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Abstract

School absenteeism remains a significant challenge across Latin America and the Caribbean, with serious implications for educational trajectories, particularly among vulnerable students. While absenteeism is determined by multiple factors, increasing attention has focused on how physical accessibility and travel conditions affect school attendance, particularly under adverse weather conditions. In Montevideo, where a substantial share of students walk to school, rainfall emerges as a particularly relevant disruptor. In this context, this study analyses the extent to which the quality of infrastructure providing access to schools mitigates the impact of rainfall on school attendance in Montevideo. To this end, a panel of data at student-day level is constructed, integrating georeferenced administrative data on students and schools, geospatial information on road and pedestrian infrastructure, and daily rainfall records. Based on this dataset, discrete choice models are estimated to assess the differential impact of rainfall on the probability of school absenteeism, considering the quality and availability of road and pedestrian infrastructure for school access. The results show that rainfall significantly increases the probability of school absenteeism in Montevideo, an effect that is mitigated under better transport infrastructure conditions, particularly where paved roads and pedestrian infrastructure are available. However, this tends not to be the context of the most vulnerable students, who are disproportionately exposed to poorer infrastructure conditions, compounding existing inequalities and increasing their exposure to rainfall disruptions, ultimately affecting effective access to education. Overall, the results indicate that better transport infrastructure can mitigate the effects of rainfall on school attendance, which provides relevant evidence for public policy design, highlighting the need to coordinate education, transport and climate resilience agendas.

Keywords: School absenteeism, Transport Infrastructure, Education, Rainfall, Uruguay

JEL Codes: I24, R41, R42, Q54, C23

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1. Introduction

Vulnerable populations are disproportionately affected by disruptions to transport infrastructure and services during extreme weather events (Hallegatte et al., 2017). Yet, Latin American and Caribbean (LAC) countries still lag in integrating climate resilience criteria into the planning and management of their transport infrastructure and systems. This lag becomes even more pronounced when explicitly considering social inclusion and protection of the most vulnerable groups from climate-related events (OECD, 2023).

The intersection of increasing climate risk and rapid urbanization in LAC makes the resilience of transport systems a pressing concern. Between 1900 and 2021, the annual frequency of floods in the region has grown more than other natural disasters such as storms, landslides and extreme temperatures (Calatayud et al., 2023). This phenomenon is occurring in parallel with an accelerated process of urbanization: currently, 81% of the region’s population lives in cities, and this figure is projected to reach 89% by 2050 (United Nations, 2018). Additionally, most urban peripheries in LAC cities lack basic local public goods like street pavement (Gonzalez-Navarro and Quintana-Domeque, 2016), which besides representing less resilient infrastructure, reduces the effective benefits associated with urban integration and access to opportunities. In increasingly dense cities exposed to growing climate risks, the proper and resilient functioning of transport infrastructure and systems is essential to ensure access to opportunities such as employment or education. In this context, their performance plays a critical role in protecting the living conditions of the most vulnerable populations, who are often most exposed to both infrastructure deficits and adverse climate impacts (Scholl et al., 2022).

This study focuses on climate resilience of urban mobility infrastructure and school attendance in Montevideo. This context is particularly relevant in Uruguay, where recent evidence points to increasing precipitation and rainfall extremes. Between 1961 and 2017, annual precipitation levels rose by roughly 10–20% across the country, accompanied by changes in the frequency and intensity of extreme rainfall events (Ministerio de Ambiente de Uruguay, 2023). At the same time, Montevideo faces persistently high levels of absenteeism (ANEP-CODICEN, Departamento de Investigación y Estadística Educativa, 2023; Cardozo, 2025). School attendance is widely recognized as a strong predictor of educational outcomes and achievements, including dropout, labor market trajectories, and social outcomes (Cabus and De Witte, 2015; Gottfried, 2009; Morrissey et al., 2014; Rumberger, 1995; Schoeneberger, 2012).

The analysis focuses on Montevideo, a city that offers a particularly relevant context for examining this issue, due to persistent levels of absenteeism in education. This is not unique to the capital: on average, students in Uruguay attend approximately 160 days per year, which means they miss around 20 school days (ANEP-CODICEN, Departamento de Investigación y Estadística Educativa, 2023). Over the six years of primary education, cumulative absenteeism can become substantial, reaching the equivalent of up to a full school year among students with the highest levels of absenteeism. This result places Uruguay, despite being a relatively high-income country in the region with broad access to education and extensive spatial coverage of public primary schools (Hernandez, 2018), among those with the highest levels of absenteeism (Cardozo, 2025). This pattern reflects that absenteeism is a multi-causal phenomenon. According to Cardozo (2025) and Administración Nacional de Educación Pública (ANEP) (2025), existing national evidence associates absenteeism with a combination of individual, family, and institutional factors, as well as behavioral dynamics—such as low perceived returns to schooling, difficulties in establishing household routines, limited family engagement, and student disengagement—which further shape daily attendance decisions.

In addition to its relevance as a case study, Montevideo offers a particularly rich data environment that enables empirical analysis of the impact of resilient transport infrastructure on school attendance. The availability of georeferenced administrative records of students and schools, combined with detailed geospatial information on road and pedestrian infrastructure and daily rainfall records, allows for the joint analysis of educational, infrastructure conditions, and climatic

variability within a unified analytical framework. This level of spatial and temporal granularity remains rare in literature and constitutes a key contribution of the study.

Although school absenteeism is influenced by multiple factors—including family, institutional, and socioeconomic conditions—this study contributes to the literature by addressing a relatively underexplored dimension: the role of school access infrastructure and its interaction with weather conditions. Specifically, it asks to what extent better and resilient transport infrastructure mitigates the impact of rainfall on students’ school absenteeism. More specifically, the study explores the extent to which the availability and quality of road and pedestrian infrastructure are associated with the likelihood of school absenteeism. In this way, the study provides empirical evidence on a specific mechanism through which climate variability and deficiencies in urban infrastructure shape inequalities in effective access to education. This contribution complements recent evidence from Uruguay showing that improvements in urban infrastructure can significantly reduce school absenteeism (Zanoni et al., 2023).

The rest of the document is organized as follows. Section 2 presents the conceptual framework underpinning the study, placing it within a relatively underexplored intersection of education, transport and climate variability. Section 3 describes the methodological approach and data sources used to address the challenge proposed in this study. Section 4 presents the empirical results of the study based on a logit model. Finally, Section 5 presents the main conclusions, public policy implications and future lines of research.

2. Background Research

Physical access to schools is a necessary condition for regular attendance, which makes transport infrastructure a key determinant of educational outcomes. Therefore, barriers to school access affect attendance, reinforcing the link between educational inequalities and disparities in transport infrastructure (Moreno-Monroy et al., 2018). Ensuring safe and effective school mobility options requires adequate and resilient infrastructure capable of providing a minimum level of accessibility even in adverse conditions; otherwise, effective access to education is compromised, especially in vulnerable contexts.

Despite the relevance of this link, there is no unified body of research that comprehensively addresses school absenteeism and the impacts on mobility of transport infrastructure that is not resilient to climate-related events such as heavy rainfall. In this regard, this study draws on insight from three bodies of literature: (i) school absenteeism, (ii) transport accessibility, and (iii) climate-related transport and social outcomes.

Within the field of education, a large body of research examines the determinants and consequences of school absenteeism, as well as its impact on educational trajectories (see, for example, Cabus and De Witte, 2015; Gottfried, 2009; King et al., 2015; Klein et al., 2020; Morrissey et al., 2014; Rumberger, 1995; Schoeneberger, 2012). This is a highly relevant issue in the region where absenteeism remains a persistent challenge, disproportionately affecting vulnerable populations, with profound implications for learning and inequality (UNESCO and UNICEF, 2021). Indeed, poverty and adverse circumstances shape children’s access to education and, consequently, their academic performance (See et al., 2023). Non-attendance not only translates into lower levels of school performance but also leads to difficulties for students associated with a lack of social integration and connection with peers, with students in turn losing a space for support and psychosocial assistance (UNESCO, 2021).

Evidence also shows that frequent absenteeism, especially in the early years of schooling, has both immediate and long-term negative effects on students’ academic performance and educational trajectories (Gottfried, 2009; Morrissey et al., 2014; Allen et al., 2018). Although there are multiple determinants of absenteeism, the literature consistently highlights the central role of socioeconomic, contextual, and cultural factors (Hoogeveen and Rossi, 2013; Gonsch, 2016; Dine, 2024; Nakamura-Thomas et al., 2021; Klein et al., 2020). Furthermore, vulnerable socioe-

conomic contexts are often characterized by deficits in urban infrastructure and reduced access to vehicles, which in turn amplifies physical and territorial barriers to school attendance.

Complementarily, the transport geography literature highlights that school accessibility depends on both the spatial organization of educational opportunities and the constraints affecting daily travel (Andersson et al., 2012; Moreno-Monroy et al., 2018; Wang et al., 2022). Building on this perspective a growing body of studies has emphasized the importance of physical accessibility to schools as a key determinant of school attendance and retention. In urban contexts, Edwards (2022) shows that in the state of Michigan, students with greater economic difficulties who qualified for district-provided transport were less likely to be chronically absent. Similarly, Silva et al. (2025), in a study of Recife, Brazil, find that each additional kilometer that students must walk to get to school increases the level of absenteeism by 22.4%, highlighting the strong impact of distance and urban accessibility barriers on school absenteeism. In rural contexts, where distances are greater and transport options more limited, these effects are intensified. Bammou et al. (2024), studying rural schools in Morocco, show that longer travel times are associated with higher rates of tardiness and absenteeism, as well as lower student performance.

Recent evidence highlights the role of the quality of the built environment surrounding students' homes and school routes, on school outcomes. Evidence from Uruguay suggests that improvements in urban infrastructure—particularly in vulnerable neighborhoods—can significantly reduce school absenteeism (Zanoni et al., 2023). In Buenos Aires, a focus group analysis revealed that families living in slums often decide not to send their children to school on rainy days due to mobility difficulties, as most streets in these neighborhoods are unpaved and lack drainage (Gutiérrez et al., 2022). In the same vein, recent evidence from The Bahamas finds that poor pedestrian and drainage infrastructure, and exposure to adverse climate events can affect children's capacity to reach schools, while also affecting caregivers' decisions regarding how children travel (Scholl et al., 2025a, 2025b). These findings underscore that school attendance is not only influenced by distance, but also by the safety, reliability, and climate resilience of the surrounding transport environment.

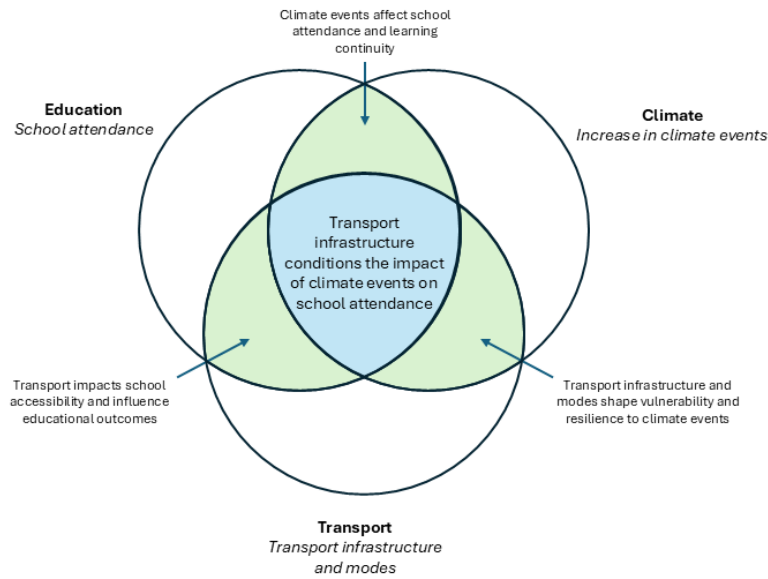
In turn, literature analyzing the relationship between climatic events and educational outcomes has begun to document significant impacts at both the aggregate and daily levels. For example, Bos et al. (2025) state that extreme heat and other climate-related events are already causing temporary school closures, reductions in the school calendar, schedule adjustments, and higher levels of student and teacher absenteeism, affecting 171 million students worldwide. Blackman et al. (2025) present evidence that extreme climate events, such as high temperatures, negatively affect educational outcomes in LAC, while also projecting that a significant number of schools and students will be increasingly exposed to extreme heat in the coming decades. The authors also present a number of studies that show that beyond extreme heat, climate-related events such as droughts, storms, and hurricanes negatively affect educational outcomes by reducing school attendance and damaging school infrastructure and connectivity. Studies in rural areas of Ethiopia show that certain climatic conditions—such as moderate temperatures and heavier rainfall during the summer agricultural season—are associated with a higher probability that students complete some level of education (Randell and Gray, 2016). Complementarily, beyond affecting school attendance, Cuartas et al. (2025) find that adverse climate conditions can also affect educational outcomes by directly impairing children's cognitive performance, with disproportionate effects on disadvantaged households and those lacking access to adequate infrastructure.

At the regional level, the effects of rainfall and temperature on school performance vary significantly depending on the context. In some regions, rainfall during childhood improves educational outcomes by strengthening agricultural production, income, and nutrition at key stages of child development. In contrast, negative effects are observed in Central America and the Caribbean, where rainfall is often associated with floods and hurricanes that affect schooling (Randell and Gray, 2019). Using daily data for the United States, McCormack (2023) finds that

absenteeism increases in extreme temperatures, both hot and cold, affecting African American, Hispanic, and low-income students more strongly. Similar results are observed in England, where hot days increase absences, especially those related to illness and authorized leave, while cold weather has no significant impact, except for absences due to illness in neighborhoods with energy poverty (Conte Keivabu, 2024).

Taken together, this literature illustrates that school absenteeism is a complex and multi-dimensional phenomenon and has motivated increasingly interdisciplinary approaches that incorporate factors related to transport, accessibility and climatic events. However, empirical evidence that simultaneously articulates these three dimensions remains unexplored. This study seeks to contribute to closing this gap by generating evidence in the space that emerges from the intersection between education, transport, and climate¹, illustrated in the shaded area of Figure 1.

Figure 1: Conceptual Framework: Education, Transport and Climate



Source: Authors' elaboration.

The figure above illustrates the components framing this study and the partial intersections among thematic areas that have been explored in the literature. As discussed earlier, a substantial body of research examines the socioeconomic and cultural determinants of school absenteeism across different contexts, with some studies beginning to incorporate transportation and climatic events as relevant determinants.

This study therefore focuses on the intersection of these three dimensions, addressing a gap in the literature by examining how transport infrastructure mediates the impact events on school attendance. Specifically, it seeks to address the following research question: to what extent does better and more resilient transport infrastructure mitigate the impact of rainfall on students' school attendance? This question places particular emphasis on vulnerable populations, as they are typically more exposed to inadequate transport infrastructure, reduced accessibility to educational centers, and more adverse socio-economic contexts. The following section presents the

¹Although not the focus of this study, there is also an extensive literature examining the links between climate change and transport, particularly in relation to infrastructure resilience and accessibility (Schweikert et al., 2014; Santos et al., 2021; Dawson, 2014; Quinn et al., 2018; de Abreu et al., 2022).

methodology developed to answer this question, based on quantifying how mobility infrastructure conditions can mitigate the adverse effects of rainfall on school attendance.

3. Methods and Data

3.1. General Aspects

The methodological strategy of this study combines inputs from the three dimensions discussed in the conceptual framework: education, transport, and climate. It relies on the compilation of data from official databases, most of which have a strong geospatial component, including detailed data on students and schools, daily records of absences, road and pedestrian infrastructure layers, and daily precipitation data. This integrated dataset underpins the empirical analysis, which aims to examine how mobility infrastructure conditions and climate events jointly influence school attendance patterns.

The implementation of this approach requires the construction of a high-resolution data panel at the student-day level for the school year. This panel includes demographic and socioeconomic characteristics, information about the school attended, and daily attendance records. The spatial dimension is central, as the geolocation of students and schools allows for capturing the territorial context in which school trips take place. This includes both socio-economic aspects of the environment (e.g., residence in informal settlements) and characteristics of urban infrastructure (e.g., such as unpaved streets or the absence of sidewalks).

In addition, the panel integrates daily rainfall data, enabling the identification of both the occurrence and intensity of rainfall and its link to school attendance decisions. This also allows for explicitly analyzing how these effects interact with the quality of school access infrastructure. Spatial variables of the urban environment and rainfall measures are incorporated into the student-day longitudinal panel, which serves as the basis for estimating a logit model to assess the probability of a student attendance given a set of determinants. This empirical strategy is consistent with the literature on school attendance and enables the identification of the specific effects of infrastructure and climate conditions while controlling for a comprehensive set of individuals, school-level, and socioeconomic factors (e.g., Duryea and Arends-Kuenning, 2003; Rephann, 2002; Thomson, 2018; Mansour et al., 2016).

3.2. Characterization of School Access Infrastructure

A key component of the proposed methodology consists of characterizing the infrastructure for accessing schools, whether in the surroundings of the child’s home environment, or—if possible—along the route used to reach the school. The literature shows a wide diversity in the criteria and metrics used to assess the quality of the road and pedestrian environment (Alves et al., 2020; Venerandi et al., 2024). Indeed, the range extends from complex indicators based on effective routes to simpler approaches focused on basic physical conditions, such as the presence of sidewalks, pedestrian continuity, type of pavement, or road safety (Bonatto and Alves, 2022; Trolese et al., 2023).

Ideally, an indicator that characterizes road and pedestrian infrastructure should accurately reflect the condition and quality of the routes actually used by students in their daily journeys to school. Such an indicator would capture the presence and condition of sidewalks—a particularly relevant aspect given that a very high proportion of students make these journeys on foot²—as well as the type and condition of road surfaces, which is relevant for other modes of transport such as bicycles or motorcycles, both of which are especially sensitive to deficiencies in infrastructure and to adverse weather conditions.

²According to the latest mobility survey for Montevideo (Mauttone and Hernández, 2017), nearly 50% of trips classified as ‘dropping off/picking up a child’ (associated with school transport) are made on foot, while that percentage rises to 72% in lower-income areas. In addition, another 14% of this group make trips by motorbike to accompany children to school.

Montevideo has a detailed and nearly complete survey of road infrastructure, publicly available through the spatial data catalogue of the Municipality of Montevideo (IM)³. It includes information on the type of pavement (cobblestone, asphalt, concrete, dirt, gravel, and bituminous treatment) and the presence or absence of sidewalks. Although this information does not capture more qualitative dimensions of the pedestrian environment, it provides a robust basis for constructing an indicator of infrastructure quality relevant for analyzing school mobility under rainy conditions.

Given the lack of information on the routes actually used by students, this study adopts a parsimonious and replicable methodological strategy based on the quality of the infrastructure in the immediate surroundings of the student’s home—type of pavement and presence of sidewalks—as a way of approximating a quantitative measure of the initial environment of the school trip. This choice seeks to minimize measurement errors derived from assumptions about potential routes (such as the shortest route or catchment areas), which may not reflect actual journeys and therefore provide an inadequate characterization of school access infrastructure. Moreover, infrastructure conditions at the point of departure constitute a necessary condition for daily mobility, particularly in contexts where a significant proportion of students travel to school on foot.

As an additional condition, the analysis is restricted to cases where the household is located within a walkable distance of the school (15 minutes⁴). This restriction increases the likelihood of capturing trips made on foot, by bicycle or by motorbike, and reduces the potential bias associated with longer-range motorized modes of transport.

3.3. Empirical Strategy

The empirical strategy is based on the estimation of a logit model using the longitudinal panel constructed with educational data (students, daily attendance and schools), road infrastructure (measured through the access infrastructure quality indicator) and daily rainfall records. This approach is aligned with a growing literature that models school attendance, absenteeism or participation using probabilistic frameworks (e.g., Duryea and Arends-Kuenning, 2003; McCormack, 2023; Rafique et al., 2020; Randell and Gray, 2016). The panel structure allows us to observe each student’s attendance decisions throughout the school year and link them to individual, school-level, territorial and climatic characteristics.

Formally, the probability of absence for student i , enrolled in school s , on day t , is specified as:

$$\Pr(Y_{ist} = 1) = \frac{1}{1 + \exp(-V_{ist})}. \quad (1)$$

where $\Pr(Y_{ist} = 1)$ denotes the probability of absence, and V_{ist} represents the systematic (deterministic) component of the model, defined as:

$$V_{ist} = f(\text{rain}_t) + \gamma' \mathbf{D}_i + \delta'(\text{rain}_t \cdot \mathbf{D}_i) + \mathbf{X}_i' \boldsymbol{\lambda} + \alpha_s + \tau_t. \quad (2)$$

In this specification, $f(\text{rain}_t)$ captures the flexible effect of precipitation:

$$f(\text{rain}_t) = \beta_1 \text{rain}_t + \beta_2 \text{rain}_{t-1} + \beta_3 \text{rain}_t^2. \quad (3)$$

$\mathbf{D}_i$ is a vector capturing the quality of the access infrastructure associated with the students’ urban context (reference: level 0), so that δ captures the differential effect of precipitation on absenteeism across infrastructure levels. $\mathbf{X}_i$ is a vector of control variables that includes

³<https://sig.montevideo.gub.uy/>

⁴Data from the same mobility survey indicate that walking trips classified as “dropping off/picking up a child” have an average duration of 13 minutes, rising to 15 minutes in the case of low-income households.

individual characteristics. The terms α_s and τ_t correspond to school fixed effects (included in the FE specification only) and calendar controls, respectively. The interaction between precipitation and infrastructure allows for the identification of heterogeneous effects of rainfall on the probability of absence, depending on the conditions of the built environment.

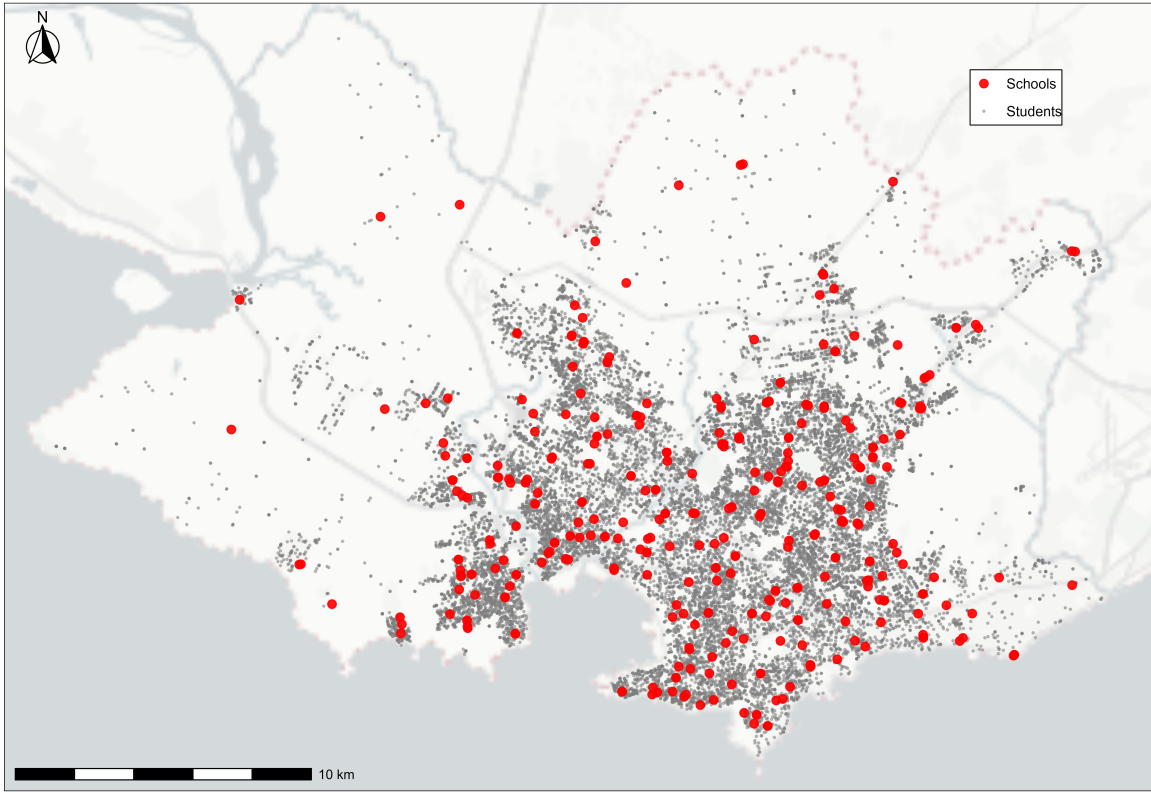
This specification enables the assessment of whether better quality infrastructure mitigates—or, conversely, whether deficient infrastructure amplifies—the impact of rainfall on school absenteeism, capturing a central mechanism through which transport resilience affects educational outcomes. Based on this specification, estimates of probability of absence is obtained, conditioned on individual, territorial and climatic characteristics. This approach allows not only for the quantification of marginal effects, but also for the capture of relevant non-linearities and heterogeneities, which are fundamental to understanding how urban mobility infrastructure conditions influence students’ ability to maintain school attendance under adverse weather conditions.

3.4. Students and Schools Data

Educational information was provided by the National Public Education Administration (ANEP). The data correspond to the 2023 school year and cover primary education. The package includes previously anonymized information at the student and school levels and allows both units to be linked using internal identifiers.

The student database was consolidated from three components: (i) individual characteristics (e.g., age, sex, grade, receipt of social benefits), (ii) residential addresses, and (iii) daily records of absences during the school year, including reason and justification status. Residential addresses were processed and geocoded to obtain coordinates, which allowed the spatial dimension to be incorporated at the individual level. In particular, geocoding was performed through automated spatial processing techniques, identifying approximately 65% of the addresses of all students. The remaining 35% were excluded from the analysis because it was not possible to obtain a reliable geographical location, mainly due to inaccuracies or inconsistencies in the recorded address information. Figure 2 shows the location of students and schools in Montevideo.

Figure 2: Location of Students and Schools in Montevideo



Source: Authors' elaboration based on ANEP data.

Daily records of absenteeism were integrated with the individual database to construct the student–day panel, which was subsequently enriched by incorporating infrastructure and precipitation information associated with each student and each date.

3.5. Transport Infrastructure Data

Information on road and pedestrian infrastructure comes from the Geographic Information System of the Municipality of Montevideo (IM), available on its official website (sig.montevideo.gub.uy). In particular, the layer “Inventario Vial” (Road Inventory) was used. This dataset, developed by the Estudios y Proyectos Viales unit of IM, contains a set of attributes describing the characteristics of urban and rural infrastructure across the department. The variables relevant to this study include the type of pavement (cobblestone, asphalt, concrete, dirt, gravel, and bituminous treatment) and the presence/absence of sidewalks (without detailed information on their type or condition). This layer is fed by surveys conducted in recent years and has been progressively updated⁵.

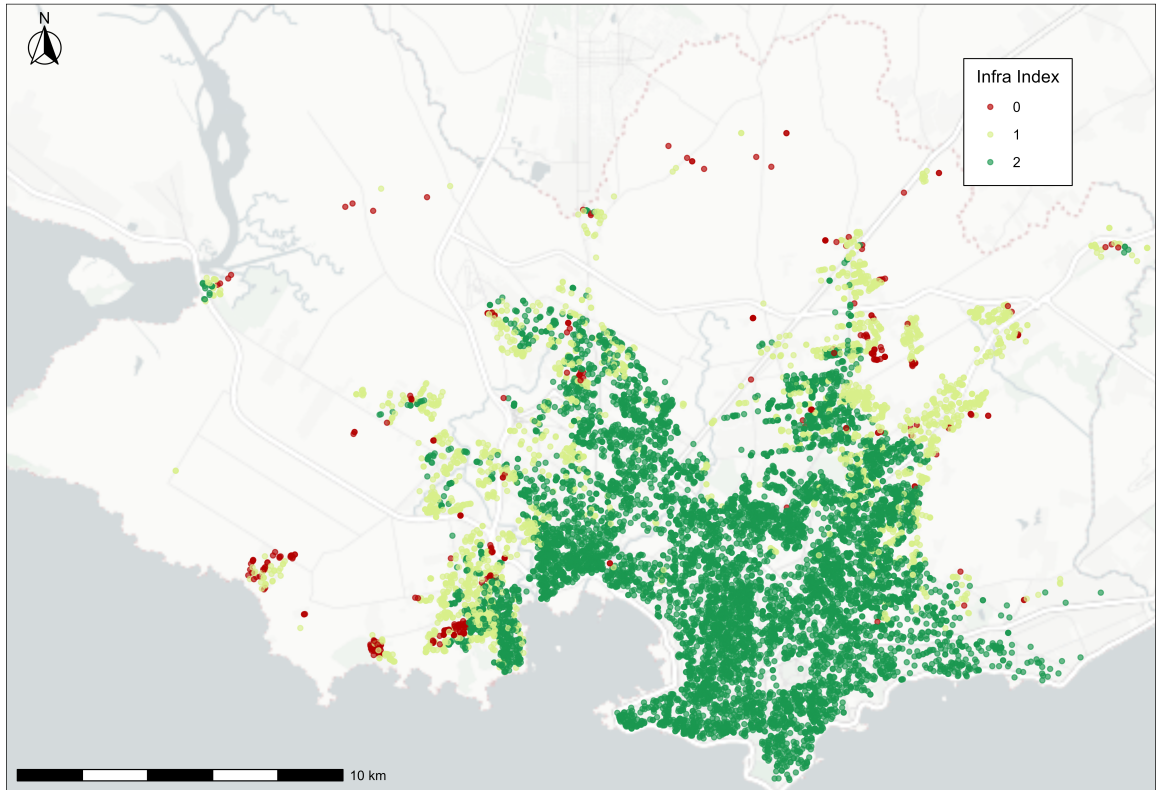
The road inventory layer was combined with student location data, with the aim of characterizing the urban infrastructure conditions. As discussed in Section 3.2, the ideal measurement would require observing each student’s actual route and assessing the quality of the infrastructure along the way; however, this information is not available. Consequently, a more parsimonious approach was adopted, based on the student’s ‘departure’ infrastructure, defined as the condition of the infrastructure based on the presence (including asphalt, concrete, bituminous treatment, and cobblestone surfaces) or absence of pavement and sidewalks on the road segment closest to

⁵As detailed below, survey campaigns conducted more than 10 years prior to the year of analysis were excluded, which results in the exclusion of students located near those streets. Nevertheless, more than 90% of the network has been surveyed within the last 10 years.

the residence. Although this approach does not capture the quality of the rest of the journey, it offers greater robustness as it is based on infrastructure that necessarily conditions the start of the journey and can constitute an immediate barrier to mobility on rainy days⁶. Specifically, an indicator was constructed that takes the value 0 if the road segment has neither pavement nor sidewalks, 1 if it has at least one of the two, and 2 if the street is paved and has sidewalks.

Figure 3 illustrates the spatial distribution of students according to the quality of the road and pedestrian infrastructure in the immediate vicinity of their residence, based on the infrastructure indicator ranging from 0 to 2. The indicator derived from this process is incorporated into the longitudinal panel as static characteristics associated with each student.

Figure 3: Students within 15-Minute School Isochrones by Residential Street Infrastructure Quality



Source: Authors' elaboration. Note: Infra Index: 0 = No pavement / no sidewalk, 1 = pavement or sidewalk, 2 = pavement and sidewalk.

3.6. Rain Data

The climate information was compiled from official data from the Uruguayan Institute of Meteorology (INUMET), available on Uruguay's national open data portal (catalogodatos.gub.uy). The records come from automatic weather stations that operate under the technical standards established by the World Meteorological Organization (WMO) and report hourly measurements of various atmospheric elements, including precipitation. The monitoring system includes rain gauges distributed across the entire country; however, for this study, the station corresponding to Montevideo was selected in order to represent local precipitation conditions.

For this study, point precipitation recorded by automatic rain gauges was used and added to daily accumulated precipitation (measured in mm). This daily indicator was incorporated into

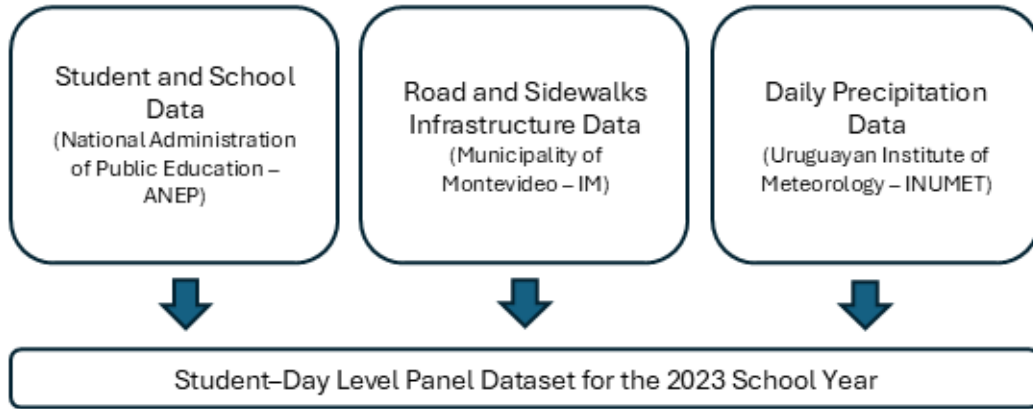
⁶For example, as mentioned in Section 2, Gutiérrez et al. (2022) find that in informal settlements of Buenos Aires, poor street conditions discourage school attendance on rainy days.

the student-day longitudinal panel, associating each day of the school year with its corresponding precipitation value.

3.7. Integrated Database

We construct a student-day panel for the 2023 school year by integrating the datasets described above (Figure 4). This structure allows for the simultaneous use of individual variation (among students), spatial variation (according to the characteristics of the access environment), and temporal variation (across days with different levels of precipitation).

Figure 4: Schematic Representation of Data Integration



Source: Authors' elaboration.

The universe of students was restricted by three main criteria. First, only students from 1st to 3rd grade of primary school were considered, given that the home address is recorded upon enrolment (grade 1) and is not necessarily updated in subsequent years; this restriction reduces the risk of measurement error due to residential relocation. Second, the sample was limited to students located within 15-minute isochrones from home to school, in order to focus the analysis on plausibly walkable routes⁷. Third, cases where access infrastructure was based on surveys conducted prior to 2013 were excluded, adopting a 10-year validity threshold to minimize inconsistencies between observed infrastructure and current conditions⁸.

Starting from an initial universe of 38,635 students in grades 1 to 3 in Montevideo and 246 schools, the final database—after applying the additional filters described above—includes 12,301 students and 243 schools. While the resulting sample from this process remains broadly comparable to the original student population, some loss of representativeness is observed (see Table A1 in Appendix), particularly for the lowest income quintile. This limitation results from the spatial filtering criteria applied and we acknowledge that it may introduce a degree of selection bias.

The panel covers working days between March and December 2023, excluding holidays and

⁷This process narrowed the sample to 56% of the geocoded students, which can be interpreted as a proxy for those likely walk to school. No direct benchmark is available for this assumption, however, data from the 2016 mobility survey indicate that approximately 70% of trips classified as “dropping off/picking up a child” are completed in less than 15 minutes. Although this result does not refer specifically to trips made on foot, it suggests that short-distance trips are predominant; and if we exclude potential motorized modes, the share of students walking is likely to be of a similar order of magnitude.

⁸More than 90% of the network has been surveyed within the last 10 years.

vacation periods⁹, totaling 175 days. Consequently, the panel contains 2,152,675 records. Table 1¹⁰ presents the main descriptive statistics of the longitudinal panel.

Table 1: Descriptive Statistics of the Student–Day Panel Dataset

Variable	Mean/%	SD	Min	Max
<i>Continuous variables</i>				
Age (years)	7.9	1.08	6	13
Home–school distance (m)	510	287	6	1,503
Daily precipitation (mm)	9.0	21.0	0.2	130.8
<i>Binary variables</i>				
Absence (1 = absent)	16%			
Sex (1 = girl)	49%			
Uruguay Social Card (1 = recipient)	30%			
Lives in informal settlement (1 = yes)	7%			
<i>Infrastructure indicator</i>				
No pavement / no sidewalk (index = 0)	3%			
Pavement or sidewalk (index = 1)	23%			
Pavement and sidewalk (index = 2)	74%			

Source: Authors’ elaboration

Note: Daily precipitation corresponds to the average of rainy days

On average, the daily absence rate is 16%, which reflects the high and persistent level of absenteeism in Montevideo’s school system mentioned in the introduction. The student population shows a balanced distribution by gender and an average age of 7.9 years, consistent with the early grades of primary school; the extreme values reflect specific cases of school lag (less than 1% of students are over 10 years old). The average distance between home and school is 510 meters, with a standard deviation of almost 300 meters. In terms of road infrastructure quality, 3% of students live on streets without pavement or sidewalks. From a socioeconomic perspective, 30% are beneficiaries of the Uruguay Social Card (TUS)¹¹ and 7% live in informal settlements. Finally, while the regression models use the full daily precipitation series (including dry days), the average precipitation among rainy days is 9 mm, with infrequent high-intensity events.

4. Results

This section presents the main results obtained from the estimation of the econometric model described in Section 3.3, which is derived from the theoretical framework that articulates three conceptual dimensions—education, transport, and climate—developed in Section 2 and illustrated in Figure 1. The estimation is carried out using the student-day longitudinal panel described in the section above. Prior to the estimation, an exhaustive exploration of the panel variables was carried out and multiple specifications were evaluated, with the aim of (i) maximizing the robustness of the estimated effects and (ii) capturing relevant heterogeneities associated with individual, socioeconomic and territorial characteristics.

⁹The first week of the school year was also removed due to enrolment adjustments and unusually high absenteeism, as well as two days for which no attendance records were generated, probably due to system failures.

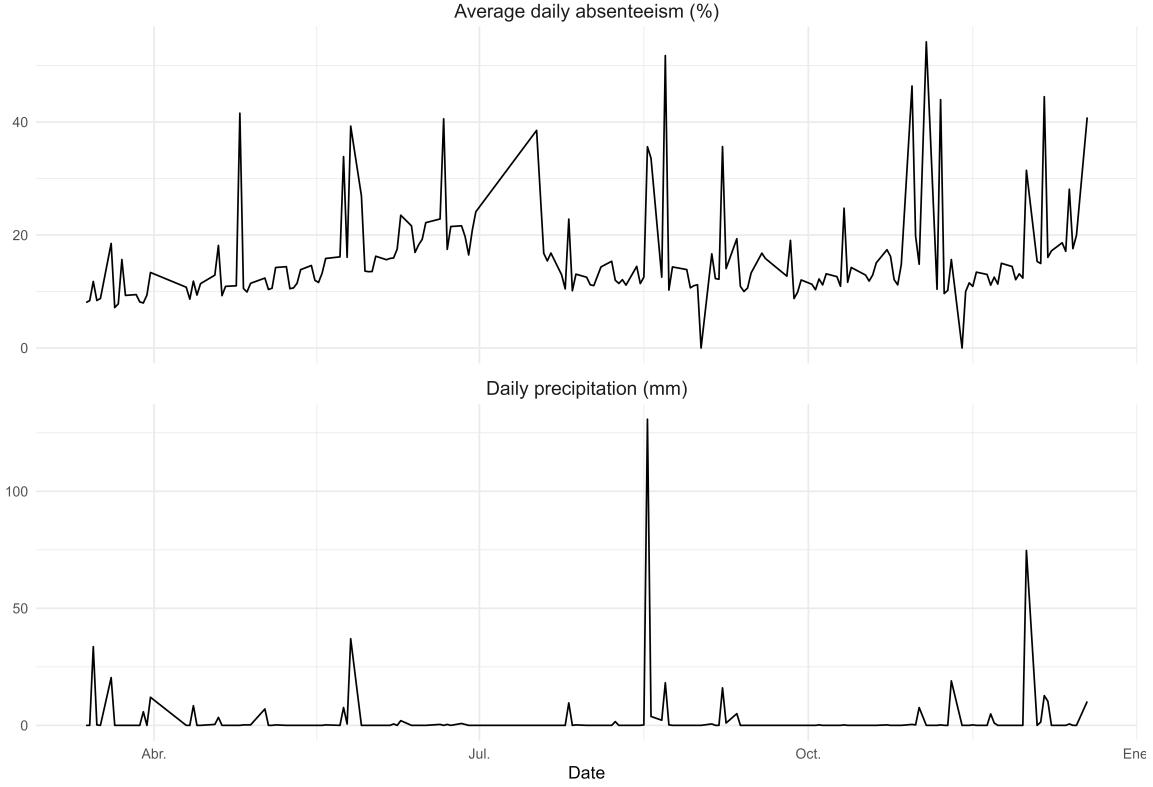
¹⁰While the expected age range for children enrolled in 3rd grade is approximately 8–9 years old, the database includes 727 students who have repeated one or more grades (630 aged 10, 91 aged 11, 4 aged 12, and 2 aged 13). This pattern is associated with delayed educational trajectories, mainly due to grade repetition. In particular, students aged 11 or older in grades 1–3 would generally have repeated more than once during their school trajectory.

¹¹TUS (Tarjeta Uruguay Social in Spanish) is a government transfer program targeting households and specific population groups under extreme socioeconomic vulnerability.

4.1. School Absenteeism and Precipitation

A first finding from the descriptive analysis refers to the high level of absenteeism among primary school students. When examining its daily evolution together with rainfall levels, a clear relationship between the two variables can be observed. Indeed, as shown in Figure 5, days with higher rainfall levels tend to coincide with increases in absenteeism.

Figure 5: Percentage of Daily Absenteeism and Rainfall



Source: Authors' elaboration.

However, the series of absences also shows peaks that do not necessarily correspond to rainfall, but rather to institutional or calendar factors, such as seasonality, strikes in the education sector, and effects associated with the proximity of holidays and recess periods. This evidence motivates the inclusion of temporal controls (e.g., day of the week and month) and specific interventions for atypical days, in order to isolate the effect of precipitation from other shocks that simultaneously affect attendance.

4.2. Model Results

Table 2 reports the results of two specifications of the logit model to explain the probability that a child does not attend school: (i) a pooled model and (ii) a model with school-level fixed effects. The estimation of both specifications allows us to compare results under different assumptions about the unobserved heterogeneity of the panel and reinforce the empirical validity of the estimated effects.

Table 2: Results of the Pooled and School FE Models

Variables	Pooled Model Coefficients	School FE Model Coefficients
<i>Dependent variable: school absence (1 if does not attend)</i>		
Constant	-2.8*** (0.08)	
Daily precipitation (mm)	0.05*** (0.0010)	0.05*** (0.01)
Lagged precipitation (t-1, mm)	0.002*** (0.0006)	0.002 (0.002)
Daily precipitation ²	-0.0003*** (3.4e-6)	-0.0003** (0.0001)
Student sex (dummy, girl = 1)	-0.04** (0.02)	-0.04* (0.02)
Student age (years)	0.05*** (0.009)	0.04*** (0.01)
TUS beneficiary (dummy, receives benefit = 1)	0.33*** (0.02)	0.21*** (0.02)
Residence in informal settlement (dummy, settlement = 1)	0.10** (0.03)	0.06 (0.04)
Distance to school (per 100 m)	0.01*** (0.003)	0.01*** (0.003)
infra_index = 1	-0.01 (0.04)	0.002 (0.06)
infra_index = 2	-0.12** (0.04)	0.03 (0.06)
Daily precipitation × infra_index = 1	-0.002* (0.0007)	-0.002* (0.0010)
Daily precipitation × infra_index = 2	-0.005*** (0.0007)	-0.005*** (0.001)
Fixed-Effects (school)	No	Yes
S.E.: Clustered	by: aluid	by: ruee & fecha
Observations	2,151,100	2,151,100
Squared Cor.	0.04154	0.05265
Pseudo R ²	0.04091	0.05196
BIC	1,813,590.9	1,796,246.9
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Source: Authors' elaboration

Notes: 1) For space efficiency, the fixed temporary effects associated with seasonality and atypical days are not presented here (see Appendix). 2) Nine students were removed for having no value for the TUS variable. 3) aluid and ruee are the identifiers for students and schools respectively.

The results show a highly consistent pattern: daily precipitation significantly increases the probability of school absenteeism in both specifications, even when controlling for individual and socioeconomic characteristics. In other words, the positive association between rainfall and absenteeism remains robust across model specifications, indicating that rainfall events increase the likelihood that a student will not attend school regardless of whether unobserved heterogeneity at the school level is controlled for. Lagged precipitation (t-1) also exhibits a positive coefficient in both models, although its statistical significance weakens once school FE and two-way clustered standard errors are introduced. This suggests that while rainy conditions may continue to affect attendance beyond the day of the event (e.g., persistent flooding or deteriorated road conditions), the delayed effects are less robust than the contemporaneous impact of rainfall. In addition, the quadratic term for precipitation is negative and statistically significant, indicating a non-linear relationship: while initial increases in rainfall substantially raise absenteeism, the marginal effect decreases at higher precipitation levels.

Regarding the control variables, the results show the following associations: greater distance from the school and older age¹² are associated with a higher probability of non-attendance, while the negative coefficient for gender (girls = 1) indicates a lower relative propensity to be absent from school compared to boys, with all other factors held constant. From a socioeconomic perspective, being a TUS beneficiary and residing in informal settlements is associated with higher absenteeism, consistent with the literature on inequalities in attendance and vulnerability. However, both variables change in magnitude—and in the case of settlement residence even in statistical significance—when the model controls for school-level fixed effects. This suggests that

¹²The positive association between age and absenteeism is in part explained by overage students who have repeated one or more grades. These students have absenteeism rates above 20%, increasing with age, whereas absenteeism is otherwise relatively stable across the first years of primary school.

part of the relationship observed in the pooled model reflects structural differences across schools or urban contexts, which are absorbed once fixed effects are included.

Regarding infrastructure quality, the pooled model results indicate a negative association between absenteeism and infrastructure quality, suggesting that students exposed to better infrastructure tend to have lower probabilities of missing school. This result is consistent with previous evidence from Uruguay showing that improvements in urban infrastructure can reduce school absenteeism (Zanoni et al., 2023). The coefficient is significant for complete infrastructure (pavement and sidewalk), suggesting that this condition is the relevant one rather than the presence of at least one of the two components (pavement or sidewalk). However, this effect disappears when introducing fixed effects by school, indicating that the observed association is mainly driven by structural differences across environments rather than by variations among students attending the same school.

The main finding of the analysis emerges from the interaction between precipitation and infrastructure quality, which is negative as the quality of road and pedestrian infrastructure improves. This suggests that better transport infrastructure mitigates the impact of rainfall on student absenteeism, which is consistent with a mitigating role of infrastructure in reducing climate-related shocks. This result is robust and consistent across both specifications, pooled and school fixed effects. Both intermediate infrastructure conditions (pavement or sidewalks) and complete infrastructure (both pavement and sidewalks) are associated with a weaker impact of rainfall on absenteeism relative to locations with neither pavement nor sidewalks. The mitigating effect is larger in locations with complete infrastructure. In fact, it suggests that the identified mechanism does not respond solely to a territorial correlation or persistent characteristics of the school environment but rather reflects a specific effect whereby the lack of pavement and sidewalks amplifies the impact of rainfall on school absenteeism.

Although the base specification, presented in Table 2, models rainfall using a quadratic functional form, this approach imposes a specific parametric relationship between precipitation and school absenteeism. While flexible, this functional form does not necessarily reflect the underlying relationship between rainfall intensity and absenteeism outcomes. Therefore, in order to assess the robustness of the results against alternative functional forms, we chose to specify a model in which rainfall is transformed using an inverse hyperbolic sine transformation. This transformation is frequently used in empirical literature (Aihounton et al., 2021; Shenoy et al., 2022; Bellemere & Wichman, 2020) as it allows for the capture of non-linear effects by accommodating the presence of zero values and reducing the impact of extreme observations. The following table shows the results of the model with this transformation of the rainfall variable.

Table 3: Results of the Pooled and School FE Models with IHS Transformation for Rain Variable

Variables	Pooled Model Coefficients	School FE Model Coefficients
<i>Dependent variable: school absence (1 if does not attend)</i>		
Constant	-2.9*** (0.08)	
Asinh(Daily precipitation)	0.28*** (0.01)	0.29*** (0.04)
Asinh(Lagged precipitation) (t-1)	0.006 (0.008)	0.002 (0.02)
Student sex (dummy, girl = 1)	-0.04** (0.02)	-0.04* (0.02)
Student age (years)	0.05*** (0.009)	0.04*** (0.01)
TUS beneficiary (dummy, receives benefit = 1)	0.34*** (0.02)	0.21*** (0.02)
Residence in informal settlement (dummy, settlement = 1)	0.10** (0.03)	0.06 (0.04)
Distance to school (per 100 m)	0.01*** (0.003)	0.01*** (0.003)
infra_index = 1	-0.01 (0.04)	0.002 (0.06)
infra_index = 2	-0.10* (0.04)	0.04 (0.06)
Asinh(Daily precipitation) $\times$ infra_index = 1	-0.01 (0.010)	-0.01 (0.01)
Asinh(Daily precipitation) $\times$ infra_index = 2	-0.05*** (0.009)	-0.05** (0.02)
Fixed-Effects (school)	No	Yes
S.E.: Clustered	by: aluid	by: ruee & fecha
Observations	2,151,100	2,151,100
Squared Cor.	0.04532	0.05663
Pseudo R^2	0.04381	0.05487
BIC	1,808,105.6	1,790,727.1
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

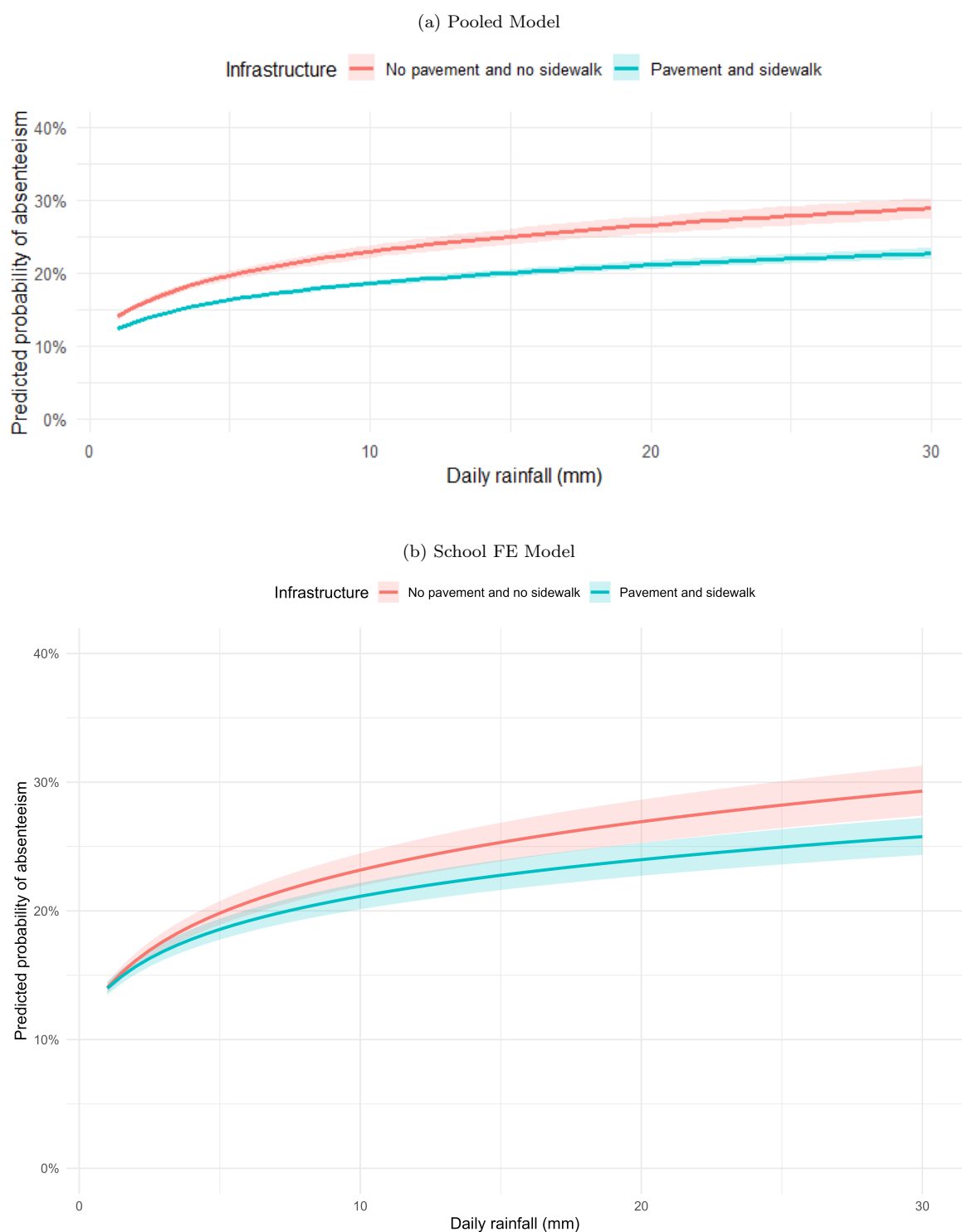
Notes: 1) For space efficiency, the fixed temporary effects associated with seasonality and atypical days are not presented here (see Appendix). 2) Nine students were removed for having no value for the TUS variable. 3) aluid and ruee are the identifiers for students and schools respectively.

As shown in Table 3, the results remain robust with respect to the baseline model, even when a specific functional form for the relationship between precipitation and absenteeism is not assumed. First, daily precipitation maintains the same sign and relevance in both specifications, which indicates the key role of rainfall in school absenteeism, although its lagged effect is no longer statistically significant. Second, the coefficient associated with the highest level of the infrastructure index (**infra_index** = 2) shows a slight reduction in its level of significance in the pooled specification, although it maintains the same sign and a marginal level of significance. Finally, the interaction between precipitation and higher-quality infrastructure continues to be negative and statistically significant, confirming that better infrastructure mitigates the impact of rainfall on school absenteeism, as had been found in the baseline model. However, unlike the baseline specification, the intermediate infrastructure category (pavement or sidewalks) is no longer statistically significant, suggesting that the mitigating effect is more robustly identified for locations with complete infrastructure (both pavement and sidewalks).¹³

To facilitate the interpretation of the coefficients, predicted probabilities of absenteeism were computed using the estimated coefficients of both model specifications, holding all variables at their mean values while varying rainfall levels continuously across different infrastructure conditions. The results of this exercise are presented graphically in Figure 6.

¹³As an additional check, we estimated a model with a three-way interaction between rainfall, infrastructure quality, and TUS beneficiary status (see Appendix, Table A4). The triple-interaction terms are not statistically significant, indicating that the mitigating effect of infrastructure does not differ across TUS and non-TUS households. These findings do not alter the distributive relevance of the results, which operates through spatial concentration: in our sample, 38.5% of TUS-recipient students live in areas with incomplete infrastructure (**infra_index** $\leq$ 1), against 21.3% of non-recipients.

Figure 6: Predicted Absenteeism under Different Rainfall and Infrastructure Scenarios



Note: (i) Predictions are based on the IHS specification using pooled and school fixed-effects models. (ii) No pavement and no sidewalk (index = 0) / Pavement and sidewalk (index = 2).

Source: Authors' elaboration.

The results show that, as rainfall levels increase, the probability of absenteeism rises in both pooled and school fixed effects specifications, following a non-linear pattern associated with the IHS transformation, in which absenteeism increases more gradually at higher precipitation levels. This is an interesting result since it suggests that a large part of the impact occurs when moving from dry days to rainy days, while additional increases at already high levels of rainfall generate smaller marginal effects. In other words, once climatic conditions are already adverse, additional

increases in rainfall intensity tend to produce relatively smaller changes in the probability of absenteeism.

However, the increase is systematically lower in scenarios where students live on streets with pavement and sidewalks. In other words, even under more conservative assumptions (fixed school effects), the attendance gap between environments with better and worse infrastructure widens with heavier rainfall. This finding indicates that infrastructure conditions are associated with differences in how absenteeism relates to rainfall. The patterns are therefore consistent with a potential role of basic road infrastructure—measured here by the presence of pavement and sidewalks—in mitigation the impact of rainfall on school attendance.

5. Discussion and Conclusions

This study proposes an empirical approach to analyze a relationship that remains relatively underexplored in the literature: the interaction between school absenteeism, climatic events and the quality of transport infrastructure. Its contribution is based on two main elements. First, it develops a conceptual framework that integrates dimensions usually addressed separately in education, transport and climate variability. Second, it constructs a database by integrating administrative records of students and schools, geospatial information on road infrastructure, and daily precipitation data. This integration results in a longitudinal panel with high spatial and temporal resolution that allows for the analysis of specific mechanisms associated with school mobility in adverse weather conditions.

The results indicate that rainfall significantly increases the probability of school absenteeism in public primary education in Montevideo. This finding is consistent with patterns already observed in the raw data (see Section 4.1) but it also provides robust empirical confirmation, aligned with a growing body of research that studies the adverse effects of climatic conditions on educational outcomes (see, for example, Randell and Gray, 2016; McCormack, 2023; Conte Keivabu, 2024; Blackman et al., 2025).

More importantly, the evidence shows that road infrastructure plays a key role as a mitigating factor: students who live on paved streets with sidewalks show systematically lower probability of absenteeism during rainfall events. While this finding may appear intuitive, it represents a novel empirical contribution to literature. To our knowledge, this study is among the first to identify and quantify this mitigating effect. Previous studies—some conducted in LAC, including Uruguay—, have highlighted the importance of the quality of the urban environment and physical accessibility as determinants of school attendance and participation (Edwards, 2022; Silva et al., 2025; Bammou et al., 2024; Zandoni et al., 2023; Gutiérrez et al., 2022; Scholl et al., 2025a, 2025b). This research advances that literature by providing new evidence not only on the role of infrastructure, but also on its capacity to buffer the impact of rainfall events on school attendance.

These results are robust across multiple model specifications, including controls for individual, socioeconomic, seasonal, and territorial characteristics, as well as fixed effects at the school level, reinforcing the robustness of the results. The findings remain robust when alternative functional forms are used to model rainfall, which allows capturing nonlinear pattern of precipitation. Simulations absence probability across different scenarios indicates that the gaps between students widen as rainfall intensity increases, highlighting the importance of considering both climate and urban infrastructure factors when analyzing inequalities in effective access to education.

The results have direct implications for urban and mobility policy design. In particular, they suggest that investments in adequate and resilient infrastructure can generate benefits that transcend the realm of mobility, contributing to improved school accessibility and therefore attendance. In vulnerable urban contexts, where infrastructure deficits and exposure to climate risks tend to be concentrated, incorporating accessibility and climate resilience criteria into the prioritization and design of urban mobility infrastructure interventions can operate as a complementary policy for reducing educational inequalities.

Despite the robustness of the results, the study faces some data limitations related to the geocoding process due to availability and quality of address information of part of the student

population, and also the absence of information on effective routes and the partial availability of variables on road and pedestrian infrastructure, such as pavement quality, drainage, obstacles, and road safety. The resulting sample therefore underrepresents the students most likely to be affected, and to the extent that these students face both worse infrastructure and greater exposure to rainfall, the estimated effects are likely conservative. Future research could strengthen the evidence through: (i) improvements in address data collection and standardization to improve geocoding coverage and sample representativeness; (ii) more detailed surveys of the urban environment, including pavements and sidewalks conditions, drainage, and critical flooding points, (iii) data on students' actual school trips, collected through surveys, travel diaries, or mobility instruments; and (iv) qualitative fieldwork to capture perceptions, adaptation strategies, and family decisions in the face of climate events. Such evidence would allow for more precise estimates, exploration of additional causal mechanisms, and strengthened design of integrated policies aimed at guaranteeing the right to mobility and education in cities increasingly exposed to climate risks.

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Appendix

Table A1: Sample Comparison: From Full Students data (1–3 grade) to Final Analytical Sample

Characteristic	Full Population	Geocoded Sample	Final Analytical Sample
Absenteeism	17.8%	16.4%	16.0%
Female (%)	48.0%	48.1%	49.0%
<i>Region</i>			
Central Montevideo	33.1%	34.0%	35.8%
Eastern Montevideo	32.5%	31.9%	31.4%
Western Montevideo	34.4%	34.2%	32.8%
<i>Income Quintile</i>			
Quintile 1 (Lowest)	33.9%	29.4%	25.2%
Quintile 2	15.2%	14.9%	16.4%
Quintile 3	13.5%	13.6%	15.3%
Quintile 4	16.8%	18.0%	19.8%
Quintile 5 (Highest)	19.7%	23.1%	22.2%
Missing	1.0%	1.0%	1.1%
TUS Beneficiary Household (%)	35.7%	31.9%	30.2%
Students	38,635	25,163	12,301

Source: Authors' elaboration.

Table A2: Results of the Pooled and School Fixed Effects Models (Full Model Output)

Variables	Pooled Model Coefficients	School FE Model Coefficients
<i>Dependent variable: school absence (1 if does not attend)</i>		
Constant	-2.8*** (0.08)	
Daily precipitation (mm)	0.05*** (0.0010)	0.05*** (0.01)
Lagged precipitation (t-1, mm)	0.002*** (0.0006)	0.002 (0.002)
Daily precipitation ²	-0.0003*** (3.4e-6)	-0.0003** (0.0001)
Student sex (dummy, girl = 1)	-0.04** (0.02)	-0.04* (0.02)
Student age (years)	0.05*** (0.009)	0.04*** (0.01)
TUS beneficiary (dummy, receives benefit = 1)	0.33*** (0.02)	0.21*** (0.02)
Residence in informal settlement (dummy, settlement = 1)	0.10** (0.03)	0.06 (0.04)
Distance to school (per 100 m)	0.01*** (0.003)	0.01*** (0.003)
infra_index = 1	-0.01 (0.04)	0.002 (0.06)
infra_index = 2	-0.12** (0.04)	0.03 (0.06)
Daily precipitation × infra_index = 1	-0.002* (0.0007)	-0.002* (0.0010)
Daily precipitation × infra_index = 2	-0.005*** (0.0007)	-0.005*** (0.001)
tue	-0.008 (0.006)	-0.008 (0.12)
wed	-0.10*** (0.007)	-0.10 (0.10)
thu	-0.12*** (0.007)	-0.13 (0.09)
fri	-0.07*** (0.007)	-0.07 (0.10)
apr	0.31*** (0.01)	0.31* (0.13)
may	0.64*** (0.01)	0.65*** (0.13)
jun	0.96*** (0.01)	0.97*** (0.12)
jul	0.60*** (0.01)	0.60*** (0.14)
aug	0.66*** (0.01)	0.66*** (0.18)
sep	0.53*** (0.01)	0.53*** (0.15)
oct	0.53*** (0.01)	0.54*** (0.12)
nov	0.46*** (0.01)	0.46* (0.19)
dec	0.92*** (0.01)	0.93*** (0.20)
strike (apr 25)	1.7*** (0.02)	1.7*** (0.12)
strike (jun 21)	1.1*** (0.02)	1.1*** (0.11)
strike (oct 11)	0.80*** (0.02)	0.81*** (0.09)
winter break (jul 17)	1.3*** (0.02)	1.3*** (0.10)
weather alert (oct 30)	1.7*** (0.02)	1.7*** (0.08)
weather alert (nov 3)	2.1*** (0.02)	2.2*** (0.16)
Fixed-Effects (school)	No	Yes
S.E.: Clustered	by: aluid	by: ruee & fecha
Observations	2,151,100	2,151,100
Squared Cor.	0.04154	0.05265
Pseudo R ²	0.04091	0.05196
BIC	1,813,590.9	1,796,246.9
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Source: Authors' elaboration.

Notes: 1) Nine students were removed for having no value for the TUS variable. 2) aluid and ruee are the identifiers for students and schools respectively.

Table A3: Results of the Pooled and Fixed Effects Models with Inverse Hyperbolic Sine Transformation for Rain Variable (Full Model Output)

Variables	Pooled Model Coefficients	School FE Model Coefficients
<i>Dependent variable: school absence (1 if does not attend)</i>		
Constant	-2.9*** (0.08)	
Asinh(Daily precipitation)	0.28*** (0.01)	0.29*** (0.04)
Asinh(Lagged precipitation) (t-1)	0.006 (0.008)	0.002 (0.02)
Student sex (dummy, girl = 1)	-0.04** (0.02)	-0.04* (0.02)
Student age (years)	0.05*** (0.009)	0.04*** (0.01)
TUS beneficiary (dummy, receives benefit = 1)	0.34*** (0.02)	0.21*** (0.02)
Residence in informal settlement (dummy, settlement = 1)	0.10** (0.03)	0.06 (0.04)
Distance to school (per 100 m)	0.01*** (0.003)	0.01*** (0.003)
infra_index = 1	-0.01 (0.04)	0.002 (0.06)
infra_index = 2	-0.10* (0.04)	0.04 (0.06)
Asinh(Daily precipitation) × infra_index = 1	-0.01 (0.010)	-0.01 (0.01)
Asinh(Daily precipitation) × infra_index = 2	-0.05*** (0.009)	-0.05** (0.02)
tue	-0.01* (0.006)	-0.01 (0.12)
wed	-0.13*** (0.007)	-0.14 (0.09)
thu	-0.13*** (0.007)	-0.13 (0.08)
fri	-0.03*** (0.007)	-0.03 (0.08)
apr	0.29*** (0.01)	0.29* (0.12)
may	0.66*** (0.01)	0.66*** (0.13)
jun	0.97*** (0.01)	0.98*** (0.11)
jul	0.60*** (0.01)	0.61*** (0.12)
aug	0.62*** (0.01)	0.63*** (0.14)
sep	0.52*** (0.01)	0.52*** (0.14)
oct	0.58*** (0.01)	0.59*** (0.11)
nov	0.45*** (0.01)	0.45* (0.19)
dec	0.91*** (0.01)	0.92*** (0.16)
strike (apr 25)	1.8*** (0.02)	1.8*** (0.12)
strike (jun 21)	1.2*** (0.02)	1.2*** (0.11)
strike (oct 11)	0.81*** (0.02)	0.82*** (0.08)
winter break (jul 17)	1.4*** (0.02)	1.4*** (0.09)
weather alert (oct 30)	1.6*** (0.02)	1.6*** (0.08)
weather alert (nov 3)	2.2*** (0.02)	2.2*** (0.17)
Fixed-Effects (school)	No	Yes
S.E.: Clustered	by: aluid	by: ruee & fecha
Observations	2,151,100	2,151,100
Squared Cor.	0.04532	0.05663
Pseudo R^2	0.04381	0.05487
BIC	1,808,105.6	1,790,727.1
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Source: Authors' elaboration.

Notes: 1) Nine students were removed for having no value for the TUS variable. 2) aluid and ruee are the identifiers for students and schools respectively.

Table A4: Results of the Pooled and Fixed Effects Models with Inverse Hyperbolic Sine Transformation for Rain Variable (Full Model Output) with TUS Interaction

Variables	Pooled Model Coefficients	School FE Model Coefficients
<i>Dependent variable: school absence (1 if does not attend)</i>		
Constant	-2.8*** (0.09)	
Asinh(Daily precipitation)	0.27*** (0.01)	0.27*** (0.04)
Asinh(Lagged precipitation) (t-1)	0.007 (0.008)	0.004 (0.02)
Student sex (dummy, girl = 1)	-0.04** (0.02)	-0.04* (0.02)
Student age (years)	0.05*** (0.009)	0.04*** (0.01)
TUS beneficiary (dummy, receives benefit = 1)	0.20* (0.08)	0.09 (0.09)
Residence in informal settlement (dummy, settlement = 1)	0.10** (0.03)	0.06 (0.04)
Distance to school (per 100 m)	0.01*** (0.003)	0.01*** (0.003)
infra_index = 1	-0.04 (0.06)	-0.06 (0.07)
infra_index = 2	-0.18** (0.06)	-0.02 (0.08)
Asinh(Daily precipitation) $\times$ infra_index = 1	0.002 (0.01)	0.001 (0.01)
Asinh(Daily precipitation) $\times$ infra_index = 2	-0.05*** (0.01)	-0.05** (0.02)
TUS $\times$ infra_index = 1	0.04 (0.09)	0.11 (0.08)
TUS $\times$ infra_index = 2	0.16* (0.08)	0.11 (0.09)
Asinh(Daily precipitation) $\times$ TUS $\times$ infra_index = 1	-0.02 (0.02)	-0.02 (0.01)
Asinh(Daily precipitation) $\times$ TUS $\times$ infra_index = 2	0.005 (0.02)	0.005 (0.02)
Asinh(Daily precipitation) $\times$ TUS	0.03 (0.02)	0.03 (0.02)
Fixed-Effects (school)	No	Yes
S.E.: Clustered	by: aluid	by: ruee & fecha
Observations	2,151,100	2,151,100
Squared Cor.	0.04552	0.05668
Pseudo R^2	0.04399	0.05492
BIC	1,807,832.2	1,790,695.3
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Notes: 1) Nine students were removed for having no value for the TUS variable. 2) aluid and ruee are the identifiers for students and schools respectively.