How Events Move Us: Estimating the Causal Effects of Special Events on Shared Micromobility

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Abstract

Special events, such as festivals, parades, and protests, can cause sudden surges or disruptions in travel demand, thereby placing stress on transportation systems. As shared micromobility becomes an increasingly important part of urban transportation, understanding how these events affect its ridership is crucial for ensuring safety, efficiency, and sustainability. In this study, we investigate the causal impacts of various event types by applying Double Machine Learning (DML) to high-resolution shared micromobility trip data (e-bikes and e-scooters) and multi-source event records in Washington, D.C. These events include government-authorized large events, independently organized small events, and government-registered protests. Our results show that many events have far stronger actual influences on shared micromobility than correlational analysis suggests, as confounding factors can mask their actual impact. For instance, festivals show four to seven times greater impact under causal estimation. We also find that the increase in gas prices suppresses discretionary travel, resulting in reduced shared micromobility usage during events. Another key insight is the different demand mechanisms: large events interact with temporal and built environment features to boost ridership, whereas small events are primarily influenced by temporal features, such as event duration and weather, with little influence from infrastructure factors. These findings highlight the need for tailored policies, including infrastructure investment for large events and operational incentives for smaller ones. This research provides a causal foundation for urban mobility planning, supporting the development of more resilient and efficient transportation systems in event-dense urban areas.

Keywords: Shared micromobility; Special events; Washington, D.C.; Causal inference; Double Machine Learning; SHAP

1 Introduction

Shared micromobility has become an important piece of the urban transportation ecosystem, enhancing first- and last-mile connectivity while reducing emissions, noise, and fuel consumption (Gössling, 2020; Nikiforiadis et al., 2021; Shaheen, 2016). As its adoption speeds up worldwide, understanding when and why demand increases or decreases is important not only for researchers but also for operators and city officials (Hosseinzadeh, Algomaiah, Kluger, & Li, 2021b; Marsden & Docherty, 2013; Reck, Haitao, Guidon, & Axhausen, 2021). Past studies have linked many temporal and environmental factors to shared micromobility usage (Bai & Jiao, 2020; Elmashhara, Silva, Sá, Carvalho, & Rezazadeh, 2022; Hosseinzadeh, Algomaiah, Kluger, & Li, 2021a), but shifts driven by specific events remain less studied despite their practical significance (Younes, Nasri, Baiocchi, & Zhang, 2019; Zhu et al., 2017). Understanding the causal impacts of these events on micromobility usage will enhance user satisfaction, optimize system efficiency, and inform strategic transportation planning for safety and sustainability (Rodrigues, Markou, & Pereira, 2019).

In this study, we define special events as planned, scheduled public activities whose time, location, and duration are known in advance and that are exogenous to the shared micromobility system. Such events, including sports, festivals, concerts, parades, and protests, represent persistent yet under-examined challenges in transportation planning. This aligns with standard transportation operations terminology, where planned special events are public activities that can significantly impact normal network operations due to increased demand or decreased capacity (Dunn, 2007; Latoski et al., 2003). In contrast, non-special events in our context refer to ordinary days without an identified event. Unplanned incidents (e.g., crashes, weather disruptions, service outages/strikes) that are not scheduled fall outside our current scope as well. Accordingly, our analysis encompasses both planned and exogenous events (large permitted events, independently organized small events, and government-registered protests) and excludes unplanned disruptions (Dong, Ding, Wu, & Li, 2025; Fuller, Sahlqvist, Cummins, & Ogilvie, 2012) and endogenous shocks (C.-C. Lu, 2016; Manout, Diallo, & Gloriot, 2024) originating within the micromobility system (e.g., pricing changes, geofencing, and fleet reallocations) or stemming from policy interventions (Braun et al., 2016) enacted by the operator or regulator.

While conventional traffic models effectively capture recurrent patterns linked to habitual behaviors (Hafezi, Liu, & Millward, 2019; Moreira-Matias, Gama, Ferreira, Mendes-Moreira, & Damas, 2013; Pel, Bliemer, & Hoogendoorn, 2012), they struggle with accurately predicting disruptions caused by special events (Markou, Kaiser, & Pereira, 2019). Apart from global mega-events such as the Olympic Games or the World Cup (Currie & Shalaby, 2012; Kassens, 2009), city-scale events often receive minimal analytical attention despite their substantial impacts on overloaded transit networks, unpredictable modal shifts, and widespread travel disruption (Cottrill et al., 2017).

Two main challenges have limited research into the effects of events on micromobility. First, collecting a comprehensive, time-specific record of events across various venues and neighbourhoods is labor-intensive (Pereira, Rodrigues, & Ben-Akiva, 2015; Rashidi, Abbasi, Maghrebi, Hasan, & Waller, 2017). Second, separating an event's true causal impact from confounding influences is difficult, given co-occurring weather anomalies, concurrent events, seasonal trends, and infrastructure issues. The first challenge can now be addressed through the proliferation of internet data sources (e.g., online calendars, social media, news archives), enabling systematic event data collection (Rashidi et al., 2017). The second could be handled by robust causal inference methods to disentangle event-specific effects (Gangl, 2010; Yumin et al., 2021). These challenges are not unique to shared micromobility; they occur across various travel modes and are often amplified during unplanned disruptions. Concurrently, causal studies in transit have examined event- or disruption-driven impacts using DML designs (Huber, Meier, & Wallimann, 2022; Zhang, Wang, Fan, Song, & Shibasaki, 2024). In this study, micromobility functions as a measurement tool rather than the source of the problems. Its quick responsiveness (short booking horizons), flexibility (near-venue parking and geofenced operations), and detailed spatial coverage (dense station/zone networks) make it ideal for detecting localized, time-sensitive demand shifts around events. We focus on planned exogenous special events, where the timing and location are known in advance, allowing for clear treatment definition and credible counterfactuals. Notably, our approach is mode-neutral and applicable to other modes when data support similar levels of detail.

Washington, D.C. (DC), the capital of the United States, is a vibrant city with a rich civic and cultural calendar (Smith, 2008). We choose DC because it provides detailed micromobility data, frequent planned–exogenous events, and transportation management emphasis. Each year, it hosts hundreds of citywide special events and countless neighbourhood gatherings. A systematic understanding of their transportation impacts is important to furthering DC's sustainable transportation efforts. Accordingly, this study compiles three complementary event datasets for 2023-2024: (1) government-authorized large events, (2) independently organized small events, and (3) government-registered protests. We then link these data to 9.5 million high-resolution e-bike and e-scooter trip records. Then, the causal effects of each event category and its subcategories are estimated using state-of-the-art causal inference techniques on the micromobility ridership data. Event impacts are inherently spatial: venues create localized, short-term demand spikes and temporary supply or availability constraints that fade with distance. In this study, we analyze micromobility activity around event venues and summarize effects within set proximity zones, making these spatial patterns clear while maintaining transparency. Lastly, the causal findings are then set against the correlational results for comparison. More specifically, this work addresses the following four research questions (`RQ`):

- RQ1 **Correlational change in trip volumes:** *What is the statistical association between the occurrence of special events and shared micromobility trip volumes? Furthermore, how do these associations vary across different event categories and their respective subcategories?* To address this question, we employ a paired t-test to compare trip volumes during events with those during chosen control periods.
- RQ2 **Causal effect and comparison to correlation:** *After controlling for covariates, what is the average causal effect of each event category on shared micromobility trip volumes? How do these causal effects vary across event subcategories, and how do they differ from the correlational relationships identified in RQ1?* Here we estimate

the average treatment effect (ATE) for each event category and subcategory using *Double Machine Learning* (DML) with cross-fitting, which orthogonalizes high-dimensional covariates, producing unbiased causal estimates. We then compare the causation results with the correlations.

RQ3 **Contrasting associational and causal influences of key variables during events:** *Which variables exhibit the strongest association with micromobility trip volumes during events? How do the influences of these variables differ when estimated through a causal model versus a correlational one?* To address these points, we identify the top features using a *LightGBM* model and *SHAP* value analysis, then quantify their influence using both negative-binomial Generalized Linear Model (GLM) (association) and DML models (causation).

RQ4 **Heterogeneous causal effects within subcategories:** *To what extent do the significant variables causally affect micromobility usage when a specific subcategory of event is taking place?* Here, we estimate conditional average treatment effects (CATE) for the significant variables by limiting the sample to event-period observations and employing DML to each variable in turn.

2 Related work

2.1 Factors Influencing Shared Micromobility Usage

Shared micromobility (e-scooters, e-bikes) ridership is shaped by temporal, environmental, built-environment, and sociodemographic factors (Ahillen, Mateo-Babiano, & Corcoran, 2016; El-Assi, Salah Mahmoud, & Nurul Habib, 2017; Scott & Ciuro, 2019; K. Wang, Akar, & Chen, 2018). Temporal patterns show higher ridership during peak hours (Noland, Smart, & Guo, 2019; Shen, Zhang, & Zhao, 2018), and on weekends (Noland, Smart, & Guo, 2016). Warmer temperatures and moderate humidity boost ridership (Gebhart & Noland, 2014; Heaney, Carrión, Burkart, Lesk, & Jack, 2019; Reck, Martin, & Axhausen, 2022), whereas adverse weather conditions (e.g., rain, snow, extreme temperatures) suppress demand (An, Zahnow, Pojani, & Corcoran, 2019; Corcoran, Li, Rohde, Charles-Edwards, & Mateo-Babiano, 2014; Mattson & Godavarthy, 2017; Noland, 2021). Gasoline prices have a positive and significant correlation with micromobility ridership and duration (P. He, Zou, Zhang, & Baiocchi, 2020).

Built environment features also critically influence micromobility ridership (Huo et al., 2021; Noland et al., 2019). Infrastructure elements such as bike lanes (Buck & Buehler, 2012; Y. Sun, Mobasheri, Hu, & Wang, 2017; Zou, Younes, Erdoğan, & Wu, 2020), high intersection density (H. Yang et al., 2022), and proximity to transit stations (Lin, Weng, Liang, Alivanistos, & Ma, 2020; Tran, Ovtracht, & d'Arcier, 2015; Yan et al., 2021) significantly boost usage. And points of interest (POIs) like bars, restaurants, retail hubs, and recreational venues further attract trips (Faghih-Imani, Eluru, & Paleti, 2017; Y. He, Song, Liu, & Sze, 2019; X. Ma et al., 2020; Maas, Attard, & Caruana, 2020; R. Wang, Lu, Wu, Liu, & Yao, 2020). Distance to other bike share stations also influences dockless e-scooter and e-bike usage (X. Wang, Lindsey, Schoner, & Harrison, 2016).

Certain sociodemographic features lead to higher usage, such as younger populations (Abouelela, Al Haddad, & Antoniou, 2021; Laa & Leth, 2020), areas with lower car ownership (Günay, Dündar, & Dilekçi, 2025; Younes & Baiocchi, 2023), and higher job density (Jin & Sui, 2024). Dockless micromobility systems also show clear links to gender (Campisi, Skoufas, Kaltsidis, & Basbas, 2021; Cubells, Miralles-Guasch, & Marquet, 2023), race (Aman, Zakhem, & Smith-Colin, 2021; Sanders, Branion-Calles, & Nelson, 2020), and income (Delbosc & Thigpen, 2024; Lee, Baek, Chung, & Kim, 2021). Despite extensive work on recurrent patterns, interactions between these factors remain underexplored, especially during special events.

2.2 Special Events' Impact on Shared Micromobility

While special events disrupt conventional travel patterns, only a few studies have examined their impact on micromobility systems. Existing research primarily examines how bikeshare ridership responds to public transit disruptions (Zhu et al., 2017). For example, Fuller et al. (2012) documented ridership surges in London's bikeshare systems during transit strikes. Saberi, Ghamami, Gu, Shojaei, and Fishman (2018) found that bikeshare ridership increases during that time of disruption by up to 88%. Similarly, Younes et al. (2019) analyzed spatial-temporal ridership shifts in DC's bikeshare network during three rail closures (7-25 days each), comparing activity one week pre-disruption, one year prior, and post-disruption. Concurrently, Kaviti, Venigalla, Zhu, Lucas, and Brodie (2018) attributed ridership and revenue increases at Capital Bikeshare to the single-trip fare implemented alongside transit service interruptions in DC.

To the best of our knowledge, limited scholarship has explored the effects of holidays and special events on micromobility (Corcoran et al., 2014). In Louisville, Hosseinzadeh, Karimpour, and Kluger (2021) identified a 15% increase in e-scooter trips during holidays and special events, an effect not observed with station-based bikeshare. This indicates that people prefer the flexibility of dockless e-scooters for special occasions. In DC, Younes, Zou, Wu, and Baiocchi (2020) further demonstrated negative impacts on scooter usage during the 2019 government shutdown but significant positive demand during the National Cherry Blossom Festival for both scooters and docked bikeshare systems. However, current research depends on correlational methods, making it vulnerable to confounding factors, which restrict conclusions about causality.

2.3 Causal Inference in Transportation & Shared Micromobility

Accurately estimating causal effects from observational data is a central challenge in transportation research, primarily due to the presence of confounding variables that influence both the treatment and outcome. Traditional methods, such as linear regression or propensity score matching, struggle with high-dimensional, nonlinear data and often rely on strong, untestable assumptions (Y. Wang, Yu, & Song, 2024). DML emerged as a robust framework to address these limitations (Chernozhukov et al., 2018). DML leverages the predictive power of machine learning (ML) within a staged modeling approach to overcome the weaknesses of general ML models and deliver unbiased causal estimates (S. Yang et al., 2025).

The rapidly expanding application of DML in the broad transportation field moves beyond correlations to provide robust causal evidence on how environments, policies, and events affect travel behavior. First, a prominent application involves studying the relationship between the built environment and travel behavior while considering residential self-selection (RSS). For instance, Ding et al. (2024) applied DML with gradient boosting machines to quantify the RSS effect on driving distance in Jinan, China. Similarly, Nachtigall, Wagner, Berrill, and Creutzig (2025) used DML to capture nonlinearities in RSS and estimate spatially explicit effects of the built environment on transport CO_2 emissions. S. Yang et al. (2025) and Yin, Gui, Xu, Shao, and Wang (2025) also adopted DML to clarify the endogenous relationships between car ownership, vehicle kilometers traveled, and mode choice in Chinese cities. Second, beyond built environment studies, DML has been utilized to evaluate the impacts of policies. Huber et al. (2022) estimated how ticket discounts by Swiss Federal Railways shifted travel away from peak periods. J. Ma, Dong, Huang, Mietchen, and Li (2022) and Zhang et al. (2024) introduced causal inference to assess the effectiveness of COVID-19 policies on outbreak dynamics across U.S. counties. Third, DML has also been applied to quantify the impacts of extreme weather on transportation. C. Li, Liu, and Yang (2024) estimated the causal effect of fine-grained meteorological variations on traffic flow and speed in California. Zhiwen, Wang, Fan, Shibasaki, and Song (2023) developed a neural network-based causal inference framework to estimate the continuous effects of typhoons on human mobility in Japan. X. Yang et al. (2025) later extended this approach to analyze the causal impacts of diverse public events, including typhoons, fireworks, and earthquakes, on mobility patterns.

However, causal analysis in shared micromobility is limited, especially for applications of DML. A prominent study employed matching methods and regression analysis to establish the causal effect of low income on the reduction of dockless e-scooter usage (Frias-Martinez, Sloate, Manglunia, & Wu, 2021). Only one study implemented DML in the context of bike-sharing. Y. Wang et al. (2024) aim to evaluate how Shanghai's socioeconomic and geospatial factors influence self-looping trips, which is clearly different from our purpose.

Beyond DML, the transportation causal toolbox includes Difference-in-Differences (DiD), Instrumental Variables (IV), Regression Discontinuity (RD), propensity scores, and Structural Equation Modeling (SEM). DiD compares treated and comparison units over time (Callaway, Goodman-Bacon, & Sant'Anna, 2024; Stuart et al., 2014). IV leverages exogenous instruments to isolate variation (Andrews, Stock, & Sun, 2019). RD exploits sharp assignment cutoffs near a boundary (Imbens & Lemieux, 2008). Propensity methods balance observed covariates to approximate the effects of randomized comparisons (F. Li, Morgan, & Zaslavsky, 2018; Rosenbaum & Rubin, 1983). SEM encodes hypothesized pathways and latent constructs (Golob, 2003; Loehlin, 2004). However, our planned, venue- and time-specific events feature high-dimensional covariates. Under these conditions, DiD's conditional parallel-trends assumption is fragile (Bertrand, Duflo, & Mullainathan, 2004). IVs are scarce because venue schedules and local context correlate with demand shifters (MacKay & Miller, 2025). RD lacks credible cutoffs (Cattaneo, Idrobo, & Titiunik, 2024). Propensity methods can underperform without flexible learners and stringent diagnostics (King & Nielsen, 2019). SEM relies on strong structural assumptions and is less robust for localized, short-horizon shocks (Bollen, 1989). Consequently, we adopt DML, which flexibly learns nuisance functions, orthogonalizes estimation to high-dimensional confounding, and yields valid inference for ATE/CATE in this setting.

2.4 Research Gaps

Within this context, the literature reveals consistent methodological and conceptual gaps. Most importantly, the influence of specific types of special events on shared micromobility ridership received very little attention (Damant-Sirois & El-Geneidy, 2015; Huang, Xu, Yan, & Zipf, 2019; Rodrigues, Borysov, Ribeiro, & Pereira, 2017). The limited research that exists tends to focus on a narrow range of event categories, such as public transit strikes or service disruptions, or merely captures the influence of major holidays incidentally while investigating other factors. Furthermore, existing studies often overlook small- to medium-sized city activities, which in fact account for most events, and they seldom differentiate between event types. More critically, nearly all current studies on micromobility event impacts rely on correlational designs or simple pre- and post-analyses, which lack the strength to attribute ridership changes to specific events credibly. These approaches generally fail to disentangle event effects from potential confounders such as extreme weather, changes in gas prices, or underlying seasonal trends.

This study advances prior research by introducing a robust causal inference framework to systematically evaluate the effects of diverse event categories on shared micromobility usage in Washington, D.C. Using high-resolution destinations from dockless e-bikes and e-scooters and applying DML methods, we estimate both ATE for broad event categories and drill down into event subcategories to uncover nuanced, category-specific ridership responses. Furthermore, we estimate the CATE of key contextual factors during events and compare these causal estimates with results from traditional regression models, highlighting methodological discrepancies and reinforcing the value of causal identification.

3 Data and Methodology

There are six main steps in our methodology: (1) Data collection and preprocessing; (2) Event classification; (3) Paired t-test; (4) DML; (5) Key features identification & correlation analysis; (6) Heterogeneous causal effects within subcategories. Our analytical framework is presented in Figure 1.

The subsequent subsections detail this framework. Section 3.1 describes the collection and processing of all data and variables. Subsections 3.2 and 3.3 cover event classification and the creation of treatment/control groups and the preliminary t-test (`RQ1`). The core causal analysis using DML to estimate ATEs (`RQ2`) is outlined in Subsection 3.4. Subsection 3.5 presents associational analyses (LightGBM and GLMs) for `RQ3`. Finally, the DML framework is extended in Subsection 3.6 to compute CATEs. These CATEs are used for two purposes: to contrast causal and correlational results in

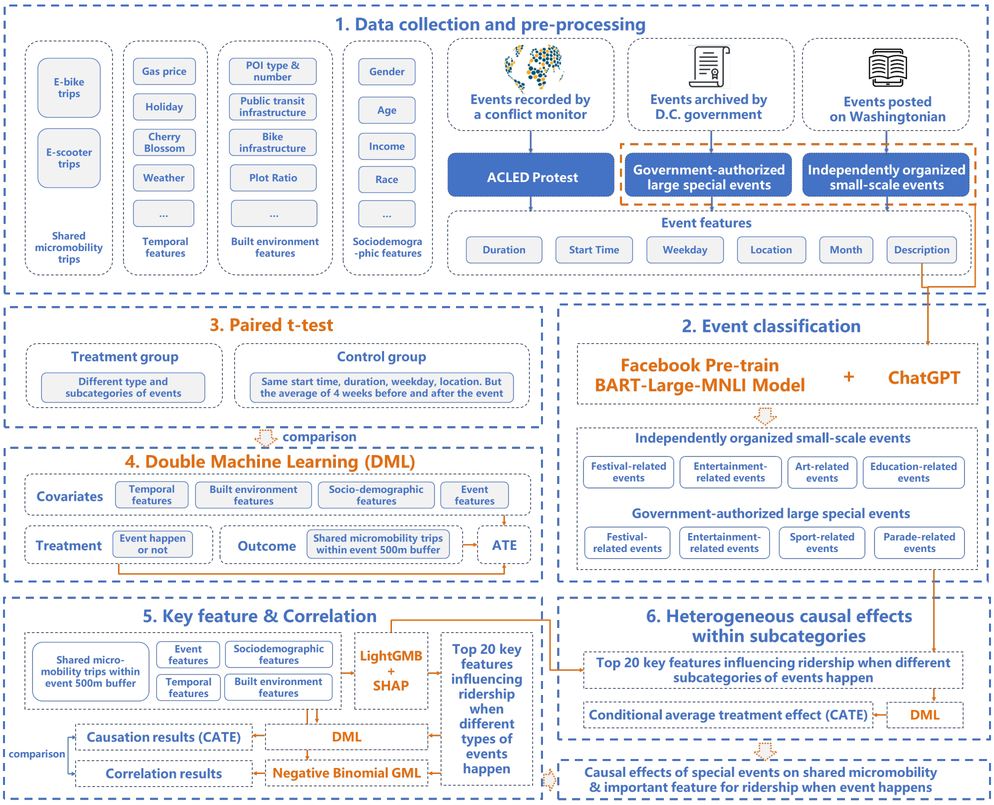


Fig. 1: Analytical framework of the six-step approach used to analyze the effect of special events on shared micromobility in Washington, D.C. Explored three different categories of special events and compared correlation and causation methods.

Subsection 3.5 (RQ3) and to analyse heterogeneous effects within event subcategories for RQ4.

3.1 Data Collection and Preprocessing

Here we detail the data and feature construction supporting our analysis. We compile three event datasets (which we refer to as large, small, and protest) for Washington, D.C., in 2023-2024 and overlay them with e-scooter/e-bike trips from the company *Lime*. Destinations within 500 meters of each venue are counted as the outcome. We then gather temporal, sociodemographic, and built-environment covariates to provide context for understanding how events influence shared micromobility.

3.1.1 Three Different Categories of Events

Washington, D.C., the nation's capital and political centre, is our chosen region of study. It hosts frequent activities at various spatial and temporal scales, ranging from small events to large parades and community gatherings (Thompson, 2022). To assess the impact of different categories of events on shared micromobility usage, we compiled three separate event datasets from January 1, 2023, to December 31, 2024: government-authorised large special events ("large events"), independently organised small-scale events ("small events"), and government-registered protest events ("protests"). Their spatial distributions are shown in Figure 2.

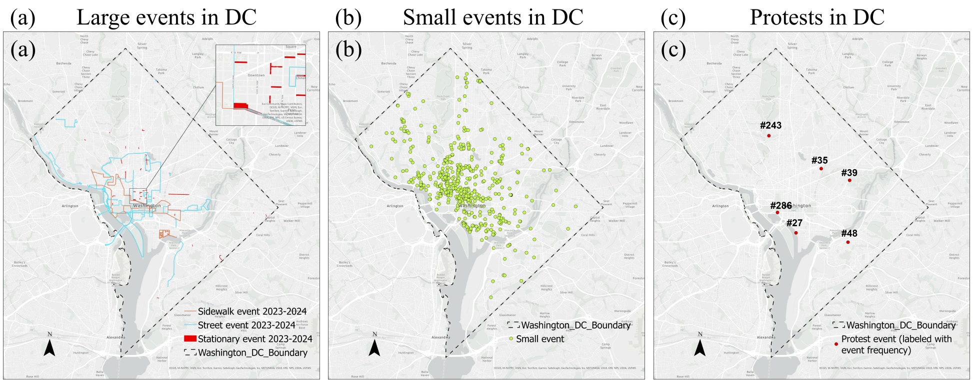


Fig. 2: Spatial distribution of the three event categories in Washington, D.C. Fig. 2a shows large events curated by official sources. The original datasets include three types: sidewalk event (orange), street event (blue), and stationary event (red). Fig. 2b displays small events published in the Washingtonian. Each small event appears as a green point. Fig. 2c illustrates protests collected by the Armed Conflict Location & Event Data Project. Protests are limited to a small number of fixed locations.

First, large events were requested from the Mayor's Special Events Task Group (MSETG) under the District's Homeland Security & Emergency Management Agency (HSEMA)[1]. These are events that required public space approval, street closures, or public safety coordination in Washington, D.C., such as parades, marathons, and approved cultural gatherings. The raw 2023-2024 large events are originally classified by venue type as professional street events, professional sidewalk events, or stationary events. After merging these three categories and excluding events that were canceled or postponed, the cleaned dataset includes 170 large events. Each event includes complete date and time details (start and end times), event name and description, ward, advisory neighborhood commission (ANC), and location polygons or lines.

Second, small events were accessed from the Washingtonian calendar website[2], where local organizers post events under one of 20 self-assigned categories (e.g. music, exhibit, workshop, food, etc.[3]) After filtering out events overlapping with the large-event dataset, recurring or multi-day listings, online-only events, duplicates, and those

[1] https://hsema.dc.gov/page/msetg-special-events-tracking-maps

[2] https://calendar.washingtonian.com/

[3] The 20 categories of Washingtonian events: food, class/workshop, reading, comedy, music-classical, art openings, performance, lecture, music, community, exhibit, family, games, festival, film, drink, dance, miscellaneous, outdoors, sports.

lacking complete start/end times or venue coordinates, we retain 2,952 unique small-scale events for 2023-2024. Each includes detailed metadata, including event name, identifier, description, venue latitude/longitude, start/end times, ticket price, and information URL.

Third, protest events were accessed from the Armed Conflict Location & Event Data Project (ACLED)[4], a publicly available, independent global dataset that provides real-time data and analysis on political violence and protest events. We extracted all "protest demonstrations" in Washington, D.C., from January 1, 2023, to December 31, 2024. After deleting duplicates, there are 678 protest records. The time precision of this data set differs from the previous two datasets. ACLED records protests at the daily level, lacking hour-level detail for start and end times. Additionally, because of government-imposed venue restrictions, protests in D.C. are limited to a small number of fixed locations.

The large-event dataset includes fewer events, but they are highly regulated with comprehensive spatiotemporal details. The small-event dataset captures detailed, self-organised activities across the city. Although the spatial and temporal accuracy of protest events is relatively coarse, it does offer essential coverage of civic unrest that could affect mobility within a city. We select a 500-meter buffer surrounding each event location to serve as the primary unit of analysis. This distance was chosen to accommodate the spatial characteristics of all three event categories. This also accounts for the actual spatial extent of small-scale events, which are reported as discrete points. However, the exact location can be anywhere in a building or park. Dockless e-bikes and e-scooters may be parked irregularly along adjacent streets. Additionally, large event areas are traffic exclusion zones with street closures and barriers, restricting vehicle access and requiring riders to park outside the immediate area and walk to the venue (Batty, DeSyllas, & Duxbury, 2003). The 500-meter buffer ensures a comprehensive capture of trips across these varied contexts.

3.1.2 Shared Micromobility Trips

Lime is one of the oldest and largest operators licensed by the District Department of Transportation (DDOT) to provide shared-fleet micromobility in Washington, D.C., offering dockless e-scooters and e-bikes since September 2017 (Zou et al., 2020). In compliance with DDOT's shared-fleet data policy, Lime publishes anonymised vehicle location data via a public application programming interface (API)[5]. We collected e-scooter and e-bike trip records for the same 24-month window as our event data (January 1, 2023 - December 31, 2024). Then, reconstructed trips using the methods proposed by McKenzie (2019). As Lime's scooters and bikes have similar spatiotemporal usage characteristics in the D.C. context (Qiang & McKenzie, 2025), we aggregated both modes into a unified trip dataset to increase coverage near event venues. Then, we applied rigorous cleaning: removing duplicate records, trips missing origin or destination coordinates, those ending outside of the D.C. boundary, and rides with unlikely durations or speeds. After cleaning, we retained 9,542,094 shared micromobility trips,

[4] https://acleddata.com/
[5] https://ddot.dc.gov/page/dockless-api

each annotated with geographic coordinates and timestamps of origin and destination, as well as trip duration.

The primary goal of this study is to evaluate whether and how special events attract or discourage shared micromobility ridership near venues, rather than measuring trips made by attendees leaving the events. We therefore focus on trip destinations, those that terminate near, rather than depart from, event locations. Specifically, we created a 500-meter buffer around every event venue. We counted only those trips whose destination fell within this zone, treating those counts as dependent variables in our correlation analyses and outcome measures in causal models.

3.1.3 Covariates

Beyond the events themselves, we incorporated multiple time-sensitive determinants known to influence shared micromobility ridership. First, weekly gas prices[6] were included, given established evidence that gas price increases correlate with higher shared micromobility ridership at the city level, particularly for short trips (P. He et al., 2020). Second, hourly weather conditions (temperature, humidity, precipitation, visibility, and wind speed) were obtained from the Ronald Reagan Washington National Airport weather station[7], reflecting their documented impact on e-bike and e-scooter usage (Kruijf et al., 2021; Y. Lu, Zhang, & Corcoran, 2024; Noland, 2021). Third, all 2023–2024 U.S. legal public holidays[8] were included because of their observed ridership effects (Palaio, Vo, Maness, Bertini, & Menon, 2021). Finally, the National Cherry Blossom Festival in D.C. is famous for causing shared micromobility ridership surges (Younes et al., 2020; Zou et al., 2020). Therefore, in this study, March 18–April 16, 2023, and March 20–April 14, 2024, were specifically singled-out to evaluate the interaction effects of Cherry Festivals on concurrent events.

Sociodemographic data for Washington, D.C.'s census block groups (CBGs) were obtained from the U.S. Census Bureau's 2019-2023 American Community Survey (ACS) 5-year estimates. We selected features established in prior literature as correlates of shared micromobility usage, including population aged 18–34 (Fitt & Curl, 2019; Laa & Leth, 2020), household income (Delbosc & Thigpen, 2024; Frias-Martinez et al., 2021), race (Aman et al., 2021), and gender (Reck & Axhausen, 2021), etc. When an event buffer intersected a single CBG, the CBG's attributes were assigned to that event. For buffers overlapping multiple CBGs, we computed a weighted average of sociodemographic features proportional to the intersecting geographic area.

Built environment features were derived from multiple sources. POI data consisting of 30,355 POI across 10 categorical labels were sourced from Foursquare[9]. Building footprints and heights were acquired through the Overture Maps Foundation[10], allowing for the calculation of plot ratios. The majority of other infrastructure variables were collected through the Open Data DC portal[11]—features such as bicycle racks,

[6] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPM0R_PTE_R10_DPG&f=W
[7] https://www.ncei.noaa.gov/access/search/data-search/local-climatological-data-v2?bbox=38.996,-77.124,38.788,-76.916&pageNum=1
[8] https://edpm.dc.gov/issuances/legal-public-holidays-2023/
[9] https://foursquare.com/developer/
[10] https://docs.overturemaps.org/guides/buildings
[11] https://opendata.dc.gov/search

sidewalks, bus stops, metro station entrances in DC, and Capital Bikeshare locations. Previous studies showed bike facilities, especially those with higher levels of physical barriers, attract more shared micromobility flows (Jin, Wang, & Sui, 2023). Bike lanes in this study are a composite feature integrating three datasets: protected bike lanes, bike trails, and signed bike routes.

Trips and covariates differ according to event category. By way of example, Table 1 provides the operational definitions and descriptive statistics for all variables within the *large event* model.

3.2 Event Classification

To better understand how different event categories influence shared micromobility, we reclassified both large and small events into new, clearer taxonomies. The existing labels for each were problematic: large events lacked subcategories entirely, while small events were over-segmented with nuanced, overlapping, or sometimes incorrect tags (e.g., "Music" vs. "Music—Classical"; "Dance" vs. "Performance" vs. "Comedy").

We used OpenAI's *ChatGPT* (GPT-4o; used on 2025/04/30) to develop a concise taxonomy for each event category separately. For each category, we separately input all event names for large and small events, tested various groupings (3-way, 4-way, 5-way, and 6-way), and cross-checked the outputs against event descriptions. After several rounds of comparison and manual validation by the authors, a separate four-class scheme proved to be the most succinct and comprehensive for each dataset. This process allowed us to consolidate the large events into one set of four categories and the small events into another four. We also explored fully automatic taxonomies using standard clustering algorithms, but the event dataset is highly heterogeneous, and the resulting clusters were unstable and mixed conceptually unrelated event types. Because the aim of the taxonomy is to support interpretable causal analysis rather than to maximize algorithmic separability, we adopted a concise, semantically meaningful four-class scheme validated against event descriptions.

Large events dataset is labelled with these four subcategories: festival-related (cordoned celebrations in fixed public spaces, e.g., Emancipation Day Celebration), entertainment-related (public or streetscape activities such as the H Street Festival), sport-related (long-distance biking, running, and walking requiring street closures, e.g., the Credit Union Cherry Blossom 5K Run/Walk), and parade (processions spanning multiple streets, e.g., the National Memorial Day Parade). Although parades usually occur on festival days, we distinguish the fixed-location festival celebrations from the moving parade, as the spread of locations varies significantly.

Similarly, we tagged *small events* as four different subcategories: festival-related (numerous grassroots micro-festivals, e.g., the Annual DC Clay Festival), entertainment-related (food/drink, comedy, concerts, performances), art-related (gallery or museum events and tours), and education-related (classes, conferences, talks/discussions, workshops). Although the first two labels appear in both categories, they denote clearly different scales and scopes for large versus small events.

After finalising the taxonomy, we assign a subcategory to each single event using the pre-trained *BART MNLI (Large)* model (Lewis et al., 2019), which is trained on the *MNLI* dataset (Williams, Nangia, & Bowman, 2017). This zero-shot classifier maps

Table 1: Descriptive statistics of variables in the *large event* model.

Name	Description	Mean or Count	S.D.	Min.	Max.
Dependent variable / Outcome (within the 500m event buffer)					
Trip Count	E-bike and e-scooter trip count	239.20	515.57	0	11224
Event features					
Event Happen	1 if the event occurs, 0 otherwise.	170	–	–	–
Event Duration	Number of minutes the event lasts.	272.54	311.33	45	3240
Spring	1 if the event is in March–May, else 0.	254	–	–	–
Summer	1 if the event is in June–August, else 0.	320	–	–	–
Fall	1 if the event is in September–November, else 0.	391	–	–	–
Winter	1 if the event is in December–February, else 0.	147	–	–	–
Weekend	1 if the event is on a weekend, else 0.	804	–	–	–
Rush Hour	1 if the event starts at 8-10am or 3-7pm, else 0.	556	–	–	–
Temporal features					
Temperature	Dry-bulb temperature at the event start time (°C)	19.14	8.81	-6.7	36.7
Humidity	Relative humidity at the event start time (%)	57.69	19.01	18	96
Precipitation	Precipitation at the event start time (mm)	0.19	1.82	0	32.5
Wind Speed	Wind speed at event start time (mph)	4.01	2.29	0	13.4
Gas Price	Gasoline price at event start time ($/gallon)	3.52	0.19	3.12	3.88
Cherry	1 if the event occurs during the cherry blossom festival, 0 otherwise.	122	–	–	–
Holiday	1 if the event occurs on a holiday, 0 otherwise.	185	–	–	–
Built environment features (within the 500m event buffer)					
Dining&Drinking POI	Number of dining and drinking POIs	184.19	156.25	2	1151
Art POI	Number of art and entertainment POIs	104.28	99.52	0	470
Transportation POI	Number of transportation POIs	105.14	96.04	2	808
Government POI	Number of community and government POIs	150.25	155.34	4	1124
Business POI	Number of business and professional services POIs	259.68	217.98	0	1353
Health POI	Number of health and medicine POIs	20.38	28.29	0	252
Retail POI	Number of retail POIs	67.94	60.03	0	436
Sport POI	Number of sports and recreation POIs	33.84	33.78	0	323
Bike Rack	Number of bike rack	112.66	106.07	1	1010
Bike Lane	Length of bike lane (km)	9.60	10.57	0.05	73.93
Sidewalk Area	Sidewalk area (100m*100m)	27.61	24.44	1.69	184.02
Area of Water	Waterbody area (100m*100m)	24.60	23.62	0	83.27
Plot Ratio	The ratio of the gross floor area of buildings and the total buildable area	3.91	1.89	1.35	7.83
House Unit	Number of house unit	515.73	139.56	181	821
Bus Station	Number of bus station	59.95	40.63	0	393
Bus Station Distance	Distance from event to nearest bus station (100m)	1.12	1.14	0.11	8.57
Metro Distance	Distance from event to nearest metro station (100m)	6.07	7.02	0.29	36.85
Metro Entrance	Number of metro station entrances	7.52	7.23	0	25
CB Station	Number of Capital Bikeshare stations	12.62	10.71	0	92
Socio-demographic features (of CBGs that intersect the event buffer)					
Female	Average number of females	415.45	187.02	90	958
Male	Average number of males	404.65	141.46	165.28	732
White	Average White population	442.60	238.16	38	969
Black	Average Black population	223.07	284.96	29.14	1091
Asian	Average Asian population	56.48	26.84	0	196
Age 18-34	Average population aged between 18-34	312.32	128.21	126	798
Labor Force	Average labor force	550.47	186.79	184	1027
House income	Average household income (1000 $/year)	137.53	29.92	57.10	222.14

free text to candidate labels without requiring task-specific training. For each event, we concatenate its name and description and then score this combined text against the four candidate subcategories. We assign the label with the highest score. If the top score is below 0.5 (out of 1), we enrich the input with content from the event's web page and rescore it. If confidence remains low after this addition, we determine the label through the authors' manual assessment. With this three-stage pipeline, every large and small event record was assigned a single, semantically appropriate subcategory, while the protest dataset retained a single class.

3.3 Treatment and Control Groups

To measure the impact of events on shared micromobility ridership, we first define the treatment group, which naturally forms whenever an event takes place. Each event generates a clear "treatment period," during which the number of trip destinations is recorded. Once the treatment group is identified, we construct a corresponding control group to represent what ridership would have looked like under comparable conditions without an event. For each event, we select trips from the same location, the same time window (matching the event's start and end times), and the same day of the week, but drawn from the four weeks preceding and the four weeks following the event date. In theory, this yields up to eight matched control observations per event. However, some control candidates may themselves be influenced by other nearby events. To prevent contamination, we systematically screened all control windows and removed any that overlapped with another event in both time and space. In particular, any control observation containing a concurrent event within a 3 km buffer of the focal event was excluded.

Empirically, the four-week window before and after a known event ensures that nearly all events have at least one uncontaminated control observation. This method is highly effective for large events and protests. However, small events tend to exhibit excessive spatial and temporal overlaps, resulting in approximately half of the treatment group being unable to identify a suitable control observation according to the established criteria. In total, after combining treatment and control observations, our dataset includes 1,112 large event observations (163 out of 170 treatments are paired), 7,166 small event observations (1480 of 2,952 paired), and 2,952 protest event observations (674 of 678 paired). This approach follows established practices in event-study causal inference design (Callaway & Sant'Anna, 2021; L. Sun & Abraham, 2021), where treatment and control periods are compared within units, and overlapping or confounding events are carefully removed to prevent contamination of the control group (Borusyak, Jaravel, & Spiess, 2024).

As a preliminary diagnostic, we then conducted paired t-tests within our 500-meter event buffers. We compared trip volumes during event hours to those during matched non-event control windows for each of the three event categories. This initial analysis provides a foundational understanding of the statistical associations before proceeding with more complex causal modeling.

3.4 Causal Analysis: Double Machine Learning

To quantify how each event category causally changes shared micromobility trip volumes, we employ the double machine learning (DML) algorithm. The core innovation of DML is its three-stage orthogonalization procedure (Chernozhukov et al., 2018). Stage 1 uses ML to capture the effect of covariates on both treatment and outcome. Stage 2 computes the residual outcome and the residual treatment. Stage 3 runs a regression using residual treatment to predict residual outcome, thereby obtaining the causal effect.

Compared with conventional approaches, such as propensity score matching, fixed-form GLMs, or difference-in-differences, DML is less sensitive to model misspecification in the covariate process. It is better suited when many controls and interactions are required. Because traffic demand arises from complex, interacting factors (e.g., weather, time, and built environment). DML enables us to capture these nonlinear interactions with flexible ML while still delivering valid causal estimates via orthogonalization and cross-fitting.

In detail, each observation is $W_i = (Y_i, D_i, X_i)$, where Y_i is the trip count within a specified time–location interval (outcome), D_i is a binary indicator for whether an event of a given category (or subcategory) occurs in that interval (treatment), and X_i is a vector of concurrent weather and temporal conditions together with built-environment and sociodemographic features (covariates). The relation between them can be formulated as follows:

$$Y = \theta D + g(X) + \zeta \tag{1}$$

where $g(X)$ is a function capturing the effect of covariates on the outcome, θ is the causal effect parameter we want to estimate for treatment D, and ζ is a residual term which represents effects from other unobserved variables. In general, covariates X also has an effect on the treatment D:

$$D = m(X) + V \tag{2}$$

where $m(X)$ is the propensity for the event to occur given the covariates and V is another residual term satisfying $\mathbb{E}[V \mid X] = 0$. Because X influences both Y and D, simple event–no-event comparisons are confounded. DML addresses this problem by first obtaining the estimators $\hat{g}(X)$ and $\hat{m}(X)$ by machine learning models (here we use random forests), which can be used to form the residual outcome $Y - \hat{g}(X)$ and the residual treatment $D - \hat{m}(X)$. These two residuals represent the components of the outcome and treatment that are unaffected by covariates X, so a linear regression on these two residuals yields an estimate for the causal effect parameter:

$$\hat{\theta} = \frac{\sum_i \left(D_i - \hat{m}_i\left(X_i\right)\right)\left(Y_i - \hat{g}_i\left(X_i\right)\right)}{\sum_i \left(D_i - \hat{m}_i\left(X_i\right)\right)^2} \tag{3}$$

To prevent overfitting, we use grouped cross-fitting: the sample is split into K folds at the event level. Each event and all of its matched "non-event" control group share a group ID and are assigned to the same fold. This ensures each fold includes both the event and its corresponding non-event control group. Then, 80% of the folds are allocated for training and 20% for testing. This proposed method to estimate $\hat{\theta}$ allows us to get the average treatment effect (ATE) of event occurrence. To address `RQ2`, the causal effect of an event happening on the trip volumes is captured by ATE, which is defined for discrete treatments:

$$ATE = \mathbb{E}[Y(D = 1) - Y(D = 0)] \tag{4}$$

3.5 Key Features & Correlation Analysis

This section outlines the key relationships between important predictors and shared micromobility ridership using two complementary methods. First, we use a non-parametric machine learning approach to identify the most influential features and capture complex nonlinear patterns. Second, we apply a traditional regression model to produce interpretable, though correlational, parameter estimates. Together, these analyses address `RQ3` and set a baseline for comparison with our causal estimates.

3.5.1 LightGBM & SHAP

To identify key predictors of shared micromobility trip volumes and visualize nonlinear and interaction effects before our causal analysis, we use a gradient-boosted decision-tree model (Friedman, 2001), specifically *LightGBM* (Ke et al., 2017). The decision tree ensemble is constructed iteratively to minimize the mean-squared-error loss:

$$\mathcal{L}(f) = \frac{1}{N} \sum_{i=1}^{N} [y_i - f(x_i)]^2 \tag{5}$$

where y_i is the observed shared micromobility trip count for sample i and $f(x_i)$ is the model's prediction. Starting from a constant baseline, we grow the ensemble iteratively by adding shallow trees to correct the remaining errors. In each round, the new tree is trained on the residuals r_i, i.e. the differences between observed volumes and the current predictions. Specifically, the m-th tree T_m is chosen to approximate the residual:

$$T_m = \arg\min_T \sum_i [r_i - T(x_i)]^2 , \tag{6}$$

Repeating this residual-fitting loop yields a flexible, nonlinear model capable of accurately estimating shared micromobility trip volumes from the input features. A further advantage of tree ensembles is their explanatory power: each prediction can be decomposed exactly with *SHAP*'s TreeExplainer (Lundberg et al., 2020). We obtain per-feature contributions $\phi_j(x)$ whose aggregated magnitudes directly address `RQ1` by ranking the variables most strongly associated with trip-volume changes. TreeExplainer assigns each observation a baseline term ϕ_0 and per-feature Shapley values ϕ_j satisfying:

$$f(x) = \phi_0 + \sum_j \phi_j(x), \tag{7}$$

so that $\phi_j(x)$ represents the marginal contribution of feature j for that prediction. Gradient-boosted decision trees automatically capture complex nonlinearities and feature interactions, and SHAP values $\phi_j(x)$ quantify each feature's context-specific contribution. This yields a more accurate and arguably richer ranking of importance than that of a standard linear regression model.

3.5.2 Negative-binomial GLM

After identifying the top 20 features that influence ridership during events, we aimed to compare the estimated effects of these features from a traditional associative model with those derived from a causal inference framework. To achieve this, we estimated separate negative-binomial GLMs for large and small event categories during event periods[12]. The negative-binomial distribution was chosen because the trip count data exhibited over-dispersion (variance > mean). A standard Poisson model would have underestimated uncertainty and overstated statistical significance, whereas the negative-binomial specification effectively accounts for this extra dispersion, providing more reliable estimates (Mehzabin Tuli, Mitra, & Crews, 2021).

The set of predictors for each model was refined from the top 20 SHAP-ranked features. To mitigate multicollinearity, we calculated the Variance Inflation Factor (VIF) and iteratively removed the variable with the highest VIF until all retained predictors had a VIF of less than 10. The resulting negative-binomial GLMs were fitted with shared micromobility trip counts as the dependent variable.

3.6 Conditional Average Treatment Effect

DML also allows us to get the CATEs of the other features in covariates for either event category or event subcategory. For `RQ3` (event category) and `RQ4` (event subcategory), we study how significant predictors (continuous and discrete) influence the outcome, conditioning on events occurring. This is represented by CATE:

$$\text{CATE}(x) = \begin{cases} \mathbb{E}[Y(D=1) - Y(D=0) \mid X=1]\,, & \text{discrete } D, \\ \dfrac{\partial}{\partial d}\,\mathbb{E}[Y(D=d) \mid X=1]\,, & \text{continuous } D, \end{cases} \tag{8}$$

Notice that the variables are now labeled differently here: $X = 1$ represents an event happening, and D represents a particular significant variable.

We estimate the CATE for each independent variable retained in the GLMs for `RQ3`. This two-step process enabled a direct comparison between the associational parameters of the negative-binomial GLMs and the causal estimates from the DML framework for the same set of predictors.

[12] We excluded the protest event category from this analysis because the DML results indicated no significant causal effect of protests on shared micromobility ridership.

4 Results

4.1 Correlation Between Event Occurrence and Shared-micromobility Volumes

The results of the paired *t*-tests, shown in Table 2, reveal significant associations between special events and shared micromobility trip volumes, with notable differences across event categories and subcategories. Overall, both small and large events had a statistically significant positive association with increased micromobility usage. The mean increase for small events was 5.13 trips ($p<0.001$), while the impact for large events was much greater, with an average rise of 128.88 trips ($p<0.001$). In contrast, protests were associated with a statistically significant decrease in trip volumes, with an average decrease of 5.23 trips ($p = 0.0057$).

Analysis of subcategories uncovered additional details. Among small events, art–related events showed no significant association with the impact on trip volumes ($p = 0.45$). However, the education, entertainment, and festival subcategories all displayed statistically significant positive effects, with mean increases ranging from 5.08 to 6.95 trips. For large events, all subcategories exhibited significant positive effects. While sports events saw a more moderate mean increase of 59.79 trips, the impacts for parade, entertainment, and festival events were notably larger, with mean increases from 145.21 to 200.84 trips.

Table 2: The results of paired t-tests for three different event categories (in bold) and their subcategories.

Event category & subcategory	N Pairs	Mean Event	Mean Control	Mean Difference
Small event	***1480***	***38.7979***	***33.6714***	***5.1265****
Art–related	290	37.4758	36.1224	1.3534
Education–related	426	32.9014	27.8239	5.0774***
Entertainment–related	441	42.1836	35.8665	6.3171***
Festival–related	323	43.1393	36.1860	6.9532***
Large event	***163***	***382.6993***	***253.8147***	***128.8845****
Sport–related	51	231.6470	171.8561	59.7909*
Parade	32	325.2812	180.0727	145.2085*
Entertainment–related	25	591.2800	390.4366	200.8433**
Festival–related	55	461.3636	310.6164	150.7472***
Protest	***674***	***77.4213***	***82.6534***	***−5.2321****

Note: $^{\dagger}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Causation of Event Occurrence on Shared-micromobility Volumes

The causal estimates derived from the DML model provide a refined understanding of the impact of special events on shared micromobility usage (Table 3). The analysis confirms a significant positive causal effect for both small events (ATE = 8.98, p < 0.001) and large events (ATE = 231.18, p = 0.002). In contrast to the correlational results, the protest event category exhibits no statistically significant causal effect (p = 0.52). At the subcategory level, the art-related subcategory again shows no effect, while the causal estimates for entertainment-related and especially festival-related events are significantly higher than their correlational means. For large events, the sport-related subcategory shows no significant causal effect, while the causal estimates for parade, entertainment-related, and festival-related events are all positive and significant, with the latter two showing notably larger effect sizes (ATE = 487.57 and 690.39).

Table 3: The results of DML for three different event categories (in bold) and their subcategories.

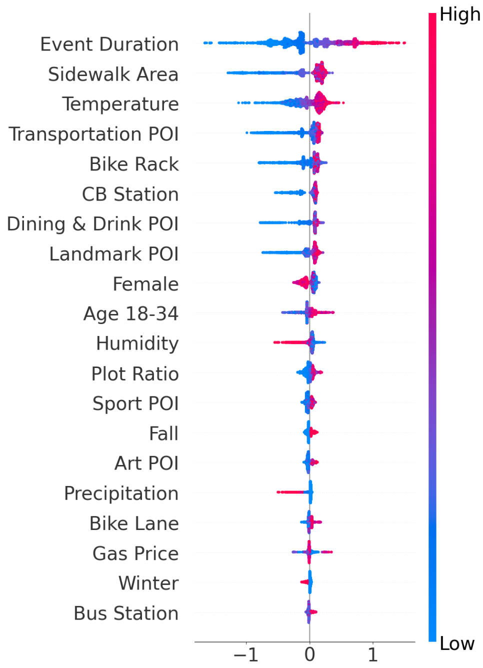
Event category & subcategory	ATEs	SE	CI 2.5%	CI 97.5%
Small event	***8.9845******	***1.0479***	***6.9306***	***11.0384***
Art–related	-1.0295	4.0090	-8.8872	6.8280
Education–related	12.9922***	1.4521	10.1461	15.8383
Entertainment–related	7.8197***	1.6062	4.6715	10.9679
Festival–related	46.5940***	11.7254	23.6125	69.5755
Large event	***231.1790*****	***75.6614***	***82.8854***	***379.4726***
Sport–related	98.4399	68.9392	-36.6785	233.5583
Parade	127.0652*	61.7028	6.1299	248.0005
Entertainment–related	487.5749*	248.2489	1.0159	974.1340
Festival–related	690.3891**	241.7065	216.6529	1164.1253
Protest	***−2.5929***	***4.0639***	***−10.5580***	***5.3722***

Note: "SE" denotes the standard error. $^{\dagger}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

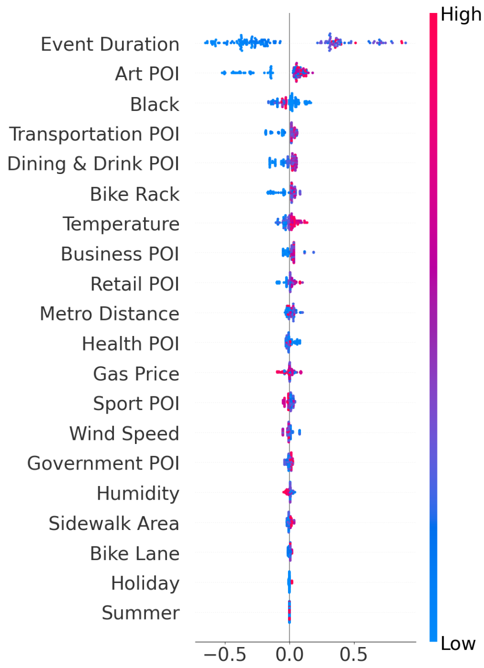
4.3 Key Variables for Shared-micromobility When Events Take Place

Figure 3 presents the top 20 predictors of micromobility trip volumes during small and large events, as identified by SHAP value analysis. While the specific rankings differ, there is considerable overlap in the influential variables across the two event categories, indicating shared underlying factors that drive demand. Key predictors for both models include Event Duration, Temperature, Transportation POI, Dining & Drink POI, Bike Rack, etc. The combined set of top predictors, along with event features, comprised 32 variables for subsequent causal and correlational modeling, excluding protests due to their previously established lack of causal impact.

Table 4 presents the results of the DML and negative-binomial GLM analyses, revealing critical distinctions between causal drivers and correlational factors. For both small and large events, the DML model demonstrates that the most substantial causal effects on micromobility trips are attributed to event and temporal features. The single strongest positive predictor is Event Duration, with a large and highly significant CATE (Small: 17.909, p<0.001; Large: 50.776, p<0.001). Seasonal effects



(a) SHAP value for small events



(b) SHAP value for large events

Fig. 3: SHAP summary plots for the LightGBM model predicting shared micromobility ridership during events. Each point represents a single event observation (Event Happen = 1). Features are ordered on the Y-axis by their impact on the model's output. On the X-axis, a positive SHAP value increases the predicted trip volume, while a negative value decreases it. The color represents the feature's raw value from low (blue) to high (red). Purple indicates intermediate values.

are also pronounced. Summer ($\text{CATE}_{Small} = 14.583$; $\text{CATE}_{Large} = 343.155$) and Fall ($\text{CATE}_{Small} = 11.011$) exhibit strong positive causal effects, whereas Winter has a high negative causal effect ($\text{CATE}_{Small} = -21.287$; $\text{CATE}_{Large} = -459.738$). Among temporal indicators, Gas Price ($\text{CATE}_{Small} = -27.075$; $\text{CATE}_{Large} = -677.280$) and Holiday ($\text{CATE}_{Large} = -226.784$) exerts a significant negative causal pressure on ridership. One explanation for this is that when a large event coincides with a holiday, people may choose to visit alternative destinations (e.g., traveling out of town for vacation), thereby reducing demand for the specific event and generating a negative causal effect on its usage during large events. In contrast, most built environment and socio-demographic features, although sometimes statistically significant, exhibit CATEs of negligible magnitude, indicating their causal effect on trip volumes during events is minimal.

Conversely, the negative-binomial GLM results, which measure association, tell a different story. While it agrees that Event Duration ($\text{Coef}_{Small} = 0.303$, $\text{Coef}_{Large} = 0.080$) and Temperature ($\text{Coef}_{Small} = 0.042$; $\text{Coef}_{Large} = 0.079$) are strong positive

Table 4: The results of DML and negative-binomial GLM for small and large event categories.

Variables	**DML**				**Negative-binomial GLM**			
	Small Event		Large Event		Small Event		Large Event	
	CATEs	SE	CATEs	SE	Coefficients	SE	Coefficients	SE
Event features								
Event Duration	17.909***	1.519	50.776***	8.879	0.303***	0.018	0.080***	0.018
Spring	−7.678***	0.790	−91.735	83.462	–	–	–	–
Summer	14.583***	0.864	343.155**	145.494	−0.085	0.100	−0.159	0.168
Fall	11.011***	0.750	158.548	127.581	0.172*	0.076	0.453†	0.130
Winter	−21.287***	0.844	−459.738***	81.614	−0.153	0.106	−0.097	0.184
Weekend	4.216*	2.203	12.003	323.513	0.120*	0.064	1.021*	0.453
Rush Hour	−0.327	3.271	215.553	358.1426	0.160**	0.067	−0.301	0.259
Temporal features								
Temperature	1.246***	0.208	42.667†	26.698	0.042***	0.006	0.079***	0.024
Humidity	−0.168***	0.038	−5.348†	3.270	−0.006***	0.002	−0.014*	0.007
Precipitation	−3.823**	2.249	73.639*	43.117	−0.192**	0.067	0.262	0.172
Wind Speed	−0.005	0.336	−10.294	16.874	−0.008	0.013	−0.022	0.063
Gas Price	−27.075***	4.418	−677.280†	416.709	−0.565***	0.152	−1.112*	0.664
Holiday	−4.689	4.418	−226.784**	92.627	0.105	0.250	−1.060*	0.579
Built environment features								
Dining&Drink POI	0.335*	0.172	0.410	1.601	0.006***	0.001	–	–
Landmark POI	−0.871	0.697	−3.295	3.137	−0.005	0.005	–	–
Art POI	−0.432	0.732	−1.666	1.316	0.003*	0.002	-0.002	0.003
Transportation POI	0.039	0.153	0.840	1.169	–	–	–	–
Government POI	0.056	0.065	−0.037	0.682	−0.0006	0.001	−0.001	0.001
Health POI	−0.428	0.130	−1.586	2.075	−0.005***	0.001	−0.004	0.004
Business POI	−0.054	0.099	0.700	1.097	–	–	–	–
Sport POI	0.234	0.291	−2.149	3.206	0.003	0.004	–	–
Retail POI	0.252	0.257	0.507	2.188	0.005***	0.001	0.002	0.005
Bike Rack	0.173	0.121	−0.127	0.866	0.002*	0.001	0.001	0.003
Bike Lane	1.334	1.383	−0.434	10.688	0.100***	0.023	0.047†	0.031
Sidewalk Area	2.842	1.833	−18.413*	9.199	0.129***	0.020	–	–
Plot Ratio	4.974	5.939	−44.556	75.545	−0.155***	0.029	−0.210*	0.111
Bus Station	−0.184	0.485	−2.490†	1.512	−0.002	0.004	0.001	0.008
Metro Distance	1.166*	0.708	−21.837	40.598	−0.005	0.008	−0.120***	0.024
CB Station	0.747	3.354	−15.867*	8.250	0.061***	0.020	–	–
Socio-demographic features								
Female	−0.079	0.066	−4.193*	2.209	−0.002***	0.000	–	–
Black	−0.004	0.013	0.323	1.108	0.000	0.000	−0.003***	0.001
Age 18-34	0.024	0.048	−3.849	2.660	0.002***	0.000	0.0007	0.001
Log-likelihood	-		-		−13579		−1102	
Pseudo R-squared	-		-		0.3989		0.5931	

Note: "SE" denotes the standard error. $^{\dagger}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

correlates and Gas Price ($\text{Coef}_{Small} = -0.565$, $\text{Coef}_{Large} = -1.112$) and Humidity ($\text{Coef}_{Small} = -0.006$, $\text{Coef}_{Large} = -0.014$) are negative correlates, it also flags a much wider array of built-environment and socio-demographic variables as significantly related to trip volumes. Features such as Dining&Drink POI, Retail POI, Bike

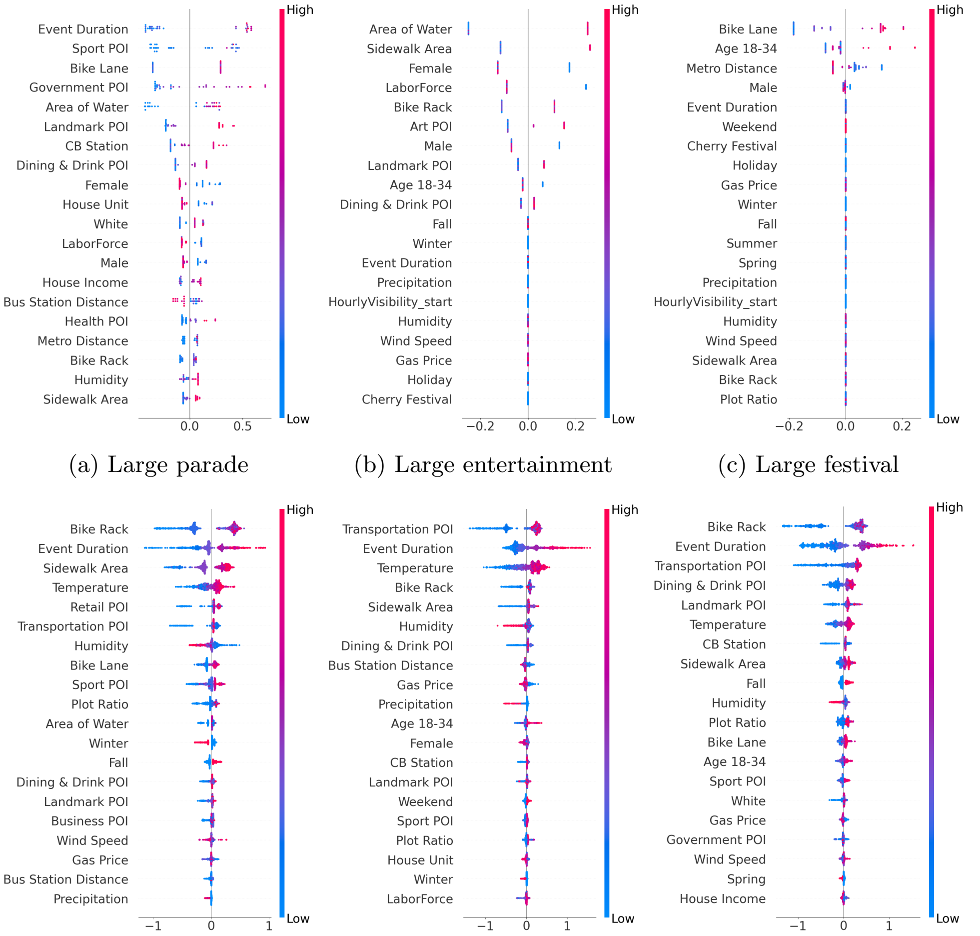
Lane, Sidewalk Area, CB Station, Female, and Age 18-34 all show significant coefficients in the GLM for small events, despite their causal effects being insignificant or trivial.

To assess the robustness of our estimated treatment effects, we further examine the predictive accuracy of the nuisance functions underlying the DML framework. The quality of nuisance models, such as the propensity and outcome models, is crucial because well-fitting models improve orthogonalization and yield more stable causal estimates. For each event category, we report the area under the receiver operating characteristic curve (ROC-AUC) for the propensity model and the coefficient of determination (R^2) for the outcome model. The results show *Protest* (ROC-AUC = 0.6739, R^2=0.7917), *Small event* (ROC-AUC = 0.8187, R^2=0.6737), and *Large event* (ROC-AUC = 0.5845, R^2=0.2842). These values indicate that the models for protests and small events achieve reasonable separation and high outcome fit, suggesting reliable nuisance estimation and robust causal inference. In contrast, the weaker performance for large events reflects their greater heterogeneity and unpredictability. Overall, the nuisance models perform adequately for causal identification, lending confidence to the robustness of our estimated treatment effects.

4.4 Key Variables' CATEs for Subcategory When Events Take Place

Figure 4 shows the most influential predictors of micromobility demand within each event subcategory based on SHAP analysis. LightGBM prediction metrics are included in the appendix. Many of the same variables are shared across small subcategories, like Event Duration and Temperature. In contrast, large subcategories display notably diverse importance profiles. For large entertainment and large festival events, only a few features carry significant signals, and many variables have SHAP values of zero, indicating no contribution under the fitted model. As in the previous subsection, we compare important variables across subcategories within the same event category and estimate DML models. However, for large-event specifications, variables with SHAP = 0 will not be included unless they are part of parade events. Finally, large sports events and small art events are excluded due to a lack of causal impact.

Tables 5 and 6 display the CATEs for these subcategories, measuring the causal impact of each variable during specific event categories. For large event subcategories (Table 5), the causal drivers of demand vary significantly across subcategories. Event Duration remains a strong positive predictor for parade (CATE = 135.094, $p<0.05$) and festival (CATE = 59.97, $p<0.001$) events, but is insignificant for entertainment events. Seasonal effects are strong but vary: Summer causes significant growth in trips during parade (CATE = 357.628, $p<0.001$) and entertainment (CATE = 495.294, $p<0.05$) events, while Winter significantly reduces trips for all large events (large entertainment events are not even held during winter). Importantly, the built environment shows a much more substantial causal impact for each large subcategory event than in the overall analysis. For parades, features such as CB Station (CATE = 90.287, $p<0.001$), Bike Lane (CATE = 53.763, $p<0.05$), and Sidewalk Area (CATE = 31.339, $p<0.05$) have notable positive effects. A similar pattern appears for entertainment events (Art POI, Sidewalk Area, CB Station, Bike Lane) and festival



(a) Large parade (b) Large entertainment (c) Large festival

(d) Small education (e) Small entertainment (f) Small festival

Fig. 4: SHAP values for small and large event subcategories. Figs. 4a, 4b, and 4c present three large-event subcategories, while Figs. 4d, 4e, and 4f display three small-event subcategories. For each plot, every point represents a single event observation (Event Happen = 1). Features are ordered on the Y-axis by their impact on the model's output. On the X-axis, a positive SHAP value increases the predicted trip volume, while a negative value decreases it. The color represents the feature's raw value from low (blue) to high (red). Purple indicates intermediate values.

events (Bike Lane, Sidewalk Area), although the specific significant variables differ. Socio-demographic variables also exhibit occasional yet significant impacts on large entertainment and festival events.

For small events, the features are remarkably consistent across education, entertainment, and festival subcategories (Table 6). Event duration is a uniformly strong

Table 5: The results of DML for the three large event subcategories.

Variables	Parade		Entertainment-related		Festival-related	
	CATE	SE	CATE	SE	CATE	SE
Event features						
Event Duration	135.094*	72.731	3.973	10.155	59.970***	9.584
Spring	−56.309	108.991	473.559	1063.844	−218.937	290.291
Summer	357.628***	97.921	495.294*	257.426	7.578	283.469
Fall	−57.499	122.691	−252.984	169.459	106.120	338.244
Winter	−326.241***	97.914	–	–	−614.666**	212.342
Weekend	114.727	130.777	−8.689	367.610	179.708	489.215
Rush Hour	153.436	174.455	−335.745	220.137	80.402	348.054
Temporal features						
Temperature	19.013***	5.909	26.712	19.090	62.431	50.875
Humidity	−0.189	1.807	0.001	4.898	−3.212	5.514
Precipitation	1.611	2.379	2.450	1.640	−10.407	6.850
Wind Speed	−47.314	49.109	−1.273	23.586	75.635	83.070
Gas Price	−91.423	155.865	370.819	363.739	−935.383	698.950
Built environment features						
Dining&Drink POI	5.692*	1.123	0.733	1.883	−1.797	1.644
Landmark POI	12.516*	5.609	2.774	9.415	−51.692	65.061
Art POI	7.360**	2.942	14.583***	4.411	−1.019	1.787
Sport POI	12.078*	6.718	0.553	8.032	4.809	14.755
Government POI	6.344*	2.928	9.122†	5.619	0.793	2.525
Health POI	15.486**	5.937	13.305†	7.822	−23.760*	13.278
Bike Rack	3.950***	1.204	5.324*	2.317	4.301	3.318
Bike Lane	52.763*	30.100	39.775†	27.537	218.517†	144.769
Sidewalk Area	31.339*	17.390	66.388†	36.220	170.666**	68.244
Area of Water	0.116	3.865	1.864	11.168	0.379	4.485
House Unit	3.373†	2.146	−0.803	1.698	−10.816	7.637
Bus Station Distance	0.317	0.462	0.873	2.331	−3.236	2.918
Metro Distance	0.7877	6.290	−21.023***	3.005	−29.935	60.362
CB Station	90.287***	14.659	58.289†	38.469	−78.291	106.174
Socio-demographic characteristics						
Female	−0.267	0.367	−0.734	0.927	−7.717	6.5455
Male	0.740	1.363	−1.219	1.177	32.735**	12.195
White	0.297	0.368	−2.807*	1.106	−2.406	2.420
Age 18-34	−0.906	0.459	−0.303	1.728	−0.745	2.329
Labor Force	2.300	2.068	−6.335*	2.757	12.666†	8.651
House Income	2.509	2.221	−7.805	5.564	25.902	30.010

Note: "SE" denotes the standard error. $^{\dagger}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Large entertainment events do not have samples in winter.

positive predictor for all three subcategories (CATE from 14.168 to 21.848, all p<0.001). Seasonal patterns are also consistent: Summer and fall lead to increases in shared micromobility ridership, while winter and spring see decreases. Temperature positively influences demand. Humidity and gas prices have a negative impact across all subcategories. Conversely, the built environment and socio-demographic factors show almost no significant causal effects on small event demand. Only a few variables,

Table 6: The results of DML for the three small event subcategories.

Variables	Education-related		Entertainment-related		Festival-related	
	CATE	SE	CATE	SE	CATE	SE
Event features						
Event Duration	18.268***	1.812	14.168***	2.202	21.848***	3.363
Spring	−5.524***	1.365	−8.388***	1.468	−17.290***	3.045
Summer	12.846***	1.731	18.750***	1.367	10.359***	3.518
Fall	12.123***	1.240	7.091***	1.293	20.023***	3.238
Winter	−16.880***	1.229	−20.557***	1.413	−29.304***	3.473
Weekend	1.168	4.586	3.622	9.003	−0.916	8.251
Rush Hour	−3.471	6.322	−2.240	5.378	−2.550	8.235
Temporal features						
Temperature	0.647*	0.315	1.337***	0.279	1.683**	0.574
Humidity	−0.174**	0.058	−0.076	0.067	−0.499***	0.135
Precipitation	0.744	4.034	−3.173	2.114	−13.339*	6.989
Wind Speed	−0.510	0.446	0.169	0.387	1.076	1.618
Gas Price	−14.365*	6.960	−28.068**	9.412	−37.724*	17.969
Built environment features						
Dining&Drink POI	0.333	0.276	0.073	0.159	0.460*	0.219
Landmark POI	0.775	0.611	−0.101	0.473	−0.708	0.881
Transportation POI	0.040	0.243	0.222	0.141	0.228	0.420
Sport POI	0.991	0.690	−0.149	0.400	0.100	0.594
Retail POI	−0.501	0.533	−0.031	0.105	−0.372	0.456
Business POI	0.016	0.120	0.257**	0.091	−0.244	0.199
Government POI	0.172	0.188	0.0517	0.045	$0.231^{\dagger}$	0.146
Bike Rack	0.203	0.187	−0.119	0.136	0.259	0.187
Bike Lane	4.243	1.974	2.170	1.512	7.920*	4.023
Sidewalk Area	−8.250	5.758	2.246	1.484	3.685	3.961
Plot Ratio	4.605	12.710	−3.850	6.185	8.556	7.773
House Unit	0.130	0.230	0.001	0.085	0.255	0.224
Area of Water	0.202	0.268	0.066	0.123	$0.210^{\dagger}$	0.127
Bus Station Distance	−0.012	0.047	−0.001	0.022	0.070	0.051
CB Station	−0.592	2.659	−2.077	2.367	1.256	3.018
Socio-demographic characteristics						
Female	−0.049	0.145	−0.014	0.033	−0.091	0.039
White	−0.002	0.033	$-0.027^{\dagger}$	0.016	0.075	0.066
Age 18-34	0.041	0.050	0.020	0.019	0.001	0.041
Labor Force	−0.051	0.077	0.017	0.032	−0.100	0.079
House Income	0.302*	0.133	0.055	0.094	$-0.279^{\dagger}$	0.159

Note: "SE" denotes the standard error. $^{\dagger}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

such as Bike Lane for festivals (CATE = 7.92, $p<0.05$), Business POI for entertainment events (CATE = 0.257, $p<0.01$), and House Income for education events (CATE = 0.302, $p<0.05$) have weak effects, suggesting demand during smaller events is mainly influenced by the event itself and weather, not built environment or demographic features.

5 Discussion

5.1 Causal vs. Correlational Effects of Event Categories on Shared Micromobility Demand

Our findings demonstrate that special events have a significant impact on shared micromobility usage, particularly during large events. Both our causal (DML) and correlational (paired t-tests) analyses reveal that the impact of a large event is over 25 times greater than that of a small one. Although the correlational analysis found a positive association between small/large events and shared micromobility, it consistently underestimated their impact. It gave inconsistent results for protest event categories compared to the causal analysis, complicating interpretation.

The use case of protest events exemplifies the critical distinction between correlation and causation. The observed negative correlation was likely not causal, but rather a result of spatial confounding. Since the protests were limited to specific government-approved locations, which are often in areas with lower population density and less micromobility infrastructure and demand. The decrease in trips is likely due to the location rather than the protest itself. This illustrates how correlational methods can mistakenly suggest a causal relationship when one does not exist.

For events with genuine causal effects, the correlational approach significantly underestimated their actual impact. This underestimation was most extreme for festival-related events, where the causal estimate was four to seven times (four for large festivals, seven for small festivals) greater than the correlational mean difference. This indicates that simple before-and-after or control-day comparisons fail to account for confounding variables, leading to a substantial undervaluation of these events' ability to generate ridership. Similarly, the significant correlational effect for large sports events vanished under causal scrutiny, suggesting that other factors drove the initial association. Moreover, the associational model (negative-binomial GLM) indicates a significant role for many built environment and socio-demographic features; however, DML reveals that these correlations are likely confounded and do not represent a genuine causal relationship. This is likely due to co-location, omitted variables, and selection bias. These results collectively argue for the adoption of causal inference frameworks in urban mobility studies, enabling the movement beyond mere association and an accurate quantification of the proper drivers of demand.

5.2 Heterogeneous Causal Mechanisms Across Event Subcategories

Examining event subcategories uncovers a split in how shared micromobility demand is driven during events. Across all events, the duration and seasonality (such as the positive effects of Summer and Fall and the negative impacts of Winter) stand out as the most consistent and influential causal factors. At the same time, Gas Prices are the most potent negative predictor. Interestingly, temporal markers like Weekend and Rush Hour have almost no apparent causal effect, indicating that the "special" nature of an event outweighs short-term daily travel patterns.

The role of the built environment, however, varies greatly depending on the scale of the event. For large events (e.g., parades, festivals, major entertainment events), shared micromobility demand is driven by the interaction between the event, temporal factors, and urban infrastructure. Features such as Sidewalk Area, Bike Lane, and dense POI are essential for supporting and increasing trip volumes during large events. Especially the first two (Sidewalk Area and Bike Lane) have a very high causal impact, and Bike Lane also has strong effects on small festivals. This shows that cities can take a proactive approach to managing mobility during large events and enhance economic benefits through strategic investments in mobility infrastructure within designated event zones. Practically, for planners, venues hosting or managing special events that want to encourage a shift from cars to micromobility should expand and connect sidewalk capacity along key access routes and establish continuous, safe bike-lane networks linked to transit hubs. These measures would be more effective than changing the station distance or transit network.

Conversely, for small events, demand is primarily driven by the event itself and immediate temporal factors. The surrounding built environment has little to no marginal causal effect. This shows that small events create a more intrinsic, localised demand that does not rely heavily on the existing urban environment. Therefore, strategies to promote micromobility for small events should prioritise operational incentives, like dynamic pricing promotions and ensuring vehicle availability, rather than capital-intensive infrastructure projects, which are less effective at this scale. This variability requires event-specific mobility policies rather than one-size-fits-all solutions.

5.3 The Counterintuitive Causal Effect of Gas Prices

Our study uncovered a counterintuitive yet important finding: rising gas prices have a significant negative causal effect on shared micromobility use during events. This seems to contradict established research, which generally shows that higher gas prices increase overall micromobility ridership in the long run by discouraging private car use (Younes et al., 2020). However, Berezvai, Basile, Kálecz-Simon, and Bakó (2024) observed that removing the gas price cap increased bikeshare usage primarily in suburban areas, with a decrease also recorded in some localities. Our results support this finding.

We propose two mechanisms for this phenomenon. First, especially for small events, where attendance is optional, an increase in gas prices can discourage attendance, particularly for those who live farther away and rely on their cars. Instead of switching to micromobility for the entire trip, potential attendees may simply choose not to attend, which eliminates the possibility of a "first-and-last-mile" micromobility trip originating from a parking spot (Badia & Jenelius, 2023). Second, the positive impact of gas prices on shared micromobility adoption is likely subject to a time lag. Behavioral shifts towards alternative transportation modes usually happen gradually over weeks or months, rather than immediately on the day of a price increase. Thus, the immediate short-term effect observed during an event is a reduction in overall travel demand that has not yet been replaced by micromobility. This highlights the importance of temporal granularity in analysis; a long-term positive correlation can hide short-term negative causal effects.

5.4 Limitations and Future Work

This study has several limitations that offer opportunities for future research. First, using a uniform 500-meter buffer for all event categories may not fully capture each event's spatial influence. Large events, like parades or festivals, likely have a broader geographic impact and might need a larger or more adaptable buffer to include all affected trips. Conversely, smaller events could be adequately covered with a smaller radius. However, a straightforward spatial buffer, using 500-meter zones centered around venues, ensures transparency in identification, comparability across categories, and consistent analysis. Future research could investigate adaptive or event-specific buffer sizes and complex network-based methods (e.g., isochrones, distance-decay) that better capture the actual spatial extent of different events.

Second, our included events were limited. Expanding the analysis to include unplanned exogenous disruptions (such as labor strikes and sudden public transit closures) would offer a more comprehensive picture of urban disruptions. This expansion would also enable systematic comparisons among planned–exogenous, unplanned–exogenous, and planned–endogenous events, helping to clarify how their effects differ. Additionally, our event data relies on automated classification systems, which, although efficient, may lead to misclassification errors or overlook subtle event details that could impact shared micromobility patterns.

Third, we focused only on shared micromobility. The data comes from a single operator, which might limit how well our findings represent the entire shared micromobility in DC, as different operators may serve different user groups and areas. Besides, since we only monitor trips but not fleet availability factors like idle locations, dwell times, or capacity, our estimates reflect actual usage rather than potential demand. During large events, limited supply might cause us to underestimate the true surge in demand. Future improvements could include operator availability data and rebalancing logs to better identify both demand peaks and stockouts. Additionally, including trip distance distributions and inferring trip purposes related to events can help differentiate mandatory trips from discretionary travel. Moreover, future research could compare these findings with the causal effects on other transportation modes, such as ride-hailing, public transit, and private cars, to create a fuller picture of mode shifts. In particular, quantifying cross-mode interactions, such as how shocks in one mode spread to shared micromobility and vice versa, would clarify substitution and complementarity at the venue scale.

Fourth, broadening the geographic scope to include cities with diverse cultural settings and transportation systems would enhance the applicability of our results in other contexts. Similarly, the policy implications are mainly based on this specific area (DC). Claims about generalizability should be approached with caution. Due to different local contexts, other cities need to verify these findings locally (considering season, time window, and venue type) and conduct sensitivity analyses before scaling up.

Methodologically, for simplicity, trip volume was measured using destination points, while a similar pattern was observed with origin points. Future research could analyze complete trip trajectories to determine if routes change during events or road closures. It is also worth noting that despite our rich set of controls, we cannot entirely eliminate the influence of unobserved confounders that might affect both event occurrence and shared micromobility usage. Broader seasonal factors, such as changes in travel behavior during holidays, are also not fully balanced by our matching strategy and may introduce residual variation. Finally, explicit causal diagrams such as directed acyclic graphs (DAGs) would clarify variable relationships, but constructing a reliable DAG isn't practical due to many correlated covariates and limited knowledge of their links. DML directly estimates causal effects, bypassing the need for a complete causal graph. Future research might explore machine-learning methods for causal structure discovery, potentially enabling DAGs to be learned from high-dimensional data to improve interpretability. Exploring more complex causal structures or natural experiments could further enhance the validity of these findings. Integrating causal inference with structural choice and route models offers a promising research path for creating hybrid methods that connect behavioral understanding with policy-relevant causal insights.

6 Conclusion

This study offers a thorough, causal understanding of how events influence shared micromobility use in Washington, D.C. Although the case is DC, the framework is mode- and city-portable wherever similar data and event records exist. By combining high-resolution trip data with a collection of event records and employing a causal inference approach, we move beyond simple correlations to identify the factors driving demand during events. The shift from correlation to causation modeling represents a major advance in urban science. In this work, we showed that traditional analytical methods can be limited, either by underestimating the appeal of major cultural events or by identifying spurious associations that do not reflect a true causal link. Policies and investments based only on correlational data risk being inefficient or misdirected. By carefully isolating the impact of events, this research provides a blueprint for accurately assessing the effectiveness of urban interventions in complex, real-world environments.

For policymakers and operators, this study offers practical insights. Urban spaces actively interact with special events to shape shared micromobility demand. The significant impact of large festivals and entertainment events requires proactive management, including targeted infrastructure upgrades in event zones and flexible resource allocation. The minor role of built environment factors for smaller events suggests that operational strategies, rather than costly infrastructure projects, are key to increasing ridership for these gatherings. Ultimately, this research enables cities to strategically utilize shared micromobility, boosting urban vitality, improving access to public life, and developing more resilient transportation networks that adapt to both daily routines and special occasions.

Appendix

Table 7: LightGBM prediction performance (R^2, RMSE, MAE) for estimating event-period shared micromobility ridership from observed covariates, conditional on an event occurring.

Event category & subcategory	Event Number	R^2	RMSE	MAE
Small event	1480	0.7843	27.55	12.89
Entertainment	441	0.9322	13.25	7.50
Education	426	0.8018	20.26	9.68
Festival	323	0.9228	24.76	9.42
Large event	163	0.1252	968.44	376.49
Parade	32	0.9738	87.19	42.82
Entertainment	25	0.6793	442.72	237.84
Festival	55	0.0495	1490.25	653.81

Note: Small art events and large sports events are excluded here due to their insignificant correlation and causal effects.

In the LightGBM model, we identified key variables correlated with ridership and evaluated how well these covariates can predict shared micromobility demand when an event occurs. Table 7 shows that the model performs substantially better for small events than for large ones. For small events, the R^2 value indicates that approximately 78% of the variation in ridership can be explained by the observed covariates, and the RMSE is comparatively low. This suggests that trip patterns during small events are relatively stable and well captured by the available data.

In contrast, predictive power for large events is considerably weaker: overall R^2 drops to around 12%, and the RMSE increases by an order of magnitude, reflecting much higher variance in ridership responses. We also observe notable differences across large-event subcategories. Ridership during parades is highly predictable. Entertainment events show moderate predictability, while festival-related ridership is nearly impossible to predict from the covariates alone. These results highlight that the mobility impacts of large events are more heterogeneous and influenced by additional unobserved factors not captured in the model.

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Author Contributions

D.Q.: Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Funding acquisition, Writing—original draft, Writing -review & editing. G.M.: Data curation, Supervision, Funding acquisition, Writing – review & editing

Data Availability

A GitHub repository is available at: https://github.com/QAVAQ/Causal-effects-of-special-events-on-shared-micromobility. It contains the exact LLM prompts, the small events, and the protest datasets. Due to third-party licensing, raw trip records and large events datasets are not redistributed. Aggregated outputs are available from the authors upon reasonable request for research purposes.

Declarations

Use of AI/LLM tools: We used ChatGPT-4o to assist with the initial categorization of event subcategories. All taxonomy options were then reviewed and finalized by the authors, who take full responsibility for the methodology and results.

Competing interests: The authors declare no competing interests

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