Transportation Research Part D 136 (2024) 104455

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Weathering the wait: Temperature impacts on school bus delays

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A R T I C L E I N F O

Keywords:
School bus delay
Temperature
Climate change
Transportation planning

A B S T R A C T

Transportation systems are growingly subject to extreme weather events induced by climate change. Yet, delays in operating public transportation systems due to adverse weather conditions are not well understood. In this study, we quantify the impact of temperature shocks on school bus delays in New York City during 2015–2019. We find that low temperatures lead to significant school bus delays regarding the frequency and delay time. Our heterogeneity analysis further shows that increased school bus delay time in cold weather is primarily driven by Curb-to-School buses (for students with special education and needs) and school bus operations in the mornings. Our findings provide new evidence on how temperature shocks affect transportation systems and highlight the need for adaptive strategies and planning that can aid school buses in better responding to adverse weather conditions.

1. Introduction

Transportation systems have become more prone to the growing number of extreme weather events induced by climate change (Gössling et al., 2023). Adverse weather conditions, including extreme temperatures, excess precipitation, and snowfall can significantly affect driver capabilities, reduce vehicle performance, and contribute to a higher incidence of collisions and injuries (Andrey, 2010; Yan et al., 2014; Saha et al., 2016). In the U.S., roughly 15 % of fatal crashes and around 20 % of injury and property damage-only crashes are attributable to weather-related factors.[1] This trend is likely to rise considering the increased number of extreme weather events with greater intensity fueled by climate change (Bellprat et al., 2019).

While vehicle crashes are deemed the most devastating outcome due to extreme weather events, another direct and important consequence of adverse weather conditions is the delay in operating public transportation systems as compromised customer services. The extant literature has quantified the relationship between various weather events and train delays in particular. For example, Ludvigsen and Klæboe (2014) examine freight train delays in Finland and show that low temperatures, heavy snowfalls, and strong winds contribute to the shutdown of rail infrastructure and train operations. Focusing on the Rapid Transit rail system in the Dublin Area, Brazil et al. (2017) find that rain is the primary reason for delays. Chen and Wang (2019) investigate the operational reliability of high-speed rails and aviation in China. They reveal that high-speed rails are less vulnerable to severe weather events than aviation. Tiong et al. (2023) use the railway data from Sweden to investigate how various factors influence train arrival delays, showing that weather is among the main reasons.

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[1] See the source: https://ops.fhwa.dot.gov/weather/q1_roadimpact.htm.

https://doi.org/10.1016/j.trd.2024.104455
Received 8 July 2024; Received in revised form 25 September 2024; Accepted 29 September 2024
Available online 3 October 2024
1361-9209/

In this study, we use a unique dataset on over 300,000 documented school bus delays in New York City (NYC) during 2015–2019 to quantify the impact of temperature on school bus operation and performance. Specifically, we estimate how temperature shocks affect two outcomes: the number of school bus delays and delay time. We further explore the nonlinear effect of temperature and potential heterogeneous responses to temperature shocks among different school buses, school services, school bus operation time, and delay reasons. Our focus on school bus delays in response to temperature provides new evidence of how transportation systems respond to adverse weather conditions. Unlike trains and rails that operate on fixed tracks with predetermined routes, school buses typically operate on public roads and highways, which are more susceptible to congestion and traffic. On the other hand, trains are less flexible in adjustments to routes or schedules, while school buses are more adaptable to changing conditions such as road closures, weather, and varying school schedules. Studying school buses can thus provide new insights into the role of adaptation in coping with temperature shocks.

We document several findings in this study. First, we find a statistically significant and negative impact of temperature on the number of school bus delays and delay time after controlling for precipitation and unobserved factors using a host of spatial and temporal fixed effects. Second, there is an evident nonlinear relationship between temperature shocks and school bus delays. Specifically, lower temperatures lead to significant school bus delays regarding the frequency and delay time, while higher temperatures have no statistically significantly different effects when compared to the baseline temperature. Third, our heterogeneity analysis further shows that increased school bus delay time in cold weather is primarily driven by Curb-to-School buses (for students with special education and needs) and school bus operations in the mornings. However, we find little evidence that colder or hotter weather differentially affects delay time due to vehicle issues. Collectively, these findings provide new evidence on how temperature shocks affect transportation systems and highlight the need for adaptive strategies and planning that can aid school buses in better responding to adverse weather conditions.

2. Study region, data, and methods

2.1. Study region

Our study region encompasses five boroughs in NYC, namely, the Bronx, Brooklyn, Manhattan, Queens, and Staten Island (Fig. 1). The public transportation system in these five boroughs is quite uneven. As shown in Fig. 2, Brooklyn has the highest number of metro stations (157 in total), followed by Manhattan (121 in total). In contrast, Staten Island has only 21 stations operated through the Staten Island Railway. The percentage of schools that offer metro card services in the region is generally high (around 70 %), with Staten Island having the lowest rate due largely to the fewer metro and railway stations. Fig. 3 further summarizes the three selected socioeconomic characteristics that are related to residents' dependence on school bus usage. Particularly, the Bronx has the highest proportion of households with children under eighteen and the highest poverty rate, with the second lowest vehicle ownership among the five boroughs.

In 2022–2023, the NYC school system accommodated more than a million students, making it the largest school district in the country.[2] To satisfy the transportation needs of such a large student body, the Department of Education (DOE) provides transportation services to all eligible NYC students from kindergarten to Grade 12 in public, charter, and non-public schools. Whether a student is eligible for transportation services is based on two factors: (i) the walking distance between the student's home and school and (ii) the student's grade level.[3] Specifically, school bus services (often referred to as the Stop-to-School bus service) are mostly provided for lower-grade students (i.e., below Grade 7) and those who live farther away from schools (i.e., greater than 0.5 mile). Besides the Stop-to-School bus service, the DOE also provides Curb-to-School bus services, aimed at picking up students from the curb nearest where they live and dropping them off at their school. This special service is mainly for students who are enrolled in the Individualized Education Program or 504 Accommodation Plan. Students who have an approved medical exception are also eligible. Additionally, children in the Preschool Special Education programs or those who receive Early Intervention services are also qualified for the Curb-to-School bus service. During the 2019–2020 school year, across all boroughs, approximately 10 % of schools provided Stop-to-School buses only, with the remaining 90 % of schools offering Curb-to-School buses or both types of school bus services.[4]

Fig. 4 illustrates the number of students who took school buses and the proportion of students in different racial groups across general and special education programs in each borough during the 2019–2020 school year. Panel (a) shows that Queens had the highest number of students who took school buses (over 30,000), while Manhattan had the lowest (approximately 7,000). Panel (b) shows that, among students who took school buses, the Bronx had the highest percentage of 65 % for special education. In contrast, Staten Island had the majority of students in general education programs (about 77 %). Panels (c) and (d) further decompose racial groups among students in general and special education programs, respectively. Notably, Black and Hispanic students for special education comprised the largest proportion in the Bronx (about 93 %), followed by Manhattan (88 %), Brooklyn (76 %), Queens (67 %), and Staten Island (56 %).

[2] See the source: https://www.schools.nyc.gov/about-us/reports/doe-data-at-a-glance.

[3] See more details: https://www.schools.nyc.gov/school-life/transportation/bus-eligibility.

[4] See the data source: https://data.cityofnewyork.us/Transportation/Transportation-Sites/hg3c-2jsy/about_data.

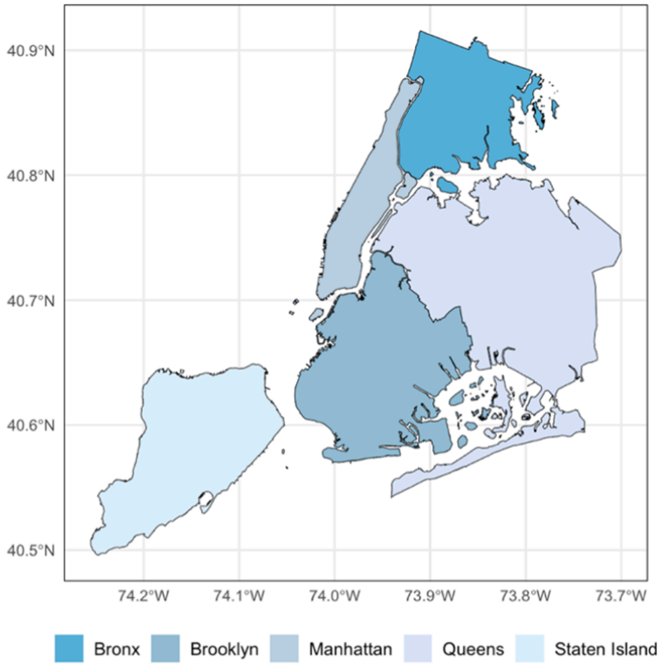

Fig. 1. Study Region.

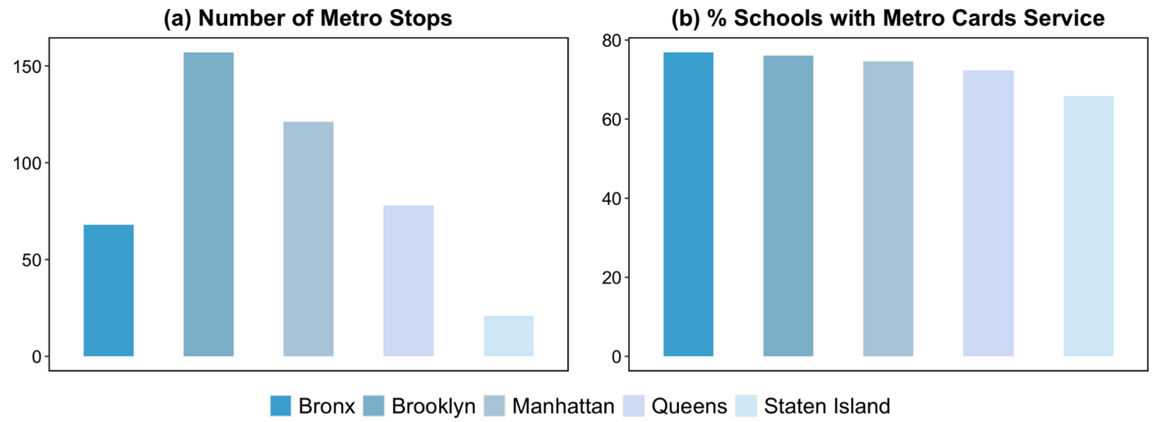

Fig. 2. Metro Stops and Schools with Metro Card Services in New York City. Notes: Panel (a) shows the number of metro stops in each borough (data). Panel (b) shows the percentage of schools that offered metro card services in each borough during the 2019–2020 school year (data source:).
Source: https://new.mta.info/agency/new-york-city-transit/subway-bus-ridership-2021https://data.cityofnewyork.us/Transportation/Transportation-Sites/hg3c-2jsy/about_data

2.2. School bus delay data

We obtained the school bus delay data through NYC OpenData, which documents daily school bus delay information since September 2015.[5] Each school bus delay record contains the date and time of the delay that occurred, the location (i.e., borough), the length of delay (in minutes), and the delay reason (i.e., heavy traffic, vehicle issues, school issues, extreme weather, route issues, and others). The data also include school bus information such as bus number, bus service categories (i.e., Stop-to-School bus service for general education and Curb-to-School bus service for special education, pre-kindergarten in the Individualized Education Program, or students in the Early Intervention Program), and school service (i.e., school-age and pre-kindergarten).

Our primary outcomes of interest are the daily number of school bus delays in each borough and the delay time (in minutes) for each school bus. Due to the concern of COVID-19 that may have substantially affected school bus operations, we used the period of

[5] See data source and description: https://data.cityofnewyork.us/Transportation/Bus-Breakdown-and-Delays/ez4e-fazm/about_data.

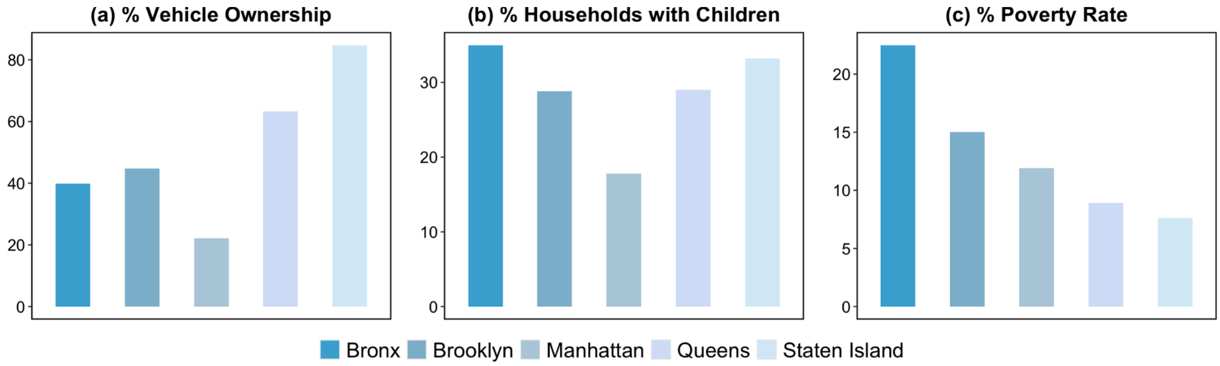

Fig. 3. Socioeconomic Characteristics in New York City. Notes: Panels (a)-(c) respectively show the average vehicle ownership rate, percentage of households with children under eighteen, and poverty rate in each borough during 2018–2022 from the American Community Survey.

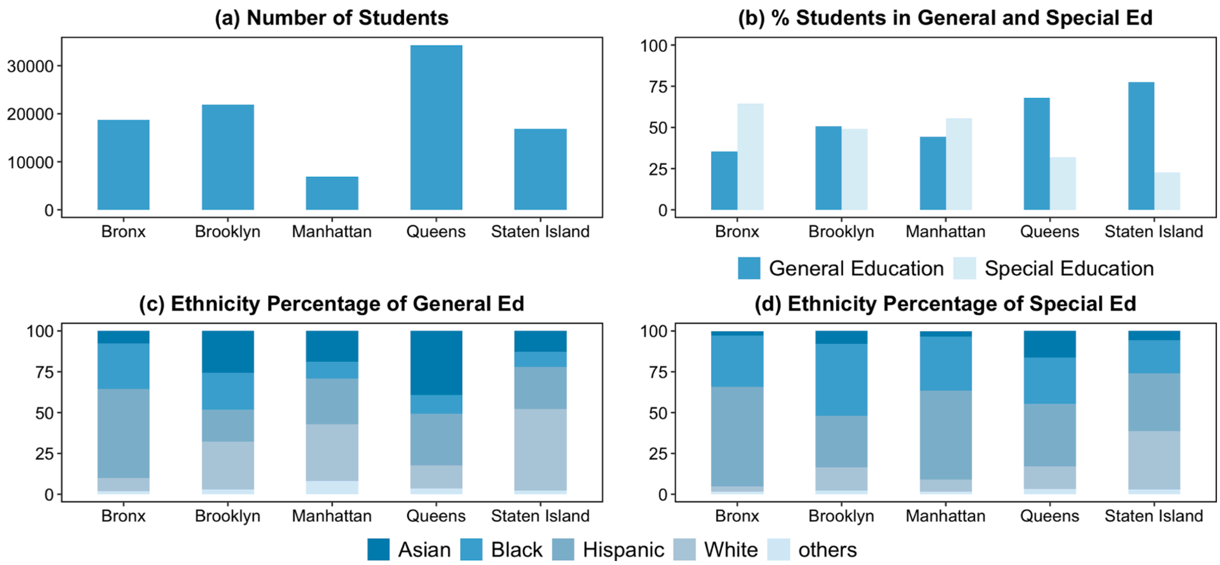

Fig. 4. School Bus Student Characteristics in New York City. Notes: Panel (a) shows the number of students who took school buses in each borough during the 2019–2020 school year. Panel (b) shows the percentages of these students in general education and special education. Panels (c) and (d), respectively, show the racial distribution of these students in general education and special education. Data Source: https://www.nyappleseed.org/wp-content/uploads/NYA_YellowBusReport_April2022_Final-1.pdf

2015–2019 in this study to establish a clear association between temperature shocks and school bus delays. To mitigate the impact of possibly spurious outliers in the data, we winsorized the school bus delay time at the 0.1st and 99.9th percentile.

Fig. 5 shows each borough's total number of school bus delays and average delay time. Among the five boroughs, Manhattan had the highest total number of school bus delays (around 97,000) and the longest average delay time (about 35 min). In contrast, Staten Island had the lowest number of school bus delays (around 15,000) and the shortest average delay time (about 24 min). Fig. 6 further illustrates the proportion of school bus delays in each borough, categorized by delay reasons, school service, school bus operation time, and school bus service. Panel (a) shows that heavy traffic was the primary cause of school bus delays across all boroughs. Panel (b) shows that, except for the Bronx, over 85 % of school bus delays involved school-age students. Regarding school bus operation time, panel (c) shows that more than 70 % of school bus delays occurred in the morning for all five boroughs. Finally, panel (d) shows that, except for Staten Island, the majority of school bus delays came from Curb-to-School buses.

The school bus delay data also documents the number of students on each delayed bus. Fig. 7 summarizes the total number of students impacted by school bus delays across five boroughs. Panel (a) shows evident regional variations in the total number of students affected by school bus delays. Specifically, the Bronx had the highest number of 427,000 students while Staten Island had the lowest number of 22,000 students. Focusing on school bus service, panel (b) shows that over 70 % of these affected students were transported by Curb-to-School buses, pointing to the fact that the majority of affected students are those who receive special education and needs. Notably, Manhattan had the highest percentage of students affected by Curb-to-School bus delays while Staten Island had the lowest.

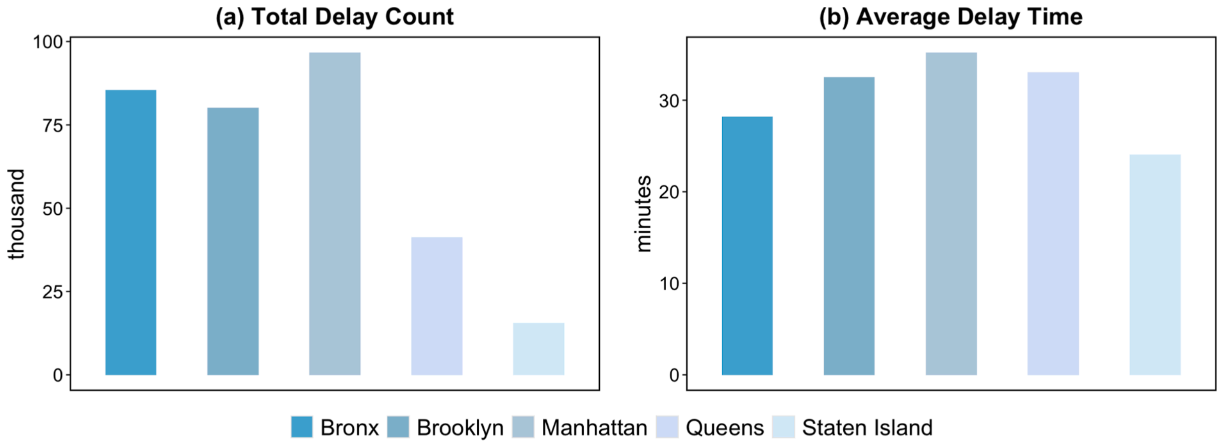

Fig. 5. School Bus Delays. Notes: Panels (a) and (b) respectively show the total number of school bus delays and the average delay time (in minutes) in each borough during 2015–2019.

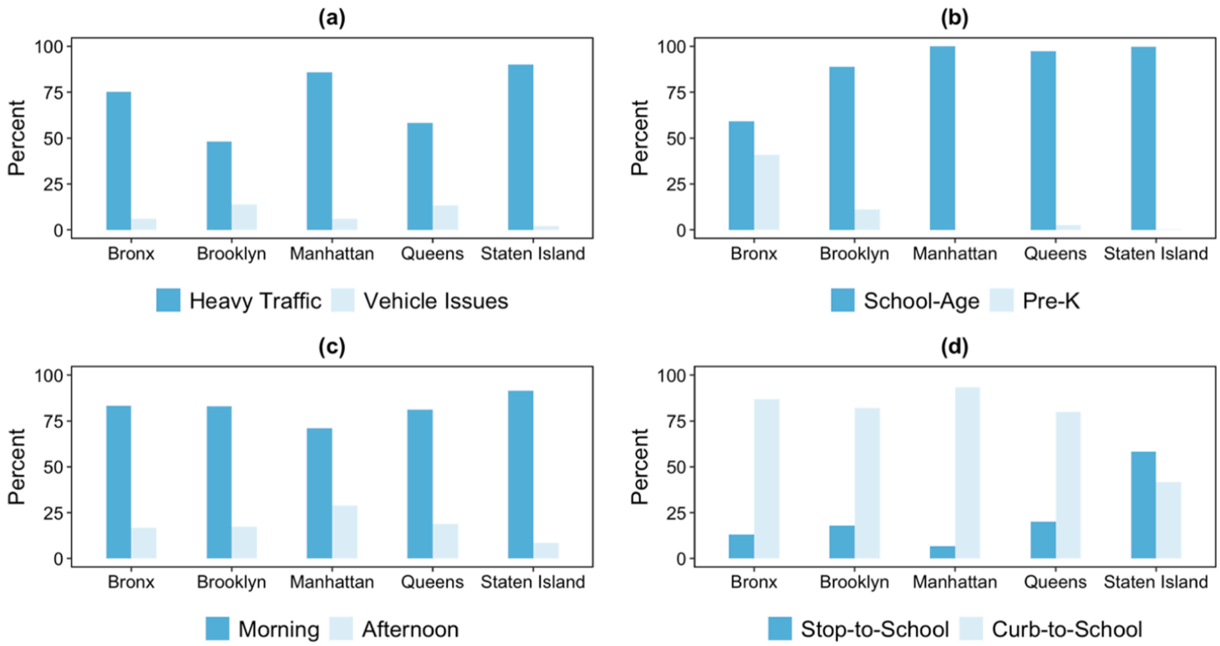

Fig. 6. Percentage of School Bus Delays by Categorization. Notes: Panels (a)-(d) respectively summarize the percentage of school bus delays by delay reason, school service, school bus operation time, and school bus service in each borough during 2015–2019.

2.3. Weather data

Following other studies that quantify the effects of adverse weather conditions on transportation systems (Wei et al., 2019; Hou et al., 2022; Han et al., 2024), we obtained the average precipitation (mm) and temperature (°C) for each borough from 2015 to 2019 at the daily level from the PRISM Climate Group.[6] The temperature and precipitation data were then merged with the school bus delay data for empirical analysis.

2.4. Summary statistics

Table 1 summarizes the school bus delay and weather data used in this study. Our total sample includes 319,326 school bus delays involving 13,904 school buses in five boroughs in NYC during 2015–2019. In detail, about 26.8 %, 25.1 %, 30.3 %, 12.9 %, and 4.9 %

[6] See the data source: https://prism.oregonstate.edu/.

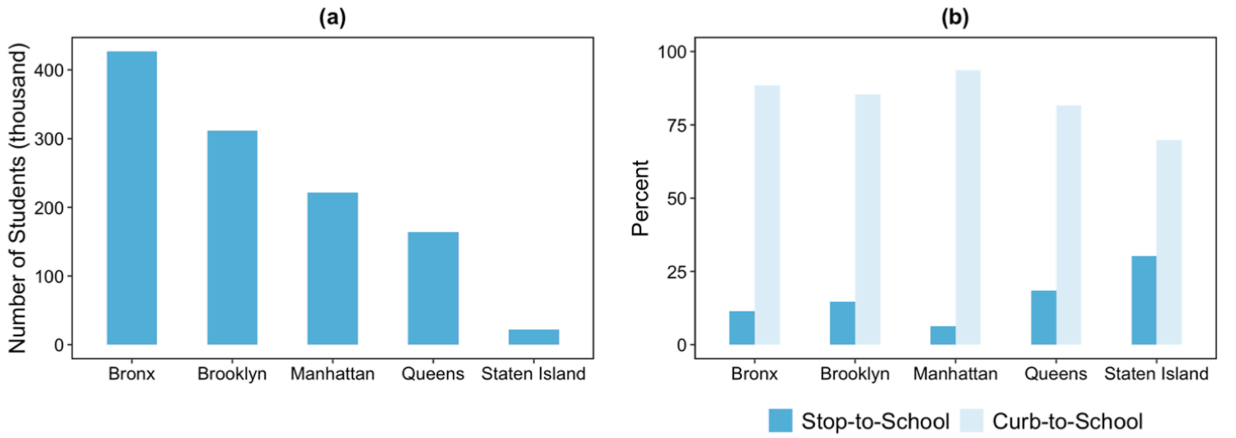

Fig. 7. Number of Students Affected by School Bus Delays. Notes: Panel (a) shows the number of students affected by school bus delays in each borough during 2015–2019. Panel (b) shows the percentage of affected students by school bus service in each borough during 2015–2019.

Table 1
Summary Statistics.

Variable	Mean	S.D.	Min.	Max.
Panel A: School bus delays				
Delay time (minute)	31.82	16.32	5	120
Borough				
Bronx (yes = 1)	0.268	0.443	0	1
Brooklyn (yes = 1)	0.251	0.434	0	1
Manhattan (yes = 1)	0.303	0.460	0	1
Queens (yes = 1)	0.129	0.335	0	1
Staten Island (yes = 1)	0.049	0.215	0	1
Delay reason				
Heavy traffic (yes = 1)	0.702	0.457	0	1
Vehicle issues (yes = 1)	0.086	0.281	0	1
School issues (yes = 1)	0.031	0.173	0	1
Extreme weather (yes = 1)	0.023	0.149	0	1
Route issues (yes = 1)	0.019	0.135	0	1
Others (yes = 1)	0.140	0.347	0	1
School bus service				
Stop-to-School (yes = 1)	0.155	0.362	0	1
Curb-to-School (yes = 1)	0.845	0.362	0	1
School service				
School-age (yes = 1)	0.859	0.348	0	1
Pre-kindergarten (yes = 1)	0.141	0.348	0	1
School bus operation time				
Morning (yes = 1)	0.795	0.403	0	1
Afternoon (yes = 1)	0.205	0.403	0	1
Panel B: Weather characteristics				
Mean precipitation (mm)	3.956	9.099	0	89.85
Mean temperature (°C)	10.99	8.761	−12.64	30.49

Notes: This table presents the statistics summarizing the school bus delay data from 2015 to 2019 involving 319,126 reported school bus delays for 13,904 school buses in five boroughs in NYC (i.e., Bronx, Brooklyn, Manhattan, Queens, and Staten Island). School bus delay time (in minutes) is winsorized as discussed in Section 2.2.

of school bus delays were in the Bronx, Brooklyn, Manhattan, Queens, and Staten Island, respectively. The average delay time was 31.82 min. Regarding reasons for delay, about 70.2 %, 8.6 %, and 2.3 % of school bus delays were due to heavy traffic, vehicle issues, and weather conditions, respectively. About 84.5 % of school bus delays were for Curb-to-School bus service. Approximately 86 % of school bus delays were for school-age students, and around 80 % of the school bus delays occurred in the morning. Lastly, the mean temperature and precipitation were respectively 10.99 °C and 3.96 mm.

2.5. Empirical strategy

We empirically investigate how temperature shocks influence two outcomes regarding school bus delays. First, we examine the average effect of temperature on the frequency of school bus delays at the borough-by-day level. Given that this dependent variable only has positive integer values, an OLS approach for estimation is inappropriate. Following the standard method for the count data of this kind (see Cameron and Trivedi, 2005), we adopt a zero-truncated negative binomial regression. Using this model, the probability of observing the number of school bus delays is:

$$f\left(y_{bt}|D_{bt}=1;T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)=\frac{f\left(y_{bt}|T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)}{Pr\left(D_{bt}=1|T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)} \tag{1}$$

where y_{bt} is the number of school bus delays in borough b on day t, T_{bt} denotes the daily mean temperature (°C) in borough b on day t, P_{bt} denotes the total precipitation (mm) in borough b on day t, and P_{bt}^2 is the quadratic term of precipitation, and $D_{bt}=1$ if borough b has any school bus delay on day t. Specifically, the numerator $f\left(y_{bt}|T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)$ is the unconditional likelihood for the number of school bus delays in borough b on day t, and the denominator $Pr\left(D_{bt}=1|T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)$ takes into account the probability of having any school bus delays in borough b on day t.

To control for unobserved factors that could confound the impact of temperature on the frequency of school bus delays, we include the borough fixed effects f_b to account for any borough-specific factors that do not change over time, a list of temporal fixed effects f_t at the day-of-week, month, and year level to account for seasonality, and the borough-by-year fixed effects f_{bt} to account for any time-varying borough-specific policies. Finally, we cluster the standard errors at the borough level to allow for any error dependence among school buses over time within the same borough.

Second, we examine the average impact of temperature on the school bus delay time at the bus-by-day level using the model specification as follows:

$$L_{ibt}=\beta_1\times T_{bt}+\theta_1\times P_{bt}+\theta_2\times P_{bt}^2+f_i+f_b+f_t+f_{bt}+\varepsilon_{ibt} \tag{2}$$

where L_{ibt} is the delay time (in minutes) for school bus i in borough b on day t and f_i is the school bus fixed effects to control for any unobserved factors associated with school buses that do not change over time. All other variables remain the same as described in Eq. (1). The coefficient of interest is β_1, which reflects the average impact of temperature on the school bus delay time.

As commonly done in the climate literature (Hsiang, 2016; Chan and Wichman, 2020), we also explore the nonlinear relationship between temperature and school bus delay outcomes using a set of temperature bins as follows:

$$f\left(y_{bt}|D_{bt}=1;\sum_{k=1}^{K}1\{T_{bt}=k\},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)=\frac{f\left(y_{bt}|\sum_{k=1}^{K}1\{T_{bt}=k\},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)}{Pr\left(D_{bt}=1|T_{bt},P_{bt},P_{bt}^2,f_b,f_t,f_{bt}\right)} \tag{3}$$

$$L_{ibt}=\sum_{k=1}^{K}\beta_k\times 1\{T_{bt}=k\}+\theta_3\times P_{bt}+\theta_4\times P_{bt}^2+f_i+f_b+f_t+f_{bt}+\varepsilon_{ibt} \tag{4}$$

where $1\{T_{bt}=k\}$ is a dummy variable indicating whether the daily mean temperature (°C) of borough b on day t falls into a tem-

Table 2
Impact of Temperature on School Bus Delays.

Variable	Dependent variable [1]	[2]
	Number of school bus delays	School bus delay time (in minutes)
Temperature (°C)	−0.016***	−0.084***
	(0.001)	(0.018)
Controls	Yes	Yes
Fixed effects	Yes	Yes
Observations	4,541	310,508

Notes: This table presents the results on the average impact of temperature on school bus delays. For the regression in column [1], the observation is at the borough-by-day level (N = 4,541). We include precipitation as the control variables and borough, day-of-week, month, year, and borough-by-year fixed effects, with standard errors clustered at the borough level. For the regression in column [2], the observation is at the bus-by-day level (N = 310,508). We include precipitation as the control variables and school bus, borough, day-of-week, month, year, and borough-by-year fixed effects, with standard errors clustered at the borough level.

perature bin k. In this study, we use the following temperature bins, including $(-\infty, -3)$, [-3, 0), [0, 3), [3, 6), [6, 9), [9, 12), [12, 15), [15, 18), [18, 21), [21, 24), [24, 27), and $[27, \infty)$, with the [12, 15) temperature bin serving as the baseline. All other variables remain the same as described in Eqs. (1) and (2). The coefficients of interest are $\beta_k(k = 1, \cdots, K)$, which reflect the impact of each temperature bin on the frequency of school bus delays and the delay time relative to the [12, 15) temperature bin.

3. Results

3.1. Average impact of temperature on school bus delays

Table 2 shows the results on the average impact of temperature on school bus delays. Column [1] presents the coefficient estimate for the impact of temperature on the number of school bus delays from estimating Eq. (1). We find a statistically significant and negative effect, indicating that a 1.6 % ($1 - e^{-0.016}$) increase in the number of school bus delays at the borough-by-day level when the average daily temperature decreases by 1℃. Column [2] presents the coefficient estimate for the impact of temperature on school bus delay time from estimating Eq. (2). The results show that low temperatures not only increase the number of school bus delays but also increase delay time. On average, a 1℃ decrease in daily temperature will result in an additional 0.084-minute (or 5 s) increase in school bus delay time.

3.2. Nonlinear relationship between temperature and school bus delays

Fig. 8 reports the nonlinear effects of daily temperature on school bus delays, where the [12, 15 °C) temperature bin serves as the baseline. Panel (a) presents the impact of exposure to different temperature bins on the number of school bus delays by estimating Eq. (3). We find that all the coefficient estimates for temperature bins below 9 °C are positive and significantly significant, indicating that colder weather aggravates school bus delays. Notably, compared to the baseline temperature bin of [12, 15 °C), the number of school bus delays increases by about 56 % ($e^{0.4416} - 1$) when the daily temperature is below −3°C. Panel (b) plots the nonlinear relationship between temperature and school bus delay time from estimating Eq. (4). We can observe that all the coefficient estimates for temperature bins below 12 °C are positive and significantly significant. This finding suggests that colder weather not only increases school bus delays but also increases delay time. Specifically, school bus delay time increases by about 2.3 min when the daily temperature is below −3°C, compared to those delays in the baseline temperature bin of [12, 15 °C).

3.3. Heterogeneity in the impact of temperature

In this section, we present a suite of heterogeneity analyses to provide additional insights into the relationship between temperature and school bus delay time. Given the available data, we specifically explore four subcategories, including delay reasons, school bus service, school service, and school bus operation time. Fig. 9 shows the results.

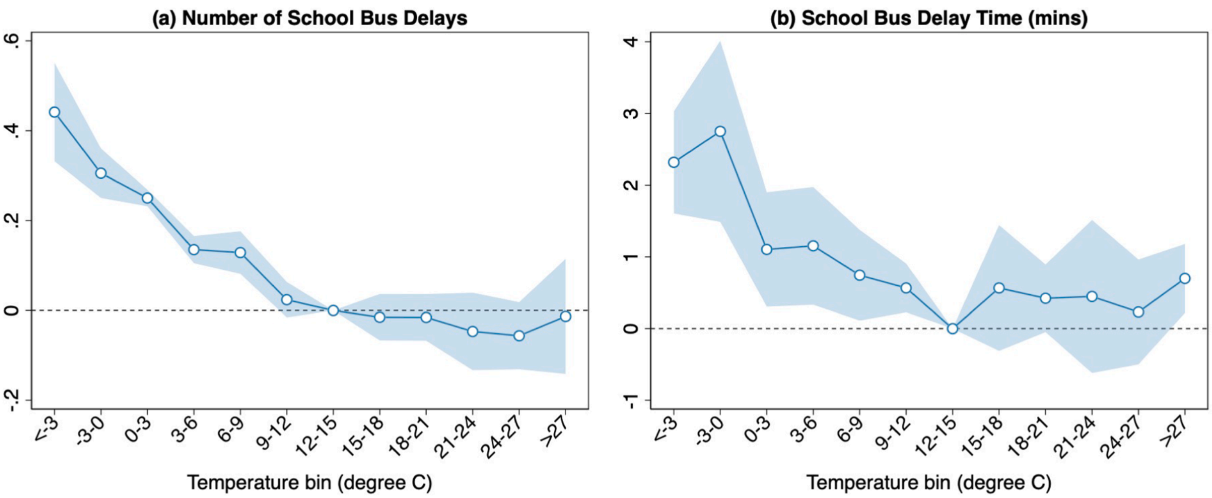

Fig. 8. Nonlinear Relationship between Temperature and School Bus Delay. Notes: This figure reports the point estimates for the nonlinear relationship between daily temperature (℃) and the number of school bus delays and school bus delay time (in minutes), respectively, from estimating Eqs. (3) and (4), with shaded areas denoting the 95 % confidence intervals. The [12, 15℃) temperature bin serves as the baseline. For panel (a), the observation is at the borough-by-day level (N = 4,541). Borough, day-of-week, month, year, and borough-by-year fixed effects are used and precipitation is included as controls, with standard errors clustered at the borough level. For panel (b), the observation is at the bus-by-day level (N = 310,508). Bus, borough, day-of-week, month, year, and borough-by-year fixed effects are used and precipitation is included as controls, with standard errors clustered at the borough level.

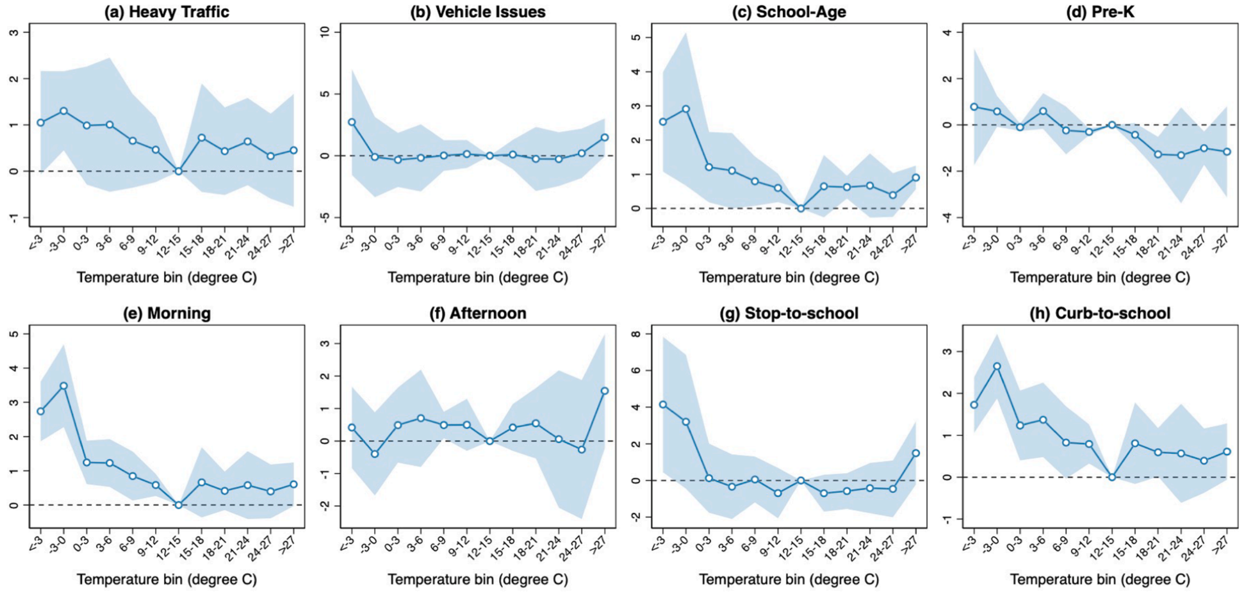

Fig. 9. Heterogeneous Impacts of Temperature on School Bus Delay Time. Notes: This figure reports the point estimates for the nonlinear relationship between daily temperature (℃) and school bus delay time (in minutes) from estimating Eq. (4) for each subgroup, with shaded areas denoting the 95% confidence intervals. The [12, 15℃) temperature bin serves as the baseline. All the model specifications control for precipitation and include bus, borough, day-of-week, month, year, and borough-by-year fixed effects, with robust standard errors.

First, we focus on two main causes of school bus delays documented in the data (i.e., heavy traffic and vehicle issues). Panel (a) shows that low temperatures (i.e., below 0 °C) significantly increase delay time for school buses that were delayed due to heavy traffic. This result makes sense intuitively and provides one possible mechanism for the relationship between temperature and school bus delays. Low temperatures can lead to ice formation, and even snow accumulation, making driving conditions more difficult and thus reducing vehicle speed. Additionally, cold weather can discourage public transportation usage and force individuals to drive for commuting, thereby causing traffic congestion on the road (Koetse and Rietveld, 2009). Interestingly, panel (b) indicates that colder or hotter weather does not differentially affect delay time for school buses that were delayed due to vehicle issues. However, there is a 1.5-minute increase in delay when the temperature exceeds 27 °C, although only marginally significant at the 10 % level.

Second, panels (c) and (d) show that the effects of temperature on school bus delay time vary by school service. We can see that both colder and hotter weather significantly increase delay time for school-age buses, whereas temperature shocks on school buses for pre-kindergarten are not statistically significant. One possible explanation is that NYC DOE offers school bus services to school-age students from kindergarten to the sixth grade (K-6). Due to the large number of this student group, bus routes are often longer and involve higher traffic volumes, making these school buses more susceptible to traffic congestion and other consequences due to extreme weather. Conversely, pre-kindergarten school buses are for four-year-old children only, which serve fewer students, resulting in shorter bus routes and less exposure to high traffic volumes. As a result, the impact of extreme temperatures on school bus delays is less pronounced for pre-kindergarten.

Third, we classify school bus delays into two groups based on when the delay occurred: in the morning when picking up students for school and in the afternoon when dropping students off after school. Panels (e) and (f) show that on low-temperature days, delay time in the morning significantly increases, particularly when the temperature is below 0 °C. In contrast, the delay time in the afternoon is not statistically significantly different across different temperature bins. One possible explanation is that cold weather may cause students to arrive late at bus stops due to oversleeping or other reasons, resulting in increased waiting time for the school buses and, consequently, longer delays. As for the afternoon, students usually finish school before the evening rush hours and are directly dropped at the designated stops, which is less likely to cause delays.

Fourth, we examine the impacts of temperature on school bus delay time across school bus services (i.e., Stop-to-School and Curb-to-School bus services). Panels (g) and (h) illustrate that apart from temperatures below −3°C, different temperature bins do not lead to statistically significantly different delay times for Stop-to-School buses. However, lower temperatures considerably increase the delay time for Curb-to-School buses. Notably, when the temperature drops below 0 °C, it results in an additional 2.6 min of delay when compared to the baseline temperature bin of [12, 15℃). There are two main reasons for this. First, Curb-to-School buses primarily serve students for special education with special needs, who may require additional help and support when boarding and alighting, especially in low-temperature conditions. In such cases, bus drivers may need more time to ensure the students' safety and comfort. Second, Curb-to-School buses operate on a "home-to-school" point-to-point basis, with more dispersed stops. Each stop's parking and starting process may take more time in low temperatures. Stop-to-School buses, however, stop at predetermined fixed locations, which are relatively concentrated and involve shorter stopping times, thus making them less affected by low temperatures.

3.4. Regional differences

Fig. 10 presents the impacts of temperature on school bus delays separately for the five boroughs in NYC. Panels (a) to (e) show the impact of exposure to different temperature bins on the number of school bus delays in each borough. We can see that the effects of temperature on the frequency of school bus delays are consistent across different regions. Lower temperatures increase the number of school bus delays, while higher temperatures have no statistically significantly different effect when compared to the baseline temperature bin of [12, 15℃). Especially when the temperature is below −3°C, the number of school bus delays in the Bronx, Brooklyn, Manhattan, Queens, and Staten Island increases by 47 %, 36 %, 51 %, 92 %, and 68 %, respectively. Panels (f) to (j) show the impact of temperature on the school bus delay time in each borough. Lower temperatures, especially below 0 °C, significantly increase the school bus delay time in all five boroughs, ranging from 1.6 to 5.0 min of additional delay time.

While the impacts of temperature on school bus delays paint a similar picture across boroughs, the consequences can differ due to uneven reliance on school bus services in the region. Particularly, the Bronx is likely most affected by school bus delays for three main reasons. First, the percentage of students in special education who take school buses in the Bronx is the highest, accounting for about 65 % (see Fig. 4), with over 12,000 students as the largest number among the five boroughs. The Curb-to-School buses, which primarily serve students in special education, are found to be negatively impacted by low temperatures. Second, 93 % of the students in special education are Black or Hispanic (see Fig. 4), and these communities generally face higher poverty rates, as shown in Fig. 3. Students from families in poverty may rely solely on school buses. Third, compared to other boroughs such as Manhattan and Brooklyn, the Bronx has a comparatively less developed subway system with fewer metro stops (see Fig. 2), which also increases students' reliance on school buses.

4. Discussion and conclusions

Global climate changes will likely affect transport infrastructures and their operations more often (Gössling et al., 2023), driven by the increasing number of extreme weather events (Bellprat et al., 2019). As transportation systems become more vulnerable to adverse weather conditions, it is imperative to gain a thorough understanding of how these volatile conditions impact transportation services so that policymakers and other related entities can enable informed planning and adaptation strategies in the future. While a large body of studies has focused on how different weather events influence trains and rails (Ludvigsen and Klæboe, 2014; Brazil et al., 2017; Chen and Wang, 2019; Tiong et al., 2023) and vehicle crashes and injuries (Naik et al., 2016; Saha et al., 2016; Wang et al., 2017), research on school bus operation and performance in response to adverse weather conditions such as temperature shocks remains scarce.

In this study, we provide new evidence by using a unique dataset on school bus delays in NYC to quantify the impact of temperature shocks on school bus operation and performance. We find that cold weather leads to significant school bus delays regarding the frequency of school bus delays and delay time. However, hot weather does not seem to cause statistically significantly different effects when compared to the baseline temperature. Our findings are consistent with prior studies that investigate the role of temperature on transportation systems. Using the Greater London area as a case study, Tsapakis et al. (2013) show that low temperatures (< 0°C) result

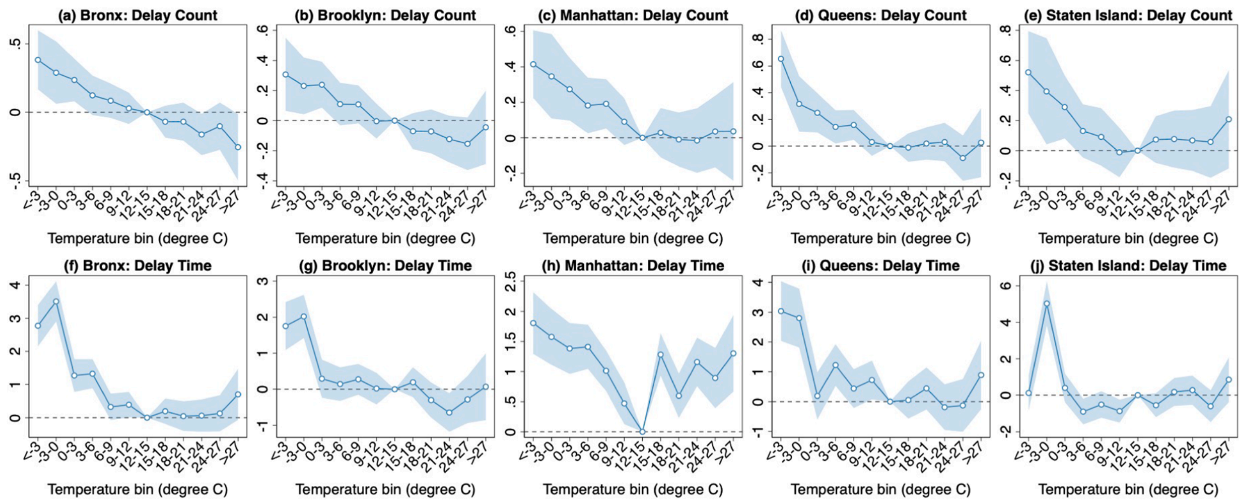

Fig. 10. Impacts of Temperature on School Bus Delays by Region. Notes: This figure reports the point estimates for the nonlinear relationship between daily temperature (℃) and the number of school bus delays and school bus delay time (in minutes), respectively, from estimating Eqs. (3) and (4), with shaded areas denoting the 95% confidence intervals. The [12, 15℃) temperature bin serves as the baseline. For panels (a) to (e), the observation is at the borough-by-day level. Day-of-week, month, and year fixed effects are used and precipitation is included as controls, with standard errors clustered at the borough level. For panels (f) to (j), the observation is at the bus-by-day level. Bus, day-of-week, month, and year fixed effects are used and precipitation is included as controls, with standard errors clustered at the borough level.

in a higher percentage of traffic delays. Under cold weather conditions, vehicle performance significantly declines (e.g., difficulty of starting), and the risk of breakdowns and traffic congestion increases (Gao et al., 2016; Hou et al., 2022). Moreover, low temperatures, especially in the presence of ice and snow, lead to slippery road surfaces, which can trigger traffic accidents (Lee et al., 2014). Additionally, in low-temperature weather, individuals are more inclined to choose private vehicles over public transportation for commuting (Koetse and Rietveld, 2009), potentially leading to traffic congestion. These factors collectively contribute to a higher likelihood of school bus delays under low-temperature conditions. However, high-temperature conditions may not substantially affect transportation systems. For example, Wu (2022) finds no statistically significant relationship between heat waves and traffic collisions considering various collision-related conditions.

Our heterogeneity analysis further indicates that increased school bus delay time due to cold weather is primarily driven by Curb-to-School buses (for students in special education and needs) and school bus operations in the mornings. To alleviate the negative effects of temperature shocks on school bus delays, especially Curb-to-School buses carrying students in special education, policy-makers and related entities may consider different adaptive strategies. First, from an operational perspective, since students with special needs may require more time to board and disembark, additional support personnel can be provided during cold weather to assist these students, minimizing the time spent getting on and off the bus. Second, since Curb-to-School bus stops are more scattered and individualized, the routes are longer and more susceptible to poor road conditions in cold weather. School bus routes can be re-evaluated to select routes with less traffic (or lanes specifically allocated for school buses), thereby potentially offsetting the delay time caused by cold weather conditions. Third, from a management perspective, students with special needs are more dependent on accurate scheduling. Real-time monitoring systems that track bus locations (Ammar et al., 2019) can be especially helpful in informing parents and students about delays and expected arrival times.

Regional differences in the impact of temperature on school bus delays are also worth noting, considering factors such as alternative transportation availability and the reliance on school buses related to socioeconomic characteristics. First, the more alternative transportation modes (e.g., metro rails) are available, the less severe the impact of school bus delays can incur. In our study region, Manhattan and Brooklyn have extensive subway networks, while the Bronx and Staten Island have much fewer metro stops (see Fig. 2). This indicates that in the event of school bus delays, students in the former can opt for the subway to attend school, while those in the latter are more severely impacted unless they resort to private cars. Second, for boroughs with a higher percentage of families in poverty and a lower percentage of vehicle ownership (e.g., the Bronx), students are more likely to be affected by school bus delays due to limited resources. To address these regional inequalities, collaboration with private transportation companies can be considered to provide supplementary transportation for students affected by school bus delays during extreme weather conditions, especially in the Bronx where such assistance is most needed. Options could include temporary shuttle services or subsidies for shared transportation options among low-income families or households without vehicles.

Although this study provides one of the first empirical evidence on how temperature shocks influence school bus delays, there are several limitations given the current data coverage and availability. First, the usage of school buses (e.g., measured as the occupancy rate) affected by extreme weather can be examined if the expected and actual number of students on each school bus is documented. Such an analysis can enrich our understanding of the weather-school bus relationship. Second, given that the majority of schools in the study region offer metro card services to students (see Fig. 2), how students substitute between school buses (which are more prone to extreme weather) and subways (which are less prone to extreme weather) regarding their commuting choices during adverse weather conditions could be further explored. This will require DOE and the Department of Transportation in NYC to collaborate on data collection and sharing. The results of this investigation can especially help government agencies to optimally allocate resources in the public transportation sector in response to behavioral changes induced by adverse weather conditions.

CRediT authorship contribution statement

Hao Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Haoluan Wang:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Yingqi Hu:** Investigation, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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