety is an important component of economic welfare, both for workers and for broader society. Workers in the United States experience nearly 3 million injuries and 5,000 fatalities annually, costing an estimated $180 billion to workers, firms, and public institutions (BLS, 2024d, 2025; National Safety Council, 2024). The determinants of occupational safety have therefore attracted long-standing interest in both the economics literature and policy debates.[1] One crucial but understudied factor is how worker behavior, shaped by financial and regulatory incentives, translates risks into realized incidents. The dearth of empirical evidence on this question is due in part to the challenges of disentangling worker behavior from other aspects of occupational safety, such as firms' safety investments or regulatory agencies' actions.

We study this question in the context of trucking by leveraging data on over 1 million truck-involved crashes. This empirical setting offers several advantages for analyzing the influence of workers' incentives on occupational safety. First, truckers face numerous risks while driving, including some that vary exogenously, such as the weather. The weather-accident relationship can provide insight into the pathway from safety risk to realized incident. Second, relative to employees in many other industries, truck drivers have a high degree of control over their responses to such risks.[2] Their responses, such as whether to drive more slowly in wet conditions, are informed by financial and regulatory incentives. For instance, many truckers are paid per shipment which, combined with legal limits on daily driving hours, can incentivize risky behaviors like speeding (Scott et al., 2021). Third, trucking offers a natural experiment that we use to test how changing workers' incentives affects the risk-incident relationship. Specifically, we study how an electronic monitoring device mandate that was binding for some, but not all, truckers, changed the strength of the effect of icy weather conditions on accidents.

[1] For an early example of policy enacted in response to occupational safety hazards, take the founding of the U.S. Bureau of Mines, established in 1910 after a series of mine disasters. Seminal economics research in this space includes several papers from the early 1970s, timing that coincides with the founding of the Occupational Safety and Health Administration (OSHA)(Oi, 1974; Russell, 1974; Smith, 1979; Chelius, 1982).

[2] In a warehouse or on a construction site, for instance, management likely have a larger influence on the effect of weather on workplace incidents. This influence can be through large upfront investments or decisions, such as installing air conditioning or instituting break policies, or due to higher frequency actions such as deciding whether to run the air conditioning or to decide to call for more breaks than is typical.

In addition to these empirical advantages, trucking is a major industry with substantial public safety implications. In the United States, trucks transport 13 million tons of goods per year, constituting over 70 percent of the total value of shipments (BTS, 2024), and over 3 million workers are employed as truck drivers.[3] Truck driving is also a relatively dangerous occupation: it has the sixth highest worker fatality rate in the United States, and an injury rate that is three times higher than the American average (BLS, 2024a,b). As they operate on public roads alongside passenger vehicles, trucks also pose an important public safety externality (Nehiba, 2020). For instance, in 2022, large trucks (over 10,000 pounds) were involved in over 500,000 crashes, resulting in 160,000 nonfatal injuries and nearly 6,000 fatalities (80 percent of whom were not large truck occupants), and costing nearly $140 billion dollars (FMCSA, 2024b).[4] Many of the regulations governing truck driver behavior are designed with the intention of reducing this safety externality (Liang, 2023).

We start by showing that extreme weather events present an important safety risk to trucks and other vehicles on the road. We pair nearly 1.4 million individual crash reports with granular information on temperature and precipitation, and aggregate these data to the county by day level. Our empirical strategy leverages daily within-county weather variation to estimate the effect of weather on truck crash risk. Our key controls include county-month, year-month, and day-of-year fixed effects, as well as state-specific linear trends. We find that a day above 35°C leads to an 18 percent increase in truck crashes and a day with 3cm or more of precipitation leads to a 60 percent increase. A day with both sub-zero average temperature and non-zero precipitation, a weather event we label as "ice," leads to a 118 percent increase in crashes. These coefficients represent the change in crash risk net of any adaptations taken by truck drivers (e.g., driving slowly), trucking firms (e.g., canceling a shipment), other drivers (e.g., staying home), and public agencies (e.g., salting the roads). A back-of-the-envelope calculation suggests that ice-induced truck accidents cost over $1 Billion per year in the United States.

[3]Two million of these workers drive heavy and tractor-trailer trucks (SOC code 53-3032) and 1 million drive light trucks below 26,001 pounds (SOC code 53-3033) (BLS, 2024c).

[4]Truck carriers are required to insure their trucks at a minimum level of $750,000, a level that has not changed since 1985 (Muehlenbachs et al., 2021). There are conflicting estimates of what percentage of accidents are covered by this minimum level of insurance, but it is far below the typical payout for a fatality or severe injury.

Extreme weather leads to a significantly larger increase in truck accidents than all-vehicle (including truck) accidents. Using data from a subsample of states where icy conditions are prevalent, we find that ice increases truck accident risk by twice as much as all-vehicle accident risk (80 vs. 40 percent).

Next, we explicitly consider the role that economic incentives play in shaping truck drivers' responses to risk. Specifically, we study the introduction of an electronic logging device (ELD) mandate in 2017. Drawing upon theory from literatures on illicit behavior and incomplete regulations (Yang, 2008; Fowlie, 2009), we outline how truckers' expected payoff from safe driving practices during inclement weather (e.g., slowing down or taking breaks) decreased under the mandate. In short, the mandate increased the probability of being caught and fined for driving longer than legally allowed, thereby decreasing the expected value of doing so. In contrast, it did not change the expected value of other forms of unsafe driving (e.g., speeding), nor did it change drivers' financial cost of not reaching their daily miles target. Economic theory, supported by anecdotal accounts from truckers, suggests that this would increase the propensity of truckers to drive unsafely, including during hazardous weather conditions (Levy, 2022).

We test the hypothesis that the mandate increased the effect of inclement weather on crashes. We do so by exploiting the fact that several large firms had already implemented the use of ELDs in their truck fleets well before the mandate. Using a triple-difference design, we estimate the change in the difference in the ice-crash relationship after the mandate between these control carriers and the treatment group, defined as for-hire general freight carriers with fewer than 100 trucks. To control for spatial and temporal differences in underlying crash risk between both groups, we interact our core fixed effects from the weather-crash model with group indicators (e.g., we include year-month-group fixed effects). Our regression therefore accounts for any group-specific changes in the baseline determinants of crash risk across time. The key assumption for causality is that, absent the mandate, and net of the fixed effects, the difference in the ice-crash relationship between these two groups would have remained stable over time. We estimate an event study regression that substantiates this assumption, and the results are robust to several alternative empirical specifications. We find that the mandate led to a 22 percent

higher effect of ice on crashes, an increase that represents a 11 percent change relative to the baseline crash risk for the treatment group. While we do not directly observe worker behavior, our findings are consistent with the hypothesis that the mandate resulted in stronger incentives for workers to drive unsafely under risky road conditions.

This paper makes three main contributions. First, we add to the literature on the determinants of workplace safety. Past work has studied the impacts of various factors on occupational injury rates, including workplace regulations and their enforcement (Viscusi, 1979; Levine et al., 2012; Johnson, 2020; Johnson et al., 2023), contracting (Jackson and Quinlan, 2024), safety training (Wilkins, 2011), firms' incentives (Kankaanpää, 2010; Elsler et al., 2010), product demand conditions (Charles et al., 2022), and environmental conditions like extreme heat (Dillender, 2021; Park et al., 2021; Ireland et al., 2023). We provide empirical evidence on the role of workers' economic incentives, an understudied area where research has largely been theoretical or descriptive (Brown et al., 2000; Seo, 2005; Johansson et al., 2010; Man et al., 2017; Belzer and Quinlan, 2024).[5] Specifically, we show that monitoring one of several risky but welfare-enhancing (in expectation) behaviors available to workers leads to increases in alternative forms of risk taking. In this sense, our study is also complementary to past research on temporal illicit behavior displacement in response to periodic and non-random monitoring, including in the case of truck drivers (Zou, 2021; Liang, 2023).

Second, we contribute to the understanding of two important aspects of road safety: weather and truck drivers' economic incentives. There is a well-established link between weather and crash rates (Deschenes and Moretti, 2009; Seeherman and Liu, 2015; Saha et al., 2016; Naik et al., 2016; Leard and Roth, 2019; Anand, 2025), though we provide what is, to the best of our knowledge, the first comprehensive study on the effects of weather on truck crashes in the United States. We also add an empirical test of the incentives that drivers have to (not) respond to the elevated risk posed by weather shocks. This analysis builds upon the body of evidence

[5]One topic that has received some attention is how the presence of workers' compensation benefits alters worker incentives. However, these analyses, which study how injury rates change in the presence of workers' compensation benefits, are unable to separate the effects on worker incentives from the effects on firm incentives (Ruser et al., 2010).

that links crashes to truck drivers' economic motivations, such as their low and piece-rate pay (Thompson and Stevenson, 2014; Belzer and Sedo, 2018), industry deregulation (Belzer, 2000; Viscelli, 2016), and regulations like the ELD mandate (Scott et al., 2021).

Finally, as we leverage climatic shocks as exogenous changes in occupational risk levels for truckers, we also contribute to a climate adaptation literature that has become increasingly interested in the barriers to adaptation (Carleton et al., 2024). In particular, we add to the body of research considering workplace adaptations to short-run weather shocks, which affect safety (Dillender, 2021; Park et al., 2021; Ireland et al., 2023) and productivity (Cai et al., 2018; Somanathan et al., 2021). Despite growing evidence on potential worker adaptations, such as reducing labor supply during extreme heat (Graff Zivin and Neidell, 2014; LoPalo, 2023; Rode et al., 2024), the factors that govern the realized level of adaptation remain poorly understood. We provide novel evidence on the role of workers' incentives, adding to a relatively sparse literature that has considered labor market conditions (Neidell et al., 2021) and regulations (Park et al., 2021). In addition, by studying ice as an occupational hazard, we complement a climate-workplace safety literature that has been primarily concerned with extreme heat.

2 Data

Truck Crashes

We use records of crashes from the Federal Motor Carrier Safety Association's (FMCSA) Crash File for the period 2006 to 2023. The Crash File includes information on crashes involving a large truck or a bus that resulted in an injury, a fatality, or a vehicle being towed. The data include the date and county of each crash, the time of the crash report, the number of associated injuries and fatalities, and the DOT number of the carrier (company) involved in the crash. We limit the data to accidents involving trucks. In the raw data, only 0.3 percent of these trucks are smaller than 10,000 pounds (roughly a small delivery van), and 84 percent of them are larger than 26,000 pounds (class 7, which includes medium semi-tractors and heavy duty tow trucks,

or above). Note that any crashes involving multiple large trucks include a separate entry for each truck. We create counts of trucks involved in crashes (which we refer to as "crashes" for simplicity), injuries, and fatalities at the county-by-day level. The analysis dataset includes nearly 1.4 million crashes, 692,337 injuries, and 46,781 fatalities over the analysis period.

Despite its temporal and geographic granularity, there are two limitations of the Crash File that are worth acknowledging. First, the dataset only includes crashes that are reported by each state to the FMCSA, resulting in potential data quality issues (e.g., underreporting) that have improved over time, but unevenly across states (FMCSA, 2024b).[6] We take these potential issues into account in our empirical strategy. Second, the data do not include driver identifiers, meaning that we cannot take into account individual driver factors (e.g., risk-aversion or driving ability). In our results section, we discuss the assumptions necessary to interpret our results as due to worker behaviors, as well as other potential explanations consistent with our findings.

Table 1 presents summary statistics at the county by year level. Annually, there is an average of 25 trucks involved in crashes, 12 injuries, and 0.8 fatalities per county. There is considerable variation across counties: the 25$^{\text{th}}$ percentile number of crashes across county-years is 2, and the 75$^{\text{th}}$ percentile is 23. Figure 1A presents a map of the yearly number of crashes per county. Crashes occur most frequently in populous counties and those with heavily-frequented highways.

Truck Census

We supplement the crash data with FMCSA Census data, which provides information on each registered truck carrier in the United States. It includes the DOT number of the carrier, the size of its fleet, number of drivers, and information on the types of cargo it transports. Note that publicly available Census data is only a snapshot at the moment of download, which in our case was August 10$^{\text{th}}$, 2024. However, in our analysis of the effect of the ELD mandate, we limit our treatment group to carriers that were initially registered by the end of 2016.

[6]Appendix Figure A1 Panel A plots the yearly number of trucks involved in crashes in the Crash File in blue, compared to the number of trucks involved in fatal or injury crashes in official FMCSA statistics in orange and the total number of trucks involved in all crashes in green. Note that the green line includes crashes that are not included in the Crash File because they do not meet the severity threshold.

Local Weather Data

We use weather data from PRISM Climate Group, which provides daily temperatures (maximum and minimum) and precipitation (which includes rain and melted snow) at a 4km by 4km resolution for the continental United States. We create 5°C maximum temperature bins from below 0°C to 35°C and above, and 1cm precipitation bins from 0cm to 3cm and above. In addition, we create a day-by-gridpoint level variable, called "ice," that captures co-occurring sub-zero mean temperatures (the average of maximum and minimum in a given day) and non-zero precipitation. In the Appendix, we show that our results are robust to defining ice as precipitation combined with sub-zero daily maximum temperature and precipitation combined with sub-zero daily minimum temperature.

We match these weather variables to the truck crash data at the county-day level. PRISM Climate Group labels days from noon UTC (7AM EST or 4AM PST) to noon UTC the next day. Using the state, month, and time of the crash, we match crashes to weather according to this definition. For instance, we relabel crashes before 7AM EST as having occurred on the same "PRISM day" as a crash that occurred at 11PM EST the day before. We average daily weather to the county level by taking a road-weighted average, using 2014 shapefiles for primary and secondary roads at the state level from the U.S. Census (U.S. Census Bureau, 2014). In Appendix Figure A3, we show the average absolute difference between unweighted and road-weighted average maximum temperature, precipitation, and ice. The difference is small in counties that are relatively small and densely populated, and large in bigger counties with significant areas without roads (e.g., mountains, deserts, or wetlands).

Table 1 and Figure 1 panels B through E present summary statistics for the number of yearly days in each temperature bin, in each precipitation bin, and with ice across county-years in our sample. There is significant variation in all weather extremes across the US. There is considerable variation in all types of weather across the United States: many counties in the South of the country experience over 200 days above 30°C, compared to below 20 in Northern and mountainous regions. Many counties in these latter regions, in turn, experience over 90

days per year with a maximum temperature below 0°C, and a similar number of icy days. Precipitation exhibits similar geographic diversity, with the Pacific Northwest and Southeast of the country experiencing many days with 2cm or more of precipitation, and the Southwest experiencing no such days.

All-Vehicle Crash Data

We supplement our analysis with daily all-vehicle crash report data from Anand (2025). The data are compiled from police reports, and so likely capture similarly (though not necessarily identically) severe crashes as those reported in the FMCSA Crash File. Based on data availability at state-year level, we limit the sample to a balanced panel of county-days covering the period 2009 to 2019 for 9 states: Colorado, Connecticut, Maine, Massachusetts, Michigan, New Jersey, Ohio, South Dakota, and Wisconsin.

3 The Impacts of Weather on Truck Crashes

3.1 Empirical Specification

To test how weather affects truck crashes, we leverage random daily variation in weather within a county. In our core specification, we estimate the following regression:

$$Crash_{c,t} = exp(\sum_{l}^{L}\left[\sum_{j=1}^{J}\beta_{T,l}^{j}T_{c,t-l}^{j} + \sum_{k=1}^{k}\beta_{P,l}^{k}P_{c,t-l}^{K} + \beta_{Ice,l}Ice_{c,t-l}\right] + \alpha_{cm} + \nu_{ym} + \gamma_{md} + \delta_{sy}), \quad (1)$$

where $Crash_{c,t}$ is the count of crashes in county c in state s on date t (day d of month m of year y). As the outcome variable is a count with a large number of zeros, we estimate a Poisson regression.

The right-hand side includes three sets of weather variables. T^j denotes a vector of J daily maximum temperature bins, from below 0°C to 35°C and above in 5°C increments, with the

10-15°C bin omitted. P^K is a vector of daily precipitation in 1cm bins, from 0 to 3cm and above. Ice represents the fraction of the county-day that experienced ice. In our core specification we include same day ($l = 0$) and one-day-lagged weather ($l = 1$).[7]

We leverage daily variation in weather within a county-month in order to identify the causal effect of weather on crashes. The term α_{cm} denotes a county-month fixed effect that accounts for any time-invariant determinants of truck crash risk by county (e.g., local driver behaviors or traffic patterns), and any seasonality in these determinants (e.g., winter road management) that could otherwise lead to spurious correlations between weather and crashes. Year-by-month fixed effects (ν_{ym}) account for any country-wide changes in truck crash risk over time (e.g., improved breaking technologies), and day-of-year fixed effects (γ_{md}) control for any country-wide differences in truck crash risk within a year (e.g., fewer shipments on the 4$^{\text{th}}$ of July or on Christmas, as in Appendix Figure A1 Panel B). We include state-by-year trends (δ_{sy}) to account for any state-specific changes in truck crashes (or reporting quality) that may be spuriously correlated with weather changes over time. In Figure 2, we plot examples of the identifying residual variation in temperature (Panel A), precipitation (Panel B), and ice (Panel C). There is considerable within county-month variation in each of these variables.

The coefficients of interest, $\beta^j_{T,l}$, $\beta^k_{P,l}$, and $\beta_{Ice,l}$ represent the effect a day within the corresponding weather bin, lagged by l, on crashes net of the controls. Temperature bin coefficients are relative to a day between 10-15°C and precipitation coefficients are relative to a day with no precipitation. Because ice occurs, by definition, on cold and rainy days, the coefficient for Ice can be interpreted as the effect of icy conditions, in addition to cold alone and precipitation alone.[8] The identification assumption to interpret these coefficients as causal is that day-to-day variation in weather within a given county-month is plausibly orthogonal to unobserved determinants of truck crash risk. Note that differences in data quality over time and space may complicate

[7]In a specification with fewer temperature and precipitation bins, available upon request, we include 2 lags and 1 lead of weather, and find that the effect of weather drops off significantly in the 2 day lag.

[8]Note that one cannot simply get a "total effect" by adding coefficients for ice with those for a specific temperature or precipitation bin, for two reasons. First, the bins do not line up neatly with the definition of ice. Second, the ice variable is calculated at the PRISM grid point level, whereas the coefficients are calculated using county level data. For instance, take a county that is partly cold, partly icy, but with only a small area of overlap. This county would be coded as around 52 percent cold and 52 percent wet, but only 2 percent icy.

cross-sectional comparisons, but, unless there are data quality differences within a county-month that are spuriously correlated with weather, they are not a threat to causal identification. As inclement weather may reduce the likelihood of a police report (Scott, 2018), our coefficients are, if anything, a lower bound on the true effect of weather on crashes. In robustness tests, we present specifications with alternative sets of fixed effects. Standard errors are clustered at the county and year-month level to account for any correlation between the error terms within a county or year-month.

3.2 Results

Figure 3 Panel A presents the same day coefficients from estimating equation 1, transformed to be interpreted as percentage changes (i.e., $(e^{\beta} - 1) * 100$). The raw coefficients, which are not transformed into percentage changes, are presented in Table 2 column 1. Temperatures above 15°C lead to higher crash risk: a day between 15 and 20°C leads to a 2.5 percent increase in crashes relative to a day between 10 and 15°C. The effect increases monotonically with higher temperatures, with a day above 35°C leading to a 18 percent increase in crashes. Crash risk also increases on cold or rainy days: a day below 0°C increases crashes by 29 percent, a day with 1cm to 2cm of precipitation increase crashes by 39 percent relative to a day with no precipitation, and a day with 3cm of precipitation or more increases crashes by 60 percent. Ice presents the greatest risk: an icy day leads to a 118 percent increase in crashes.

Weather also affects crashes the next day. We plot the coefficients for 1 day lagged weather in Figure 3 Panel B. A day with between 1 and 2cm of precipitation leads to a 5 percent increase in crashes the following day, and ice leads to a 34 percent increase the following day. However, following a day with a maximum temperature below 0°C, crashes decrease by 13 percent. We present the full next day coefficients in Appendix Table A1 column 1. These persistent effects are consistent with several explanations, including cumulative effects on driver fatigue (including disrupting sleep), weather-induced delays leading to more rushing the next day, or, in the case of precipitation and ice, road conditions continuing to be dangerous the day after the precipitation

event.

As the coefficients are estimated with a Poisson model where the outcome is the count of truck crashes, they represent the change in truck crash risk, net of any adaptations undertaken by truck drivers, passenger vehicle drivers, or other groups. For instance, in icy or rainy conditions, truck drivers may drive more slowly, alter their schedules, or take breaks during the worst weather. In addition to truckers' adaptations, passenger vehicle drivers may cancel plans and avoid driving altogether, or local municipalities may salt and clear roads of snow, both of which could reduce truck crash risk.

Next, we estimate equation 1 for two additional outcomes: truck-involved crash injuries and fatalities. We plot the estimated coefficients in Figure 4 Panels A and B (injuries) and C and D (fatalities). We list same day coefficients in Table 2 columns 2 and 3, and 1 day lagged coefficients in Appendix Table A1 columns 2 and 3. The same day coefficients for both outcomes follow the same general pattern as for crashes. For instance, a day with 3cm or more of precipitation increases same day injuries by 40 percent and fatalities by 18 percent. A day with ice increases same day injuries by 122 percent and fatalities by 95 percent. While ice increases next day injuries and fatalities, precipitation decreases both outcomes on the next day.

We perform a back of the envelope calculation to estimate the total cost of ice-induced crashes. As our baseline, we take the average number of crashes per day across the continental United States in the omitted weather conditions in equation 1 (i.e., a day with no precipitation and between 10-15°C), 224 crashes per day. We multiply this baseline by the percentage change in crashes associated with a single icy day (118 percent), and then multiply that product by the number of icy days per year, 14.6. This calculation suggests that icy conditions lead to an additional 3,859 large truck crashes per year. With the conservative assumption that ice-induced crashes are equally likely to result in fatalities or injuries as any other crash, and using an FMCSA average crash cost of $275,000[9], we estimate that ice-induced crashes cost an additional

[9]This cost is derived from the FMCSA, which displays estimates costs separately for non-injury crashes ($46,765), injury crashes ($383,168), and fatal crashes ($14,578,771) (FMCSA, 2024a). We take a weighted average across all accidents in the United States in 2022, found in FMCSA (2024b), to calculate an average cost per crash of $274,940.

$1.06 Billion per year, in 2022 dollar terms. Note that these estimates are conservative in several respects in addition to the cost calculation: 1) the 224 crashes per day only represent crashes that enter our data, which are by definition more severe than the average crash (which we use to derive cost per crash from the FMCSA estimates) 2) our calculation does not include the additional effects of cold and non-zero precipitation, and 3) our calculation does not include the effect of ice on crashes the next day. We perform similar calculations and find that ice leads to an addition 1,959 injuries and 108 fatalities from truck crashes per year.

These results are robust to several alternative specifications, presented in Appendix Tables A2 (same day coefficients) and A3 (1 day lag coefficients). First, we estimate a model that replaces county-month and year-month fixed effects with county-year-month fixed effects (column 2). In this specification, coefficients are estimated from residual variation in weather and accidents within each county, month, and year. All coefficients remain similar to the core specification. Second, we test the robustness of our findings to different definitions of the ice variable. In the core definition, ice represents the co-occurrence (at the day-grid point level) of non-zero precipitation and a mean temperature (the average of maximum and minimum temperature) below 0. We alter this definition to be based on the maximum temperature being below 0 or the minimum temperature being below 0. The results show that, as one might expect, the more extreme definition (i.e., the one requiring maximum temperature to be below 0, presented in column 3) has a slightly larger impact on crashes, both on the same day and on the next day. The less extreme definition (which uses minimum temperature below 0, in column 4) has a smaller impact on crashes on both days. The coefficients remain statistically significant at the 0.01 level. Altering these definitions also results in slightly different estimates for other bins, especially for low temperatures and precipitation.

To benchmark the magnitudes of the crash coefficients, we compare them to the effect of weather on accidents involving all types of vehicles. We use data from Anand (2025) covering 9 states over the period 2009 to 2019. For these states and time period, we estimate equation 1 on two outcomes 1) the number of crashes involving trucks (from the FMCSA Crash File) and 2) the number of crashes involving all vehicles. Note that our core outcome is the total number

of trucks involved in crashes, but we change that here for comparability with the all-vehicle crash data. So for instance, if a single crash involves two trucks, that would be counted as 2 crashes in our core estimates (e.g., Figure 3), but only as 1 crash for this comparison exercise.

We plot the results in Figure 5, with Panel A showing same day weather's effects and Panel B showing 1 day lagged weather. Extreme weather poses significantly stronger risks to same day truck crashes than to crashes of all kinds. For instance, a day with ice increases crashes involving trucks by 80 percent, compared to only 40 percent for all crashes. Truck-involved crashes also increase by a higher percentage due to extreme cold (30 percent vs. 12 percent for a day below 0°C), extreme heat (23 percent vs. 12 percent for a day above 35°C) and extreme precipitation (37 percent vs. 23 percent for a day with 3cm or more). With the exception of cold temperatures, which decrease truck crashes the next day, the larger effects of weather on truck crashes persist the next day as well.

There are several potential explanations for why extreme weather may pose a higher risk for truck-involved crashes than for all crashes. In the case of heat, the differences may be partly explained by differences in exposure to the same outdoor temperature. While many trucks have air conditioning in their cabs, truck drivers may be more likely to not run their A/C to save on fuel costs, especially if they are independent contractors who pay for these variable costs themselves. In addition, truck drivers often sleep in their cabs while on the road, and rarely run their air conditioning at night. Extreme heat during the day may be correlated with hot night-time temperatures, which can negatively impact sleep for truck drivers in ways that they do not for passenger vehicle drivers (Viscelli, 2016).

Physical differences between trucks and smaller vehicles likely explain part of the differences in the effects of ice and precipitation on crashes for trucks compared to smaller vehicles. Even assuming similar percentage increases in break distance due to wet or icy conditions for all types of vehicles, the distance increase in levels is larger for trucks, who have a higher baseline break distance. In addition, unevenly distributed cargo in a truck can compound stability issues faced by vehicles in wet conditions. Trailer-trucks can also experience "jackknifing," which is when a truck's trailer swings out of alignment with the cab, a risk that increases in wet conditions.

Finally, trucks create a larger spray in wet conditions than passenger vehicles, which could lead to other vehicles crashing into trucks.

Another potential explanation is the difference in incentives faced by truck drivers and drivers of non-commercial vehicles. During inclement weather, drivers can adapt on the extensive margin (i.e., delay driving until after the weather, or choose not to drive at all) or on the intensive margin (i.e., drive more slowly or defensively). While protective against crash risk, these adaptations also come with the cost of a driver arriving to their destination late or, in the extreme, the next day. The cost of a late arrival is likely larger for the average truck driver than for the average non-commercial vehicle driver. A truck driver arriving late might miss the delivery window and have to wait until the next morning to drop off their shipment, which in turn could cause them to miss their next day pickup time, potentially losing out on that job and a day's wages. At best, by driving slowly, truck drivers, most of whom are paid per delivery, are working longer hours for the same amount of pay. For the average non-commercial driver, in contrast, a two hour delay likely imposes a much smaller welfare penalty. Given these cost disparities, it may be the case that truck drivers are less likely to engage in these adaptations.

In the next section, we leverage a natural experiment to test the impact of a change in drivers' incentives on the weather-crash relatoinship.

4 ELD Mandate and Weather's Effects on Crashes

In this section, we test the effect of an electronic logging device (ELD) mandate, which altered truck drivers' incentives to respond to inclement weather, on the ice-crash relationship. To estimate causal impacts, we leverage the fact that, prior to the mandate, several truck carriers had already installed compliant electronic logging devices in their fleets, and were thus unaffected by the mandate. We estimate the effect of the policy with a triple-difference regression that compares the ice-crash relationship for these carriers versus affected carriers, before versus after the mandate.

4.1 The Mandate

Due to the fact that they are paid relatively low piece-rate wages, truck drivers have an incentive to drive many miles per day to meet their target earnings (Ryley and Belzer, 2024). This has led to an issue of overwork in trucking, the safety consequences of which have been a long-standing concern among drivers, carriers, industry experts, and safety officials. Since the 1930s, the FMCSA has imposed hours-of-service (HOS) rules, which currently limit drivers to 11 hours of actual driving, within 14 hours of starting to drive. After one of these limits is reached, the driver must take a 10 hour break. Prior to 2020, drivers were able to extend their driving time by up to 2 hours due to unforeseeable adverse driving conditions, such as unexpected weather or unusual traffic conditions, that were not known when the driver began their route. However, they were not able to extend their 14 hour window. In late 2020, after our study period, the FMCSA amended this rule to also allow drivers to extend the 14 hour window by up to 2 hours (FMCSA, 2021).

Drivers can face harsh penalties for HOS violations. For example, a driver who exceeds their HOS can be fined up to $4,812 for a minor violation, with violations of over 3 hours resulting in even larger fines or license suspension (FMCSA, 2025). Despite these potential consequences, prior to the ELD mandate, these limits were easily and frequently surpassed. Drivers used paper logs to track their hours, and they frequently manipulated these to appear as if they were in compliance (Viscelli, 2016). Therefore, the expected cost of violating HOS rules, taking into account the low probability of being caught, was much lower than the cost of being caught.

This widespread fraudulent paper logging, and consequent violations of HOS rules, led to Congress requiring the FMCSA to impose a mandate for electronic logging devices, which are much more difficult to manipulate. The rule was announced on December 16th, 2015, and required that all carriers use ELDs to track driver hours by December 17th, 2017. The mandate was welcomed by large carriers, many of whom were already using ELDs prior to the announcement of the rule. They accused smaller carriers, who still used paper logs, of knowingly flouting the HOS rules, giving them an unfair advantage. Importantly for our empirical strategy,

small carriers and trucker organizations vehemently opposed the rule, including via several legal challenges, and resisted installing the devices prior to the mandate (Levy, 2022).

Empirical research and anecdotal accounts from truckers suggest that, while this mandate did decrease the prevalence of HOS violations, it may have had the unintended consequence of increasing other forms of unsafe driving (Scott et al., 2021; Levy, 2022). By raising the probability (to very close to 1) of getting caught, the mandate led to a much larger expected cost of HOS violations. In contrast, drivers' incentives to drive as many miles per day as possible, and the costs of other unsafe driving practices, such as speeding, did not change. According to theories of illicit behavior and incomplete regulations, stricter monitoring of one illicit welfare-enhancing behavior (driving beyond one's HOS) can lead to an increase in other types of illicit behaviors (speeding) (Yang, 2008; Fowlie, 2009). In an analysis of the weeks before and after the mandate, Scott et al. (2021) find that the mandate led to an increase in unsafe driving violations among treated carriers, along with suggestive evidence that it also increased crashes.

These unintended consequences may have also affected the way that truck drivers respond to hazardous driving situations. Take a driver with an 11 hour driving assignment facing inclement weather who decides to drive more slowly due to icy road conditions (that are forecast and therefore not subject to the adverse condition exception). Prior to the mandate, the cost of this safety-enhancing response would be the additional (unpaid) time spent driving, but the driver would have the choice to drive more than 11 hours and falsify their hours on their paper log. The truck carrier may agree with its driver's actions, or just not know about it, but given the lack of a paper trail documenting the driver's HOS violation, it would have plausible deniability. In contrast, after the mandate, the driver, having slowed down, would reach their 11 hour driving limit prior to arriving at their destination. With the ELD on their truck, the expected cost of continuing to drive beyond their HOS is now much higher, and their carrier might also urge them to stop driving. They would likely have to stop driving, sleep on the road, and drop off their shipment the next day. This would impose additional costs of missing a trip (and the associated wages) scheduled for the next day, driving an empty truck (unpaid), or returning

home a day later than expected. In sum, the mandate increased the expected costs of driving slowly, potentially incentivizing less careful driving during inclement weather, and increasing the weather-crash relationship. This is the hypothesis we test in this section.

4.2 Control and Treatment Groups

Prior to the mandate, several large firms already had compliant ELDs (or similar technologies called automatic on-board recording devices) that were integrated with their fleet management systems. In contrast, the vast majority of small firms delayed the purchase of ELDs until right before the December 17$^{\text{th}}$, 2017 deadline. Miller et al. (2020) estimate that only 13 percent of carriers with 5 to 99 trucks in their fleet had implemented ELDs by September of 2017.

The control group comprises firms that we can identify as having implemented ELDs in their fleets well before the mandate. For publicly-traded carriers, we search their United States Securities and Exchange Commission (SEC) filings for mentions of ELDs prior to 2017. For private carriers, we search their websites and other documents. We identify 29 carriers, with a combined fleet of 115,805 trucks in 2024, that fit this definition.

The treatment group comprises firms that were unlikely to have ELDs prior to the mandate, and whose drivers likely faced the incentive structure that we describe. Using information from the FMCSA Census, we include carriers with fewer than 100 trucks who are "authorized for hire," which means that they ship cargo for customers. This selection criteria excludes private carriers (e.g., florists or moving companies who use their own trucks) whose drivers face different pay structures and incentives. We also limit the treatment group to carriers that ship general freight (e.g., paper products, produce, or beverages) and do not ship any specialized cargo, such as logs, oil tankers, garbage, or mail. We exclude these specialized carriers because their drivers are often more involved in the handling of cargo, and they may also be paid for their time doing so. Therefore, they also face a different set of incentives than do general freight drivers. Finally, to address the possibility that some small truck carriers may have entered the shipping space after (and possibly in response to) the ELD mandate, we limit the treatment group to carriers

whose initial registration was by the end of 2016. This leaves us with 372,863 carriers with a combined fleet of 836,810 trucks in 2024. Note that a small percentage of these carriers may have already had ELDs in their fleets, which, if anything would push the estimated effect of the mandate towards zero.

We plots graphs showing summary statistics for the treatment and control groups in Appendix Figure A4. Over the mandate study period of 2014 to 2019, the control group experienced 31,975 crashes and the treatment group experienced 47,097 crashes. We estimate equation 1 with the outcome the number of trucks involved in crashes for the treatment group and the control group during the triple-difference study period, 2014 through 2019. We plot these results in Appendix Figure A5. Ice increases cumulative crashes on the same day and the next day for the control group by 213 percent (Panels A and B) and by 192 for the treatment group (Panels C and D).[10]

4.3 Empirical Specification

Given the outsized risk posed by icy conditions to trucks, we focus on the ice-crash relationship. In the core specification, we do not include any other weather variables, though we show that our results are robust to including weather controls. We include same day and 1-day-prior ice in the model.

We estimate a triple-difference model to measure the impact of the mandate on the ice-crash relationship. This model compares how the ice-crash relationship changed for the treatment group after the mandate, relative to how it changed for the control group. For simplicity, we define the pre-policy period as the full years 2014 to 2017, and post-policy as 2018 to 2019. As the policy came into effect on December 17th, 2017, two weeks of the post period are assigned to the pre-period. We show that our findings are robust to a more precise definition of pre and post periods. Ending in 2019 avoids the effects of the COVID-19 pandemic, which possibly affected the two groups differently.

[10]We calculate this combined effect as $(e^{\beta_{Ice,0}}-1)*100+(e^{\beta_{Ice,1}}-1)*100$, rather than $(e^{(\beta_{Ice,0}+\beta_{Ice,1})}-1)*100$, which would represent the impact of two consecutive days of ice on crashes, relative to two days without it.

The empirical model is as follows:

$$Crash_{c,t} = exp(\sum_{l=0}^{1}[\beta_l Ice_{c,t-l} + \Omega_l \mathbb{1}_{Post2017} * Ice_{c,t-l} + \Theta_l \mathbb{1}_{Treat} * Ice_{c,t-l} + \omega_l \mathbb{1}_{Post2017} * \mathbb{1}_{Treat} * Ice_{c,t-l}] + \alpha_{cmg} + \nu_{ymg} + \gamma_{mdg} + \delta_{sy}), \quad (2)$$

The core coefficients of interest, ω_l, represent how the effect of ice (separately on day t and $t-1$) on crashes changed after the policy ($\mathbb{1}_{Post2017}$), for the treatment group ($\mathbb{1}_{Treat}$) relative to the control group. Relative to the core weather-crash model, we amend the fixed effects to vary by group (so, e.g., county-month fixed effects become county-month-group fixed effects). The model therefore controls for group-specific seasonality in the ice-crash relationship in each county, group-specific nation-wide differences in crash risk across the year, and any group-specific changes to the baseline crash risk over time (e.g., changes in passenger vehicle behavior in a part of the country more frequented by treatment group trucks).

The identification assumption for a causal interpretation of ω_l is that, absent the policy, and net of all fixed effects, the ice-crash relationship would have evolved in the same manner for both groups. We explicitly test this assumption in an event study framework detailed below.

4.4 Results

We plot the main coefficients of interest, the post-mandate change in the effect of ice for the treatment group relative to the control group, in Figure 6. The left-most coefficients correspond to the core treatment group, general-cargo for-hire carriers with fewer than 100 trucks. The point estimate for γ_0 (same day ice), in black, is 6 percent, but it is not statistically significant. The point estimate for γ_1 (1 day lagged ice), in light gray, is 15 percent, and it is statistically significant at the 0.05 level. In Table 3, we show the effect of the mandate on the ice-crash relationship over a two day period.[11] After the mandate, the cumulative two-day effect of ice

[11]We calculate this combined effect as $(e^{\omega_0} - 1) * 100 + (e^{\omega_1} - 1) * 100$, rather than $(e^{(\omega_0+\omega_1)} - 1) * 100$, which would represent the impact of the mandate on crashes resulting from two consecutive days of ice.

on crashes for trucks in the treatment group increased by 22 percent more than it did for the control group, an effect that is statistically significant at the 0.05 level. This change in the effect of ice represents a 11 percent increase on the baseline of 192 percent for the entire period.

The fact that the mandate affects the lagged ice-crash relationship more than the same day ice-crash relationship is consistent with a couple of different explanations. First, the mix of weather that our ice variable captures (i.e., co-occurring sub-zero average temperature and non-zero precipitation on the same day) may be severe enough on its own that additional time pressure does not affect it. For instance, while driving through cold and rainy conditions, a trucker may be more focused on the weather than anything else. The day after, in contrast, the weather might be clearer but the road may still be iced over in some areas. A trucker with a higher expected cost of driving carefully (e.g., due to the ELD mandate) may be more susceptible to crashes caused by such conditions. A second possibility is that icy weather could lead to delays that could persist into the next day. The mandate may make truckers more likely to drive quickly, rather than drive longer than legally allowed, to make up for this lost time.

We split the treatment group into carriers with fewer than 10 trucks and those with 10 to 99 trucks, and plot the estimated effect of the mandate for each of those groups to the right of the dashed line. The effect of the mandate on the ice-crash relationship is larger for the <10 group, but smaller and not statistically significant at conventional levels for the 10 to 99 group.

We estimate several robustness tests. First, we estimate the effect of the ELD mandate on the ice-crash relationship only in the winter, defined as running from October to April, the months with non-zero levels of ice (Figure A2 Panel H). In this model, which corresponds to the event study described below, we extend the sample period to October 2013 through April 2020 (thereby including the beginning of the COVID-19 pandemic) in order to include full winters. Second, we include additional weather controls: two temperature bins, below 0°C or 20°C and above, and one precipitation bin, above 0cm. In this model, we do not interact the weather controls with the policy. Third, we include triple-difference interactions with these temperature and precipitation bins. Fourth, we replace year-month-group and county-month-group fixed effects with county-year-month-group fixed effects. This highly saturated model controls for any

group-specific changes that might differ by county across time in the sample. Fifth, we test the robustness of the results to a more precise treatment period definition. Specifically, we exclude the period of December 18th, 2017 to March 31st, 2018. During this period, the mandate was subject to "Light Enforcement," meaning that non-compliant drivers were only served citations. April 1st, 2018 and onwards marks the period of "Strict Enforcement" when drivers could be given "out of service" citations for non-compliance (Scott et al., 2021). Sixth, we test the robustness of our results to maximum or minimum temperature thresholds in defining ice.

We list the coefficients from these robustness tests in Appendix Table A6. The coefficient for the two-day effect of the mandate is similar to that in the core model, and statistically significant at the 0.1 level with two exceptions: the temperature and precipitation interaction model (column 4), and the minimum temperature model (column 8). In the case of the minimum temperature ice model, however, the effect of the mandate on the 1 day lagged ice-crash relationship is statistically significant at the 0.1 level. One additional difference worth noting is that, in the model that defines ice using a maximum temperature threshold (column 7), the effect of the mandate is larger for the same day ice-crash relationship than for the 1 day lagged ice-crash relationship. This result, which is the opposite of that in the core model, is consistent with the possibility that the time pressure imposed by the mandate affects the ice-crash relationship by increasing crashes caused by already-formed ice. Specifically, already-formed ice exists for a longer part of the day that precipitation occurs when the temperature never reaches above 0°C.

4.5 Event Study

The key assumption for a causal interpretation of the triple-difference coefficients is that, absent the policy, the ice-crash relationship would have evolved similarly for the treatment and control groups. To test the validity of this assumption, we estimate an event study regression. This model estimates the between-group difference in the ice-crash relationship in each time period, relative to the between-group difference in a reference time period. Instead of using calendar years, we use winters (October to April) as the time periods for the event study. This approach

allows, for instance, for October 2013 to April 2014 to be considered one time period, rather than January through April and October through December, 2014, being grouped together. As the effect we are examining is that of ice, we only include winters in the regression. The baseline winter is 2016-2017, the last full winter prior to the mandate.

The empirical model is as follows:

$$Crash_{c,t} = exp(\sum_{l=0}^{1}[\beta_l Ice_{c,t-l} + \Theta_l * \mathbb{1}_{Treat} Ice_{c,t-l} + \sum_{n=-3}^{3}[\Omega_{l,n} * \mathbb{1}_{y=n} Ice_{c,t-l} + \omega_{l,n} * \mathbb{1}_{y=n} * \mathbb{1}_{Treat} Ice_{c,t-l}]] + \alpha_{cmg} + \nu_{ymg} + \gamma_{mdg} + \delta_{sy}), \quad (3)$$

Here, the $\omega_{l,n}$ represent the change in the difference in the effect of ice (lagged by l) on crashes between the treatment and control groups, relative to the difference in the 2016-2017 winter. We let n run from -3 to 3, with 0 omitted, so the regression includes winter 2013-2014 through winter 2019-2020. This time period corresponds to that use in the "Only Winter" model presented in Table A6 column 2.

We plot these coefficients in Figure 7. Panel A shows the combined effects across the same day and 1 day lag coefficients, Panel B shows the same day coefficients, and Panel C shows the 1 day lag coefficients. Overall, the coefficients support the assumption of parallel trends: there is no evidence that the difference in the effect of ice on crashes between the treatment and control groups was trending in a particular direction prior to the policy. In addition, no pre-mandate coefficients are statistically significantly different from 0 at conventional levels. In the winter of 2018-2019, the first full winter after the mandate (which took effect on December 17, 2017) the two day cumulative effect of ice for the treatment group, compared to the control group, is 28 percent higher than the difference in the winter of 2016 to 2017. In accordance with the main triple-difference coefficients, this change is driven by changes in the 1 day lagged ice-crash relationship.

5 Discussion

Workers across many industries face risks to their safety on a regular basis. The levels of risk they experience are dictated by a number of factors, such as firm safety investments and workplace regulations. Due to differences in worker behavior, however, the same physical level of risk may not result in the same realized change in workplace incidents and injuries. Careful consideration of how workers' contractual and regulatory incentives may inform their responses to risks is crucial to designing socially optimal workplace safety policies.

In this paper, we first show that inclement weather has a strong influence on truck crashes. Using granular data on 1.4 million truck crashes, we find that a day with ice increases crashes by 122 percent. This effect is twice as large as that for crashes involving all vehicles. We then leverage the 2017 ELD mandate as a natural experiment to demonstrate the role that worker incentives may inform their responses to, and thus the consequences of, risks on the job. The results from a triple-difference analysis suggest that the mandate, which decreased the incentive for workers to drive carefully during inclement weather, led to a 22 percent increase in the effect of ice on crashes. These findings are particularly important in light of the large public safety externality posed by trucks. They are also, to our knowledge, the first quantitative account of the role of worker incentives in responding to occupational hazards. While the specific sets of incentives may differ across other occupational settings, they may matter in industries outside of trucking as well, which is a question that future research should address.

While our findings are suggestive of changes in worker behavior, it is important to note some possible alternative mechanisms. The highly saturated model includes fixed effects that account for any changes in average (non-weather related) crash risk over time, separately for the treatment and control groups. So, for instance, changes in technology that affect ice-related crash risk proportionally to all crash risk would be controlled for. However, ice-specific technology would not be controlled for. Another possible alternative channel is that the mandate, which effectively limited daily hours per worker and per truck for carriers in the treatment group, resulted in these carriers hiring new workers or using additional trucks. These new drivers, who

may have limited experience, and trucks, which may be older models, may be differentially poor at handling icy conditions. If this is the case, that would result in increased ice-related crashes for the treatment group. We note that truck driving tends to have high levels of turnover generally, and drivers must go through relatively rigorous training to obtain their certifications. In addition, carriers could have purchased newer models of trucks, which would decrease the ice-crash relationship.

Finally, this paper is not an analysis of the ELD mandate's overall efficacy. It is plausible that decreased HOS violations, and their benefits to public safety and driver welfare, outweigh the increase in the ice-crash relationship found here. We also do not make concrete proposals for the optimal combination of driver contracts and regulations. Doing so would require considering many other factors, including additional dimensions of driver welfare, carrier profits, and consumer welfare, which increases with cheaper and faster delivery of goods. We see such an endeavor as an important direction for future research.

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6 Tables and Figures

Table 1: Temperature and Truck Accident Summary Statistics

	Mean	Median	SD	25th	75th
Crashes/County-year	24.97	8.00	66.33	2.00	23.00
Injuries/County-year	12.38	4.00	32.72	1.00	11.00
Fatalities/County-year	0.84	0.00	2.13	0.00	1.00
Days/Year $\geq 35°$C	12.71	3.80	20.28	0.08	16.41
Days/Year 30-35°C	54.57	51.09	33.18	28.50	76.30
Days/Year 25-30°C	70.17	69.38	18.56	58.20	81.49
Days/Year 20-25°C	56.11	55.48	12.37	47.69	64.02
Days/Year 15-20°C	47.32	46.96	12.71	39.67	54.21
Days/Year 10-15°C	40.97	40.97	13.59	33.14	48.38
Days/Year 5-10°C	33.22	34.45	15.78	22.70	43.15
Days/Year 0-5°C	26.39	26.31	18.62	9.06	40.15
Days/Year $<0°$C	23.40	12.94	26.71	1.90	37.96
Days/Year $\geq$3cm Prec.	6.96	6.39	4.77	3.28	10.00
Days/Year 2-3cm Prec.	7.34	7.49	3.78	4.65	9.98
Days/Year 1-2cm Prec.	17.98	18.61	7.33	12.73	23.19
Days/Year 0-1cm Prec.	97.55	95.97	25.90	81.52	111.76
Days/Year 0cm Prec.	235.03	233.59	33.12	214.19	255.07
Days/Year with Ice	14.62	9.65	15.74	2.00	23.00

This table shows the distribution of crashes, injuries, fatalities, and weather variables for the continental U.S. over the period 2006 to 2023. The crash, injury, and fatality data (at the county-day level) are from the Federal Motor Carrier Safety Association, and the weather data (at the county-year level) are from the PRISM Climate Group.

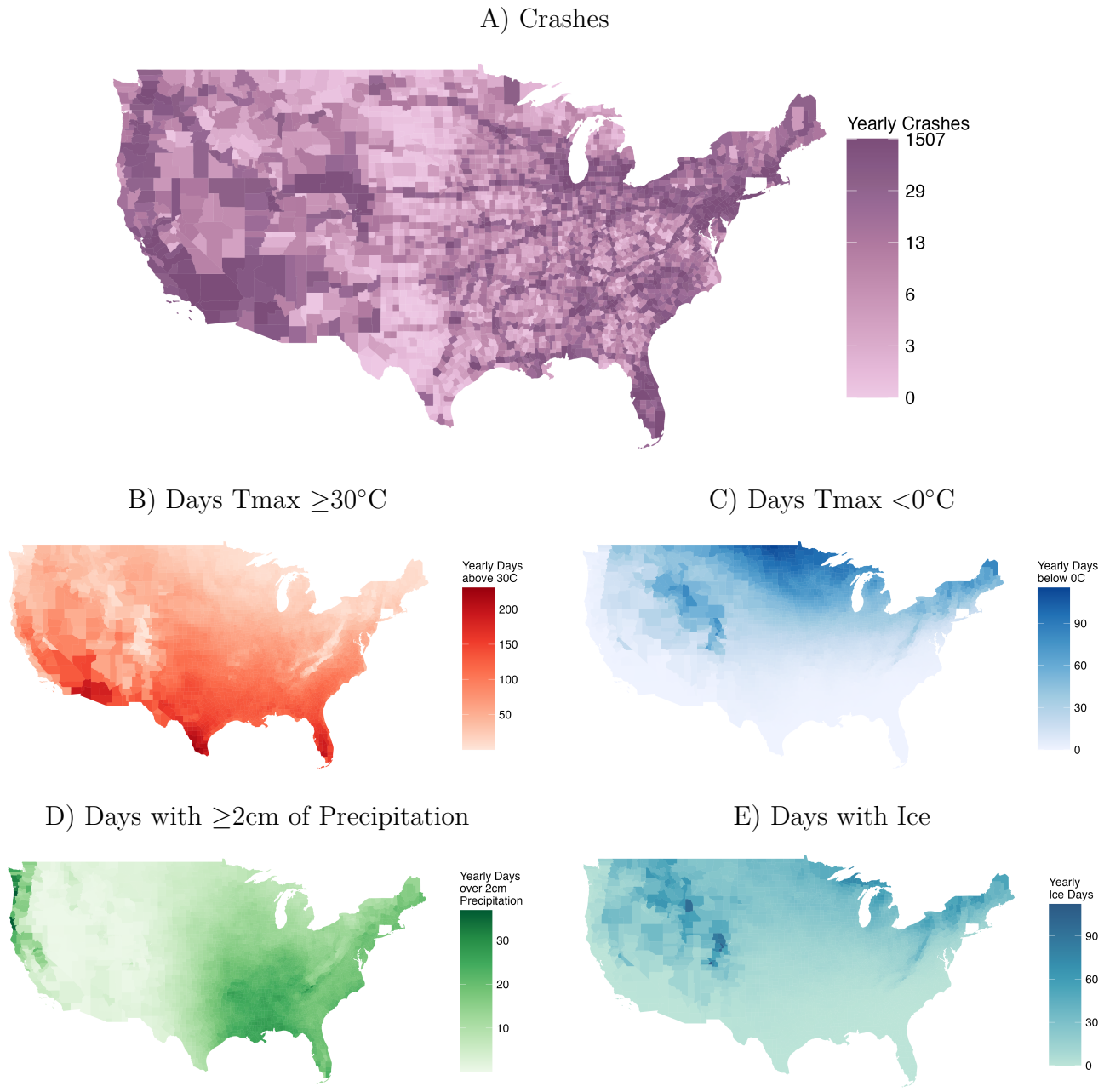


Figure 1: Yearly Crashes and Weather by County

This Figure maps the core variables at the county-year level. Panel A maps the average yearly number of truck crashes per year. Note that the color scale is broken up by percentiles, in order to show detail below the top few counties. Panel B maps the number of days per year above 30°C, panel C plots the number of days per year below 0°C, panel C plots the number of days per year with more than 2cm of precipitation, and panel D plots the number of days with ice (mean temperature below 0°C combined with non-zero precipitation). The data cover the period 2006 to 2023.

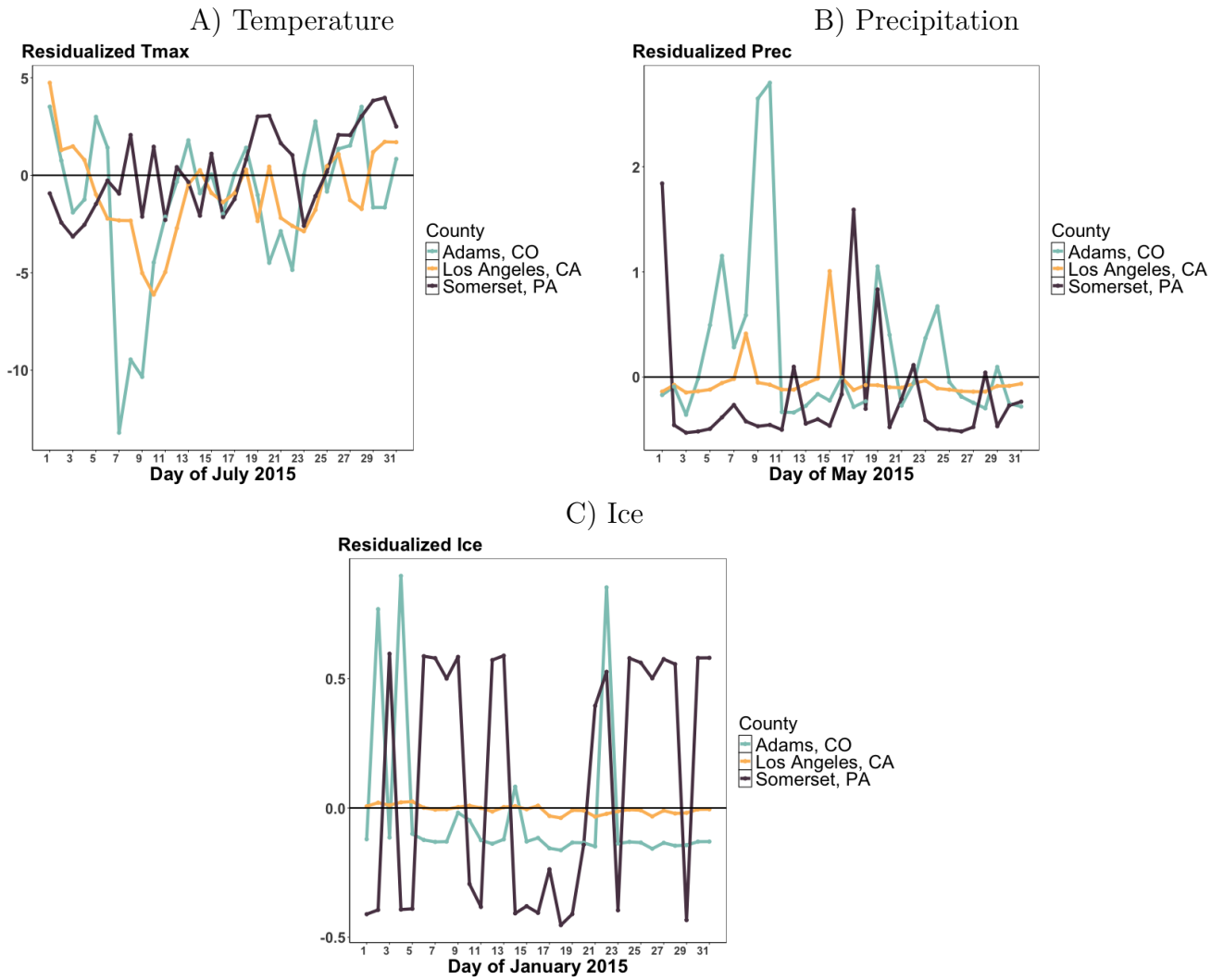


Figure 2: Residual Variation in Weather

This figure shows the residual variation in the weather variables after controlling for the fixed effects in the core specification: county-month, year-month, and day-of-year, as well as state-by-year linear trends. Panel A shows residual variation in temperature in July 2015 across three counties: Adams, Colorado (FIPS code 8001); Los Angeles, California (6037); and Somerset, PA (42111). Panel B plots residual variation in precipitation in May 2015, and Panel C plots residual variation in ice in January 2015.

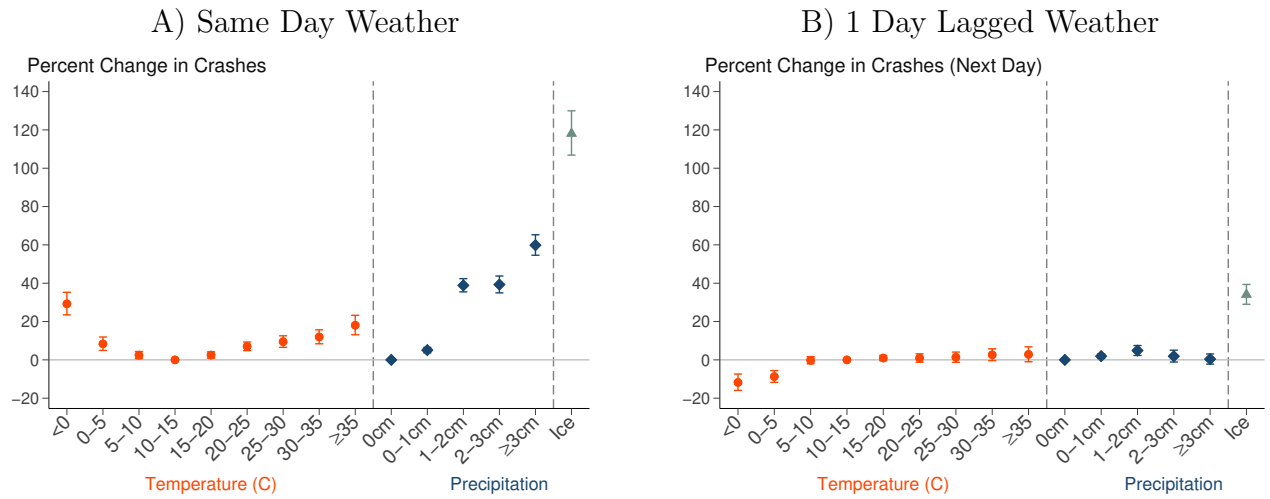


Figure 3: Weather and Crashes - Primary Specification

Panel A plots the set of same day weather coefficients obtained from regressions specified in equation 1 with the outcome crash counts per county and day (point estimates are in Table 2 column 1). Panel B plots the coefficients for 1 day lags in weather (point estimates are in Appendix Table A1 column 1). All coefficients are obtained from Poisson regressions of the outcome on same day and 1 day lagged weather variables. They reflect residual variation in the outcome and weather after regressing on county-month, year-month, and day-of-year fixed effects, and state-by-year linear trends. Daily maximum temperatures are assigned to a vector of 9 bins from below 0°C to 35°C and above in 5°C increments. Precipitation is assigned to a vector of 4 bins from 0 precipitation to 3cm and above in 1cm increments. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Temperature and precipitation coefficients should be interpreted as the percentage increase in crashes for a day in that range relative to their respective omitted categories (10-15°C and 0cm), and the ice coefficient should be interpreted as the additional interaction effect of co-occurring sub-freezing temperature and precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The model includes 19,534,840 observations across 3,107 counties from 2006 to 2023.

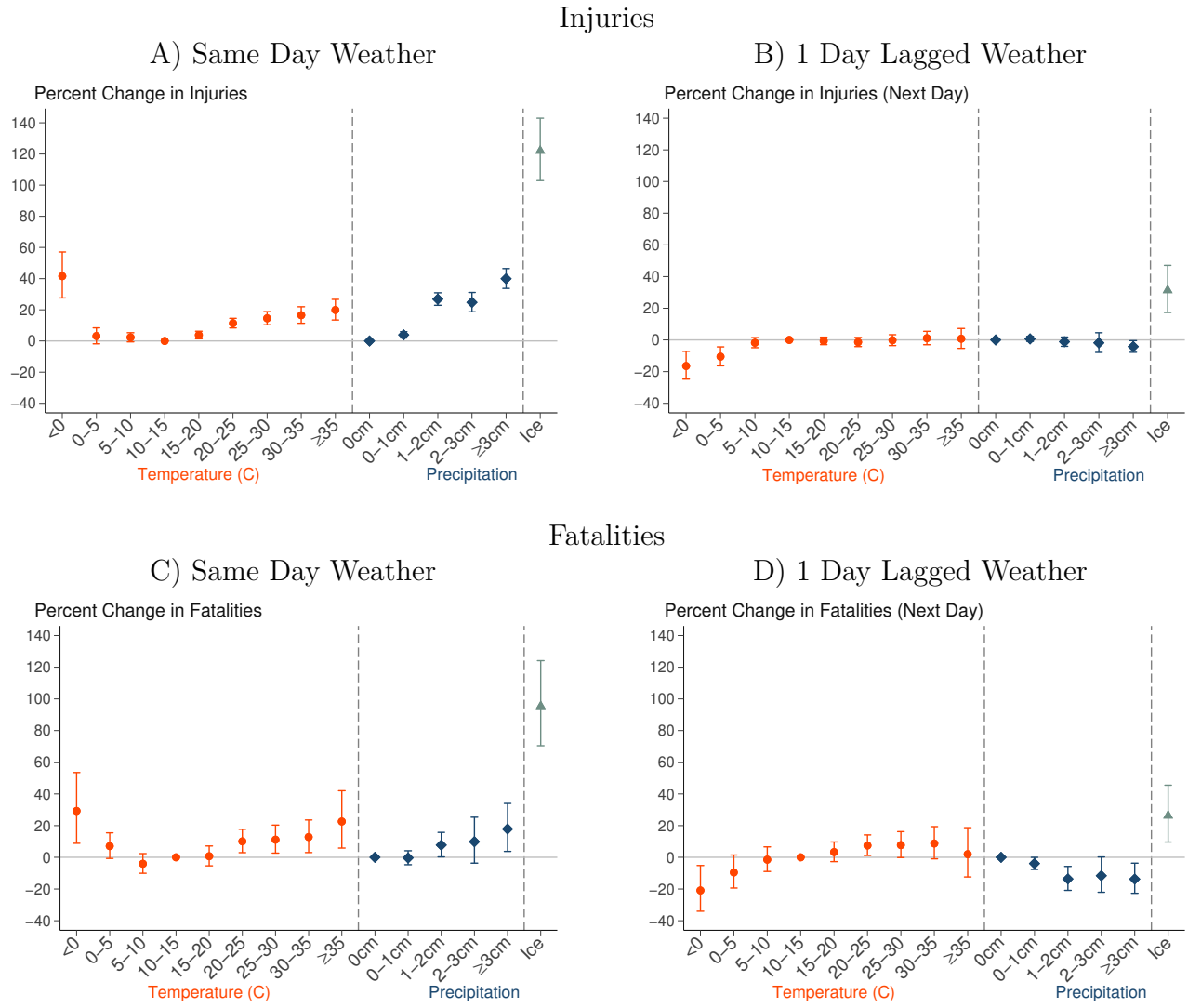


Figure 4: Weather, Injuries, and Fatalities - Primary Specification

Panel A plots the set of same day weather coefficients obtained from regressions specified in equation 1 with the outcome truck-crash injury counts per county and day. Panel B plots the coefficients for 1 day lags in weather. Panels C and D are the same as Panels A and B, respectively, but for the outcome truck-crash fatality counts. Point estimates are in Table 2 columns 2 and 3 and Appendix Table A1 columns 2 and 3. All coefficients are obtained from Poisson regressions of the outcome on same day and 1 day lagged weather variables. They reflect residual variation in the outcome and weather after regressing on county-month, year-month, and day-of-year fixed effects, and state-by-year linear trends. Daily maximum temperatures are assigned to a vector of 9 bins from below 0°C to 35°C and above in 5°C increments. Precipitation is assigned to a vector of 4 bins from 0 precipitation to 3cm and above in 1cm increments. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Temperature and precipitation coefficients should be interpreted as the percentage increase in crashes for a day in that range relative to their respective omitted categories (10-15°C and 0cm), and the ice coefficient should be interpreted as the additional interaction effect of co-occurring sub-freezing temperature and precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The model in Panels A and B include 17,797,692 observations across 3,107 counties from 2006 to 2023, and Panels C and D include 9,368,850.

Table 2: Same Day Weather and Truck Accident Outcomes

	(1) Crashes	(2) Injuries	(3) Fatalities
Ice	0.780***	0.798***	0.670***
	(0.027)	(0.046)	(0.070)
Precipitation			
≥3cm	0.469***	0.336***	0.165**
	(0.017)	(0.023)	(0.065)
2-3cm	0.331***	0.221***	0.094
	(0.016)	(0.025)	(0.067)
1-2cm	0.328***	0.238***	0.074**
	(0.013)	(0.016)	(0.037)
>0-1cm	0.050***	0.038***	-0.004
	(0.007)	(0.010)	(0.023)
Max Temperature			
<0°C	0.256***	0.348***	0.257***
	(0.023)	(0.053)	(0.088)
0-5°C	0.080***	0.031	0.068*
	(0.017)	(0.025)	(0.038)
5-10°C	0.024***	0.023	-0.042
	(0.009)	(0.015)	(0.033)
15-20°C	0.025***	0.037***	0.007
	(0.008)	(0.012)	(0.032)
20-25°C	0.068***	0.108***	0.096***
	(0.011)	(0.014)	(0.034)
25-30°C	0.091***	0.136***	0.106***
	(0.014)	(0.019)	(0.041)
30-35°C	0.113***	0.153***	0.121***
	(0.017)	(0.023)	(0.046)
≥35°C	0.166***	0.181***	0.204***
	(0.022)	(0.028)	(0.075)
Observations	19,534,840	17,797,692	9,368,850
County-Month FEs	X	X	X
Year-Month FEs	X	X	X
Day-of-Year FEs	X	X	X
State-Year Trends	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of same day weather on crashes, injuries, and fatalities involving trucks for the continental U.S. over the period 2006 to 2023. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables (same day and 1 day lagged), as well as the listed fixed effects. All columns include county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Heteroskedasticity robust standard errors are clustered at the county and year-month level
*p<0.1 **p<0.05 ***p<0.01

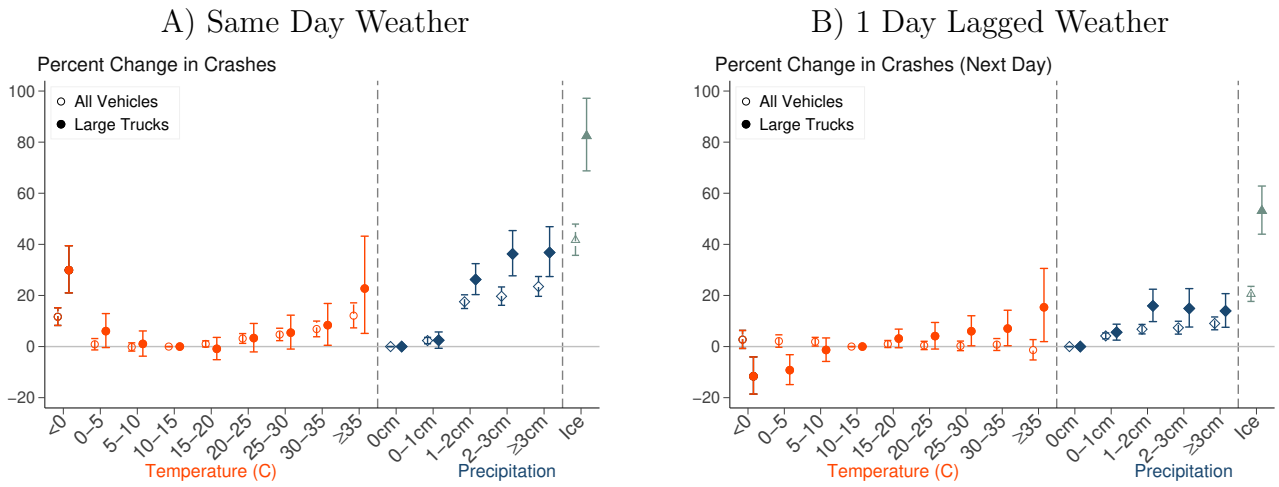


Figure 5: Weather and Crashes: Trucks vs. All Vehicles

Panel A plots the set of same day weather coefficients obtained from regressions specified in equation 1, separately for truck crashes (solid points) and crashes involving all vehicles (hollow points). Panel B plots the coefficients for 1 day lags in weather. Point estimates are in Appendix Tables A4 and A5. All coefficients are obtained from Poisson regressions of the outcome on same day and 1 day lagged weather variables. Note that, for comparability with the all vehicle crash data, the outcome variable is the number of crashes involving trucks, rather than the number of trucks involved in crashes, as in Figure 3. The coefficients reflect residual variation in the outcome and weather after regressing on county-month, year-month, and day-of-year fixed effects, and state-by-year linear trends. Daily maximum temperatures are assigned to a vector of 9 bins from below 0°C to 35°C and above in 5°C increments. Precipitation is assigned to a vector of 4 bins from 0 precipitation to 3cm and above in 1cm increments. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Temperature and precipitation coefficients should be interpreted as the percentage increase in crashes for a day in that range relative to their respective omitted categories (10-15°C and 0cm), and the ice coefficient should be interpreted as the additional interaction effect of co-occurring sub-freezing temperature and precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The truck crash model includes 2,077,397 observations across 9 states (Colorado, Connecticut, Maine, Massachusetts, Michigan, New Jersey, Ohio, South Dakota, and Wisconsin) from 2009-2019, and the all crash model includes 2,204,784.

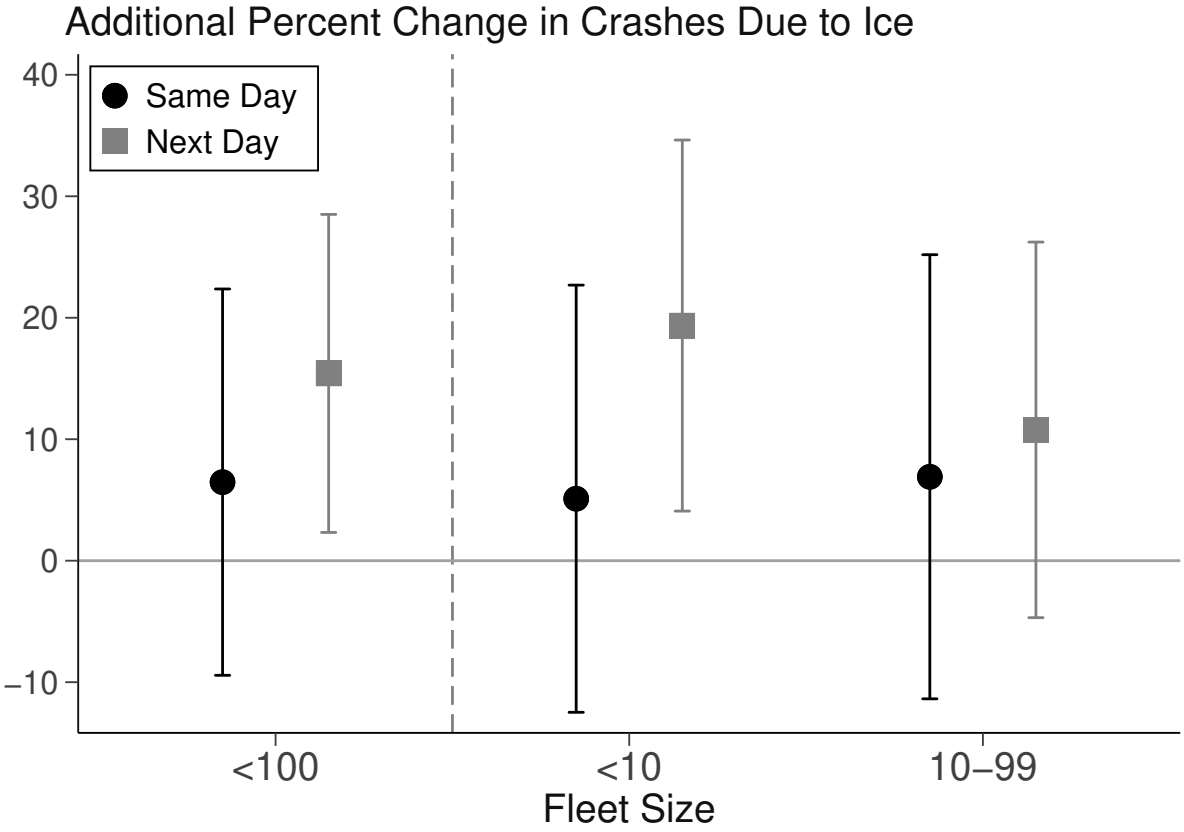


Figure 6: Effect of Ice after ELD Mandate, Triple-Difference

This graph plots the triple-interaction coefficient between the indicator for the post-mandate period, the treatment group, and ice. Same day ice coefficients are plotted with black circles, and next day ice coefficients are plotted with grey squares. Each pair of coefficients represents treatment groups of different sizes: the core treatment group, on the left, is below 100 trucks, and the coefficients to the right of the dashed line decompose this group into two subgroups: below 10 trucks and 10 to 99 trucks. The coefficients are obtained from estimating the triple-difference model specified in equation 2. The full set of coefficients from this model is listed in Table 3. The coefficients reflect residual variation in the outcome after regressing on county-month-group, year-month-group, and day-of-year-group fixed effects, and state-by-year linear trends. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The core model includes 4,724,864 observations.

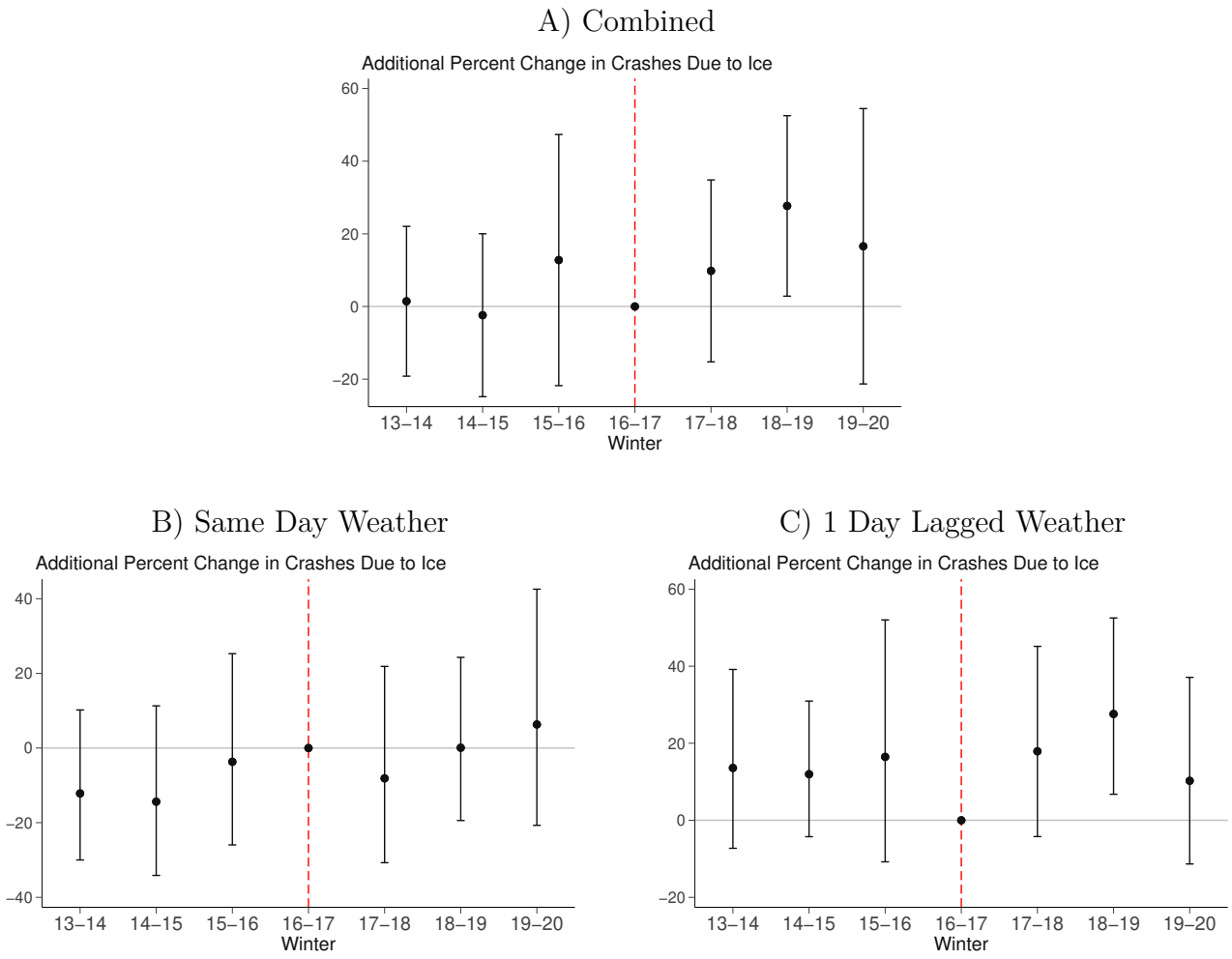


Figure 7: Effect of Ice after ELD Mandate, Event Study

This figure plots the event study coefficients between the indicator for a given winter, the core treatment group (<100), and ice. Panel A plots combined coefficients, which add up the effects of same day ice (plotted in Panel B) and 1 day lagged ice (plotted in Panel C). Winters are defined as running from October in year y to April in year $y+1$. The reference winter is the 2016-2017 winter, the last full winter before the ELD mandate. The coefficients are obtained from estimating the event-study model specified in equation 3. The coefficients reflect residual variation in the outcome after regressing on county-month-group, year-month-group, and day-of-year-group fixed effects, and state-by-year linear trends. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The model includes 3,514,513 observations.

Table 3: ELD Mandate and Ice's Effect on Crashes

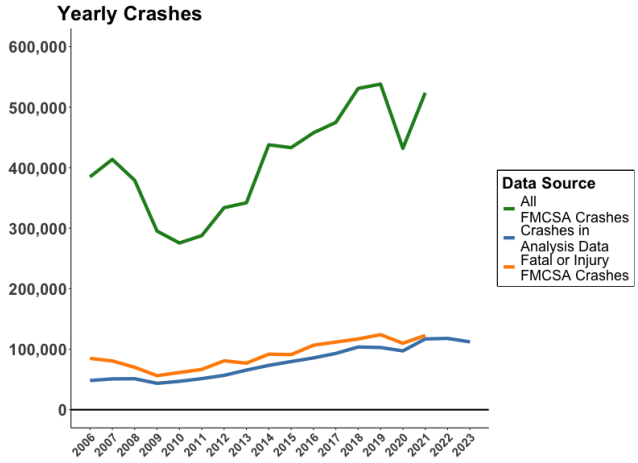
	(1)	(2)	(3)
Fleet Size	<100	<10	10-99
2 Day Ice x	21.883**	24.460**	17.681
Treat x Post (%)	(10.069)	(10.833)	(11.245)
Ice	1.157***	1.156***	1.154***
	(0.046)	(0.047)	(0.046)
Ice x Treat	-0.076	-0.077	-0.071
	(0.047)	(0.052)	(0.057)
Ice x Post	-0.024	-0.020	-0.015
	(0.076)	(0.077)	(0.075)
Ice x Treat x Post	0.063	0.050	0.068
	(0.076)	(0.085)	(0.087)
Ice (lag)	0.489***	0.488***	0.486***
	(0.053)	(0.053)	(0.053)
Ice (lag) x Treat	-0.083**	-0.129***	-0.039
	(0.039)	(0.046)	(0.049)
Ice (lag) x Post	-0.138*	-0.135*	-0.130
	(0.082)	(0.082)	(0.083)
Ice (lag) x Treat x Post	0.145**	0.177***	0.105
	(0.058)	(0.065)	(0.071)
Observations	4,724,864	3,969,872	3,984,466
County-Month-Group FEs	X	X	X
Year-Month-Group FEs	X	X	X
Day-of-Year-Group FEs	X	X	X
State-Year Trends	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effects of ice on trucks involved in crashes for the continental U.S. over the period 2014 to 2019. The coefficients are obtained from Poisson regressions of counts of the outcome (at the county-day level) on ice, the interaction of ice and the treatment group (which varies by size in each column), the interaction of ice and the post-mandate period (2018 to 2019), and the triple interaction of ice, the treatment group, and the post-mandate period. The first row of coefficients represents the combined effect of the mandate on the ice-crash relationship over two days (i.e., the effect on same day crashes and on next day crashes). Column 1 includes carriers with fewer than 100 trucks in the treatment group, column 2 includes carriers with fewer than 10 trucks, column 3 includes carriers with 10 to 99 trucks, and column 4 includes carriers with 100 to 999 trucks. All columns include county-month-group, year-month-group, and day-of-year-group fixed effects, as well as state-specific linear trends. Heteroskedasticity robust standard errors are clustered at the county and year-month level
*p<0.1 **p<0.05 ***p<0.01

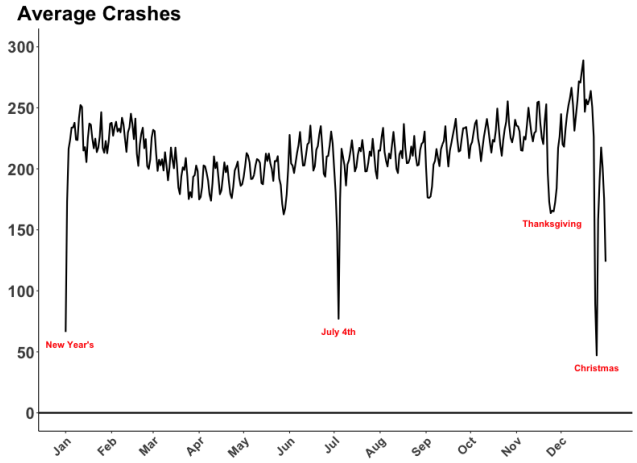
A Appendix

Summary Statistics

A) Total Crashes by Year
Analysis Data vs. All
Official Crashes



B) Average Crashes by Day



C) Percentage of Crashes by Hour of Day

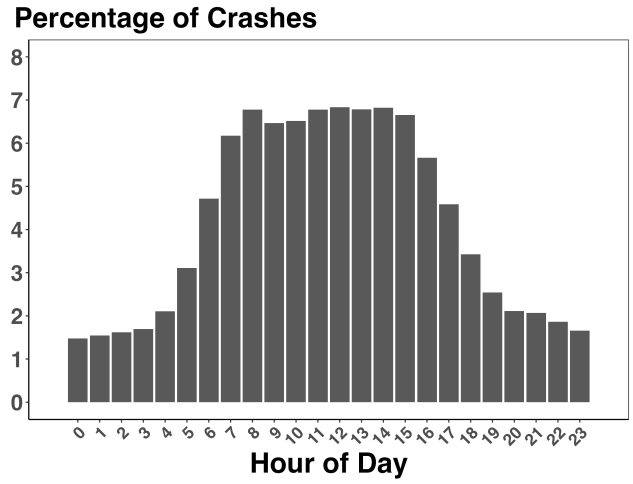
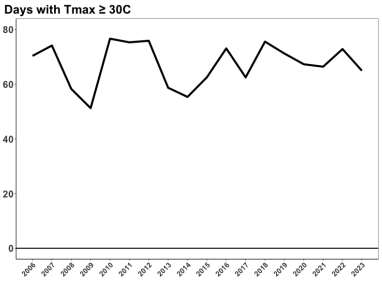


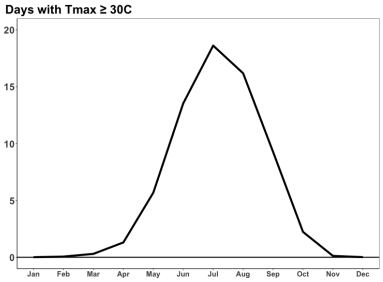
Figure A1: Crashes by Time Period

Panel A plots the total number of trucks in crashes in the analysis dataset in blue, the yearly total number of trucks in crashes involving injuries or fatalities from the *Large Truck and Bus Crash Facts 2021* from the Federal Motor Carrier Safety Administration in orange, and trucks involved in all crashes (adding property damage only crashes to those involving injuries or fatalities) in green. Panel B plots the average number of crashes per day, and Panel C plots the percentage of crashes by hour of day.

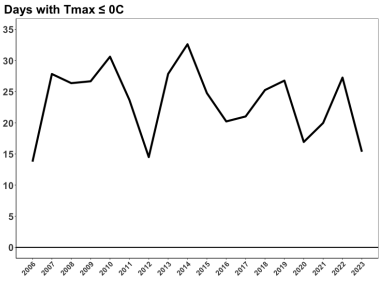
A) Yearly Days with Max Temp ≥ 30°C



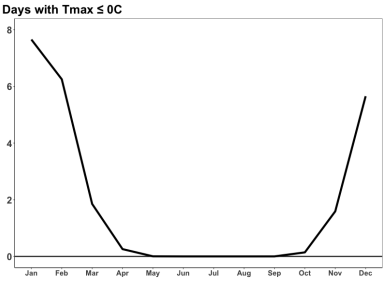
B) Monthly Days with Max Temp ≥ 30°C



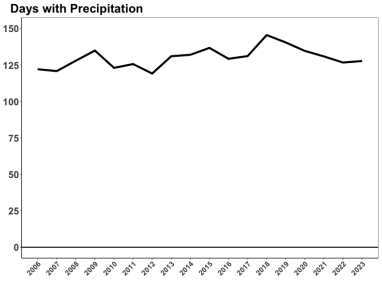
C) Yearly Days with Max Temp < 0°C



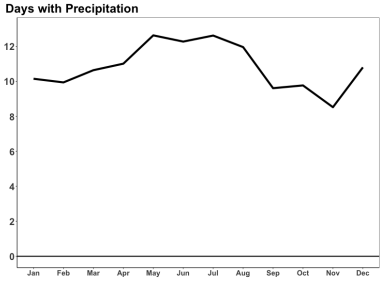
D) Monthly Days with Max Temp < 0°C



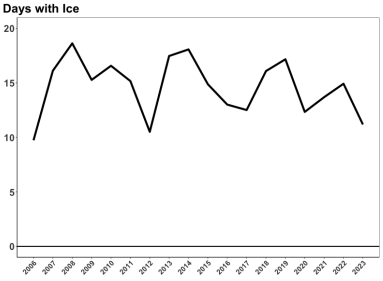
E) Yearly Days with precipitation



F) Monthly Days with precipitation



G) Yearly Days with Ice



H) Monthly Days with Ice

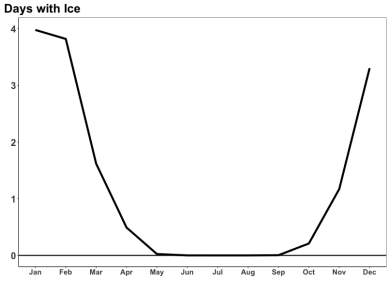


Figure A2: Weather by Year and Month

Panel A plots the average number of days per year, across counties, with a maximum temperature of 30°C and above. Panel B plots the average number of days per month, across counties, with a maximum temperature of 30°C or above. Panels C and D are the same as A and B, respectively, for days with a maximum temperature below 0°C, Panels E and F are for days with precipitation, and Panels G and H are for days with ice.

Road-weighting Weather Data

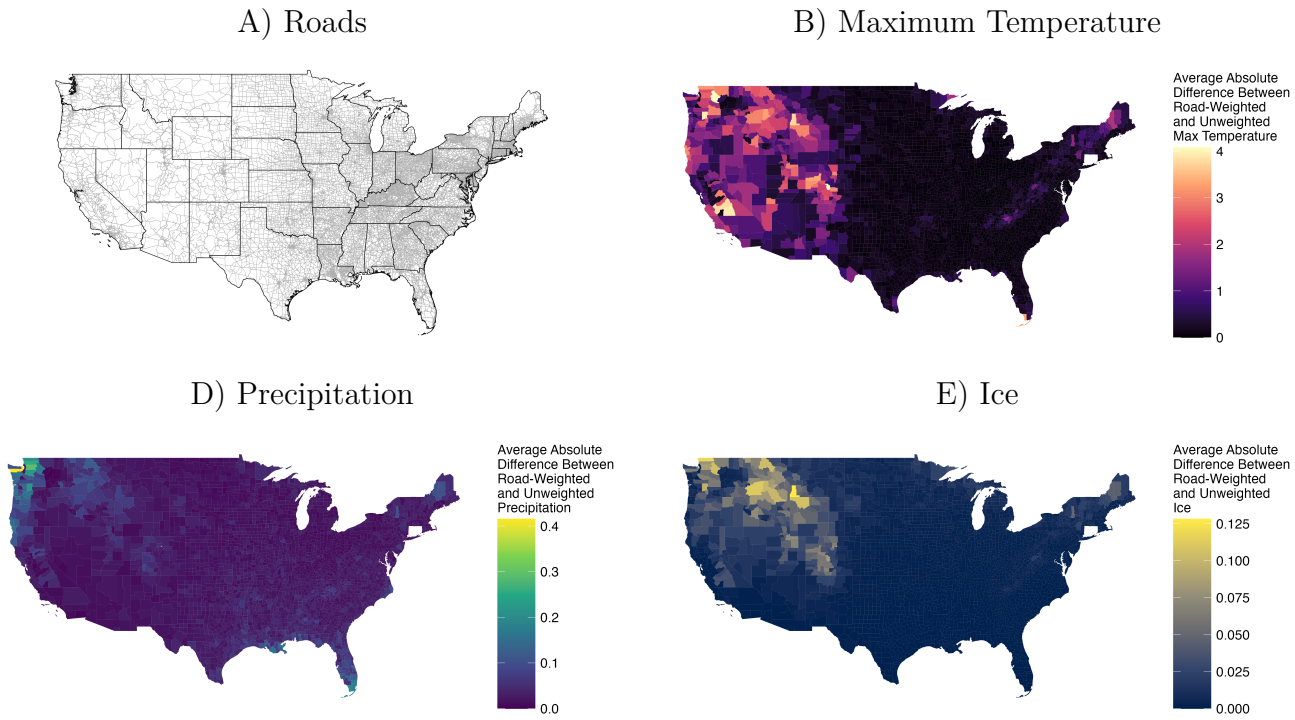
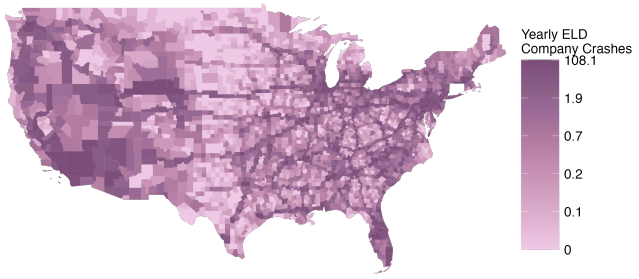


Figure A3: Road-weighted vs. Unweighted Weather

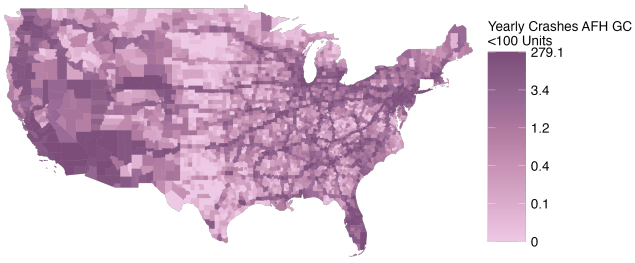
Panel A maps the roads used to calculate road-weighted weather data. Panel B maps the average absolute difference in °C between the road-weighted and unweighted maximum temperature. Panel C maps the average absolute difference between the road-weighted and unweighted daily cm of precipitation . Panel D plots the average absolute difference between road-weighted and unweighted daily county ice coverage.

ELD vs. other carrier crashes

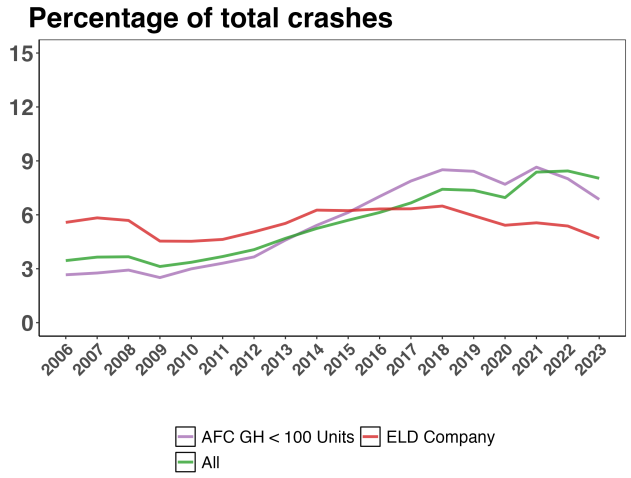
A) ELD Carrier Crashes



B) <100 Unit Carrier Crashes



C) Percentage of crashes by year for each carrier type



D) Percentage of crashes by day of year for each carrier type

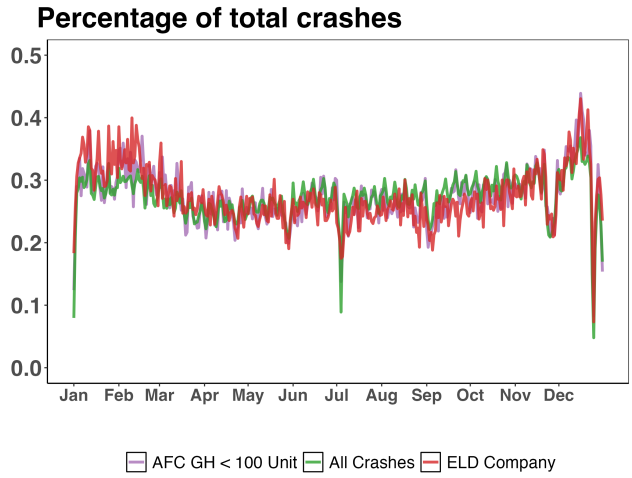


Figure A4: ELD Carrier and <100 Unit Carrier Summary Statistics

Panel A maps the yearly crashes per county for ELD carriers, the control group in the ELD mandate analysis. Panel B maps yearly crashes per county for authorized-for-hire general-cargo carriers with under 100 units, the treatment group. Panel C maps crashes by year for different carrier types, and Panel D does the same by day.

Additional Results

Table A1: 1 Day Lagged Weather and Truck Accident Outcomes

	(1) Crashes	(2) Injuries	(3) Fatalities
Ice	0.293***	0.273***	0.234***
	(0.020)	(0.058)	(0.072)
Precipitation			
≥3cm	0.004	-0.043**	-0.148***
	(0.013)	(0.020)	(0.056)
2-3cm	0.019	-0.019	-0.123*
	(0.015)	(0.032)	(0.064)
1-2cm	0.047***	-0.012	-0.147***
	(0.013)	(0.015)	(0.045)
>0-1cm	0.019***	0.007	-0.040**
	(0.006)	(0.008)	(0.020)
Max Temperature			
<0°C	-0.125***	-0.179***	-0.234**
	(0.025)	(0.053)	(0.092)
0-5°C	-0.091***	-0.112***	-0.100*
	(0.017)	(0.034)	(0.059)
5-10°C	-0.002	-0.018	-0.015
	(0.010)	(0.017)	(0.040)
15-20°C	0.009	-0.007	0.032
	(0.007)	(0.012)	(0.031)
20-25°C	0.009	-0.014	0.072**
	(0.011)	(0.015)	(0.031)
25-30°C	0.013	-0.002	0.074*
	(0.013)	(0.018)	(0.039)
30-35°C	0.026*	0.011	0.084*
	(0.015)	(0.021)	(0.048)
≥35°C	0.028	0.008	0.020
	(0.019)	(0.032)	(0.078)
Observations	19,534,840	17,797,692	9,368,850
County-Month FEs	X	X	X
Year-Month FEs	X	X	X
Day-of-Year FEs	X	X	X
State-Year Trends	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of 1 day lagged weather on crashes, injuries, and fatalities involving trucks for the continental U.S. over the period 2006 to 2023. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables (same day and 1 day lagged), as well as the listed fixed effects. All columns include county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01

Table A2: Same Day Weather and Truck Accident Outcomes: Robustness

	(1)	(2)	(3)	(4)
	Core Model	CYM FEs	Max Temp Ice	Min Temp Ice
Ice	0.780***	0.769***	0.845***	0.517***
	(0.027)	(0.027)	(0.036)	(0.018)
Precipitation				
≥3cm	0.469***	0.478***	0.490***	0.462***
	(0.017)	(0.017)	(0.017)	(0.017)
2-3cm	0.331***	0.338***	0.358***	0.316***
	(0.016)	(0.016)	(0.017)	(0.016)
1-2cm	0.328***	0.328***	0.361***	0.314***
	(0.013)	(0.013)	(0.014)	(0.013)
>0-1cm	0.050***	0.050***	0.097***	0.041***
	(0.007)	(0.007)	(0.009)	(0.007)
Max Temperature				
<0°C	0.256***	0.239***	0.209***	0.408***
	(0.023)	(0.023)	(0.026)	(0.024)
0-5°C	0.080***	0.082***	0.296***	0.118***
	(0.017)	(0.016)	(0.020)	(0.016)
5-10°C	0.024***	0.024**	0.023**	-0.032***
	(0.009)	(0.009)	(0.009)	(0.010)
15-20°C	0.025***	0.028***	0.029***	0.050***
	(0.008)	(0.008)	(0.008)	(0.008)
20-25°C	0.068***	0.071***	0.078***	0.095***
	(0.011)	(0.011)	(0.011)	(0.011)
25-30°C	0.091***	0.093***	0.105***	0.114***
	(0.014)	(0.014)	(0.014)	(0.014)
30-35°C	0.113***	0.117***	0.133***	0.133***
	(0.017)	(0.017)	(0.017)	(0.017)
≥35°C	0.166***	0.167***	0.195***	0.183***
	(0.022)	(0.022)	(0.022)	(0.022)
Observations	19,534,840	10,094,906	19,534,840	19,534,840
County-Month FEs	X		X	X
Year-Month FEs	X		X	X
County-Year-Month FEs		X		
Day-of-Year FEs	X	X	X	X
State-Year Trends	X		X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of same day weather on trucks involved in crashes for the continental U.S. over the period 2006 to 2023. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables (same day and 1 day lagged), as well as the listed fixed effects. Column 1 is the core model and includes county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Column 2 replaces county-month and year-month fixed effects with county-year-month fixed effects. Column 3 defines ice based on a maximum temperature threshold of 0°C, rather than a mean temperature threshold. Column 4 defines ice based on a minimum temperature threshold. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01

Table A3: 1 Day Lagged Weather and Truck Accident Outcomes: Robustness

	(1)	(2)	(3)	(4)
	Core Model	CYM FEs	Max Temp Ice	Min Temp Ice
Ice	0.293***	0.289***	0.365***	0.226***
	(0.020)	(0.019)	(0.026)	(0.016)
Precipitation				
≥3cm	0.004	0.014	0.002	-0.003
	(0.013)	(0.013)	(0.013)	(0.014)
2-3cm	0.019	0.027*	0.023	0.012
	(0.015)	(0.016)	(0.016)	(0.016)
1-2cm	0.047***	0.050***	0.053***	0.039***
	(0.013)	(0.013)	(0.013)	(0.012)
>0-1cm	0.019***	0.020***	0.026***	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)
Max Temperature				
<0°C	-0.125***	-0.143***	-0.155***	-0.025
	(0.025)	(0.025)	(0.027)	(0.024)
0-5°C	-0.091***	-0.091***	-0.008	-0.056***
	(0.017)	(0.018)	(0.016)	(0.016)
5-10°C	-0.002	-0.002	-0.004	-0.027***
	(0.010)	(0.010)	(0.009)	(0.009)
15-20°C	0.009	0.013*	0.008	0.018***
	(0.007)	(0.007)	(0.007)	(0.007)
20-25°C	0.009	0.012	0.006	0.018*
	(0.011)	(0.011)	(0.011)	(0.011)
25-30°C	0.013	0.015	0.007	0.023*
	(0.013)	(0.013)	(0.014)	(0.013)
30-35°C	0.026*	0.029*	0.016	0.037**
	(0.015)	(0.015)	(0.016)	(0.015)
≥35°C	0.028	0.027	0.015	0.039**
	(0.019)	(0.019)	(0.019)	(0.019)
Observations	19,534,840	10,094,906	19,534,840	19,534,840
County-Month FEs	X		X	X
Year-Month FEs	X		X	X
County-Year-Month FEs		X		
Day-of-Year FEs	X	X	X	X
State-Year Trends	X		X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of 1 day lagged weather on trucks involved in crashes for the continental U.S. over the period 2006 to 2023. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables (same day and 1 day lagged), as well as the listed fixed effects. Column 1 is the core model and includes county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Column 2 replaces county-month and year-month fixed effects with county-year-month fixed effects. Column 3 defines ice based on a maximum temperature threshold of 0°C, rather than a mean temperature threshold. Column 4 defines ice based on a minimum temperature threshold. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01

Table A4: Same Day Weather and Unique Accident Counts: Trucks vs. All Vehicles

	(1) Crashes Involving Truck	(2) All Crashes
Ice	0.601***	0.348***
	(0.040)	(0.022)
Precipitation		
≥3cm	0.313***	0.211***
	(0.036)	(0.016)
2-3cm	0.309***	0.180***
	(0.033)	(0.015)
1-2cm	0.233***	0.162***
	(0.024)	(0.012)
>0-1cm	0.024	0.023***
	(0.016)	(0.006)
Max Temperature		
<0°C	0.262***	0.110***
	(0.036)	(0.016)
0-5°C	0.059*	0.009
	(0.032)	(0.011)
5-10°C	0.010	-0.002
	(0.025)	(0.008)
15-20°C	-0.009	0.010*
	(0.022)	(0.006)
20-25°C	0.033	0.031***
	(0.027)	(0.009)
25-30°C	0.053*	0.046***
	(0.032)	(0.012)
30-35°C	0.080**	0.066***
	(0.038)	(0.015)
≥35°C	0.205***	0.114***
	(0.079)	(0.022)
Observations	2,077,397	2,204,784
County-Month FEs	X	X
Year-Month FEs	X	X
Day-of-Year FEs	X	X
State-Year Trends	X	X
Clustering	County, Year-Month	County, Year-Month

This table shows the effect of temperatures trucks involved in crashes and all crashes for 8 U.S. states (Colorado, Connecticut, Maine, Massachusetts, Michigan, New Jersey, Ohio, South Dakota, and Wisconsin) over the period 2009 to 2019. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables, as well as the listed fixed effects. All columns include county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01

Table A5: 1 Day Lagged Weather and Unique Accident Counts: Trucks vs. All Vehicles

	(1) Crashes Involving Truck	(2) All Crashes
Ice	0.426***	0.187***
	(0.031)	(0.012)
Precipitation		
≥3cm	0.130***	0.087***
	(0.029)	(0.012)
2-3cm	0.139***	0.071***
	(0.033)	(0.012)
1-2cm	0.148***	0.066***
	(0.028)	(0.009)
>0-1cm	0.054***	0.041***
	(0.015)	(0.006)
Max Temperature		
<0°C	-0.124***	0.027
	(0.042)	(0.018)
0-5°C	-0.097***	0.021*
	(0.033)	(0.012)
5-10°C	-0.013	0.019**
	(0.024)	(0.009)
15-20°C	0.031*	0.010
	(0.018)	(0.007)
20-25°C	0.040	0.004
	(0.025)	(0.008)
25-30°C	0.058**	0.003
	(0.028)	(0.010)
30-35°C	0.068**	0.008
	(0.033)	(0.012)
≥35°C	0.143**	-0.014
	(0.063)	(0.021)
Observations	2,077,397	2,204,784
County-Month FEs	X	X
Year-Month FEs	X	X
Day-of-Year FEs	X	X
State-Year Trends	X	X
Clustering	County, Year-Month	County, Year-Month

This table shows the effect of temperatures trucks involved in crashes and all crashes for 8 U.S. states (Colorado, Connecticut, Maine, Massachusetts, Michigan, New Jersey, Ohio, South Dakota, and Wisconsin) over the period 2009 to 2019. The coefficients in all columns are obtained from Poisson regressions of counts of the outcome (at the county-day level) on the listed temperature and precipitation variables, as well as the listed fixed effects. All columns include county-month, year-month, and day-of-year fixed effects, and state-specific linear trends. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01

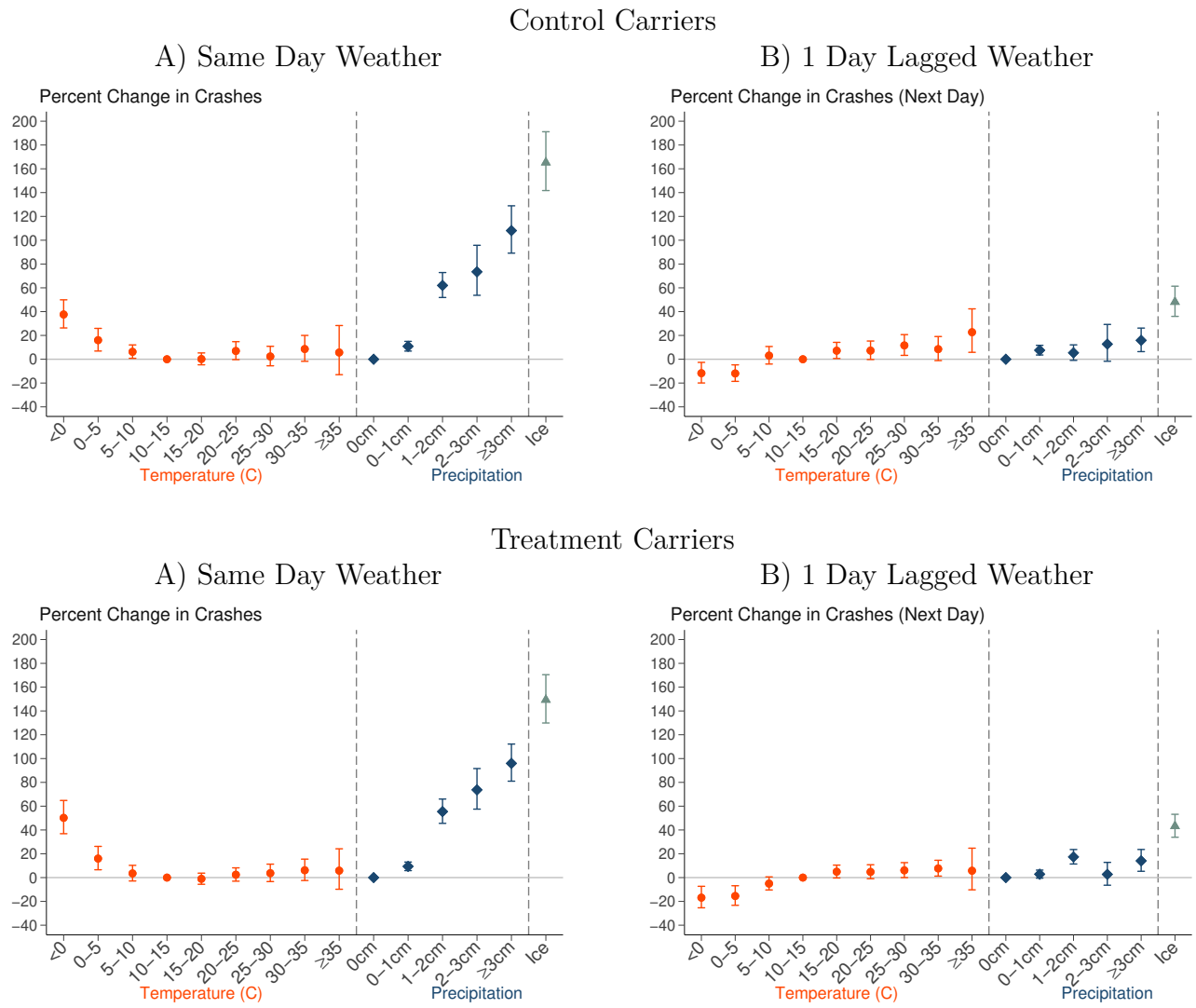


Figure A5: Weather and Crashes - Control vs. Treatment Carriers

Panel A plots the set of weather coefficients obtained from regressions specified in equation 1 with the outcome crash counts for carriers in the ELD control group per county and day. The outcome in Panel B is crash counts for carriers in the ELD treatment group. All coefficients are obtained from Poisson regressions of the outcome on weather variables. They reflect residual variation in the outcome and weather after regressing on county-month, year-month, and day-of-year fixed effects, and state-by-year linear trends. Daily maximum temperatures are assigned to a vector of 9 bins from below 0°C to 35°C and above in 5°C increments. Precipitation is assigned to a vector of 4 bins from 0 precipitation to 3cm and above in 1cm increments. Ice represents co-occurring (at the PRISM gridpoint level) mean temperature (the average of maximum and minimum temperature) below 0°C and non-zero precipitation. Temperature and precipitation coefficients should be interpreted as the percentage increase in crashes for a day in that range relative to their respective omitted categories (10-15°C and 0cm), and the ice coefficient should be interpreted as the additional interaction effect of co-occurring sub-freezing temperature and precipitation. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The model in Panel A includes 2,156,866 observations across 3,107 counties from 2014 to 2019 and Panel B includes 2,567,998.

Table A6: ELD Mandate and Ice's Effect on Crashes: Robustness

	(1) Core	(2) Only Winter	(3) Temp and Prec. Controls	(4) Temp and Prec. Interactions	(5) County-Year Month-Group FEs	(6) No Light Enforcement	(7) Max Temp Ice	(8) Min Temp Ice
2 Day Ice x Treat x Post (%)	21.883**	20.699**	21.350**	11.398	18.795*	21.161**	25.527*	13.015
	(10.069)	(9.541)	(9.984)	(12.501)	(11.265)	(10.667)	(13.575)	(8.242)
Ice	1.157***	1.181***	0.917***	0.904***	1.125***	1.170***	1.170***	0.860***
	(0.046)	(0.047)	(0.045)	(0.048)	(0.050)	(0.046)	(0.081)	(0.047)
Ice x Treat	-0.076	-0.092**	-0.073	-0.061	-0.064	-0.064	-0.049	-0.075*
	(0.047)	(0.046)	(0.047)	(0.053)	(0.052)	(0.049)	(0.082)	(0.039)
Ice x Post	-0.024	-0.037	-0.006	0.035	0.020	-0.061	-0.054	-0.057
	(0.076)	(0.069)	(0.074)	(0.082)	(0.081)	(0.062)	(0.104)	(0.068)
Ice x Treat x Post	0.063	0.082	0.061	0.019	0.056	0.091	0.162	0.053
	(0.076)	(0.071)	(0.076)	(0.084)	(0.081)	(0.061)	(0.102)	(0.059)
Ice (lag)	0.489***	0.485***	0.375***	0.369***	0.450***	0.493***	0.510***	0.425***
	(0.053)	(0.048)	(0.048)	(0.048)	(0.052)	(0.053)	(0.066)	(0.042)
Ice (lag) x Treat	-0.083**	-0.073**	-0.081**	-0.073*	-0.066*	-0.076**	-0.121	-0.054*
	(0.039)	(0.036)	(0.039)	(0.039)	(0.035)	(0.039)	(0.077)	(0.029)
Ice (lag) x Post	-0.138*	-0.137*	-0.120	-0.087	-0.077	-0.123	-0.141	-0.043
	(0.082)	(0.075)	(0.076)	(0.091)	(0.080)	(0.092)	(0.098)	(0.053)
Ice (lag) x Treat x Post	0.145**	0.115**	0.142**	0.090	0.122*	0.112*	0.080	0.074*
	(0.058)	(0.056)	(0.058)	(0.083)	(0.064)	(0.059)	(0.100)	(0.041)
Observations	4,724,864	3,514,513	4,724,864	4,724,864	1,569,930	4,570,136	4,724,864	4,724,864
County-Month-Group FEs	X	X	X	X		X	X	X
Year-Month-Group FEs	X	X	X	X		X	X	X
County-Year-Month-Group FEs					X			
Day-of-Year-Group FEs	X	X	X	X	X	X	X	X
State-Year Trends	X	X	X	X	X	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effects of ice on trucks involved in crashes for the continental U.S. over the period 2014 to 2019. The coefficients are obtained from Poisson regressions of counts of the outcome (at the county-day level) on ice, the interaction of ice and the treatment group (which varies by size in each column), the interaction of ice and the post-mandate period (2018 to 2019), and the triple interaction of ice, the treatment group, and the post-mandate period. The first row of coefficients represents the combined effect of the mandate on the ice-crash relationship over two days (i.e., the effect on same day crashes and on next day crashes). In all cases, the treatment group includes carriers with fewer than 100 trucks. Column 1 corresponds to the core specification, as in Figure 6 and Table 3 column 1. Column 2 includes only winters (October through April), from October 2013 through April 2020. Column 3 adds temperature bins (20°C and above, and below 0°C) and precipitation above 0cm as controls. Column 4 performs the full triple-difference with each of the weather controls from column 2. Column 5 includes county-year-month-group fixed effects, and column 6 removes the "light enforcement" period (from December 18, 2017 to March 31, 2018) and adds the first two months of 2020. Column 7 defines ice using maximum temperature, and column 7 defines ice using minimum temperatures. Heteroskedasticity robust standard errors are clustered at the county and year-month level *p<0.1 **p<0.05 ***p<0.01