Developing Effective Traffic Management Strategies for Special Events based on ADMS Dataset

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract
Major events are a significant source of traffic congestion, especially in large metropolitan areas. We conduct a case study of football games played at the Los Angeles Memorial Coliseum; a venue located near downtown Los Angeles with a capacity of about 80,000. Two teams play home games at the Coliseum, the Los Angeles Rams, and the University of Southern California Trojans. These events take place in an area that already has a high level of recurrent congestion. We analyze the impacts of game days by comparing game day traffic with traffic on control days on both the highway and arterial systems. Our data are speed records from in-road detectors. We estimate two sets of models to test relationships between game attributes and traffic performance. The first set are traditional regression models controlling for spatial and temporal correlation. The second set are Random Forest, a type of machine learning estimation. We find that Random Forest performs better, as it allows for complex nonlinearities in variables. Our results show that Rams and USC impacts are different. Rams' fans arrive in a more concentrated time interval closer to start time of the games, and therefore have a greater impact on the major approach routes than USC fans. The greatest impacts on highways are around nearby freeway-to-freeway interchanges. Arterial traffic is more consistently affected with distance from the venue. The case study provides the basis for better management of major planned events.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Principal Investigator Genevieve Giuliano conducted this research titled, "Developing Effective Traffic Management Strategies for Special Events based on ADMS Dataset" at the Sol Price School of Public Policy, University of Southern California, along with her research team: Yougeng Lu, Sean Soni, Alanna Coombes. The research took place from March 15, 2018 to June 30, 2021 and was funded by a grant from LA Metro in the amount of $316,808. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Abstract

Major events are a significant source of traffic congestion, especially in large metropolitan areas. We conduct a case study of football games played at the Los Angeles Memorial Coliseum; a venue located near downtown Los Angeles with a capacity of about 80,000. Two teams play home games at the Coliseum, the Los Angeles Rams, and the University of Southern California Trojans. These events take place in an area that already has a high level of recurrent congestion. We analyze the impacts of game days by comparing game day traffic with traffic on control days on both the highway and arterial systems. Our data are speed records from in-road detectors. We estimate two sets of models to test relationships between game attributes and traffic performance. The first set are traditional regression models controlling for spatial and temporal correlation. The second set are Random Forest, a type of machine learning estimation. We find that Random Forest performs better, as it allows for complex nonlinearities in variables. Our results show that Rams and USC impacts are different. Rams' fans arrive in a more concentrated time interval closer to start time of the games, and therefore have a greater impact on the major approach routes than USC fans. The greatest impacts on highways are around nearby freeway-to-freeway interchanges. Arterial traffic is more consistently affected with distance from the venue. The case study provides the basis for better management of major planned events.

Developing Effective Traffic Management Strategies for Special Events based on ADMS Dataset

CHAPTER 1 Introduction

Special events – major sports events, concerts, or organized demonstrations – are regular occurrences in Los Angeles. These events and their associated traffic are overlaid on to an already congested transportation system. The purpose of this research is to use the Archived Data Management System (ADMS) data set to examine the impacts of special events and develop strategies to manage related traffic as effectively as possible.

Special events, such as sports games and concerts, generate temporary increases in traffic which currently are predictable only in general terms. Unlike recurring commuting behaviors, we have little information about event travel. We do not know where attendees come from, how far they travel, how they choose their mode, or how they schedule their trip. Event traffic managers have information on site and parking access, but typically not on the broader network surrounding the event site. Most event management is limited to the immediate venue area and concentrated on local access and egress.

The number of studies on traffic management on major events is increasing, but operational strategies are still largely adopted from manuals and checklists (Anbaroglu et al., 2014; Amini et al., 2016). Despite advances in computation and traffic simulation models that have made real-time short-term traffic prediction possible, application of such tools for large-scale urban road network remains a challenge (Dowling et al., 2004; Anbaroglu et al., 2014; Amini et al., 2016).

ADMS historical data provides a rich resource to examine the impacts of special events. Since the database now has 10 years of data, we have many occurrences of events at the same venue. We can compare traffic patterns with and without events taking place to identify likely paths through the network to and from the venue, as well as timing of arrivals and departures.

In this research, we select the Los Angeles Memorial Coliseum (the Coliseum) as a case study to explore traffic flow patterns on event days. The Coliseum provides a good case study for the following reasons: it is the home of the USC football team and was the home of the Los Angeles Rams football team from 2016 to 2020, providing a relatively large sample of game days to study. The Coliseum is within the LADOT ATSAC system, providing extensive sensor data on the local streets that is stored in the ADMS database. Finally, the research team has access to local agencies that make possible a comprehensive data collection effort.

We use a multiple methods approach to examine impacts on traffic, parking, and transit use. We develop models to estimate the traffic impacts of major events on highways and the local arterials. and we examine transit date to estimate mode share of game attendees. Data analysis is supplemented with interviews of event managers. We present a series of recommendations to improve special events management, including parking management, real-time information services, and enhanced game day transit services.

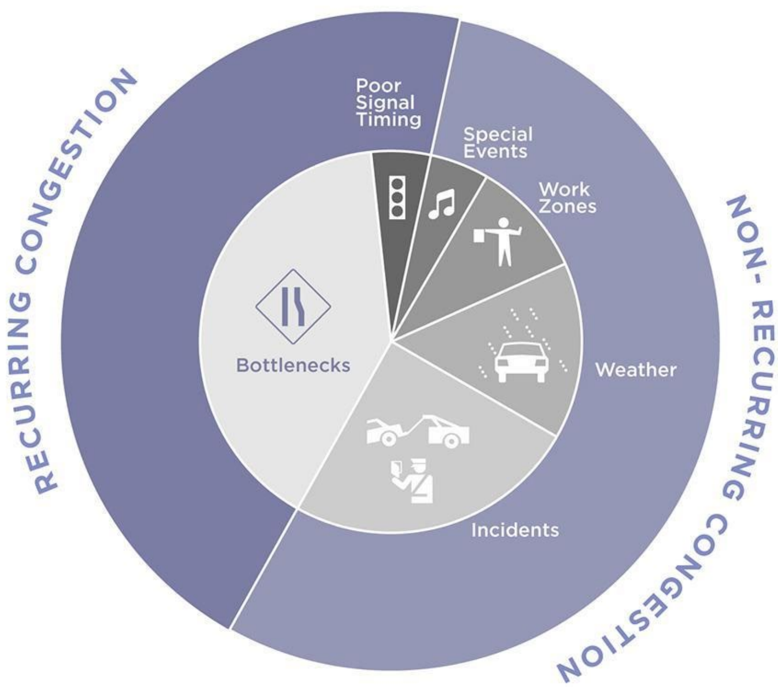
The remainder of this report is organized as follows. Chapter 2 provides a review of the literature on special events management and impacts. Chapter 3 introduces the study area and our research approach. We describe the ADMS data, and provides an overview of event traffic trends. Chapter 4 presents a traffic impact analysis, and Chapter 5 presents a transit analysis. In Chapter 6 we conduct a simulation analysis to test options for reducing game day congestion. Chapter 7 presents our recommendations for better managing special events.

CHAPTER 2: Literature Review

2.1 Recurrent and non-recurrent congestion

Traffic congestion on highways or surface roadways is subject to the effects of recurring and non-recurring events (Bremmer et al., 2004; Dowling et al., 2004). In a widely accepted definition, recurring congestion refers mostly to congestion that is relatively predictable and happens periodically at certain hours due to a large number of vehicles on the road network, such as morning peak period congestion on weekdays. Non-recurring congestion can be defined as unusual congestion caused by unpredictable incidents such as traffic accidents, vehicle breakdowns, adverse weather conditions, or planned events including sporting games and concerts (Amini et al., 2016) (Figure 2.1).

Figure 2.1. Causes of Congestion: Recurring and Non-recurring Congestion



Source: Adapted from Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation, Figure ES.2, Federal Highway Administration

There is no standard definition of recurring and non-recurring congestion. For urban road networks, travel speed and travel time are the most used indicators to determine whether congestion is recurring or not. Continuous speed data is used to estimate the expected travel time for a specific road segment. A recent study measured the expected travel time in an urban road network using Automated License Plate Recognition (ALPR) cameras and defined non-recurring congestion as an average travel time greater than 20% of the expected travel time, with the expected travel time based on the level of recurrent congestion (Anbaroglu et al., 2014). An often-quoted statistic is that about half of all congestion is recurrent, and the other half is non-recurrent (He and Ding, 2013). Recent research by

Hojati et al. (2016) shows that unexpected incidents and scheduled events are the dominant sources of travel time unreliability, which imposes additional costs on travelers and firms.

As the number of special events attendees is large (generally more than 10,000), an increase in travel demands can be created. The performance of the urban transportation system may be impacted, and traffic management and control measures would be required to mitigate the associated congestion. Unlike recurring congestion, delay patterns during special events are one time occurrences and end in a short period of time before the start or end of events.

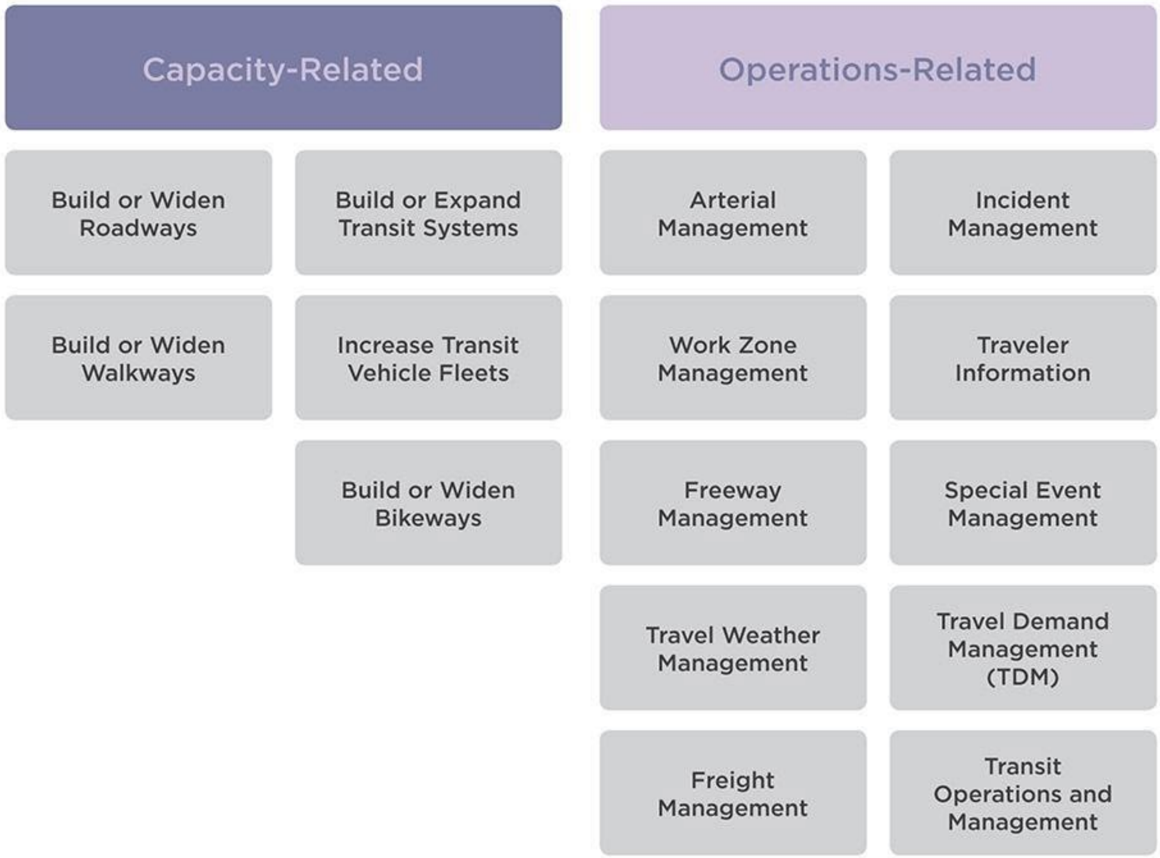
Little is understood about travel behaviors induced by special events. It is hard to know where attendees come from, how far they travel, how they choose their mode, or how they schedule their trips. Event traffic managers have information on site and parking access, but typically not on the broader network surrounding the event site. Most event management is limited to the immediate venue area and concentrated on local access and egress. Variety of data such as loop detectors spanning highways and surface roads, surveys, and social media have been collected to study the travel behaviors of event attendees (Amini et al., 2016; Kwoczek et al., 2015; Lassacher et al., 2009), but there are few studies on traffic impact of special events.

2.2 Special even traffic management

According to Federal Highway Administration's statistics, nearly half of total traffic delay has long been ascribed to non-recurring events (Federal Highway Administration, 2017). Extensive effort has already been invested in studying how to alleviate recurrent congestion with treatments of bottlenecks, automatic signal control methods and smart transportation plans. Although the number of studies on traffic management on major events is increasing, operational strategies are still largely adopted from manuals and checklists (Anbaroglu et al., 2014; Amini et al., 2016). Despite advances in computation and traffic simulation models that have made real-time, short-term traffic prediction possible, application of such tools for large-scale urban road network remains a challenge (Dowling et al., 2004; Anbaroglu et al., 2014; Amini et al., 2016). Figure 2.2 summarizes commonly used strategies to mitigate both types of congestion. Figure 2.3 gives an example of a non-recurrent congestion management strategy.

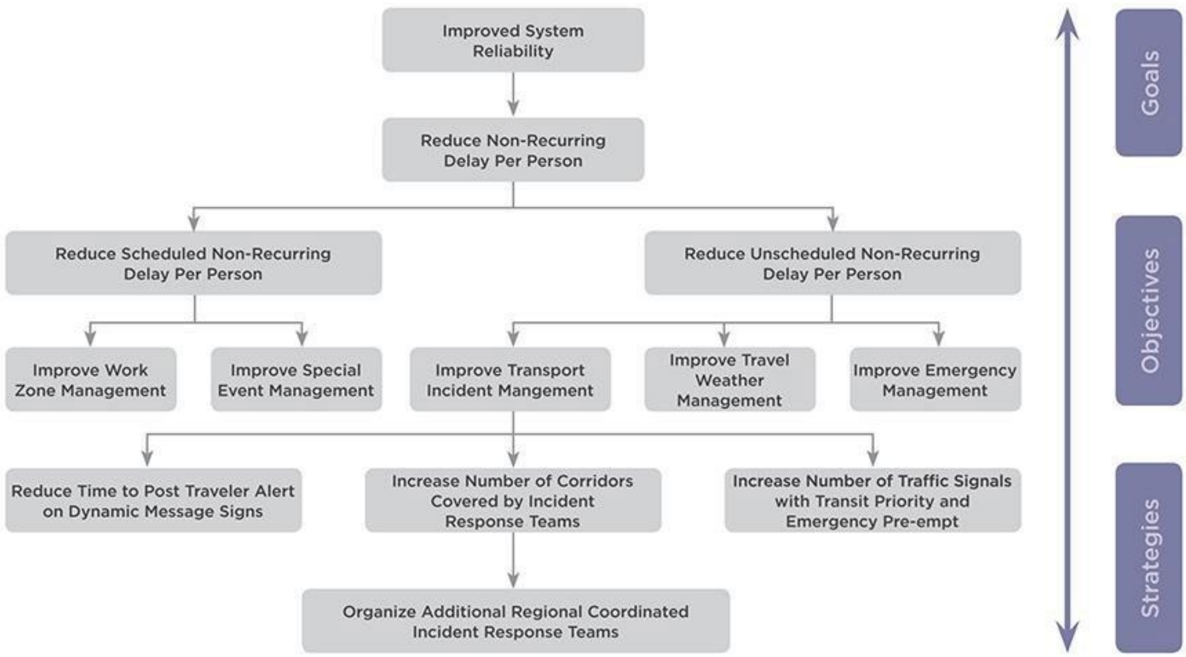
Our report's primary focus is on traffic impacts of special events. There are about 2,500 special events held in the City of Los Angeles every year. The traffic demand induced by these events affects the existing road network and increases congestion.

Figure 2.2. Typical Capacity and Operations Related Strategies



Source: Adapted from Incorporating Travel-Time Reliability into the Congestion Management Process (CMP): A Primer, Chapter 1, Figure 4, Federal Highway Administration

Figure 2.3. An Example of Non-recurring Congestion Management Strategy



Source: Adapted from Advancing Metropolitan Planning for Operations: The Building Blocks of a Model Transportation Plan Incorporating Operations - A Desk Reference, Figure 2, Federal Highway Administration, FHWA-HOP-10-027.

2.2.1 Manual traffic control management

Manual intersection control near the event venue still plays a significant role in traffic management for large special events. He and Ding (2013) argued that human intervention for event traffic, conducted by traffic control agencies (TCAs), who override traffic lights to direct traffic movements, still serves as the most commonly adopted approach to handle severe event traffic congestion. The handbook of managing special events emphasizes that traffic control officers have a large role in maximizing intersection operating efficiency (Turnbull, 2005).

A study by Lassacher et al. (2009) examined traffic management strategy for a large football game at Montana State University in Bozeman, Montana. They examined the impact of various management strategies on congestion reductions including signal retiming, manual traffic control, real-time traveler information, road closure, and real-time traffic monitoring. Results focused on flexibility in modifying strategies as key to manage traffic at planned special events and concluded that the combination of these strategies allowed for dramatic improvements in traffic level of service. However, these traffic management strategies are only applicable in a small area (e.g. the catchment area surrounding the event venues). A reliable tool to alleviate special event induced congestion or at the large-scale urban road network level is necessary.

2.2.2 Smart event traffic management

Aside from the conventional manual traffic control management strategy, many planning agencies also adopt technology-based strategies to alleviate traffic congestion generated by special events. For example, Consoli et al. (2013) presented a smart event traffic management technique designed for special events held at the Amway Center in Orlando, Florida. They concluded that the integration of various systems and plan components such as Intelligent Transportation System (ITS) infrastructure and integrated software and hardware, traffic control device upgrades, regional planning efforts, and state-of-the-art safety and security protocols address the challenges of event traffic management while at the same time minimizing environmental impacts. Other technologies including real-time traffic monitoring and real-time traveler information by cameras in highways and surface roadways can also contribute to event-related congestion reductions (Figure 2.4). The ITS and real-time traveler information allow attendees to schedule their departure time, routes, and travel modes to avoid potential traffic congestion.

Figure 1.4. Real-time Traveler Information

2.3 Characteristics of special events traffic demand and flow

Traffic demand during special events is a combination of normal daily traffic demand that is unrelated to special events (i.e. background traffic demand) and traffic demand created by the special events themselves (i.e. induced traffic demand).

To investigate induced traffic demand by special events and relative traffic flow characteristics, Wang et al. (2017) summarized a set of classification standards relating to special event characteristics: property, level, scale, time, location, planning period, and service range (Table 2.1). Planning period is the time needed to prepare the special event before its opening. Larger scale events usually require a longer planning period and more detailed traffic management (e.g. Olympic Games). Scale also partly determines the level of measures that may be used and event duration also plays a role. Short duration events such as concerts or sports games will have short peaks of demand before and after the event. Conversely, an event of several days (such as a conference, expo, or exhibition) would have longer and flatter peaks as participants arrive and leave the event venue at any time.

Table 2.1. Classification of Special Events

Standard	Special Events
Property	Sports, shows, conferences, expos, and exhibitions
Level	International, national, regional, and municipal
Scale	Large, medium, and small (depend on the number of attendees)
Time	Fixed opening and ending/unfixed opening and ending
Location	Single/multiple, fixed/unfixed, long-term/temporary
Planning period	Long-range, medium-range, and short-range
Service range	Short-aging/long-aging

Source: Wang et al., 2017

Larger scale special events generate heavy traffic demand that is spatially and temporally concentrated near the event venue. The extent of the resulting congestion is difficult to predict, as it depends on from where attendees come, which routes they take, and when they plan to arrive. The user equilibrium concept of each traveler using an optimal path does not necessarily apply in this case, because for example, travelers have limited information, or may be unfamiliar with routes and the destination.

Event-related congestion tends to expand outward through the surrounding road network from the core (the event venue). The nearer to the core, the more serious is the event-related congestion. As traffic disperses in all directions from the venue, congestion gradually declines with distance from the venue. Event traffic is dissipated when traffic from the event can no longer be distinguished from the background average traffic. This distance is called the cut-off point.

A San Francisco case study revealed that sporting events contributed on average 1,000 vehicle-hours of delay on the highways close to the event venue before and after the event, which accounted for 4.5% of all daily congestion on a 45 mile section of northbound I-880 in the San Francisco Bay Area (Kwon et al., 2006). In Germany, Kwoczek et al. (2015) used a simulation to forecast congestion in and around a soccer stadium and found that many attendees used a different route via a side road that the researchers did not expect. Seeherman and Anderson (2016) analyzed the contribution of a baseball game to highway flow and occupancy in San Francisco and Anaheim, California. Their findings suggest that in both cases, a baseball game added approximately 1,000 vehicles over the afternoon commute. Factors such as event date, the month of the event, the competing teams or individuals, and relevant transit services are all likely to contribute to the emerging traffic congestion generated by sporting games.

Factors such as transit access and parking supply would also impact event-related traffic demand and flow. Seeherman and Anderson (2016) found that public transit service (e.g. light rail) absorbed significant passenger volumes induced by sporting games that otherwise would be on the freeway. Kuppam et al. (2013) developed a survey to collect traffic data to special event venues including sporting games, concerts, shows, and expos in Phoenix, Arizona. The survey results indicated that 13.3% of special event attendees would choose traveling by light rail rather than driving to events with light rail access. Another case study in Denver, Colorado, demonstrated parking supply, the venue location, and built environments surrounding the event venue would be some of the factors that influence the attendees' decisions on travel modes to sporting events (Henao and Marshall, 2013).

According to previous research described above, we conclude that the induced traffic demand by special events has three characteristics that are different from normal daily traffic: heavy and short-term demand, spatial concentration, and temporal concentration.

2.3.1 Concentrated and short-term demand

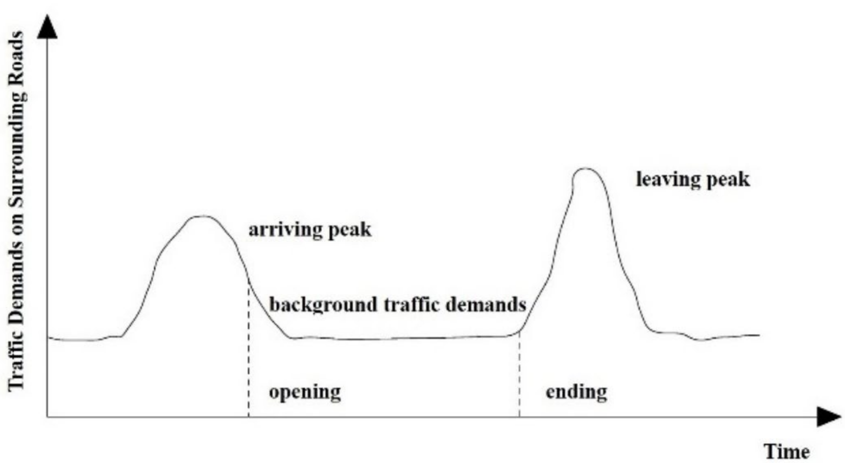
An important characteristic of special events is the number of attendees converging on a small space. For example, in the 2018-2019 season, the Coliseum attracted 72,429 participants per event on average. The large number of attendees generates short-term incremental traffic on the congested road near the event venue, which usually lasts for a few hours before the opening of an event and after the ending of an event and dissipates gradually as the distance from the venue increases. This short-term traffic demand generated by special events may overwhelm the existing urban road network. Also, the route of attendees to special event venues varies from person to person. Various factors, such as traffic conditions, expected travel time, remaining time from the opening of the event, and weather conditions, may all contribute to an attendee's travel route choices; but little is known about how much weight should be assigned to each factor.

2.3.2 Spatial and temporal concentration

Traffic demand created by various types of special events is both spatially and temporally centralized. Traffic demand created flows into the surrounding road network in a short period (the period of time arriving or leaving), and puts high pressure on regional road networks, in particular, the primary ingress and egress roads to an event venue.

Figure 2.5 show the temporal concentration of traffic demand caused by special events. The event induced traffic demand would generate significant traffic volumes a few hours before the special event and reach a peak one or two hours before the event. The traffic then returns to normal traffic level during the special event until the end of the event. As compared to the arriving, the leaving process usually puts more pressure on the urban road network as arrival time is usually less peaked than departure time.

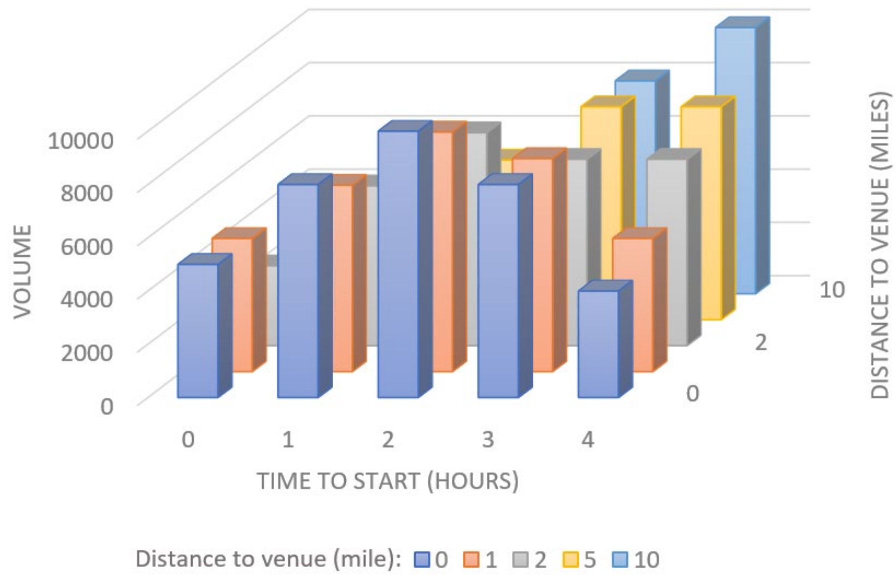
Figure 2.5 Time variation of traffic demand during a special event



Source: Wang et al, 2017

In addition, traffic flow generated by special events has obvious spatial-temporal fluctuating properties across the network. Figure 2.6 provides a stylized 3-D view. More distant parts of the network have increased demand more hours before the game. As attendees gather and approach the venue, demand increases closer to the venue.

Figure 2.6 Special events traffic volumes by distance to venue and time to start



2.4 Studies of special event impacts

A small number of studies have examined special event impacts.

2.4.1 Traffic impacts

Seeherman and Anderson (2016) used Performance Measurement System (PeMS) data to evaluate traffic performance near event venues during baseball games in San Francisco and Anaheim, California. Kwoczek et al. (2014) used traffic data collected from GPS sensors in vehicles and machine learning-based techniques to predict and visualize non-recurring traffic congestion in urban environments caused by special events. The work was expanded to identify road segments that were affected by planned special events for soccer games in Germany using Artificial Neural Networks (ANN) (Kwoczek et al. 2015). The goal of the research was to identify the length of the affected highway stretch. They found substantial variability due to many factors, such as the popularity of an event, the target group of people, and the choice of transportation. They identified affected road segments by comparing traffic on the event and non-event days, while excluding road segments that are always congested (bottlenecks on the highways). The soccer game was selected as the study objective due to its relatively stable number of attendees and duration as compared to other events such as. concerts. Wojtowicz and Wallace (2010) performed a similar simulation for evacuation of a baseball stadium and urban indoor arena in Albany, NY.

2.4.2 Mode choice

Kuppam et al. (2013) performed an in-depth event survey in Phoenix, AZ, trying to capture travel data related to special events and develop a standalone special event model for the Phoenix metropolitan area. Their surveys indicated that 13.3% of special event attendees would switch from driving to traveling by light rail if the event was near light rail lines. Similarly, Henao and Marshall (2013) collected event travel data from all the sporting venues in Denver, CO via survey. The purpose was to test relationships between travel mode choices and parking size and location. They found that the amount of parking supply was associated with mode choice. However, little impact was found on travel mode choices if the parking supply exceeded demand. In Sweden, Ahmadi (2012) collected travel data relating to a ski event through online surveys to find the movement patterns in the area and estimate origin-destination matrices for the ski event. Ahmadi found that twice as many participants drove to the venue than took public transit.

Another latent source of event travel data is social media. Zhang et al. (2016) used location data of Twitter posts to predict transit mode share for New York Mets baseball games and the US Tennis Open. They argued that the usage of social media data was able to “fill the gap between daily passenger volumes and abruptly changing non-recurrent event volumes”. Daly et al. (2013) suggested that social media can be used for capturing useful information and visualizing current traffic conditions. Their work focused on surfacing relevant information and explaining the underlying reasons behind traffic conditions, such as accidents, broken traffic lights, or large events. They combined static data from event providers and planned road works in Dublin, Ireland together with dynamic data derived from social media such as traffic accidents, weather conditions, or unplanned obstructions to update users about traffic conditions.

CHAPTER 3: Research approach and data

3.1 Research approach

The purpose of this research is to understand the impacts of planned events on the highway system, local roads, and public transportation. We use the Los Angeles Memorial Coliseum as our case study. The Coliseum provides a good case study given the frequency of similar events (football games), data availability, and access for the research team. We have the following research questions:

1. What is the impact of planned events on the highway system? What is the duration and intensity of the impact with respect to system performance?
2. What is the impact on local streets? Are there identifiable hot spots? How are local street impacts related to parking demand and queueing?
3. What is the role of public transportation? What share of attendees use public transit?

Answering these questions increases our understanding of planned event impacts and provides the basis for developing recommendations to better manage these impacts. We use a mixed methods approach due to the range and complexity of our research questions. Our methods include the following:

1. Descriptive analysis: traffic patterns on highways and on local streets, parking and arrival patterns, public transit ridership patterns. The descriptive analyses help us understand spatial and temporal patterns of demand associated with the events.
2. Analytical models: spatial econometric models to formally test hypotheses on relationships between highway and local street traffic and event attendance.
3. Qualitative analysis: interviews with event managers and other stakeholders to document and understand current management practices and possible improvements.
4. Simulation modeling: traffic simulation models to test and compare impacts of different traffic management strategies.

The study area is the Coliseum, home to college football teams USC Trojans since 1923 and professional football team, the Los Angeles Rams, from 2016 to 2020. Located in Exposition Park, two interstate highways – I-110 and I-10 provide regional access. Figure 3.1 shows a map of the study area with the closest on and off ramp locations identified. The local road network is dense with major arterials located on all sides of the Coliseum area. The area is part of the Los Angeles ATSAC system, so is heavily instrumented. Traffic signals can be managed in real time.

Figure 3.1. Map of study area

3.2 Data

Many types and sources of data are required to conduct our analysis. In this chapter we present and describe our various data sources.

3.2.1 Game data

Football game information for LA Rams and USC Trojans were collected from the respective team official website.[1] We selected all football game-days in the years 2016 through 2018 as our case study 'treatment' days. To eliminate the traffic impact of other events at nearby venues (venues with at least 5000 seats located within 3 miles of the Coliseum), games that took place on days when other events were also taking place at nearby venues were excluded from the study.[2] USC games generally take place on Saturday, and Rams games take place on Sunday. We selected a set of paired control non-game-days that were as similar as possible to game-days, e.g. same day of week, either one week before or after a game-day, no unusual weather, and no major events at nearby facilities.

There were 44 game-days during the 3-year period, and we identified 42 control days based on the above criteria. However, due to missing traffic data (further explained in section XXX below), our final sample is 29 game-days (19 Rams and 10 USC) and 39 control days. Most of the missing data was in

[1] Los Angeles Rams, https://www.theRams.com/schedule/; University of Southern California Trojans, https://usctrojans.com/schedule.aspx?schedule=606.

[2] Nearby venues are Exposition Park, Banc of California Stadium, USC campus, Galen Center, and LA Live.

2017, and consequently we have fewer observations for that year. Table 3.1 lists game-days and control days.

Table 3.1. Game-days (treatment date) and paired control days

Year	RAMS		USC	
	Treatment date	**Paired control date**	**Treatment date**	**Paired control date**
2016	8/13/2016	7/30/2016	10/1/2016	9/17/2016
	8/20/2016	8/27/2016	11/5/2016	10/29/2016
	9/18/2016	9/11/2016		11/12/2016
	11/6/2016	11/13/2016	11/26/2016	11/19/2016
	11/20/2016	11/27/2016		12/3/2016
	12/11/2016	12/4/2016		
		12/18/2016		
	12/24/2016	12/17/2016		
2017	8/12/2017	8/5/2017	9/9/2017	8/19/2017
		8/19/2017	9/16/2017	9/30/2017
	8/26/2017	8/19/2017	10/7/2017	9/30/2017
	9/10/2017	9/3/2017		
	9/17/2017	10/1/2017		
		9/3/2017		
2018	8/18/2018	8/4/2018	10/13/2018	10/6/2018
	8/25/2018	8/4/2018	10/27/2018	11/3/2018
		9/8/2018	11/10/2018	11/3/2018
	9/16/2018	9/9/2018	11/24/2018	12/1/2018
	9/23/2018	9/9/2018		
		10/7/2018		
	10/28/2018	11/4/2018		
	11/11/2018	11/4/2018		
	12/16/2018	12/9/2018		
		12/23/2018		

	12/30/2018	12/23/2018		

For each game we collected data on attendance, opponent, score, and scheduled start time. The number of attendees is the clearest indicator of how much additional traffic is generated by a given game. We hypothesize that opponent influences attendance, and score influences game departure time, as a close game is more likely to keep attendees until the end of the game. Start time of game is important as daily traffic varies by time of day. In order to compare the flow of arrivals and departures, we set game start time as time zero, and all time intervals are relative to the start time. For example, time -2 is 2 hours before start time.

Tables 3.2 and 3.3 give additional information on the game-days, including opponent, winning team, and attendance. The first year for the Rams had the highest attendance, followed by a drop in 2017 and increase in 2018. USC attendance shows a general decline over the three year period.

Table 3.2. Los Angeles Rams game-days

Date	Day	Home	Away	Result*	Attendance
8/13/2016	Saturday	Rams	Dallas Cowboys	W	89140
8/20/2016	Saturday	Rams	Kansas City Chiefs	W	84121
9/18/2016	Sunday	Rams	Seattle Seahawks	W	91046
11/6/2016	Sunday	Rams	Carolina Panthers	L	86109
11/20/2016	Sunday	Rams	Miami Dolphins	L	83483
12/11/2016	Sunday	Rams	Atlanta Falcons	L	82495
12/24/2016	Saturday	Rams	San Francisco 49ers	L	83656
8/12/2017	Saturday	Rams	Dallas Cowboys	W	60000
8/26/2017	Saturday	Rams	Los Angeles Chargers	L	60000
9/10/2017	Sunday	Rams	Indianapolis Colts	W	60128
9/17/2017	Sunday	Rams	Washington Redskins	L	56612
8/18/2018	Saturday	Rams	Oakland Raiders	W	72429
8/25/2018	Saturday	Rams	Houston Texans	W	72429
9/16/2018	Sunday	Rams	Arizona Cardinals	W	66515
9/23/2018	Sunday	Rams	Los Angeles Chargers	W	68947
10/28/2018	Sunday	Rams	Green Bay Packers	W	75822
11/11/2018	Sunday	Rams	Seattle Seahawks	W	72755
12/16/2018	Sunday	Rams	Philadelphia Eagles	L	74210

12/30/2018	Sunday	Rams	San Francisco 49ers	W	72161

**** W represents home team won the game, while L means home team lost.***

Table 3.3. USC Trojans game-days

Date	Day	Home	Away	Result*	Attendance
10/1/2016	Saturday	USC	Arizona State	W	71214
11/5/2016	Saturday	USC	Oregon	W	74625
11/26/2016	Saturday	USC	Notre Dame	W	72402
9/9/2017	Saturday	USC	Stanford	W	77614
9/16/2017	Saturday	USC	Texas	W	84714
10/7/2017	Saturday	USC	Oregon State	W	60314
10/13/2018	Saturday	USC	Colorado	W	57615
10/27/2018	Saturday	USC	Arizona State	L	47406
11/10/2018	Saturday	USC	California	L	56721
11/24/2018	Saturday	USC	Notre Dame	L	59821

**** W represents home team won the game, while L means home team los***

3.2.2 Traffic data

Detector data on speed, volume and occupancy are drawn from the Archived Data Management System (ADMS) at USC [11]. ADMS gives directional volume, speed and occupancy for each highway segment at 30 second intervals.

We use the Archived Data Management System (ADMS) at USC to obtain data for the state highway system and local arterials. ADMS is an archive of real-time data from the state highway system, local streets, and public transportation. Detector data on speed, volume and occupancy are available for each highway segment at 30 second intervals. Midblock speed and volume at one minute intervals is available for each arterial segment. We aggregate the data to 15 minute intervals. There are 1822 highway and 11933 arterial sensors in Los Angeles County. Unfortunately, the ADMS data is not complete. Detectors stop working or give erroneous data, and the feeds from which ADMS is gathered are interrupted by malfunctions or system repairs. Missing data reduced our original sample of 44 game days and 42 control days to 29 game days and 29 control days.

We cannot expect that football games at the Coliseum have a measurable effect throughout the County. Rather, we expect that the most observable effects would be near the Coliseum and on the major freeway routes leading to the area. Table 3.4 shows the comparison of average traffic speed between game-days and non-game-days on our study road corridors. For highways, the most significant traffic differences were detected within ten miles of the Coliseum and 0 to 6 hours before the game start. Beyond ten miles from the Coliseum, few speed differences between game-days and non-game-days' traffic speed can be detected. For all highway corridors, significant differences were usually detected within five miles of the Coliseum and within four hours of the start of the game.

Table 3.4. Pre-game traffic speed comparison between game-days and non-game-days on highway corridors

	Game-days						Non-game-days					
Distance to the Coliseum (mile)	< 3	3-5	5-10	10-15	15-25	>25	< 3	3-5	5-10	10-15	15-25	>25
Pre-game (hours before the game)												
I-110 South												
0-1	34.53	52.40	68.21	68.07	68.64		45.62	64.70	68.02	68.33	68.70	
1-2	40.88	39.95	64.30	68.38	68.56		41.32	58.14	68.32	68.68	68.75	
2-3	51.11	41.51	63.09	68.74	68.87		50.55	54.01	68.65	68.87	69.01	
3-4	56.65	41.24	68.41	68.49	68.95		51.95	47.59	68.14	68.35	68.31	
4-5	62.54	58.26	68.57	67.71	68.41		65.30	64.37	68.22	68.47	68.37	
5-6	66.56	67.65	68.55	69.32	68.24		66.82	67.39	68.69	69.04	68.23	
I-110 North												
0-1	51.06	25.57	61.05	68.62			66.01	22.08	56.81	68.73		
1-2	44.21	18.88	56.81	68.75			66.32	27.72	59.16	68.82		
2-3	61.46	20.36	58.10	69.23			67.81	35.86	61.34	68.49		
3-4	67.39	40.81	61.92	68.44			68.33	47.29	61.41	67.90		
4-5	67.99	59.40	63.01	69.11			68.23	57.59	62.83	68.95		
5-6	68.07	57.54	63.96	68.90			68.74	64.62	63.50	68.57		

I-10 West												
0-1	36.22	59.43	65.10	62.34			48.41	48.96	57.53	56.67		
1-2	48.78	46.22	64.34	62.35			54.10	58.07	60.81	53.87		
2-3	56.33	51.91	64.55	62.73			58.49	59.19	64.28	61.29		
3-4	64.30	60.07	65.92	63.61			65.29	59.61	65.18	62.63		
4-5	65.90	60.66	66.35	64.72			66.14	60.27	65.93	63.49		
5-6	66.36	61.34	66.41	64.28			66.68	60.84	66.14	64.16		
I-10 & SR-60 East												
0-1	62.74	69.56	64.53	64.11	58.19	65.09	62.65	69.71	64.87	64.15	62.23	65.09
1-2	62.73	68.81	65.10	64.74	66.65	64.34	62.50	69.45	64.97	63.30	63.33	64.34
2-3	64.09	69.68	65.65	64.37	67.29	64.85	63.52	69.65	65.34	65.60	63.25	64.85
3-4	64.69	68.97	65.57	65.62	68.08	65.07	63.35	69.59	65.52	65.06	67.86	65.07
4-5	65.65	69.73	64.50	65.14	67.47	65.26	61.00	68.66	64.84	66.02	68.19	65.26
5-6	65.40	69.50	65.51	66.23	67.73	65.28	64.96	69.26	65.55	67.24	67.70	65.28

Table 3.5 shows the difference in traffic speeds between game-days and non-game-days for arterial roads with respect to distance to Coliseum and time before the game start. There is a dramatic speed decrease within one mile of the Coliseum from six hours before kickoff. Beyond that point, no significant traffic speed difference is detected.

Table 3.5. Pre-game traffic speed comparison between game-days and non-game-days on arterial roads

	Game-days						Non-game-days					
Distance to the Coliseum (mile)	< 1	1-2	2-3	3-5	5-10	>10	< 1	1-2	2-3	3-5	5-10	>10

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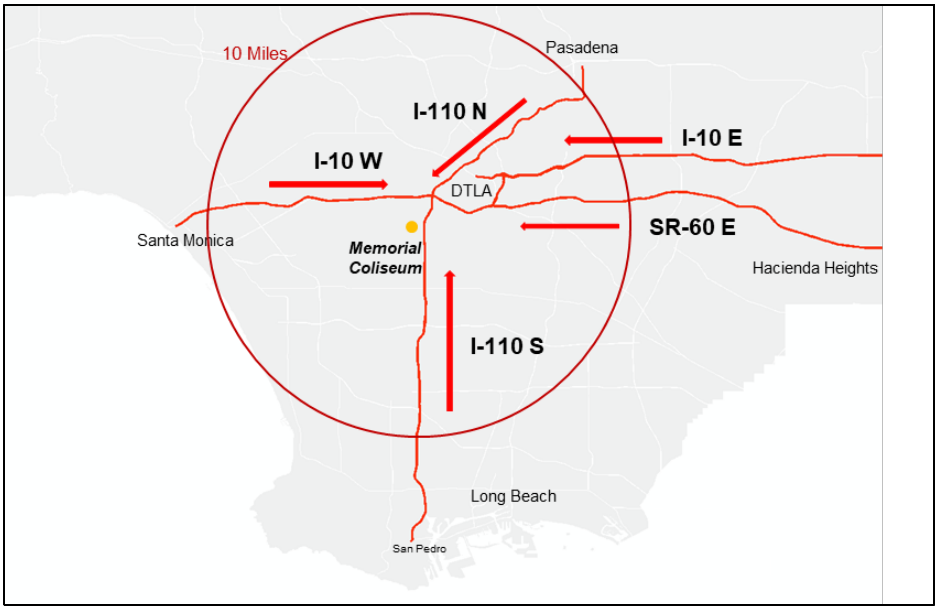
Pre-game (hours before the game)												
Arterial roads												
0-1	22.78	26.73	24.86	26.50	27.54	30.65	27.04	27.14	24.73	26.37	27.36	30.46
1-2	24.36	27.23	25.18	26.71	27.80	30.81	27.21	27.33	25.00	26.59	27.64	30.67
2-3	24.00	27.49	25.52	27.03	28.14	30.97	27.34	27.52	25.29	26.89	27.95	30.84
3-4	22.91	27.45	25.90	27.26	28.36	30.93	27.58	27.78	25.66	27.14	28.20	30.80
4-5	24.28	27.17	25.87	27.19	28.16	30.53	27.62	27.84	25.79	27.14	28.06	30.44
5-6	26.94	27.70	25.88	27.01	27.80	29.88	27.45	27.82	25.82	27.03	27.76	29.84

Based on findings above, we ultimately chose a study area radius of ten miles from the Coliseum for freeways and five miles for arterials. We also used a time limit of six hours before and after the start of the game. Table 3.6 give the number of sensors and number of observations for the highways and arterials in the study area. Figure 3.2 shows the selected study area for the traffic analysis..

Table 3.6. Number of traffic detectors in study area

Corridor	N of detectors	N of observations
I-110 South	21	68544
I-110 North	11	35904
I-10 West	27	88128
I-10 & SR-60 East	41	133824
Arterial Road	4,017	13111488

Figure 3.2 Study area for traffic analysis



3.2.3 Parking data

We collected parking data from both Coliseum/Exposition Park and the USC campus. Parking demand is a measure of total vehicle traffic flowing to the area, and as parking lots fill up, searching for parking contributes to local congestion and delay. We were able to collect data only on the number of spaces available for the Coliseum area lots. In 2016 there were 6197 spaces available. Three lots were closed over the study period, and total spaces declined to 4343 by 2018. There are eight parking structures at USC and all are open for both USC and Rams games. Total spaces available is 8882, of which 1398 are in a structure about 1 mile from campus. Therefore there are in the range of 13,000 to 15,000 formal parking spaces available. Given that some games attract close to 90,000 attendees and most arrive by private vehicle, the parking problem is obvious. As would be expected, there is a lot of informal parking in the surrounding neighborhoods. We were unable to gather data on informal parking.

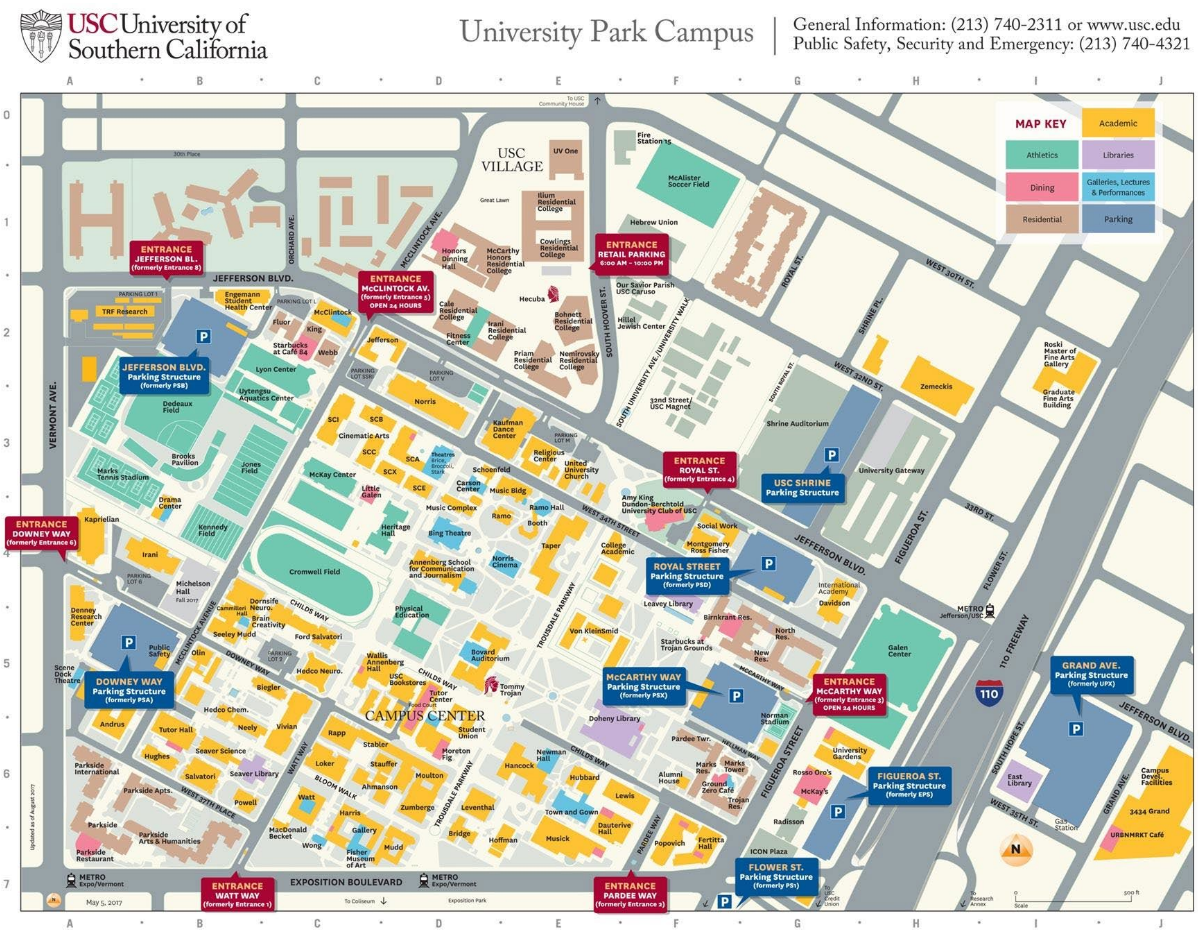
USC provided detailed parking data from the parking fee system. Each entry is time stamped and identified by gate, shift, payment type, amount, and type of permit. The price varies from $0 to $50, where $0 indicates a quick drop off with the vehicle parked near the gate. $12 is an approved rate for a special class or event. USC charges $50 for Rams football parking and is therefore a last choice for Rams attendees. Table 3.7 lists the USC parking structures and their capacity. Figure 3.3 shows their locations.

Table 3.7 Parking area and spaces at USC campus

Parking Area	Parking Space Number
Downey Way (PSA)	1,451
Jefferson Blvd. (PSB)	821
Royal Street (PSD)	1,156
McCarthy Way (PSX)	734
Flower Street (PS1)	1,102

Figueroa Street (PS2)	1,028
Grand Avenue (UPX)	1,398
USC Shrine Structure	1,192

Figure 3.3 Location of USC parking structures



3.2.4 Transit ridership data

Exposition Park is located about 3 miles south of downtown Los Angeles, the center of the region's transit network. There are local bus route, rapid bus routes and one light rail line serving the Coliseum and surrounding areas. All are operated by LA Metro. There is also a local shuttle system, DASH, operated by LADOT. Figures 3.4 and 3.5 show Metro and DASH transit services respectively. The services include:

- ***Metro Expo Line***: Expo/Vermont and Expo Park/USC stations
- ***Metro Silver Line***: 37th St/USC station (rapid bus)
- ***Metro Rapid bus***: 754
- ***Metro bus***: 38, 40, 81, 102, 200, and 204
- ***DASH Transit***: DASH F, DASH Southeast Clockwise Route, DASH Southeast Counterclockwise Route, and DASH King-East

The Los Angeles region also has a commuter rail service, Metrolink, that connects downtown Los Angeles to cities to the north, east, and south, Metrolink could be used by game attendees coming from longer distances. The closest station is about 3 miles distant and the last mile journey could be made via transit, taxi, or ridehail.

Figure 3.4. Metro service to the Coliseum Source: LA Metro

Figure 3.3. LADOT DASH Transit Service to the Coliseum Source: LADOT

Local transit data was provided by LA Metro (bus and light rail). LADOT (DASH bus), and Metrolink. The data vary in scale and level of detail. The most detailed data is for Metro bus service and LADOT DASH. Both give boardings and alightings by location and time of day. Metrolink provides total daily boardings by route. The Metro Expo Line data is limited average monthly trips. This is unfortunate, as the Expo Line is by far the most heavily used transit option for game attendees. CHECK TRANSIT CHAPTER ON THIS

3.2.5 Attendee data

Traffic impacts depend on where attendees are traveling from and when they are traveling. Ideally we would have a sample of attendees by place of residence. We requested ticket purchase information from the Rams and USC. Rams management declined to provide any ticket information. USC provided zipcode level location data for season ticket purchases during the study period. There were 14,798 season tickets sold, and 93% of purchasers were located in California. We used the season ticket data to develop a "best guess" origin-destination matrix for game attendees. CHECK FOR YOUGENG'S MAP

3.2.6 Weather events

We collected data on weather condition on our sample of game-days and control days. Adverse weather conditions contribute to traffic congestion and therefore must be controlled for in our analysis. Adverse weather conditions may also affect people's travel mode choice to the game, or whether they attend the game at all. We use meteorology data is from the EPA meteorology monitoring station located near the USC campus. The data includes temperature, humidity, precipitation, and wind speed by hour.

3.2.7 Traffic management plans

Our analysis will reflect the traffic management strategies employed on game days. We therefore collected information on traffic management practices via interviews with public agency representatives, published plan documents, attendance at pre-game preparation planning meetings, and game day field observations.

Managing game day traffic is a collaborative effort of LA Department of Transportation (LADOT), USC Transportation Department, LA Police Department (LAPD), Coliseum management, LA Metro and California Highway Patrol (CHP). Different agencies play specific roles and have different responsibilities; for example, LADOT is the agency that decides pre/post-game road closures according to the estimated number of attendees before a game. However, LAPD has the right to over-ride the plan in response to real-time observations. The game-day traffic management plan includes a pre-game ingress plan and post-game egress

The plans are comprehensive. Deployment of road closures and traffic officers is based on day and start time of the game. The ingress plan is put into operation as early as seven or eight hours before the game kickoff. Examples of deployment are given in Table 3.8. Intersection control plays a significant role. Traffic control personnel (e.g. LADOT, LAPD), overriding traffic lights to direct traffic movements, still serves as the most commonly adopted approach to handle severe event traffic congestion.

LADOT has different strategies for the assignment of transportation engineers and traffic control officers for USC and for Rams games. USC games are usually larger in scale due to tailgating and other pre-game events. Thirteen transportation engineers are assigned for USC games while only eleven are assigned for Rams games. For both USC and Rams games, a consistent number of at least fifty traffic control officers are deployed at intersections near the Coliseum and USC campus (the locations of which are decided by transportation engineers) to direct traffic flows manually before and after games.

Table 4.7. the Coliseum football game key timelines

	Rams/USC	Rams	USC	USC	USC
Game time	1:00 PM	1:25 PM	5:30 PM	12:30 PM	7:30 PM
LADOT Traffic Management Call	6:00 AM	6:00 AM	10:30 AM	5:30 AM	12:30 PM
LADOT Traffic Management/Engineer Pocket Closures	6:00 AM	6:00 AM	11:00 AM	6:00 AM	6:00 AM
LADOT Traffic Control Early Call (Figueroa)	6:45 AM	7:00 AM	11:15 AM	6:15 AM	1:15 PM

LADOT Traffic Management Post	7:00 AM	7:00 AM	11:30 AM	6:30 AM	1:30 PM
LADOT Traffic Control Early Post (Figueroa)	7:15 AM	8:00 AM	11:45 AM	6:45 AM	1:45 PM
LADOT Traffic Control Main Call	8:15 AM	8:30 AM	12:45 PM	7:45 AM	2:45 PM
LADOT Traffic Control Main Post	9:00 AM	9:30 AM	1:30 PM	8:30 AM	3:30 PM
Coliseum Parking Lots Open	8:00 AM	8:00 AM	8:00 AM	7:00 AM	8:00 AM

Source: The Coliseum

In addition to intersection control, restrictions and closures are implemented. First, left turns are prohibited at key intersections around the Coliseum to force clockwise rotation around the venue and some local streets are closed to all traffic. Second, traffic signals are controlled manually in response to real-time traffic conditions. Traffic control officers may override traffic signals to direct traffic manually if obvious traffic blocks occur. Third, on-street parking is restricted in areas close to the Coliseum. Traffic information signs are placed on major arterial roads to the Coliseum three days prior to game-days reminding drivers of the coming traffic restrictions (usually within five miles of the Coliseum). Parking lots and garages at Expo Park and USC campus open as early as seven or eight o'clock in the morning depending on the kickoff time, which allows game attendees to be more flexible when choosing their travel time to avoid the perceived worst of the traffic. Figure 3.5 shows photos of traffic management before one of the games in 2019. Figure 3.6 maps deployment of traffic officers and access flows for each major parking facility. Figure 3.7 shows the location of on-street parking prohibitions, and Figure 3.8 shows the street closures.

Figure 3.5. Traffic control officer (in reflective vest) directing traffic near USC campus on game-day (left), example of road closure (right).

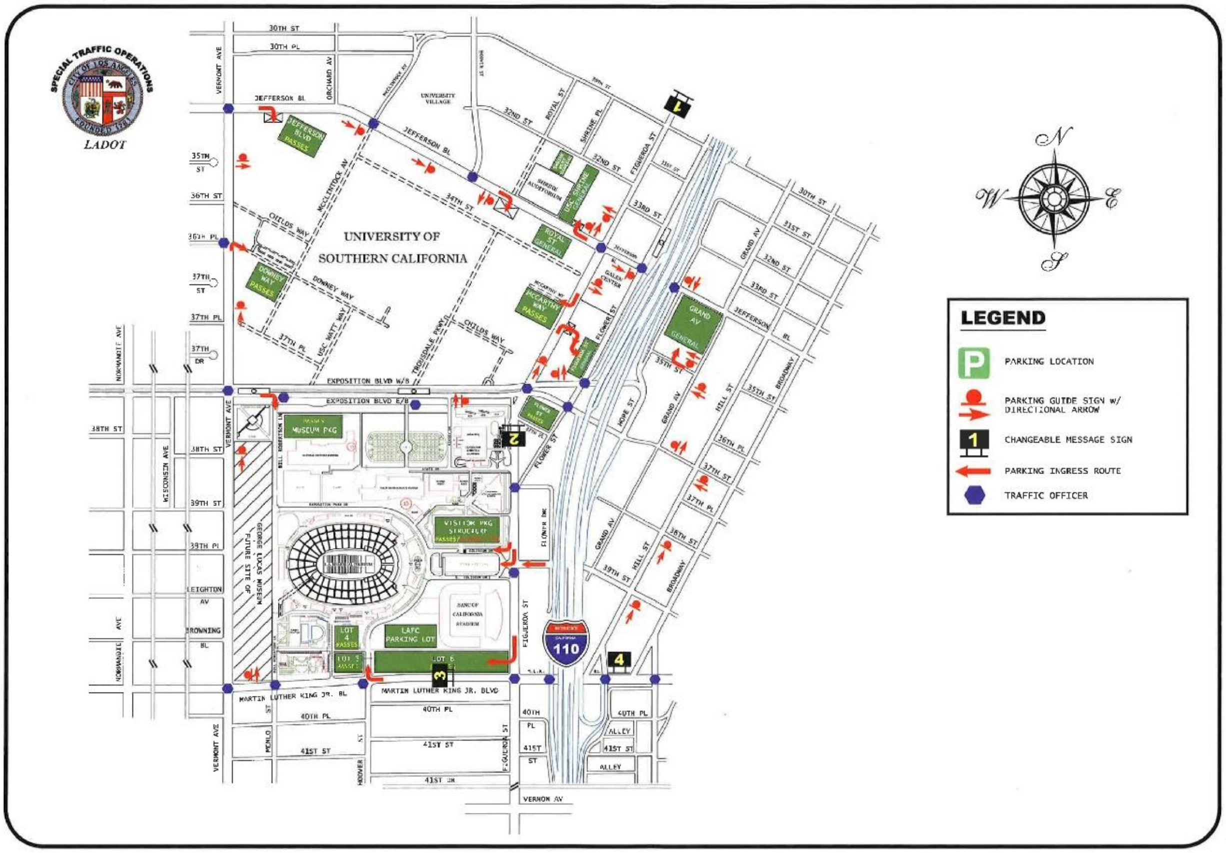


Figure 3.6. Coliseum football ingress plan

Source: LADOT

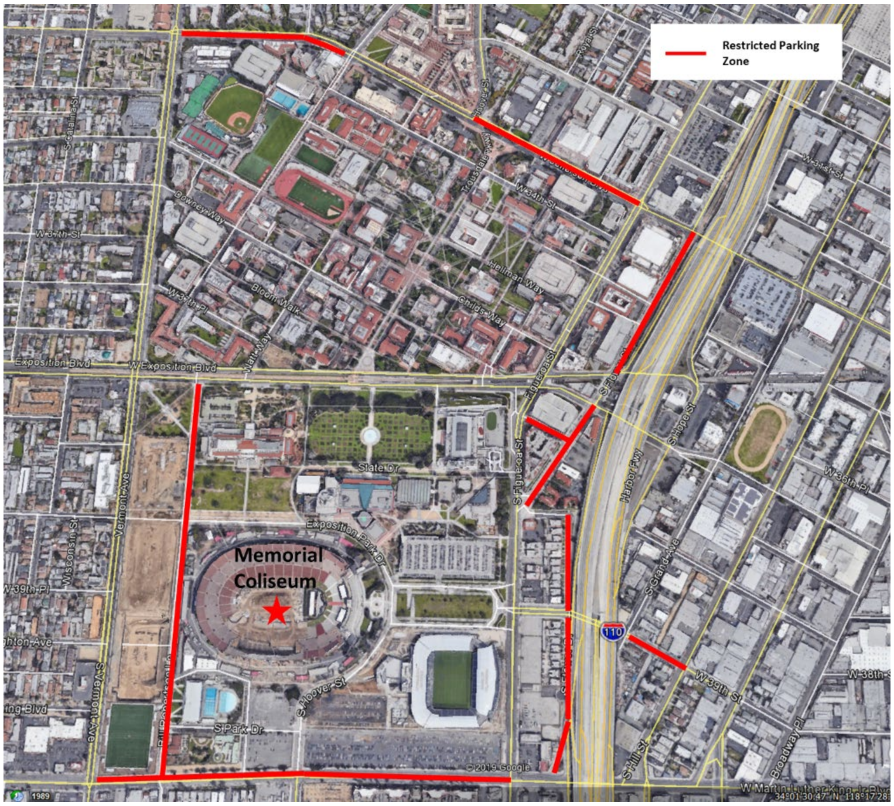


Figure 3.7. Restricted on-street parking zones on game-days

Source: LADOT

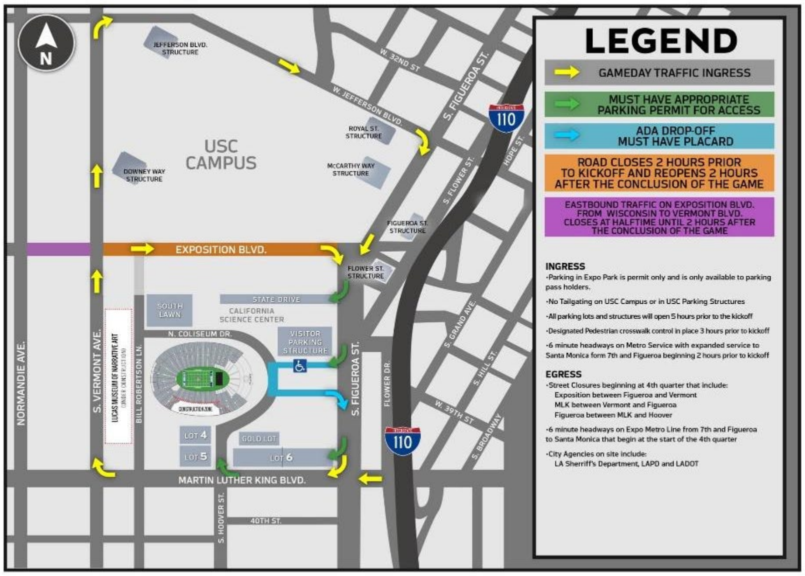


Figure 3.8. Street closure on game-days (in orange and purple)

Source: LADOT

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The egress traffic management plan is designed to “flush out” traffic as quickly as possible. Traffic is guided out of each parking structure in a single direction (right turns only). All the major arterials surrounding the venue are closed (except for egress from parking on Vermont Ave) and special pedestrian only zones are set up to manage pedestrian egress, A special ride-hailing pick-up zone is set on Vermont Avenue between Exposition Blvd and Jefferson Blvd, and ride-hail pickup are not allowed anywhere else.

Traffic managers state that their biggest challenges are the volume of traffic coming to and from the venue, the shortage of parking, and ride-hailing vehicles. If more attendees could be persuaded to use transit or remote parking lots with shuttle services both traffic volume and parking demand would decline. If attendees had better information about parking availability there would be less searching. Ride-hail vehicles conflict with pedestrian traffic and buses around the venue. We consider these challenges in our analysis and policy recommendations.

CHAPTER 4 Traffic Analysis

We conducted four different analyses of special event impacts: impacts on the highway system, impacts on the arterial system, parking analysis, and transit analysis. This chapter presents the highway and arterial system analysis.. We present a descriptive analysis first. We then estimate econometric models to explain traffic performance during game days.

4.1 Descriptive Analysis

We first examine traffic speed on the major freeways leading to the Coliseum by hours before game start time. We focus on the corridors linked with the Coliseum area. The main corridors are the freeways providing access from north and south (I-110), and from west and east (I-10/SR 60). See figure 5.6. Our study area includes four highway corridors within ten miles of the Coliseum and arterial roads within five miles of the Coliseum.

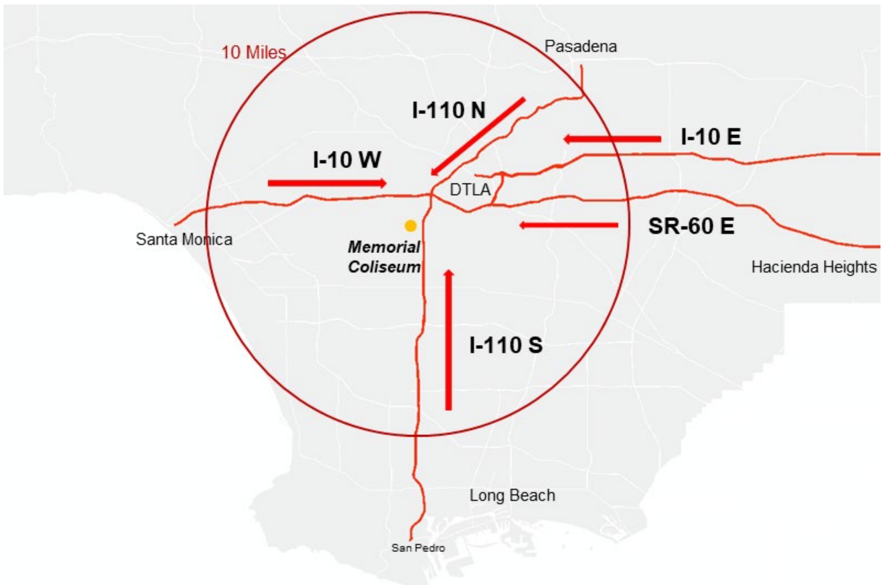
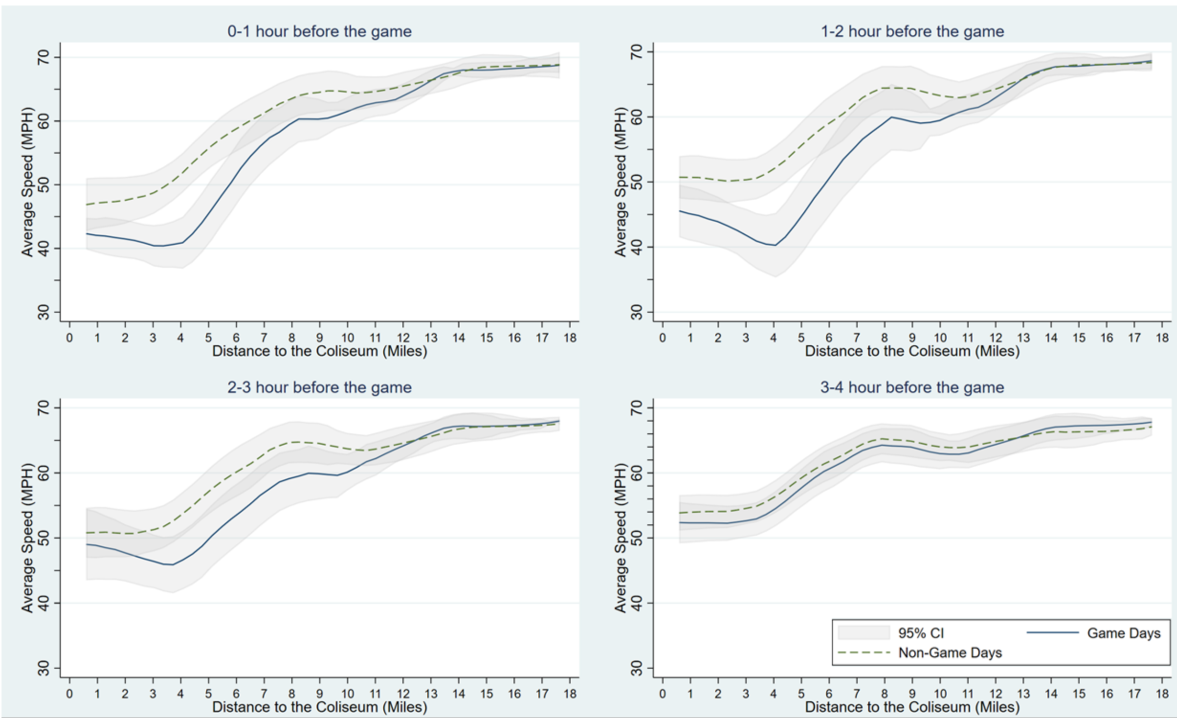


Figure 4.1. The spatial distribution of the Coliseum and four highway corridors

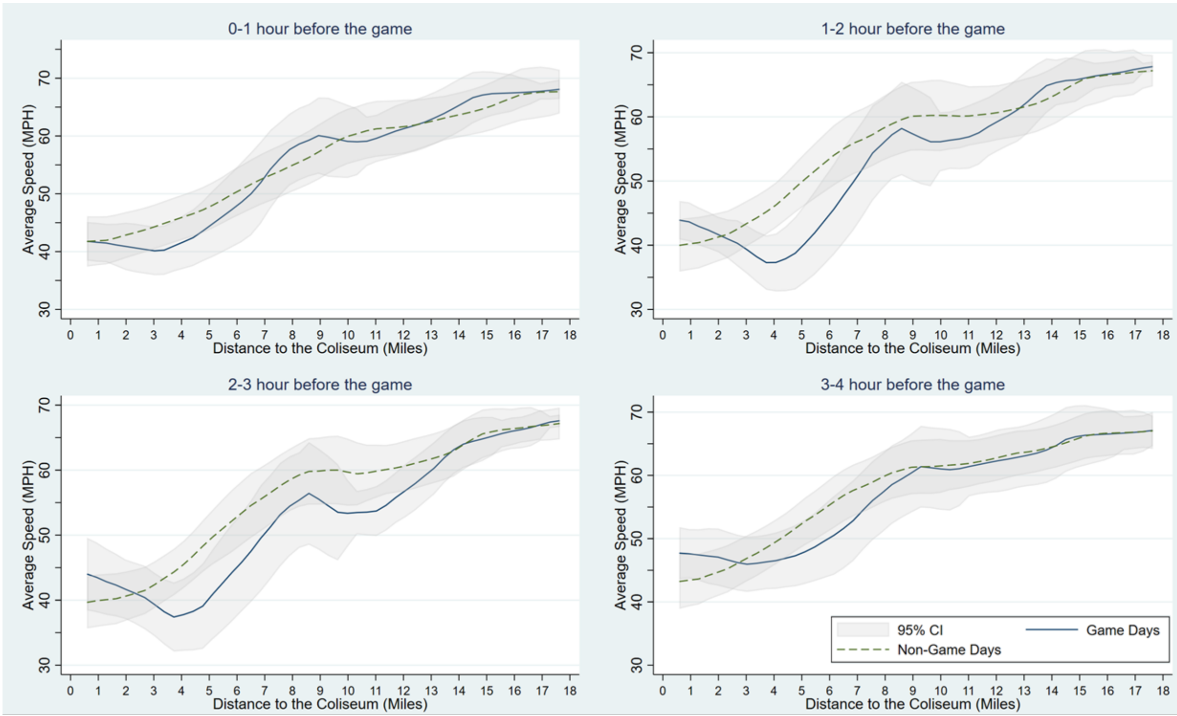
4.1.1 Average speed

We start with a series of figures showing average speed by distance to Coliseum and time before game start time. Note that by organizing the temporal data relative to game start time, the hour intervals do not map to hours of the day. Figure 4.2 shows average speed by distance to the Coliseum for the I-110 South. Panels 4.2a and 4.2b show results for Rams games and USC games respectively. The solid line denotes game days and the dotted line denotes control days. The gray shading gives the 95% confidence level for each line. Within each panel the figures show 0-1, 1-2, 2-3, and 3-4 hours before game start time respectively. There is a general trend of game day speeds being lower than control day speeds. Differences in the line patterns are statistically significant only when the confidence levels do not overlap. It can be seen that most of the differences are not statistically significant. For Rams games there are significant differences in the 0-1 and 1-2 hours before game start time within about 7 miles of the Coliseum. There is less difference for USC games, with only the 1-2 hour within 4 to 7 miles being significant. Note that speeds are always low within a few miles of the Coliseum, reflecting the high congestion level of everyday traffic in the area. Also, the lines converge beyond about 15 miles.

Figure 4.3 gives the same information for I-110 North. Similar patterns are observed (game day speed generally lower), but none of the differences are significant. There is a consistent dip in speed at about 4.5 miles for all time periods, suggesting a bottleneck. The location is the interchange of the I-110 and I-105.

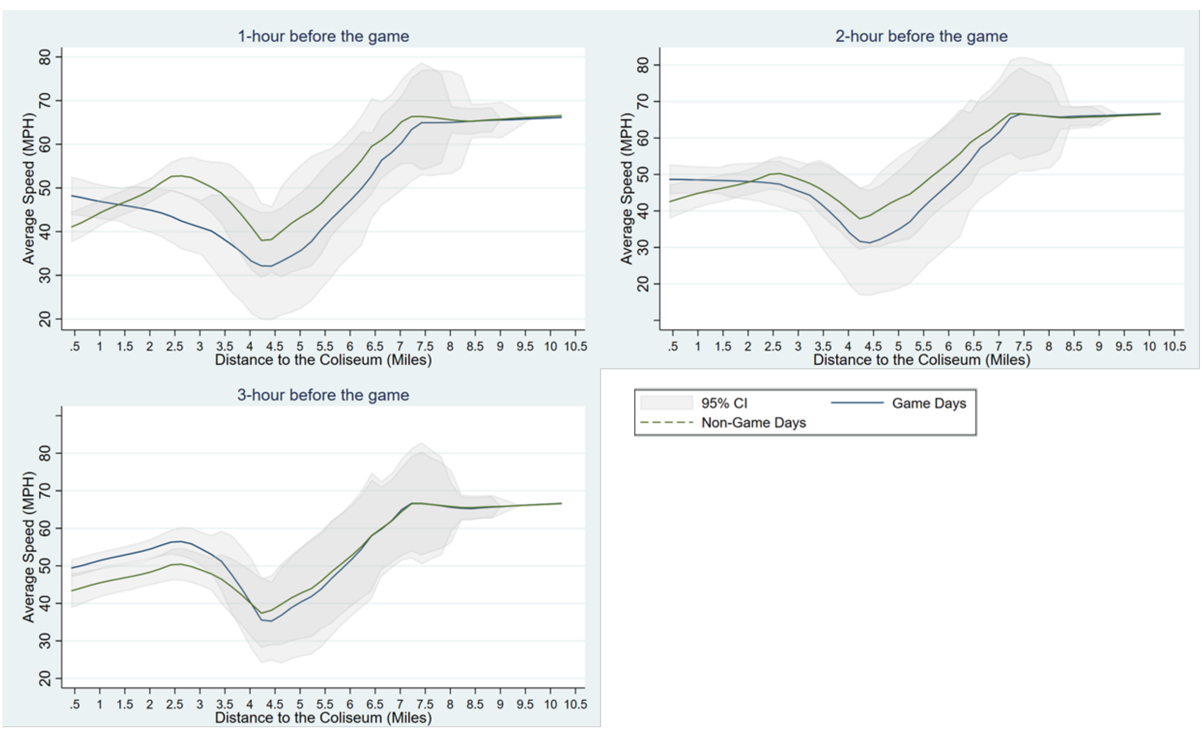


(a) Pre-game traffic pattern on I-110 S on Rams game days

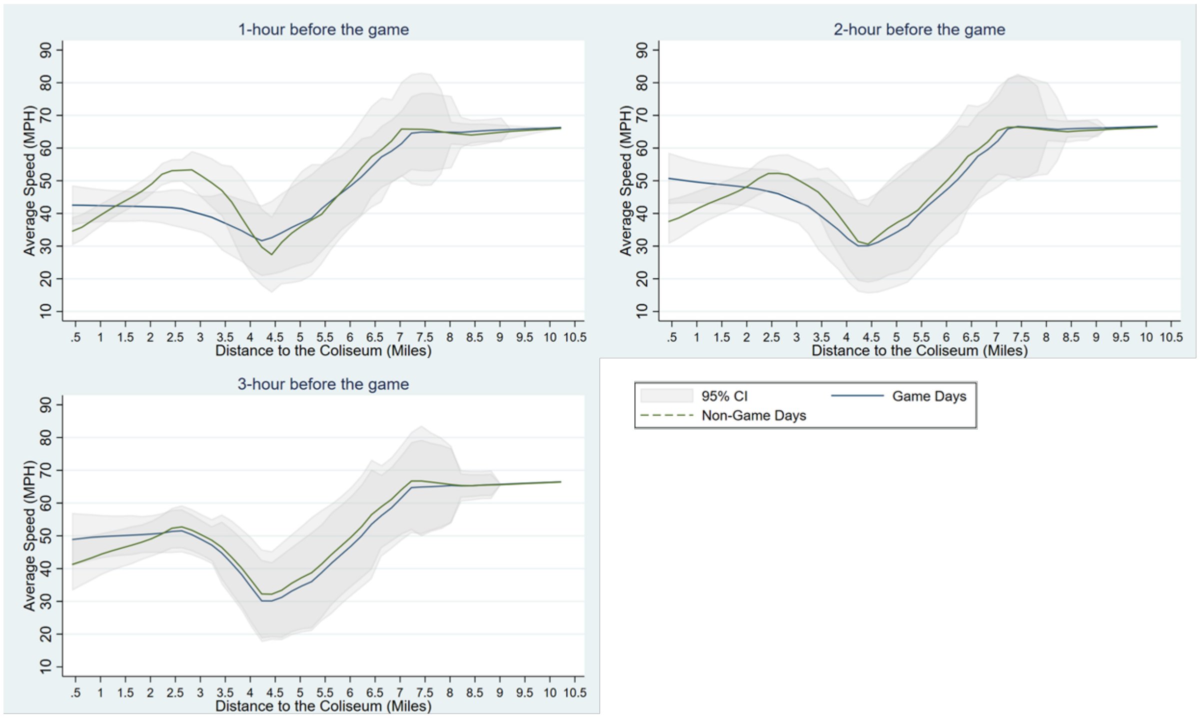


(b) Pre-game traffic pattern on I-110 S on USC game days

Figure 4.2. Pre-game traffic speed on game-days and non-game-days in I-110 S for (a) Rams game, and (b) USC games



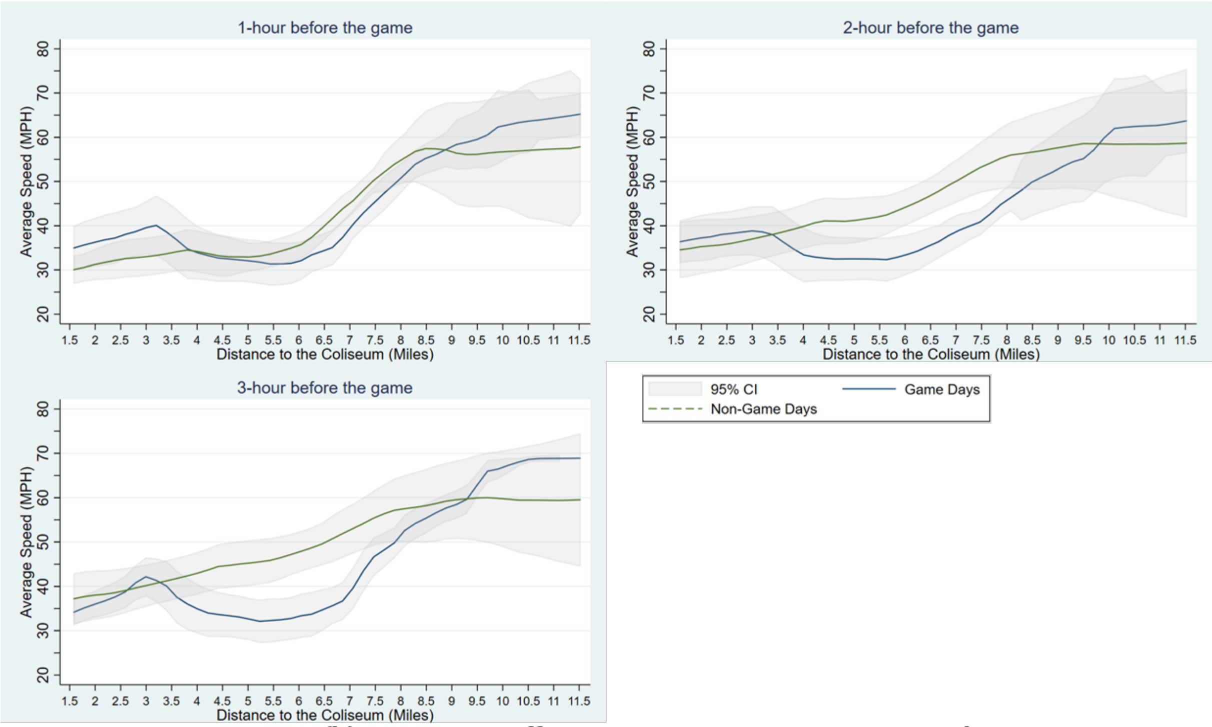
(a) Pre-game traffic pattern on I-110 N on Rams game days



(b) Pre-game traffic pattern on I-110 N on USC game days

Figure 4.3. Pre-game traffic speed on game-days and non-game-days in I-110 N for (a) Rams game, and (b) USC games

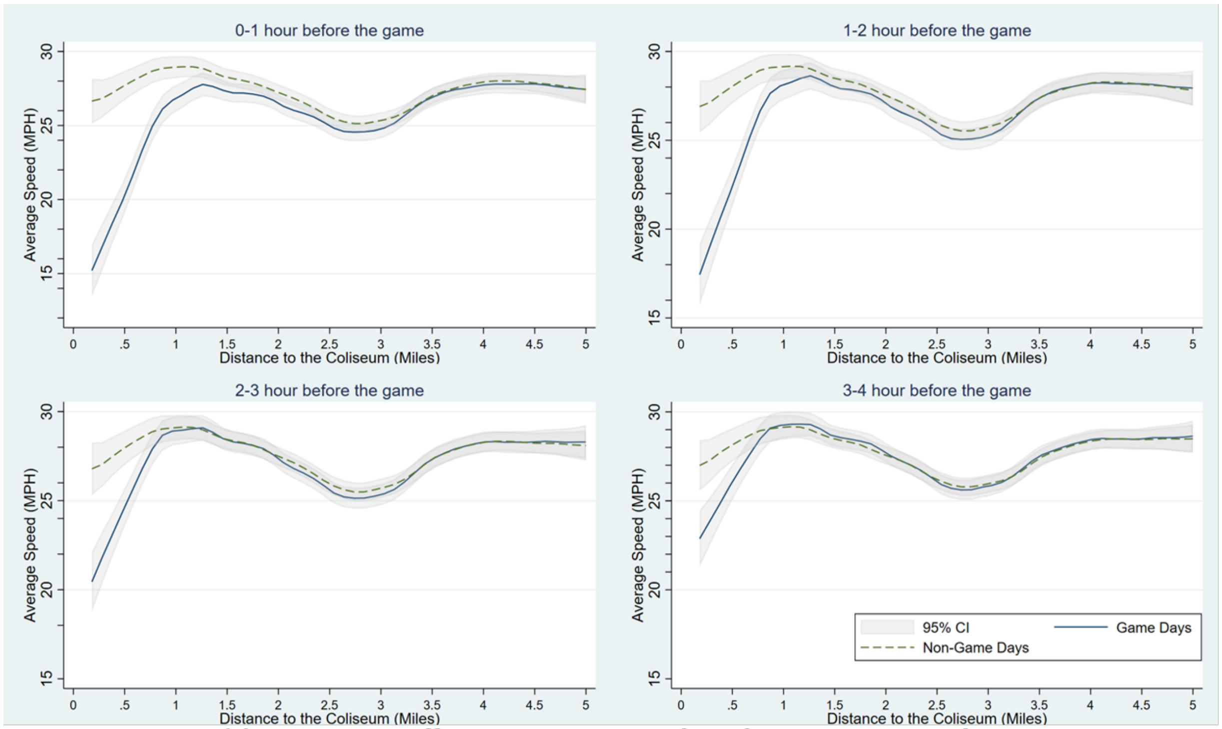
Figure 4.4 gives similar information for the I-10 West for USC games. Again there is an inverse relationship between average speed and distance to the Coliseum, and game day speed is generally lower than control day speed. The difference is significant for 1-2 and 2-3 hours before game day within a distance interval of 3 to 7 miles. This series of figures suggests that game effects differ by corridor. Although not significant in the aggregate, there is some evidence of impacts at specific times and locations.



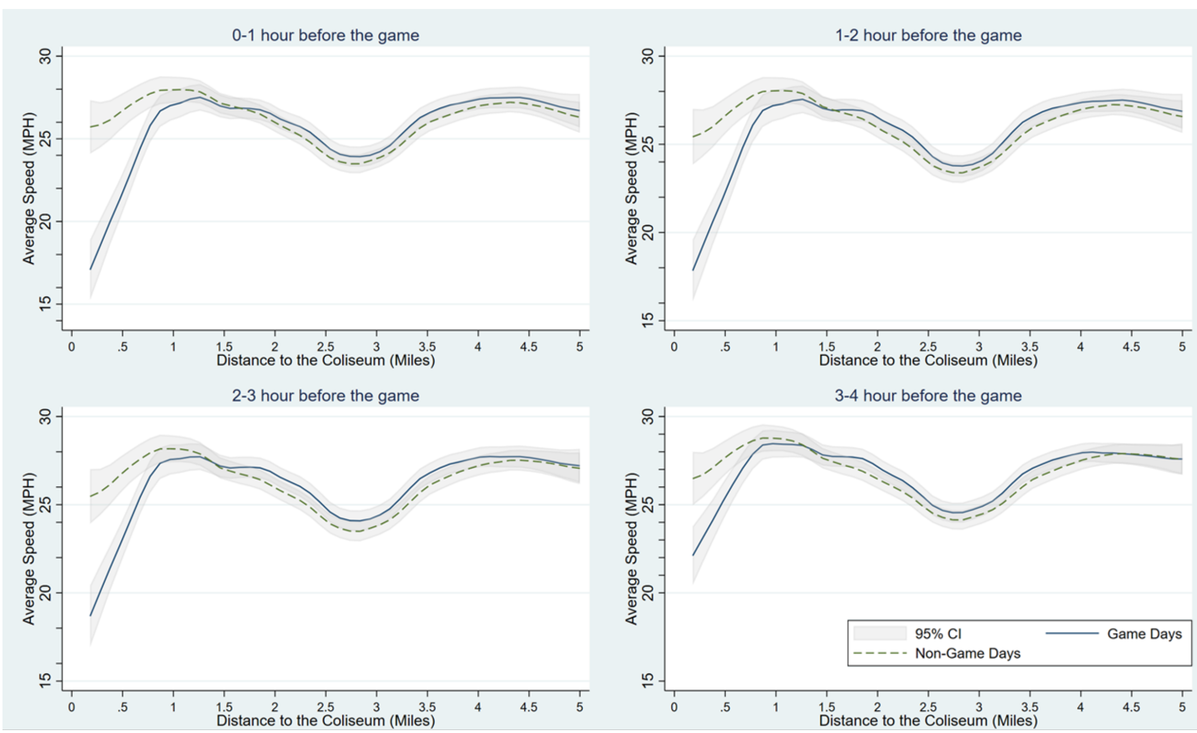
(b) Pre-game traffic pattern on I-10 W on USC game days

Figure 4.4. Pre-game traffic speed on game-days and non-game-days in I-10 W for (a) Rams game, and (b) USC games

Figure 4.5 shows pre-game traffic patterns on arterial roads for Rams and USC game days and comparable non-game-days, respectively. In this case we have aggregated all of the arterial data so do not control for direction. Significant traffic speed difference between game-days and non-game-days is detected within one mile of the Coliseum for both Rams and USC games. Clearly the games have a large impact near the venue.



(a) Pre-game traffic pattern on arterial roads on Rams game days



(b) Pre-game traffic pattern on arterial roads on USC game days

Figure 4.5. Pre-game traffic speed on game-days and non-game-days on arterial roads for (a) Rams game, and (b) USC

4.1.2 Spatiotemporal analysis

We conduct a spatiotemporal analysis to understand the time-space patterns of game day traffic. Coliseum football games attract attendees from across the region. We expect attendees to begin journeys anticipating arrival within a given time window, say two hours before the game start time. Early arrivals allow for pre-game tailgating and greater likelihood of finding preferred parking. We expect a distribution of arrivals; some participants will arrive earlier, and some will arrive later. For any given time window group of travelers, volumes on the major access routes will increase as distance to the venue decreases, because the number of main routes to the Coliseum is limited and Coliseum traffic will be funneled to these routes.

We generated 3-D and contour spatiotemporal traffic speed maps to show traffic patterns of game attendees on highway corridors and arterial roads for Rams and USC games, respectively (Figures 4.6 through 4.9). Traffic speed difference between game-days and non-game-days is used to reveal the traffic pattern of game attendees. In both speed 3-D and contour maps, the X axis shows distance from the Coliseum, the Y axis shows time with respect to the start of football game, and the Z axis of 3-D maps shows traffic speed difference between game-days and control non-game-days. The difference between game day and control day traffic is shown by color: yellow indicates the greatest difference and dark blue indicates the smallest difference.

Figures 4.6 through 4.9 show that for both Rams and USC games, the most significant traffic impact of the games is detected at freeway interchanges. For instance, a large speed difference is identified at around 5-6 miles from the Coliseum on I-110 South at the interchange of I-110 and I-105 (Figure 4.6). The spatiotemporal traffic maps demonstrate that traffic impact is not linearly related with distance from the Coliseum or time to kickoff. Traffic speed hotspots tend to be at upstream bottlenecks.

From the above speed maps, traffic patterns of Rams game attendees and USC game attendees can be differentiated. Attendees are more likely to arrive earlier for USC games than Rams games. Traffic speed hotspots of USC games usually occur about five hours before kickoff, while arrival of Rams attendees at the Coliseum mostly concentrate within three hours before kickoff. Many factors may cause the different arrival pattern between USC and Rams game attendees. One most important could be more diverse pre-game activities (e.g. tailgating and on-campus events) for USC games. The USC campus is not available for tailgating for Rams games.

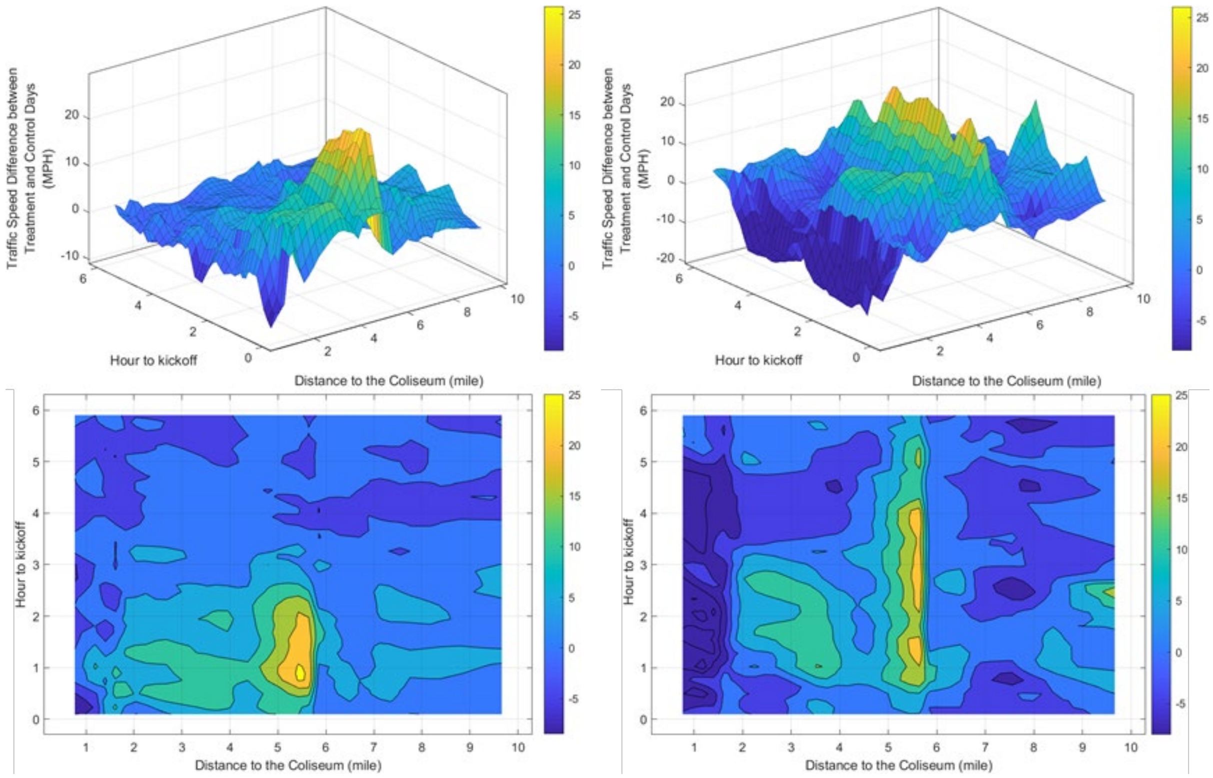


Figure 4.6. Spatiotemporal map of pre-game traffic patterns of weekend football games at the Coliseum for highway corridors I-110 S for Rams games (left) and USC games (right)

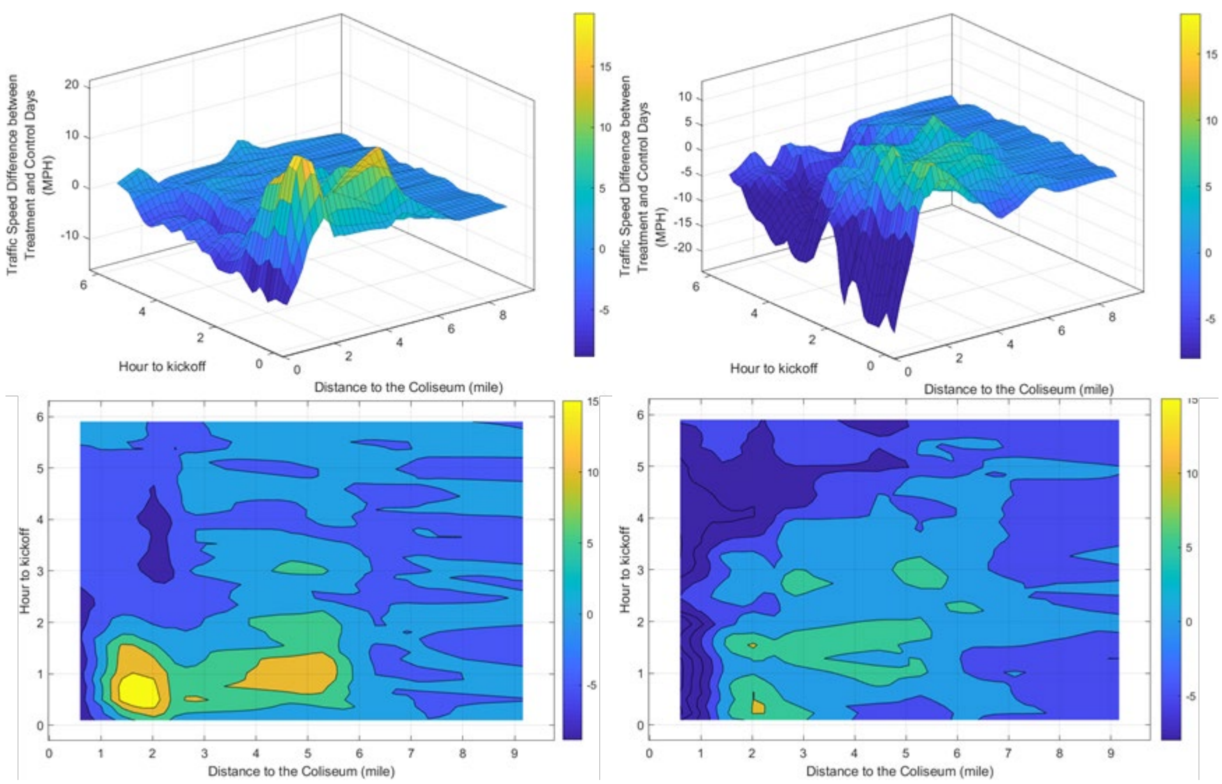


Figure 4.7. Spatiotemporal map of pre-game traffic patterns of weekend football games at the Coliseum for highway corridors I-110 N for Rams games (left) and USC games (right)

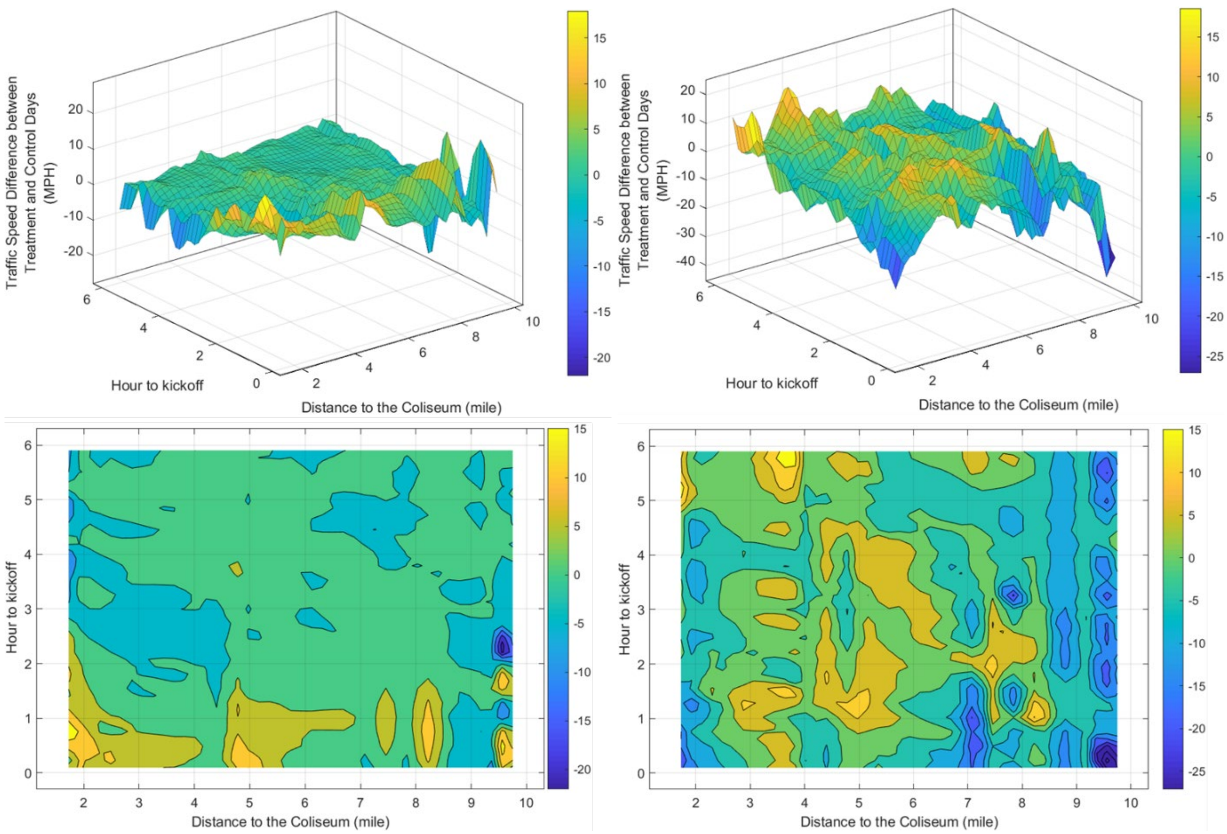


Figure 4.8. Spatiotemporal map of pre-game traffic patterns of weekend football games at the Coliseum for highway corridors I-10 W for Rams games (left) and USC games (right)

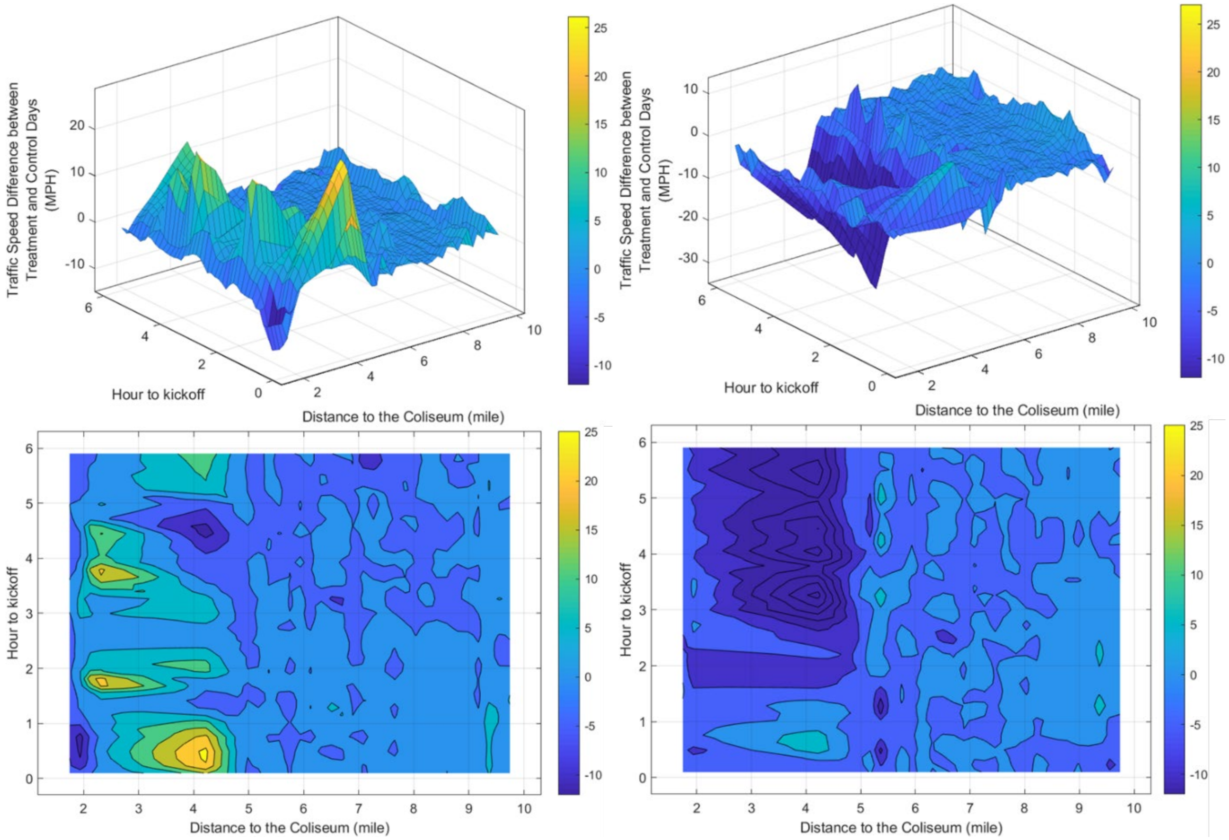


Figure 4.9. Spatiotemporal map of pre-game traffic patterns of weekend football games at the Coliseum for highway corridors I-10 & SR-60 E for Rams games (left) and USC games (right)

Arterial patterns are quite different; see Figure 4.10. The relationship is much smoother with respect to both time and space. Arterial traffic increases with the peak arrival time of attendees. The figure again shows that USC attendees arrive earlier than Rams attendees. On Rams game-days, peak arterial congestion is within one hour of start time. USC game attendees arrive over a longer period of time, and hence the peak is lower than that of the Rams.

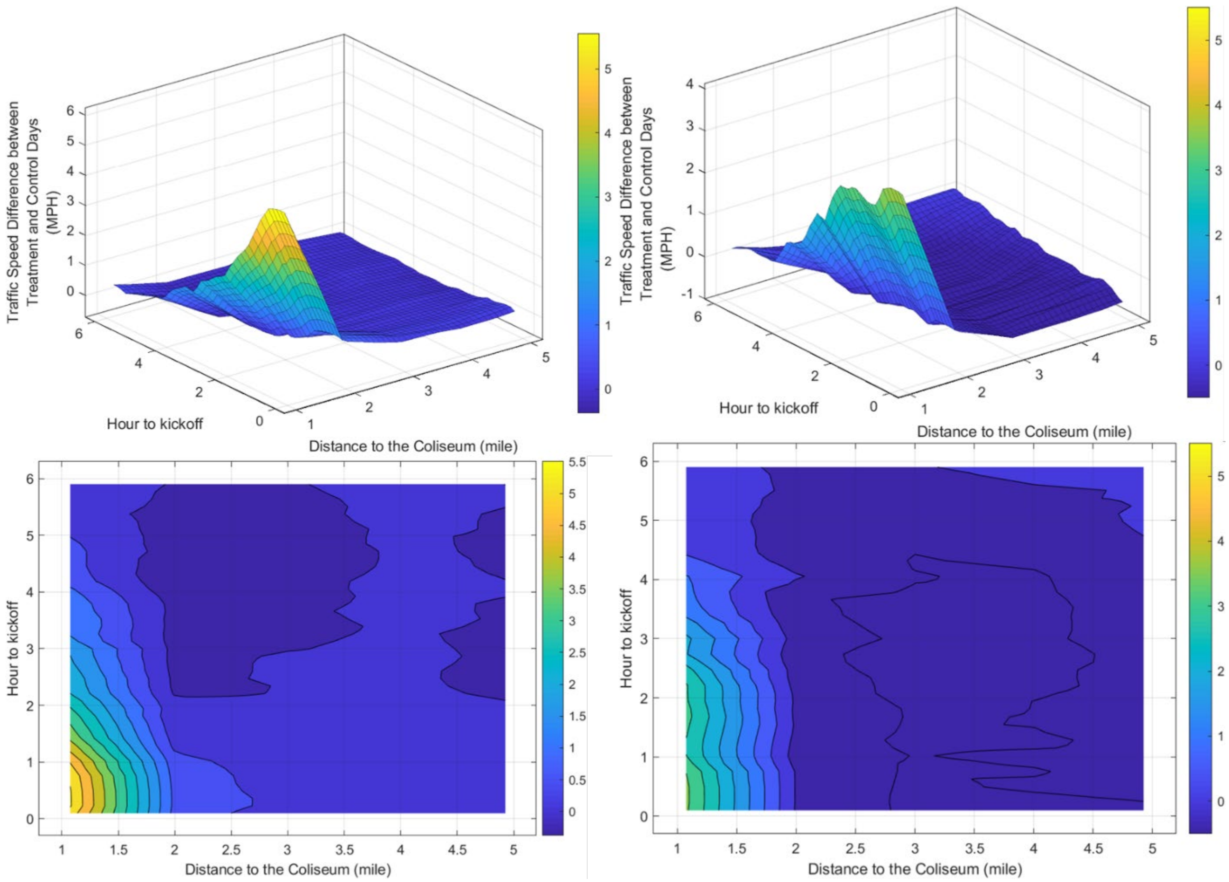


Figure 4.10. Spatiotemporal map of pre-game traffic patterns of weekend football games at the Coliseum for arterial roads for Rams game (left) and USC games (right)

4.2 Statistical analysis

We estimate a set of models to explain the difference in traffic level between game days and control days.as a function of game attributes and all other factors.

4.2.1 Variables

This section describes our model variables. The dependent variable is the pre-game traffic speed difference between game-days and baseline control days, which can be expressed in equation (1) as follows:

$$\triangle s_{it} = s_{it_{non-game\ day}} - s_{it_{game\ day}} \tag{1}$$

Where

i = traffic detector i,

t = time before kickoff

$s_{it_{non-game\ day}}$ = traffic speed at detector i and time t on non-game-days.

The dependent variable $\triangle s_{it}$ is calculated separately for Rams and USC game-days. The traffic speed on control non-game-days is defined as follow:

$$s_{it_{non-game\ day}} = \frac{\sum_{d=1}^{n} \quad s_{itd}}{n} \qquad (2)$$

Where

n = total number of non-game-days;

d = the dth non-game-day.

Using equation (2), we calculate the average non-game-day traffic speed at detector i and time t for Rams and USC in 2016, 2017, and 2018, respectively. These values are used to calculate the dependent variable. Recall that only highway traffic and arterial detectors located within ten miles and five miles of the Coliseum are included. The time interval for arrivals is within six hours of the start of the game.

Summary statistics of pre-game traffic speed difference for the Rams and USC games in the four highway corridors are shown in Tables 4.1 and 4.2. It can be seen that there is a great deal of variability at the sensor level, and the mean is skewed towards larger differences. For Rams games, I-110 from the south has the largest mean difference, followed by I-10 from the west. For USC games, we see a very similar pattern to the Rams games. The highway corridor I-110 S has the largest mean difference, followed by I-10 W and I-110 S. The only exception is the highway corridor I-10 & SR-60 E, where the mean speed difference is negative, meaning that, on average, traffic speed on I-10 & SR-60 E is higher on game-days than on control days. This is counter to our expectations.

Table 4.1. Summary statistics of traffic speed difference for Rams games

	Observation	Mean	Median	25th percentile	75th percentile	Maximum	Minimum
I-110 S	7,401	2.50	0.28	-1.27	5.77	62.21	-48.27
I-110 N	4,427	0.90	0.07	-1.28	2.13	56.44	-54.53
I-10 W	9,760	2.02	0.10	-0.77	2.12	57.91	-49.59
I-10 & SR-60 E	12,960	0.37	-0.18	-1.30	0.99	67.27	-40.65

Table 4.2. Summary statistics of traffic speed difference for USC games

	Observation	Mean	Median	25th percentile	75th percentile	Maximum	Minimum
I-110 S	3,960	3.14	1.65	-2.58	9.02	54.52	-44.31

Pacific Southwest Region UTC
University Transportation Center

I-110 N	2,233	1.10	-0.17	-2.51	3.04	49.55	-54.06
I-10 W	4,327	2.23	0.18	-2.79	5.50	58.95	-50.67
I-10 & SR-60 E	6,809	-0.06	-0.42	-1.81	1.03	56.20	-40.16

Several factors may explain traffic impacts of football games. The opponent determines the attraction of the game and hence the number of spectators. We expect that a stronger rival will attract more game attendees. The attendee number should be the clearest indicator of how much additional traffic is generated by a specific game. Kickoff time influences game attendees' travel behavior and consequent traffic patterns. We include the time to game start and two dummy variables controlling for impact of different kickoff times, one for games with kickoff before 2 PM and one for games with kickoff between 2 PM and 6 PM. Games with kickoff time after 6 PM is the baseline (omitted group).

The traffic impact of an event should decline with distance from the venue. This is simply a matter of concentrating demand within a smaller circumference as the venue is approached. We also expect distance to a freeway interchange to have an effect, since most attendees arrive by car via the major freeway routes. We include both distance-related terms in our models. Finally, we also control for effects that may be associated with baseline traffic, for example seasonality or state of the economy. We include fixed effect variables for year and month. Tables 4.3 and 4.4 present descriptive statistics of the independent variables for highway and arterial roads respectively.

Table 4.3. Summary statistics of independent variables for highway

	Rams				**USC**			
Independent variables	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Time to kickoff (hour)	3.02	1.80	0	6	3.00	1.80	0	6
Distance to Coliseum (mile)	5.21	2.82	0.43	9.9	5.18	2.79	0.43	9.9
Distance to nearest freeway interchange (mile)	1.04	0.77	0.06	3.44	1.02	0.77	0.06	3.44
Attendee number (1,000)	73.81	10.21	56.61	91.05	66.03	11.17	47.41	84.71
AM game (bivariate value)	0.73	0.45	0	1	0.27	0.44	0	1
PM game (bivariate value)	0.16	0.37	0	1	0.52	0.50	0	1
Year	2017.09	0.88	2016	2018	2017.15	0.84	2016	2018
Month	9.62	1.54	8	12	10.2	0.76	9	11

Table 4.4. Summary statistics of independent variables for arterial roads

	Rams				USC			
Independent variables	Mean	SD	Min	Max	Mean	SD	Min	Max
Time to kickoff (hour)	3.03	1.8	0	6	3.00	1.80	0	6
Distance to Coliseum (mile)	3.00	1.17	0.18	5.00	3.00	1.17	0.18	5.00
Attendee number (1,000)	74.11	10.33	56.61	91.05	65.79	10.56	47.41	84.71
AM game (bivariate value)	0.74	0.44	0	1	0.27	0.45	0	1
PM game (bivariate value)	0.16	0.37	0	1	0.55	0.50	0	1
Year	2017.06	0.88	2016	2018	2017.09	0.79	2016	2018
Month	9.67	1.55	8	12	10.08	0.79	9	11

4.2.2 Spatial and temporal autocorrelation

Our traffic data is correlated with respect to both time and space. For example, the speed at a given time and location is likely to be similar to the speed 15 minutes earlier or 15 minutes later at that location. Similarly, speed at a given time and location is likely to be similar to the nearest upstream and downstream locations. The premise of using linear models to estimate traffic speed differences in a transportation network is that the data are statistically spatially and temporally independent and normally distributed. Clearly this is not the case with our data. The conventional way to deal with spatial and temporal autocorrelation is to test for the degree and pattern of autocorrelation and incorporate appropriate lag variables in the model.

We use Moran's I statistic to test for spatial autocorrelation and use a time autocorrelation function (ACF) and partial autocorrelation function (PACF) to test for temporal autocorrelation.. We use the Global Moran's I statistic to test the degree of correlation between all traffic detectors on either highway corridors or arterial roads. Taking the speed difference between game-days and baseline control days as variables, we use ArcMap (version 10.2) software to calculate the global Moran's I value for the various corridors and years of data. See Table 4.5 for results. In 9 out of 12 cases, Moran's I values are significant and positive, meaning that spatial correlation exists within the speed data.

Table 4.5 Multiyear global spatial autocorrelation for highway corridors

Corridors	I-110 S			I-110 N			I-10 W			I-10 & SR-60 E		
Year	2016	2017	2018	2016	2017	2018	2016	2017	2018	2016	2017	2018
Moran's I	**0.39**	0.10	**0.61**	-0.20	**0.28**	**0.19**	**0.56**	**0.46**	0.07	**0.28**	**0.46**	**0.82**
Z-value	2.87	1.22	3.32	-0.73	2.69	1.86	2.68	2.41	0.82	1.90	3.28	4.21
p-value	0.004	0.22	0.0009	0.47	0.007	0.06	0.007	0.02	0.41	0.06	0.001	0.00003

To control for spatial autocorrelation, we use a distance inversed weighted average function as a spatial lag. For each traffic detector, we generate a weighted speed. The weighted speed is a function of the value at the given sensor adjusted by the values at neighboring sensors, with each neighbor weighted by the inverse of distance to the given sensor. The kernel function can be expressed in general terms as

$$ws_i = \frac{\sum_{i=1}^{n} \quad w_{ik}s_k}{\sum_{i=1}^{n} \quad w_{ik}} \qquad (3)$$

where w_{ik} = value of spatial weight at detector i,

s_k is traffic speed difference at detector k;

$w_{ik} \propto 1/d_{ik}$; d_{ik} = distance between detectors i and k located within the same highway corridor.

We use two measures to examine time series autocorrelation in the data. The first is the autocorrelation function (ACF):

$$r_k = \frac{\sum_{t=k+1}^{T} \quad (y_t - \underline{y})(y_{t-k} - \underline{y})}{\sum_{t=1}^{T} \quad (y_t - \underline{y})^2}$$

Where r_k = index for autocorrelation function,

T = length of time series,

y_t = traffic speed difference at time t,

y_{t-k} is = lagged traffic speed difference.

Results are given in map form. In our case we map the degree of autocorrelation with respect to 15 minute time lags to the target time period. The ACF score has a range from −1 to 1, with 1 being perfect autocorrelation and -1 completely dispersed.

Our second measure is the PACF. Unlike the ACF, PACF can detect correlation of the residuals that may remain even after we have removed the effects which are already explained by the earlier lags identified by ACF. Each regression coefficient in PACF indicates the autocorrelation coefficient between x_t and x_{t-k} which excludes the influence of the intermediate variables x_{t-1}, x_{t-2}, . . ., x_{t-k+1}.

Figures 4.12 and 4.13 show the ACF plot and PACF plot of traffic speed difference on I-110 South and I-110 North corridor respectively for all football games. The dashed line is the 95% confidence interval approximation. The ACF map shows that traffic speed difference in the current time period has a strong correlation with the traffic speed difference in the previous time period. As expected, the ACF decreases as the lag period gets further away from the current time period. The PACF has a score of 0.8 for the first lag, but is within the 95% confidence interval of zero after that, which means that current traffic speed difference is most correlated with one-lagged traffic speed difference. From the ACF and PACF plots, we detect strong temporal autocorrelation among our data, especially at the immediate one-time lag (i.e. 15 minute ago).

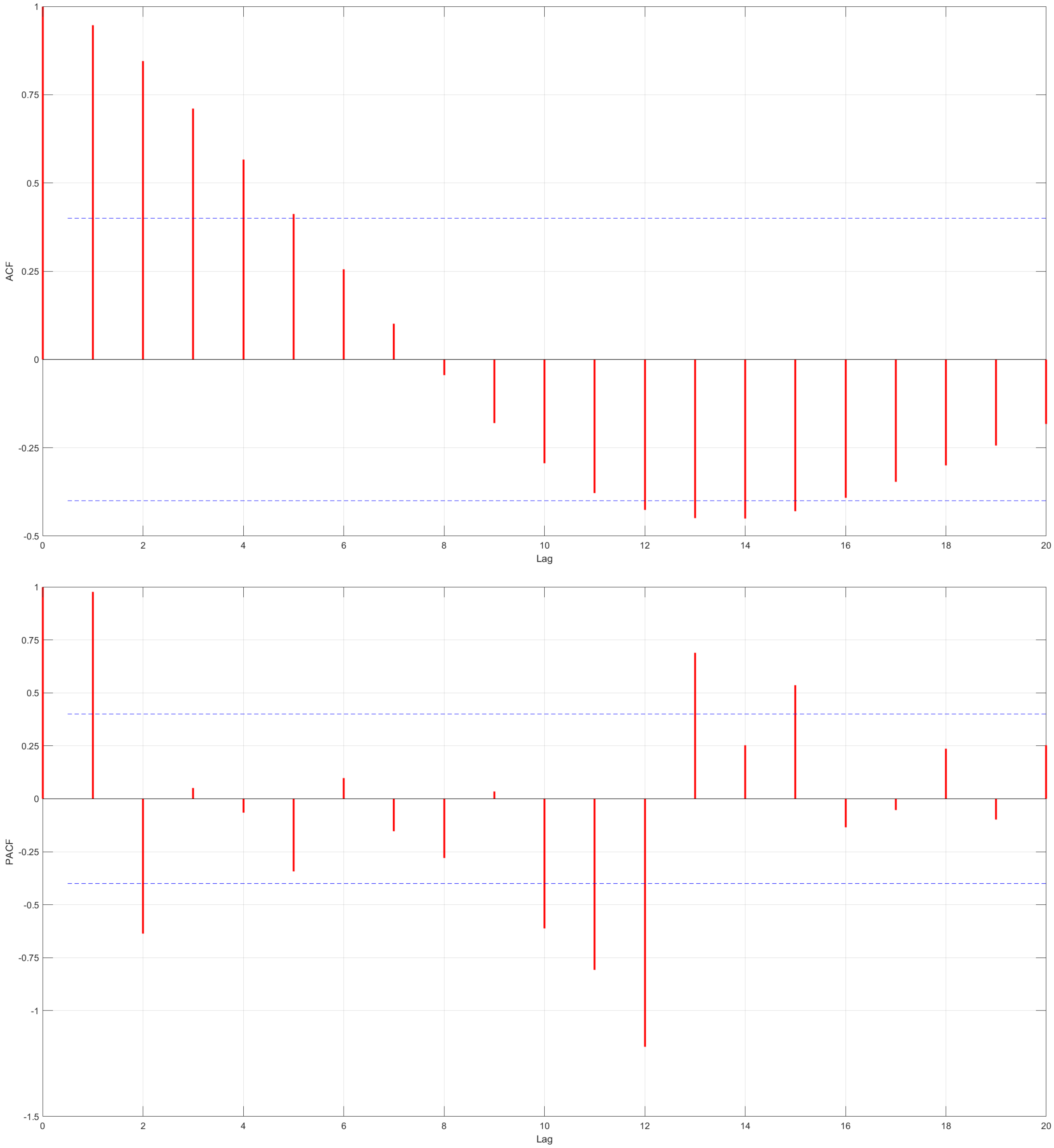


Figure 4.12. Time autocorrelation function plot of traffic difference on I-110 S for Rams game (Top); partial autocorrelation function plot of traffic difference on I-110 S for Rams game (Bottom).

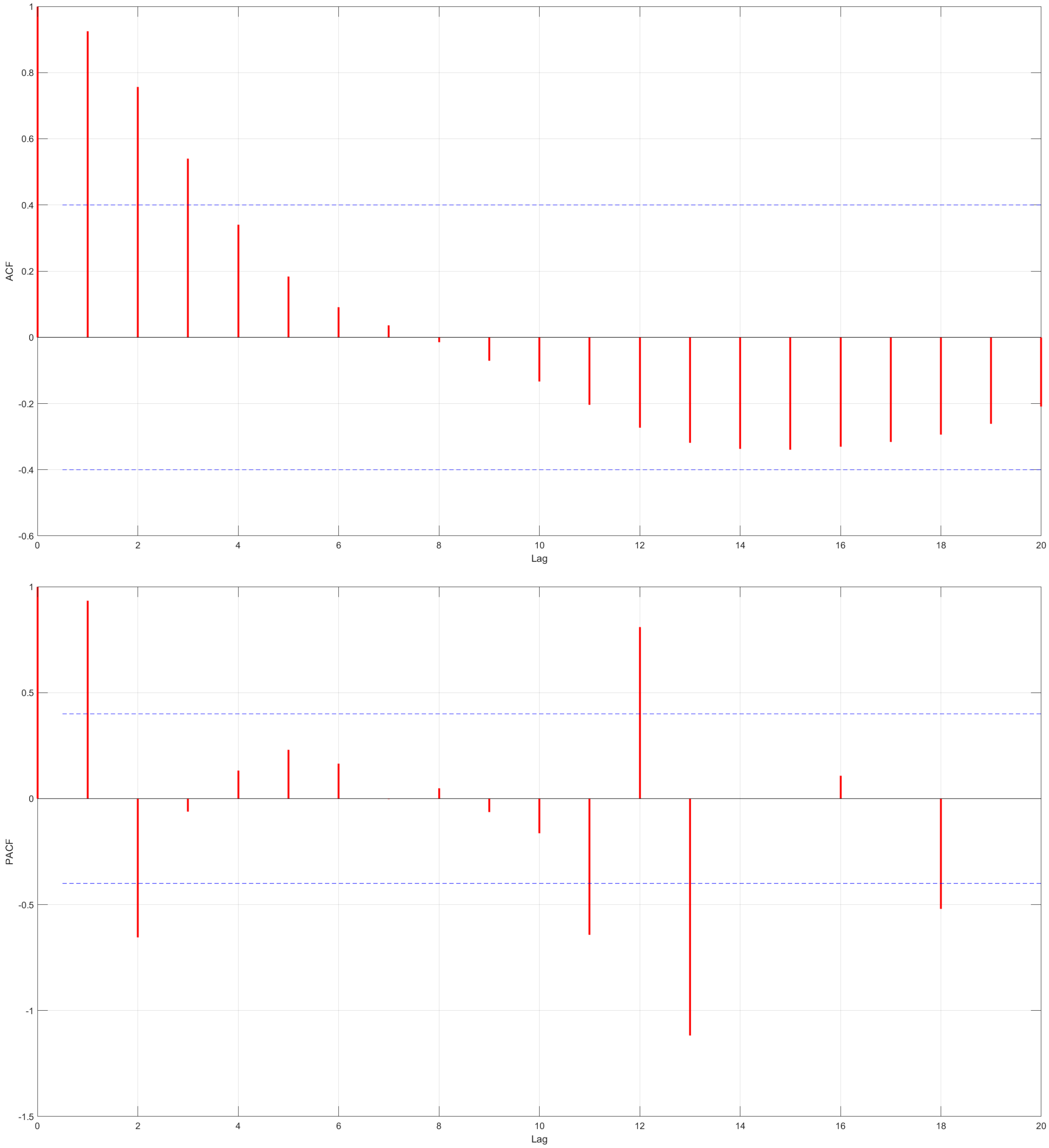


Figure 4.13. Time autocorrelation function plot of traffic difference on I-110 N for Rams game (Top); partial autocorrelation function plot of traffic difference on I-110 N for Rams game (Bottom).

4.2.3 Model 1: Multiple Linear Regression (MLR)

We estimate two models to examine factors associated with game-day traffic impacts. The first is a linear regression that includes spatial and temporal lags. The linear model is:

$$\triangle s_{it} = f(\triangle s_{i(t-1)}, ws_i, D_i, T_t, X_i, y, m) \qquad (4)$$

Where

$\triangle s_{it}$ = difference of traffic speed of traffic detector i at time t between game-days and control non-game-days

α = constant

$\triangle s_{i(t-1)}$= 15-minute lagged speed difference for sensor i at time t

$ws_{i(t-1)}$ = weighted traffic speed difference of nearby detectors at the same highway corridor

D_i = distance of detector i to Coliseum

T_t = Time to game kickoff in 15-minutes interval

X = vector of control variables (e.g. attendee number, kickoff time dummy)

y, m = year and month fixed effects

Results are given in Tables 4.6 and 4.7 for Rams and USC game-days respectively. Each table has 5 columns of results, four for the highway corridors and one for arterials. Starting with Table 4.6 (Rams games), the time and spatial lagged term coefficients are highly significant and positive, as expected for all studied highway corridors and arterial roads. None of the other variable coefficients have such high T-score values. Distance to nearest freeway interchange is significant with expected signs. The impact of distance to the Coliseum is mixed. Significant coefficients are detected only on I-110 N and I-10 W corridors, although the signs of distance coefficient are as expected. Time to game start is not a significant predictor for most highway corridors. These results suggest that game-day factors do not matter very much. This is due to the strong spatial and temporal correlations in the data. Whether game-day or not, the correlations exist and explain traffic variation.

For arterials, time and spatial lag terms are again the two most significant contributors to speed difference between game-days and non-game-days. After we control for temporal and spatial autocorrelation, coefficients for distance to Coliseum, time to kickoff, and month game occurs are significant, but of much smaller magnitude compared to the time and spatial lagged terms. The negative signs of distance and time indicates that relationship between speed and distance and time is likely to be linear, which is consistent with our finding of pre-game traffic analysis for arterial roads. Moreover, more traffic congestion is found near the end of football season in November.

Table 5.6. Spatiotemporal autoregressive regression results for Rams game

	(1)	(2)	(3)	(4)	(5)
	I-110 N	I-110 S	I-10 W	I-10 & SR-60 E	Arterial
Time lagged term	0.634***	0.636***	0.454***	0.559***	0.527***
	(59.72)	(79.60)	(59.79)	(84.21)	(815.85)

Spatial lagged term	0.371***	0.374***	0.623***	0.508***	0.403***
	(28.31)	(38.41)	(65.21)	(54.74)	(328.28)
Distance to Coliseum (mile)	-0.138**	-0.0237	-0.0437*	-0.0245	-0.0296***
	(-3.15)	(-0.66)	(-1.97)	(-1.79)	(-13.01)
Time to kickoff (hour)	0.0786	0.0749	0.0887**	-0.00603	-0.00971***
	(1.51)	(1.70)	(3.15)	(-0.35)	(-6.59)
Distance to nearest freeway interchange (mile)	-1.225***	-0.305**	-0.273***	0.189***	
	(-6.91)	(-2.94)	(-3.83)	(4.01)	
Attendee number (1,000)	-0.0106	0.000975	-0.000246	-0.0195	0.000538
	(-0.24)	(0.03)	(-0.01)	(-1.36)	(0.44)
AM game	0.0570	0.0802	0.452*	0.0308	-0.00270
	(0.15)	(0.24)	(2.03)	(0.23)	(-0.23)
PM game	0.00327	0.114	0.265	0.0315	0.00747
	(0.01)	(0.36)	(1.15)	(0.24)	(0.63)
2017.year	-0.0732	-0.0660	0.210	-0.480	0.0348

	(-0.06)	(-0.07)	(0.33)	(-1.20)	(1.02)
2018.year	0.0685	0.0253	0.0530	-0.253	0.0144
	(0.10)	(0.05)	(0.15)	(-1.14)	(0.76)
September	-0.164	-0.0517	-0.0525	-0.0620	0.0292**
	(-0.51)	(-0.19)	(-0.32)	(-0.58)	(3.20)
October	-0.193	-0.511	-0.240	-0.0201	0.0298*
	(-0.38)	(-1.19)	(-0.95)	(-0.12)	(2.06)
November	0.0997	-0.194	-0.00258	-0.150	0.0484***
	(0.28)	(-0.63)	(-0.01)	(-1.26)	(4.82)
December	-0.0470	-0.302	0.0141	-0.112	-0.0114
	(-0.15)	(-1.15)	(0.09)	(-1.07)	(-1.30)
constant	2.037	0.172	-0.276	1.733	0.0632
	(0.54)	(0.06)	(-0.14)	(1.40)	(0.60)
N	4,427	7,401	9,760	12,960	1,685,995
adj. R^2	0.703	0.726	0.719	0.591	0.404

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.7 shows the results for USC game-days. For both highway and arterial models, variation is largely explained by temporal and spatial lag terms. For the highway model, most of the football game related predictors are not significant. For the arterial model, distance to Coliseum, attendee number and game played time are found to impact pre-game traffic.

Table 5.7. Spatiotemporal autoregressive regression results for USC game

	(1)	(2)	(3)	(4)	(5)
	I-110 N	I-110 S	I-10 W	I-10 & SR-60 E	Arterial
Time lagged term	0.652***	0.621***	0.535***	0.631***	0.534***
	(46.82)	(58.49)	(52.25)	(74.08)	(642.19)
Spatial lagged term	0.341***	0.401***	0.525***	0.432***	0.391***
	(19.78)	(30.76)	(40.85)	(29.94)	(235.68)
Distance to Coliseum (mile)	-0.0420	-0.108*	0.0386	-0.0613**	-0.0280***
	(-0.54)	(-1.98)	(0.91)	(-2.71)	(-9.54)
Time to kickoff (hour)	-0.0546	0.0706	0.0448	-0.00308	-0.000520
	(-0.66)	(1.10)	(0.87)	(-0.12)	(-0.28)
Distance to nearest freeway interchange (mile)	-0.765**	-0.187	0.259	0.0603	
	(-2.62)	(-1.18)	(1.92)	(0.85)	
Attendee number (1,000)	0.00160	-0.00278	0.0629	0.0191	0.00147*
	(0.02)	(-0.05)	(1.43)	(0.90)	(2.35)

AM game	-0.375	0.163	0.360	0.221	-0.0516***
	(-0.57)	(0.32)	(0.89)	(1.05)	(-3.97)
PM game	-0.376	0.118	0.313	0.0811	-0.0570***
	(-0.74)	(0.31)	(1.02)	(0.49)	(-4.54)
2017.year	-0.0537	-0.125	0.907	-0.0799	0.0408*
	(-0.07)	(-0.21)	(0.91)	(-0.31)	(2.55)
2018.year	0.205	0.0874	1.563	0.488	0.0167
	(0.16)	(0.09)	(1.85)	(1.23)	(1.10)
October	-0.326	-0.273	1.430	-0.316	0.0158
	(-0.27)	(-0.28)	(1.19)	(-0.77)	(0.90)
November	-0.380	-0.265	1.136	-0.416	-0.0311
	(-0.35)	(-0.31)	(1.00)	(-1.17)	(-1.68)
constant	1.293	0.359	-6.909	-0.861	0.00889
	(0.22)	(0.08)	(-1.69)	(-0.45)	(0.16)
N	2,233	3,935	4,327	6,809	1,000,273
adj. R^2	0.769	0.756	0.787	0.592	0.394

t statistics in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

In summary, we find that game specific factors (e.g. distance to venue, time to kickoff, attendee number, etc.) are largely swamped by the correlation effects. We note that this does not mean that these factors are unimportant. It simply means that once we control for the correlations in the data, the game-day specific factors have a modest effect.

4.2.4 Model 2: Random Forest estimation

One of the problems with our linear model is the nonlinearity of some of the variables, as illustrated in the distance-time-speed diagrams in section 4.1. These non-linearities are beyond the typical solutions of transforming variables (e.g. log form, parabolic, etc.). We tried several different specifications of key variables, but results were basically unchanged (results not shown). We therefore use a different approach based on machine learning.

Machine learning (ML) techniques typically focus on developing models that predict as accurately as possible. Part of the data is used to “train” the model, meaning testing alternative variable structures to generate what is likely to be the best fit model. The trained model is then applied to the remaining data, and its performance is measured with respect to fit and predictive ability. Conventional hypothesis testing is typically not possible, as variables are measured only with respect to contribution to fit.

We tested several ML models and chose to use the Random Forest (RF) algorithm. RF is an “ensemble learning” method generating a number of decision trees and aggregating the regression results from these trees (Breiman, 2001). Random Forest is widely used in prediction and optimization. It allows for many different types of non-linearities (Breiman, 2001) and is widely used to predict traffic. For example, Liu and Wu (2017) used RF to successfully predict traffic congestion. Dogru et al. (2018) compared three machine learning models’ performance on detecting real-time traffic accidents. They found Random Forest outperforms the other two algorithms - Artificial Neural Networks (ANN) and Support Vector Machine (SVM). More importantly, as compared to other machine learning algorithms, Random Forest is not a completely “black-box” tool. The random forest model provides variable importance measures to establish the prediction strength of each variable as well as measures to illustrate the relationships between one or more input variables and the predictions, thereby yielding more interpretable results than other approaches.

Figure 4.14 shows a typical structure for a RF regression model. The number of decision trees in the forest (k) and the number of predictors randomly tried at each split (m) are two major hyperparameters of RF. RF uses the bootstrap method, which is a randomly sampled-with-replacement method, to select k different sample subsets of data. The k sample subsets are then used to construct k unrouted decision trees. In the process of generating each decision tree, in order to generate the nodes of the decision tree, we need to select m attributes from the M attributes of the original data set as the candidate feature attributes ($m \leq M$). The decision tree is constructed by using the m randomly selected candidate attributes. The final regression model will be obtained by averaging the results of k regressions. In implementation of RF algorithm, each tree is trained on about 2/3 of the total training data. As the forest is built, each decision tree can thus be tested on the samples not used in building that tree and the test result is referred to as out of bag (OOB) error - an internal error estimate of a random forest as it is being constructed. In this study, the number of trees (k) was set to be 2,000 to guarantee the stability of predictions, and the candidate feature attribute number (m) was determined to be 5 according to OOB error measurement.

We use MATLAB to train and test the RF models (version R2020a, The MathWorks, Inc.). Again we generate separate models for each team and each corridor. We calculated statistical indicators as R^2 and root mean squared error (RMSE) between RF predictions and observations to assess the prediction accuracy of the proposed model. The increase in mean square errors (MSE) of predictions is calculated to examine how each variable affects predictions. MSE increase is estimated using out-of-bag samples as a result of each predictor variable being permuted. The higher the number, the more important the predictor variable. The visual Partial Dependence (PD) Plot is used to illustrate the relationship between one or more predictor variables and predictions, which can be either linear or nonlinear.

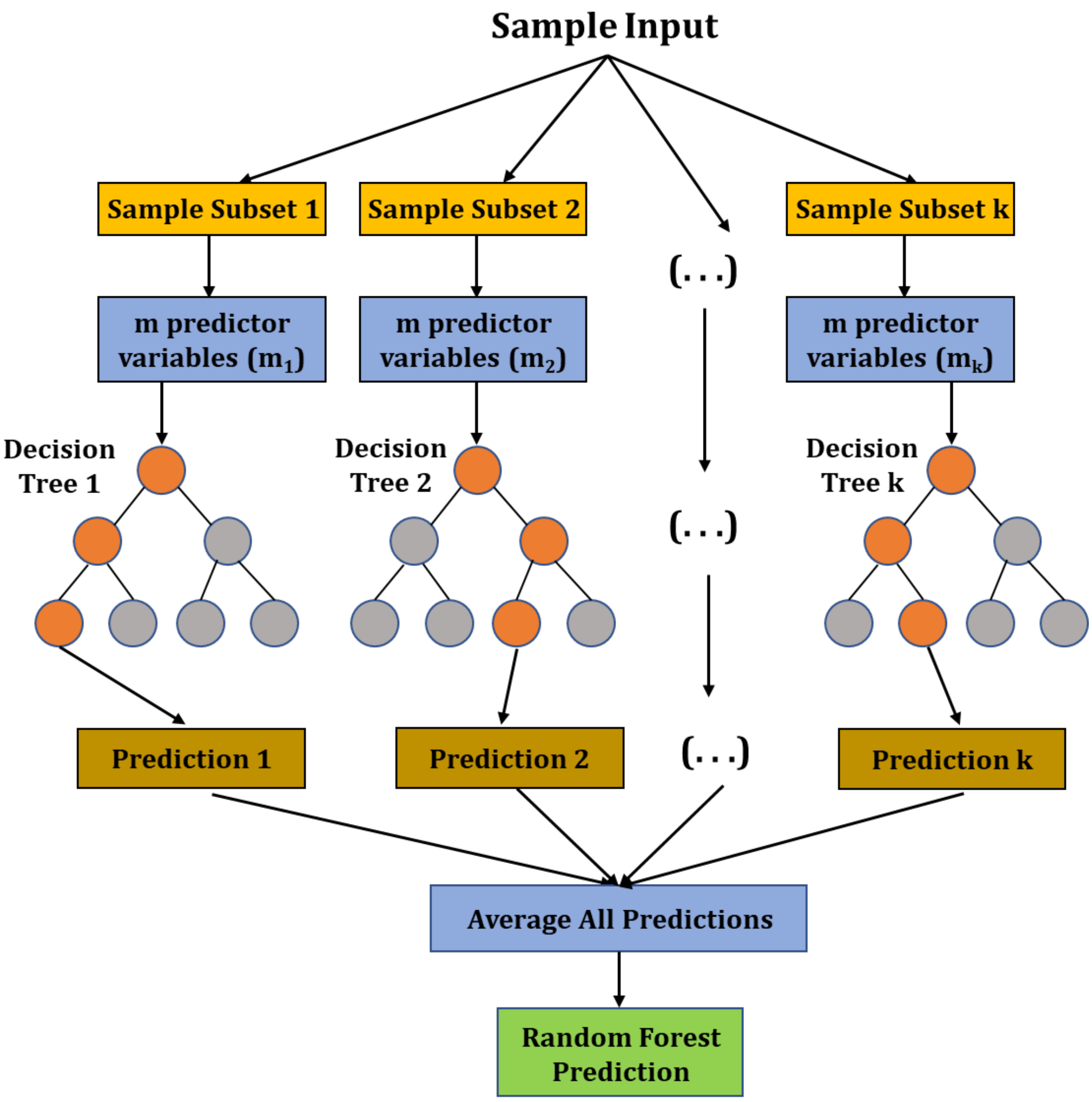


Figure 4.14. Structure of a Random Forest (RF) regres

Figure 4.15 through figure 4.19 shows the prediction results for the four highway corridors and arterials, on Rams and USC game-days respectively. The figures show the prediction scatter plots of Random Forest regression models in terms of the measured traffic speed difference and predicted speed difference. The R^2 and RMSE values indicate that Random Forest models outperform the linear regression models. For Rams models, R^2 improves from 0.73 to 0.90, 0.70 to 0.88, 0.72 to 0.88, and 0.59 to 0.83, and 0.40 to 0.75 for highway corridor I-110 S, I-110 N, I-10 W, I-10 & SR-60 E and arterial roads. A prominent improvement can also be found for USC RF models compared to linear regression models, RF regression R^2 improves for all the corriders and arterial roads. We infer that the better performance is a result of RF being able to capture nonlinear relationships between predictor variables and dependent variable.

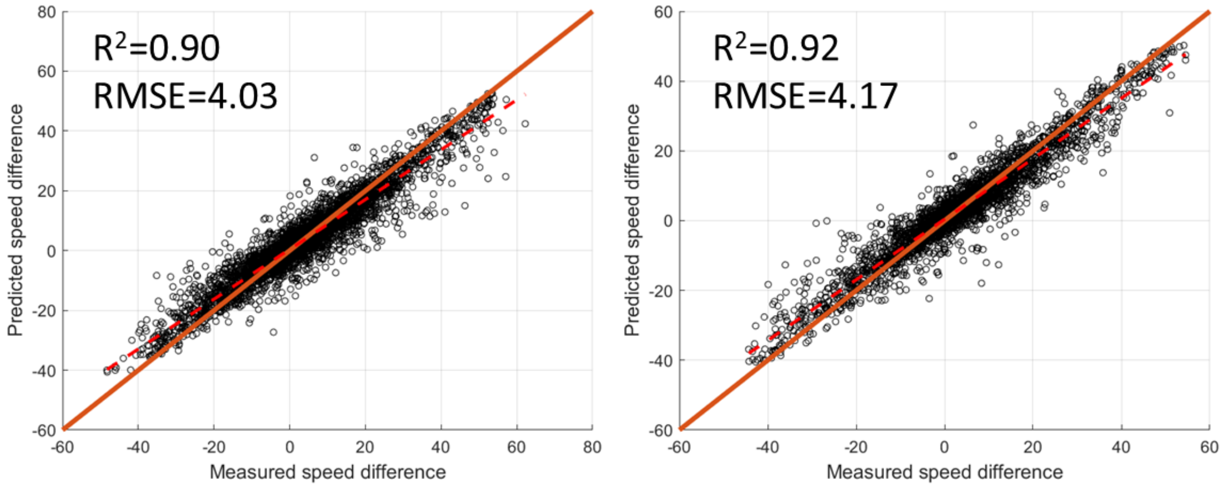


Figure 4.15. Random Forest scatter plot for highway corridor I-110 S on Rams game-days (left) and USC game-days (right)

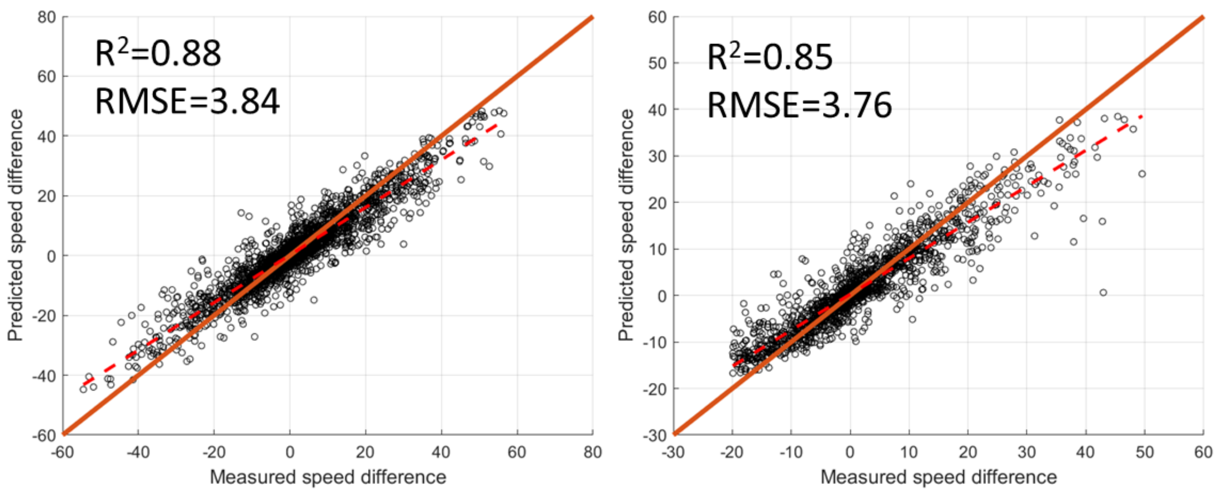


Figure 4.16. Random Forest scatter plot for highway corridor I-110 N on Rams game-days (left) and USC game-days (right)

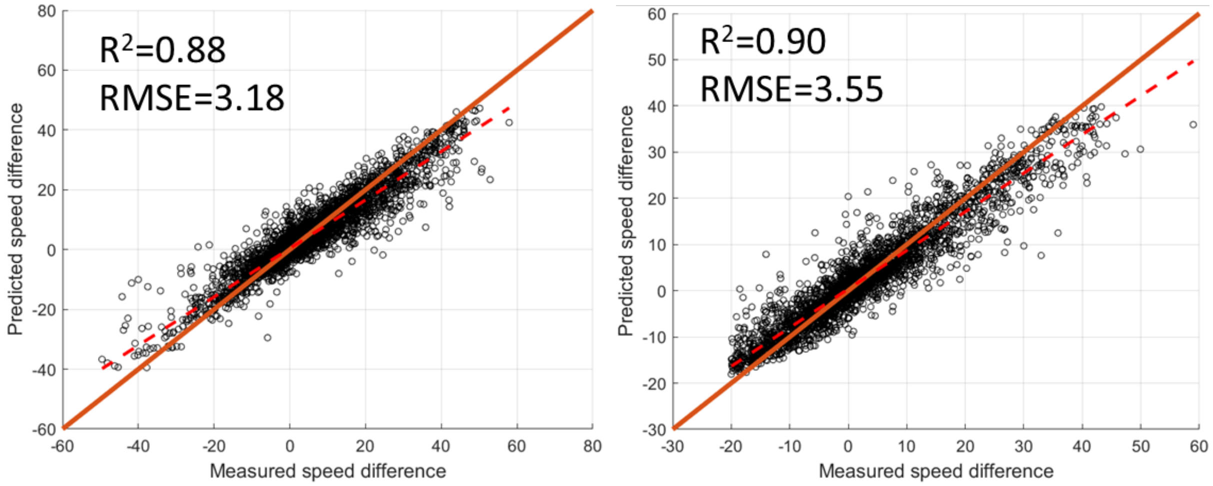


Figure 4.17. Random Forest scatter plot for highway corridor I-10 W on Rams game-days (left) and USC game-days (right)

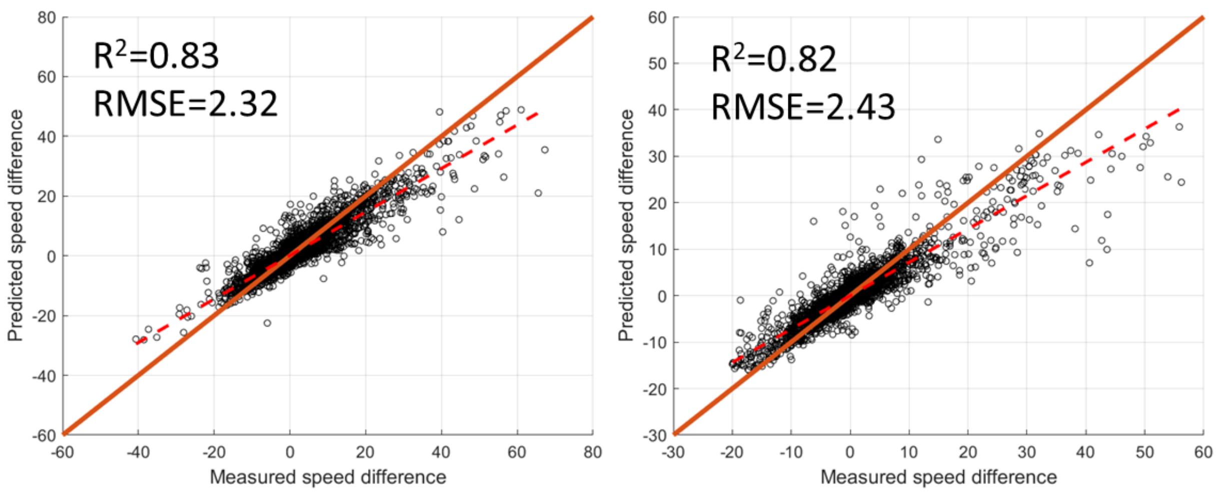


Figure 4.18. Random Forest scatter plot for highway corridor I-10 & SR-60 E on Rams game-days (left) and USC game-days (right)

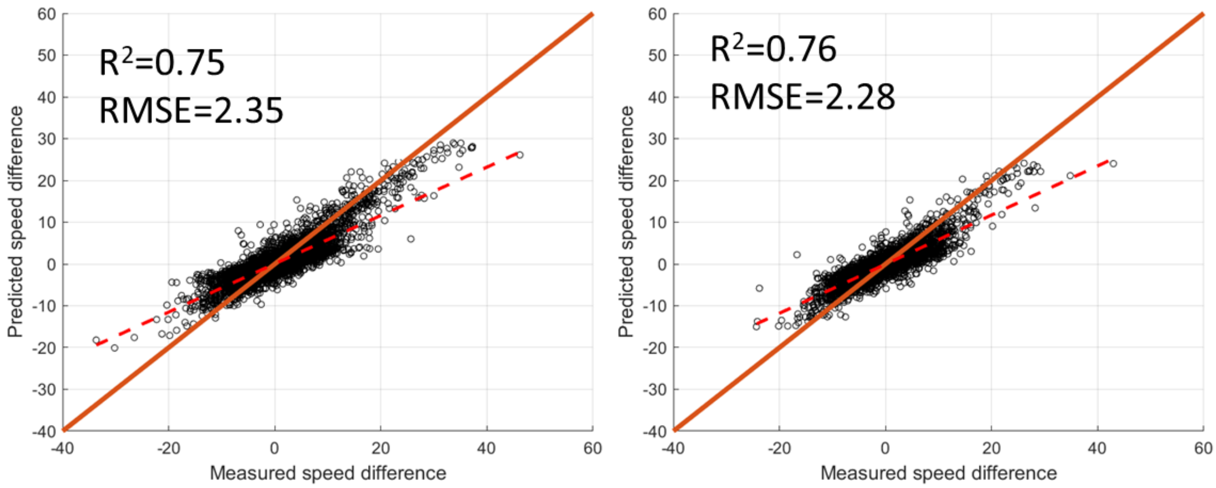


Figure 4.19. Random Forest scatter plot for arterial roads on Rams game-days (left) and USC game-days (right)

The contribution of Random Forest models is also illustrated by the importance of predictor variables in the models. Table 4.8 shows the top-6 important covariates determined by the RF algorithm for all highway corridor models. The rank of important variables is quite consistent across models. For all highway models, the temporal and spatial lagged terms dominate as the most important covariates, consistent with our linear regression model results. Three out of the top six significant predictor variables are event related: distance to the Coliseum, time to kickoff, and attendee number, all consistent with the descriptive results. It is worth noting that the distance to nearest freeway to freeway to freeway interchange also plays a quite important role in pre-game traffic patterns on game-days, indicating football games may add more traffic burden to existing bottlenecks at freeway interchanges.

Table 4.8. Top-6 important covariates determined by the RF algorithm for highway corridors

	Rams				USC			
Rank	I-110 S	I-110 N	I-10 W	I-10 & SR-60 E	I-110 S	I-110 N	I-10 W	I-10 & SR-60 E
1	Time lagged term	Time lagged term	Spatial lagged term	Time lagged term	Spatial lagged term	Time lagged term	Spatial lagged term	Time lagged term
2	Spatial lagged term	Spatial lagged term	Time lagged term	Spatial lagged term	Time lagged term	Spatial lagged term	Time lagged term	Spatial lagged term
3	Distance to Coliseum	Distance to Coliseum	Distance to nearest freeway interchange	Distance to nearest freeway interchange	Distance to Coliseum	Distance to Coliseum	Distance to nearest freeway interchange	Distance to nearest freeway interchange

4	Time to kickoff	Time to kickoff	Distance to Coliseum	Distance to Coliseum	Time to kickoff	Distance to nearest freeway interchange	Distance to Coliseum	Distance to Coliseum
5	Distance to nearest freeway interchange	Distance to nearest freeway interchange	Time to kickoff	Attendee number	Attendee number	Time to kickoff	Time to kickoff	Attendee number
6	Attendee number	Attendee number	Attendee number	Time to kickoff	Distance to nearest freeway interchange	Attendee number	AM game	Time to kickoff

We produced partial dependence plots using the RF algorithm to illustrate the relationships between event-related variables and traffic speed difference between game-days and non-game-days. A partial dependence plot demonstrates the marginal effect of an independent variable on the predicted response while controlling for all other variables in the model.

Figures 4.20 and 4.21 illustrate the impact of time to kickoff on pre-game traffic speed on highway corridors for Rams games and USC games respectively. Time to kickoff has non-linear effects on pre-game traffic. For Rams games, traffic patterns are similar for all four highway corridors. The difference in traffic speed increases rapidly around three hours before the game, stays at a high level, and then begins to decline just before game start time. For USC games, the pattern is not as consistent across the corridors, but we can see a generally more gradual increase around 5 hours before game start time. These patterns are consistent with the descriptive data presented earlier.

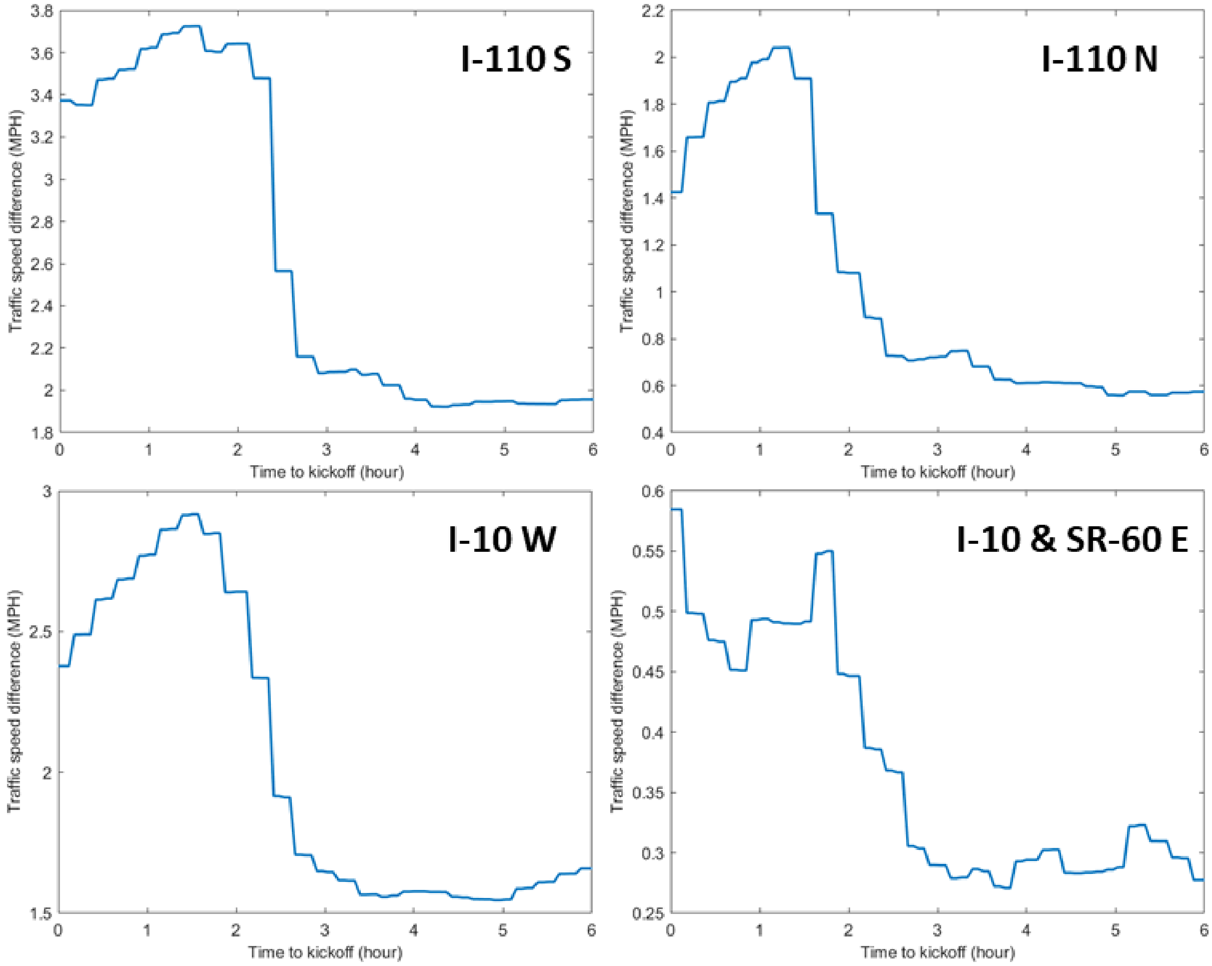


Figure 4.20. The relationship between traffic speed difference between game-days and non-game-days and time to kickoff for highway corridors on Rams game-days

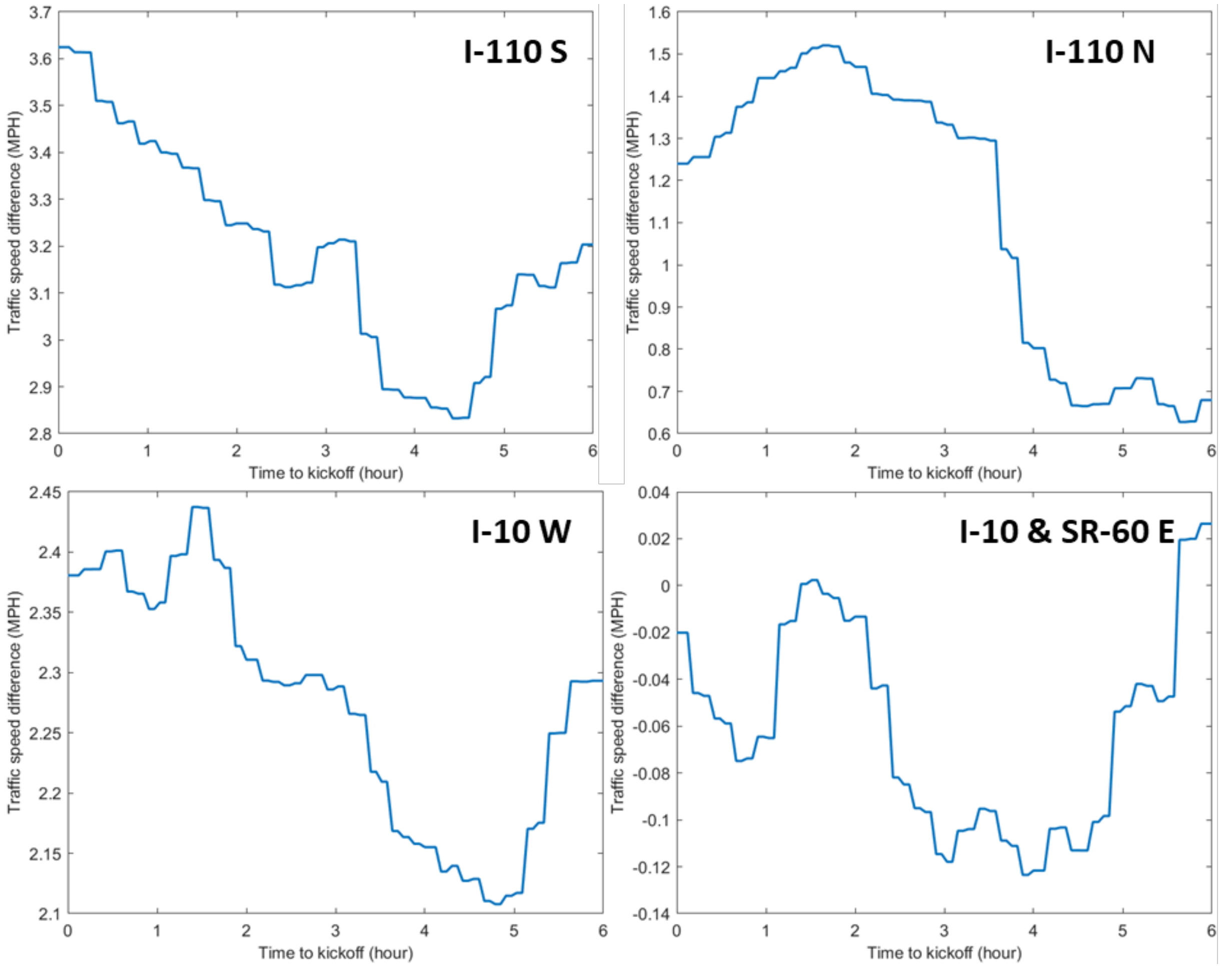


Figure 4.21. The relationship between traffic speed difference between game-days and non-game-days and time to kickoff for highway corridors on USC game-days

The plots in Figures 4.22 and 4.23 illustrate the associations between pre-game traffic speed difference and distance to the Coliseum for highway corridors. Overall, the association between traffic and distance is not linear. The partial dependence plots show the peak speed difference usually appears further from the Coliseum. The pattern suggests that game attendees are more likely to use more distant exits on approach to the Coliseum. Two possible factors may contribute to using more distant exits: 1) drivers leave highways earlier to avoid possible congestion caused by road closure near the Coliseum on game-days (e.g. Exposition Blvd. and Martin Luther King Blvd.); 2) relatively high parking fees near the Coliseum incentivize drivers to search for cheaper parking spaces in local communities. Figures 4.16 and 4.17 also show that peak traffic speed difference normally appears at freeway to freeway interchanges, adding more traffic burden to the existing traffic bottle neck.

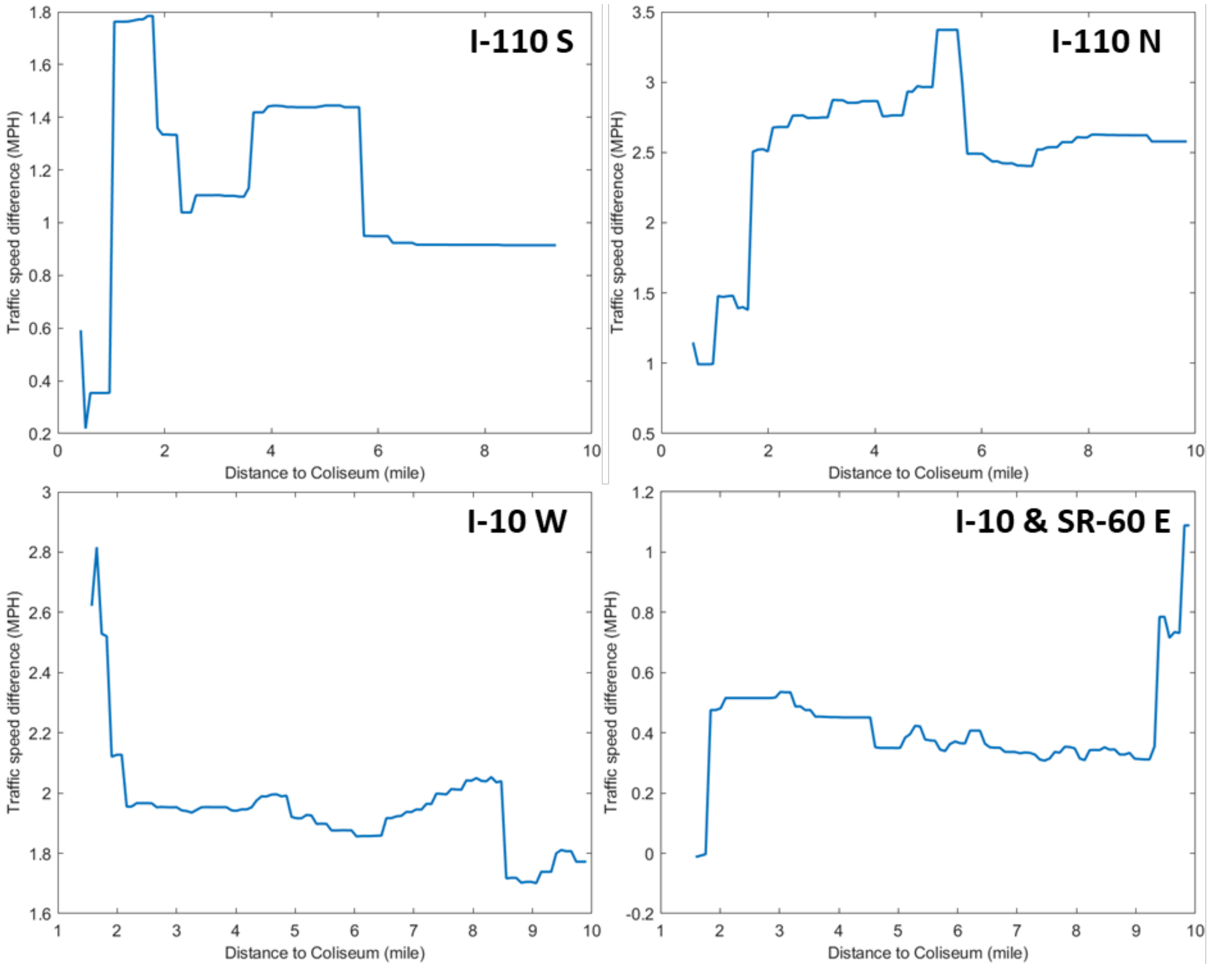


Figure 4.22. The relationship between traffic speed difference between game-days and non-game-days and distance to Coliseum for highway corridors on Rams game-days

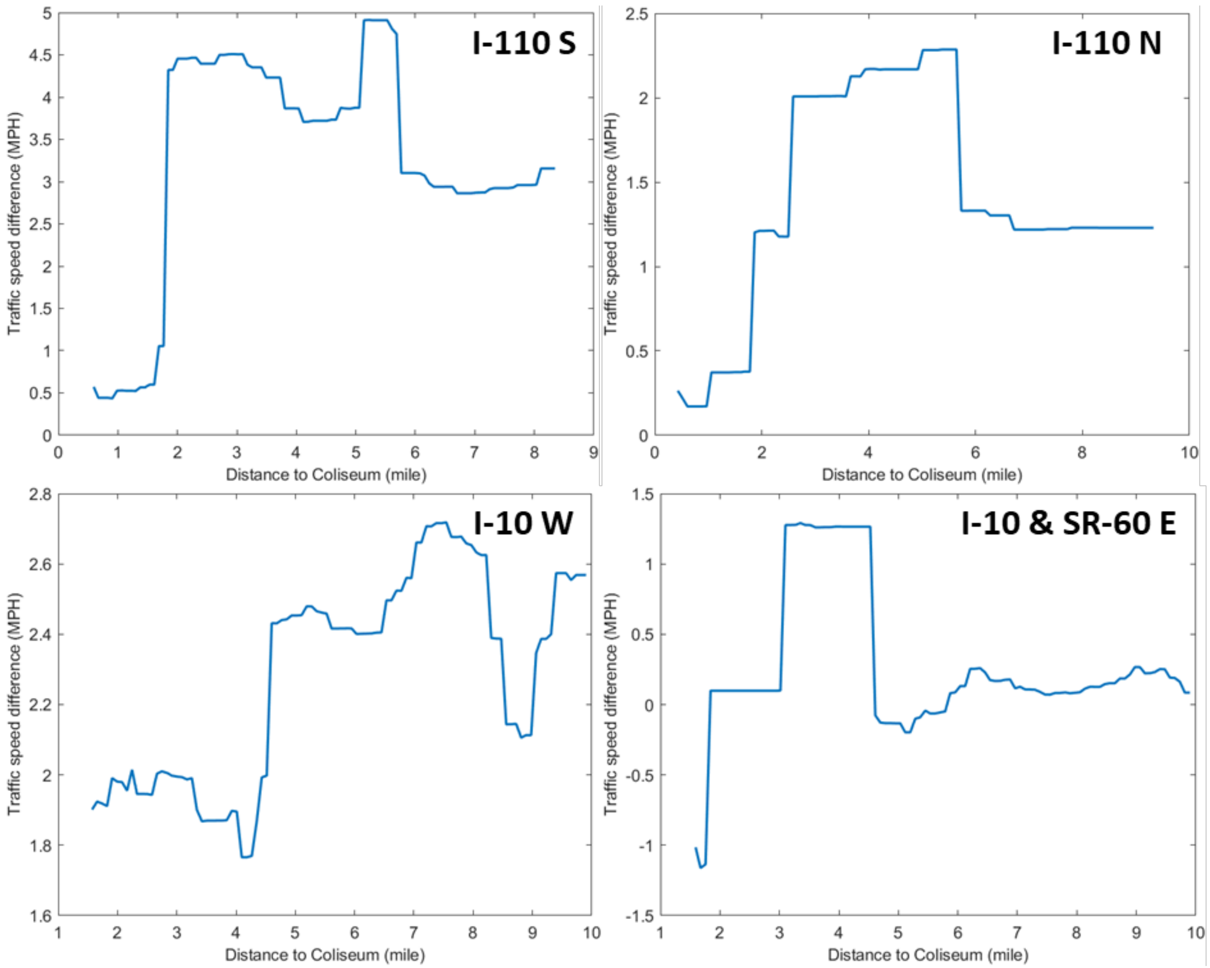


Figure 4.23. The relationship between traffic speed difference between game-days and non-game-days and distance to Coliseum for highway corridors on USC game-days

Since the relationships between time/distance and traffic speed difference are nonlinear, to better capture the variable, we produced a partial dependence plot to visualize the relationship between predicted responses (traffic speed difference) and the predictor variables distance to Coliseum and time to kickoff (Figures 4.24 through Figure 4.27). The horizontal axis is the distance to the Coliseum and vertical axis is the time to kickoff. Different colors represent predicted traffic speed difference between game-days and non-game-days, with light yellow representing greater difference and dark blue represents smaller differences. The plots further verify that Rams game attendee arrivals are more concentrated in time and occur mostly within 2 to 3 hours of start game time. USC attendee arrivals are earlier and less concentrated in time. The plots also confirm that the added demand of weekend football games has a greater impact on nearby freeway to freeway bottlenecks than on the highway segments closer to the Coliseum. Finally, the plots show that game attendees who drive to the Coliseum do not use the closest highway exit.

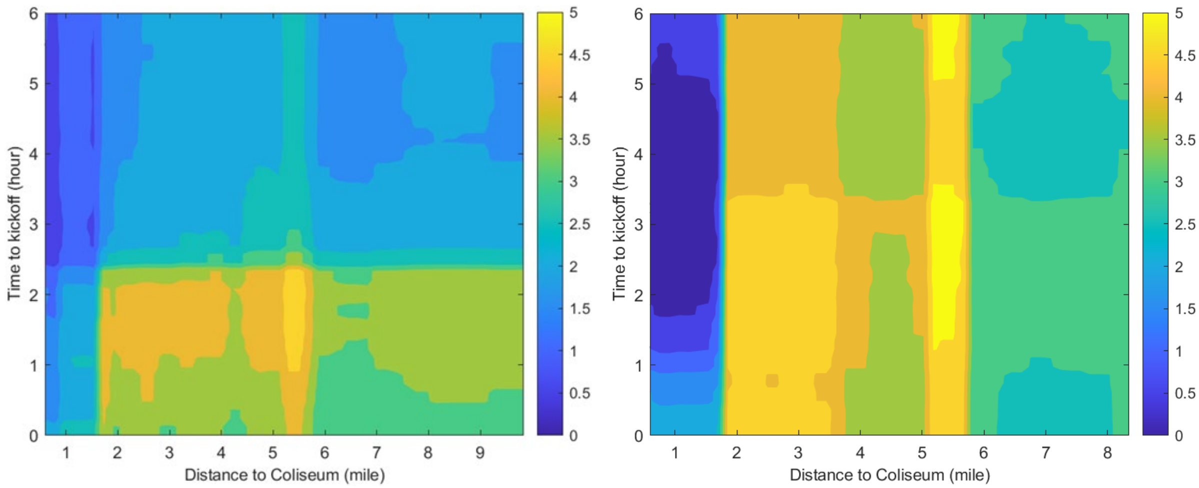


Figure 4.24. The relationship between traffic speed difference and distance to Coliseum and time to kickoff for highway corridors I-110 S on Rams game-days (left) and USC game-days (right)

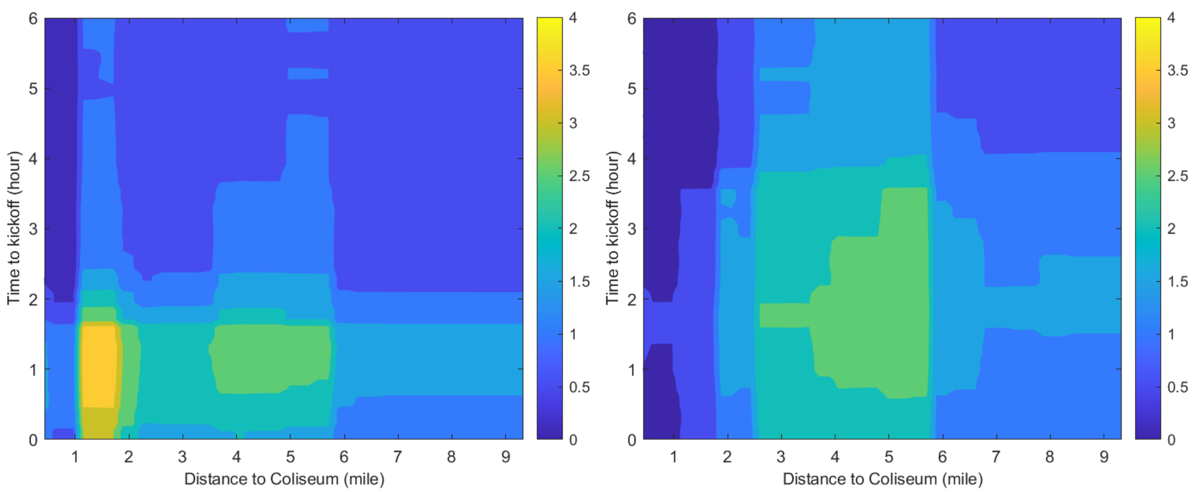


Figure 4.25. The relationship between traffic speed difference and distance to Coliseum and time to kickoff for highway corridors I-110 N on Rams game-days (left) and USC game-days (right)

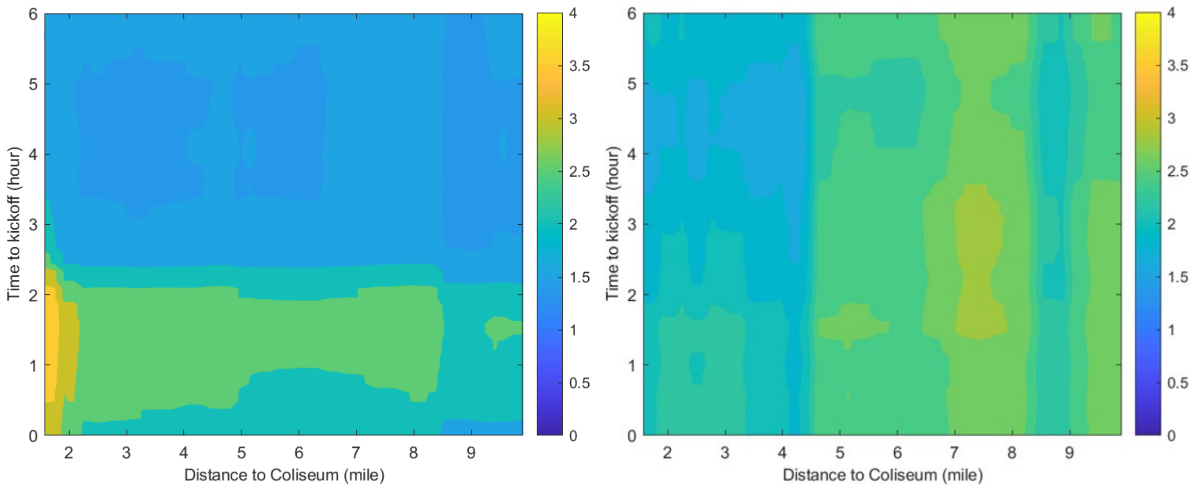


Figure 4.26. The relationship between traffic speed difference and distance to Coliseum and time to kickoff for highway corridors I-10 W on Rams game-days (left) and USC game-days (right)

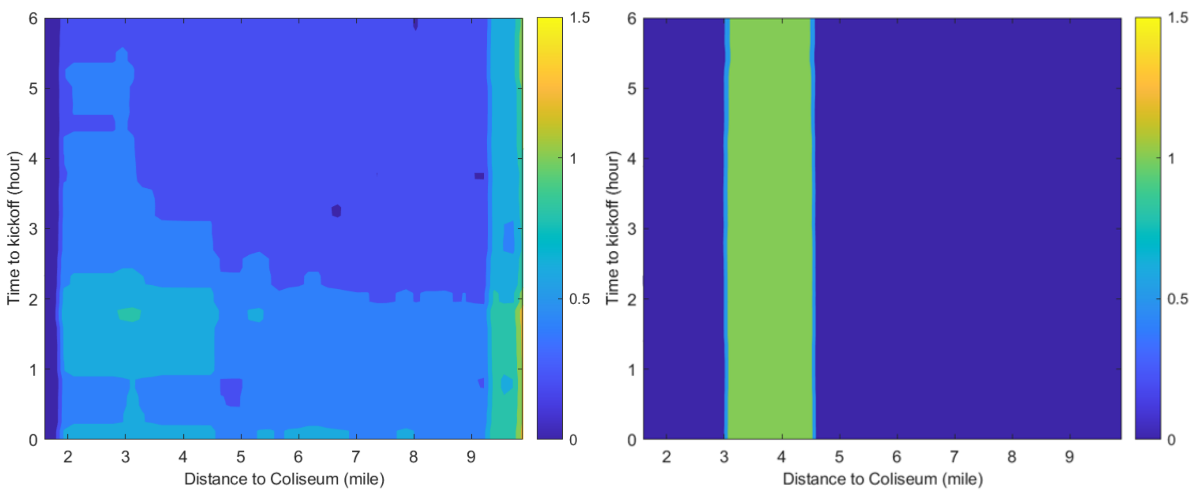


Figure 4.27. The relationship between traffic speed difference and distance to Coliseum and time to kickoff for highway corridors I-10 & SR-60 E on Rams game-days (left) and USC game-days (right)

Arterial roads

We produced similar partial dependence plots for arterial roads to illustrate the relationship between traffic speed difference and time to kickoff (Figure 4.28) and distance to Coliseum (Figure 4.29), respectively. Figure 4.28 indicates that the arrival pattern of Rams game attendees on arterials is highly consistent with results on highways. Arrivals are concentrated within two hours before game start. However, for USC games, several peaks were observed until six hours before game start, indicating arrival of USC game attendees is more dispersed.

Differing from the highway results, distance to the Coliseum has a linear and negative relationship with traffic speed difference for arterial roads (Figure 4.29). For both Rams and USC games, the effect of distance to Coliseum reaches a low point at about one mile and then stays stable. The one-mile distance threshold reflects that arterial roads are less affected by events than highways.

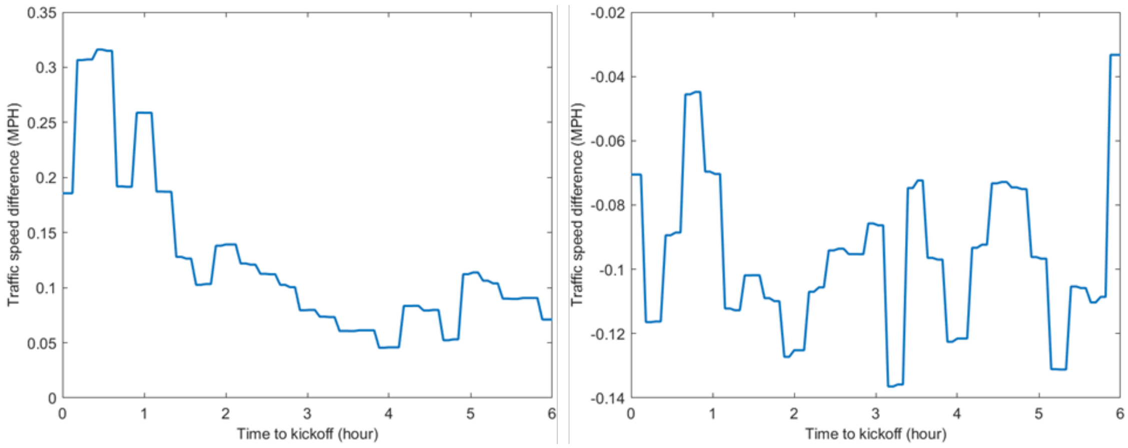


Figure 4.28. The relationship between traffic speed difference between game-days and non-game-days and time to kickoff for arterial roads on Rams game-days (left) and USC game-days (right)

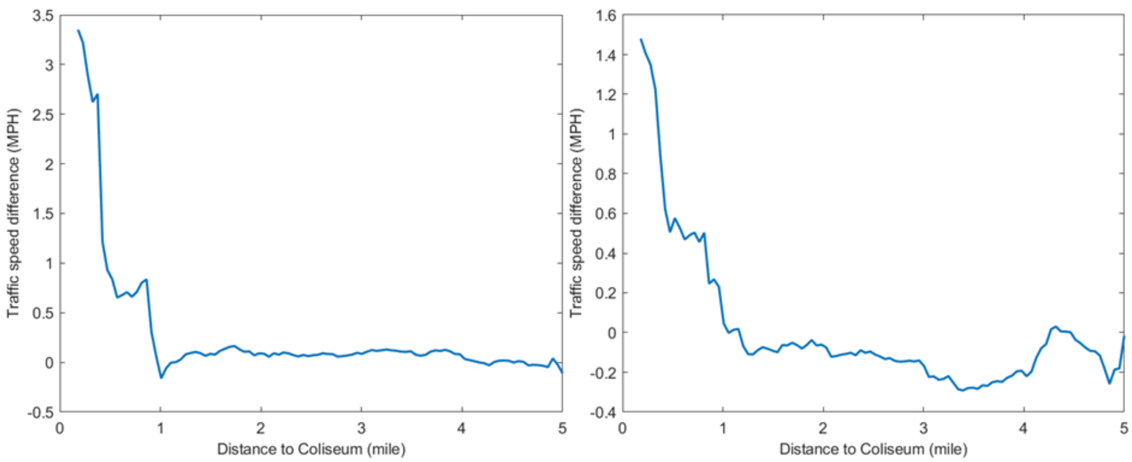


Figure 4.29. The relationship between traffic speed difference between game-days and non-game-days and distance to Coliseum for arterial roads on Rams game-days (left) and USC game-days (right)

Figure 4.30 shows the relationship between traffic speed difference and distance to Coliseum and time to kickoff for arterial roads. The linear relationship between traffic speed difference and distance and time on arterial roads is clear. Additionally, as compared to Rams games, USC games have less impact on arterial roads (smaller traffic speed difference for USC games). We surmise this is explained by generally lower USC game attendance and student attendees who live near campus.

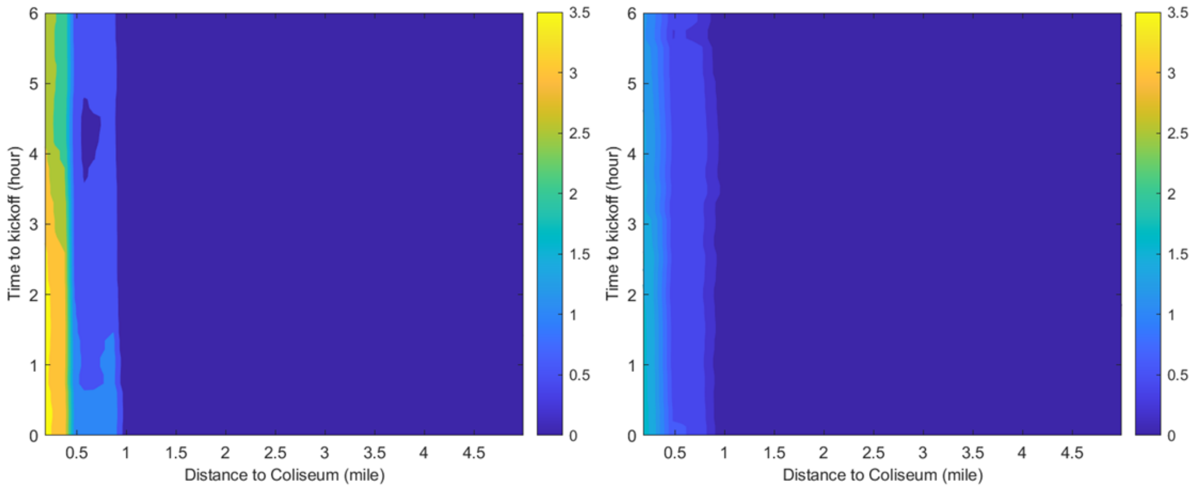


Figure 4.30. The relationship between traffic speed difference and distance to Coliseum and time to kickoff for arterial roads on Rams game-days (left) and USC game-days (right)

4.3 Conclusions

The purpose of this research is to provide guidance for better managing the impacts of planned special events. Both conventional and machine learning statistical tools were used to gain the best possible understanding of how Coliseum football games affect the surrounding transportation system. The results have important implications for local transportation planning. They show that Rams and USC attendees have completely different travel behavior on game days. Therefore, strategies to smooth traffic need to be different. Rams attendees might be incentivized to arrive earlier with pre-game activities or preferential parking. USC volumes might be further spread by various parking policies. Freeway-to-freeway interchanges—typically serious bottlenecks in Los Angeles—are trouble spots, even when located miles away from the venue. This suggests that traffic management strategies should extend beyond the immediate venue area. In all cases, travelers could benefit from information on anticipated traffic at the major bottlenecks as well as in the local area.

Chapter 5 Transit analysis

Mode share of game attendees is another important factor affecting traffic impacts. The venue is well served by public transit. The Expo rail line has a stop at the Coliseum, and there are several bus lines with stops on the main arterials leading to the venue.

5.1 Transit service on game days

There are two major bus systems serving the Coliseum area: LA Metro and LA DOT. LA Metro is a regional bus system covering most areas of Los Angeles County. LA DOT has a smaller service area in Downtown Los Angeles and 27 nearby neighborhoods across the city. Figure 5.1a-b shows the bus service areas of LA Metro and LA DOT near the Memorial Coliseum. Within one mile of the Coliseum (the maximum acceptable walking distance for most people), there are 170 bus stops (Table 5.1). The main transit mode for game day is the LA Metro Expo Line, which runs from Santa Monica to USC to downtown Los Angeles, with connections to other rail lines at its downtown terminus.

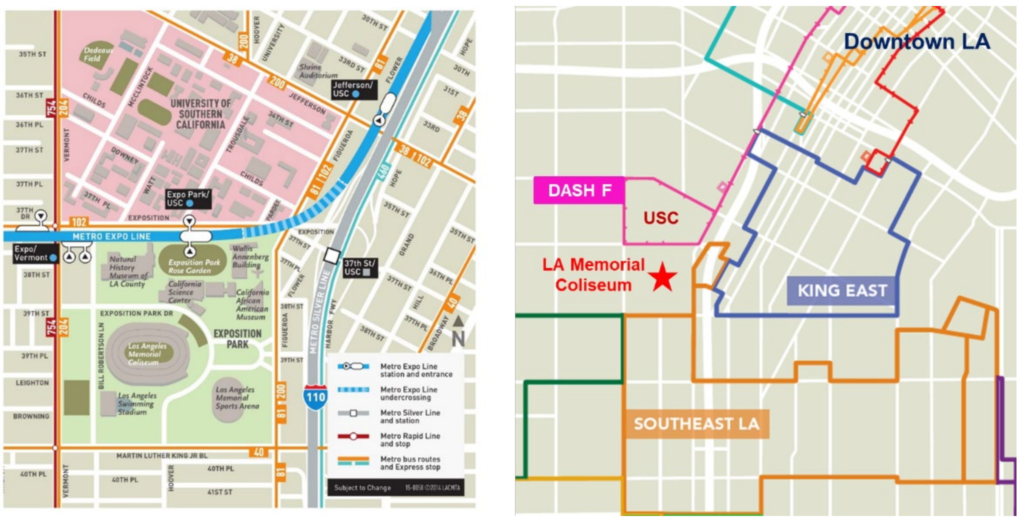


Figure 1. Service area of LA Metro bus (left) and LA DOT bus (right).

Table 2. Bus stop distribution within one mile of the Coliseum.

Distance to Coliseum	Bus stop number
0-0.25 mile	6
0.25-0.5 mile	29
0.5-0.75 mile	57
0.75-1 mile	78
total	170

6.2 Transit use on game days

We obtained boarding and alighting data by time of day for all bus services operating within one mile of the Coliseum. We were able to compare stop by stop boardings and alightings between game days and control days. We estimated the share of bus use based on differences in boardings and alightings. Use of bus transit is quite limited. Only 2% of attendees take the bus to Rams games, while the number drops to 1.3% for USC game attendees (Table 1).

Expo Line trains do not have automated passenger counters. Passenger data is available only for entire days, and we therefore cannot make the same comparisons as with the bus data. Table 1 shows the share of Expo Line boarding we estimate to be game attendees. Rams game attendees are more likely to use transit than USC game attendees. We surmise that there are more USC attendees who live near campus and walk to the game, and the practice of tailgating makes transit a less attractive option for USC attendees. Based on attendance, traffic volumes, and an assumed average vehicle occupancy of 2.5 persons per vehicle, our rough estimate of transit mode share is 18% for Rams games and 13% for USC games.

Table 1. USC and Rams games total transit boardings

	Rams			USC		
	2016	2017	2018	2016	2017	2018
Metro Expo line	9273	9899	10291	5822	7392	5626
Percent of Attendance	13.3%	18.6%	16.6%	10.5%	12.1%	11.7%
Local bus	1189	1074	1357	456	1044	684
Percent of Attendance	1.7%	2.0%	2.2%	0.8%	1.7%	1.4%

We further study the spatial and temporal pattern of pre-game alightings of bus stops within one mile of the Coliseum between game days and control days (Figure 2). More bus riders arrived within three hours before the game start and get off at bus stops within 0.5 mile of the Coliseum (Table 3). We also investigate the post-game boardings of the same bus stops between game days and non-game days. We find a similar pattern. More people take the bus after Rams games than USC games, and most of them happen within one hour after the game (Figure 3).

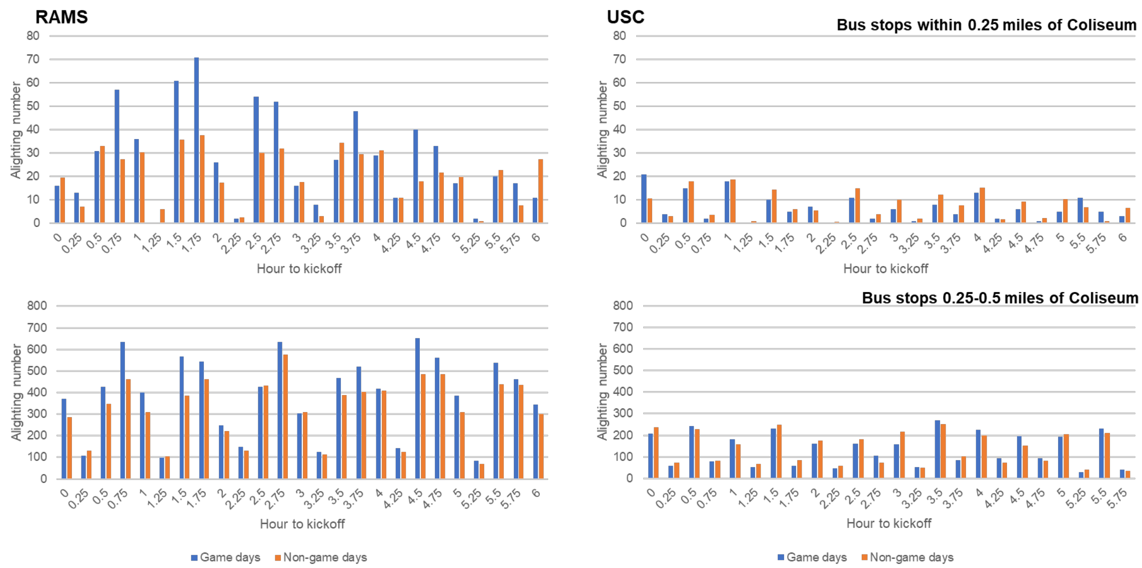


Figure 2. Pre-game alightings of bus stops within 0.5 mile of the Coliseum for 2016 Rams game days (left) and USC trojans game days (right) and corresponding non-game days.

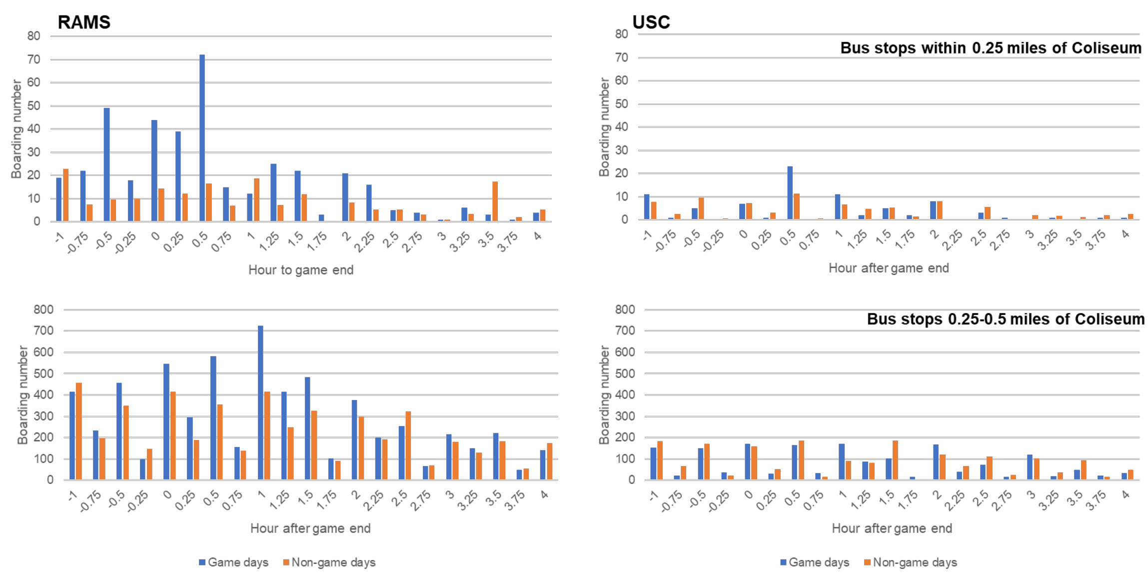


Figure 3. Post-game boardings of bus stops within 0.5 mile of the Coliseum for 2016 Rams game days (left) and USC trojans game days (right) and corresponding non-game days.

Tables 3 and 4 show the difference in the average number of pre-game alightings and post-game boardings respectively. There is a consistent but small increase in ridership in all years except USC games in 2016. We conclude that but transit plays a small role in transport for game attendees. The Expo Line is much more important, but due to data limitations we are unable to quantify effects by time or station location. Recommendations for increasing transit mode share are presented in the final chapter.

Table 3. Difference of pre-game alighting number between game days and non-game days

Distance to Coliseum	Rams			USC		
	2016	2017	2018	2016	2017	2018
0-0.25 mile	25	33	14	-12	12	10
0.25-0.5 mile	212	219	234	-16	207	45
0.5-0.75 mile	185	100	191	-22	171	47
0.75-1 mile	-46	75	-41	-50	93	-148
Total (except 0.75-1 mile)	421	352	439	-50	390	102
Percent of Attendance	0.49%	0.59%	0.61%	-0.07%	0.55%	0.18%

Table 4. Difference of post-game boarding number between game days and non-game days

Distance to Coliseum	Rams			USC		
	2016	2017	2018	2016	2017	2018
0-0.25 mile	30	51	13	0	25	0
0.25-0.5 mile	180	242	130	-83	206	65
0.5-0.75 mile	124	178	214	-57	135	73
0.75-1 mile	31	97	131	-238	81	15
Total	366	569	489	-378	446	154
Percent of Attendance	0.43%	0.96%	0.68%	-0.52%	0.63%	0.28%

Chapter 6 Traffic Simulations

6.1 Introduction

The previous chapters have shown that planned events are a significant source of traffic congestion, especially in large metropolitan areas. Our analysis of football games played at the Los Angeles Memorial Coliseum revealed that Rams and USC game impacts are different. Rams fans arrive in a more concentrated time interval closer to start time of the games, and therefore have a greater impact on the major approach routes than USC fans. USC fans arrive up to 6 hours before the game starts. The greatest impacts on highways are around nearby freeway to freeway interchanges. Arterial traffic is more consistently affected with distance from the venue, with the most impact within 1 mile of the venue. Our findings suggest that impacts depend on the behavior of event attendees, and that impacts can extend up to 10 miles away from the venue.

In this chapter we address mitigation: how can major events be better managed to reduce congestion and the associated pollution and GHG emissions? We use micro and macro- simulation models to examine impacts of two strategies: shifting arrivals (a form of peak spreading), and shifting modes to increase transit use. We find that the effectiveness of these strategies is different for Rams and USC games. Peak spreading is effective for Rams games, but not for USC games. Increasing transit use has a more positive impact for USC games. Simulation modeling provides useful insights on the effectiveness of different management strategies, but does not provide guidance on policies that could achieve implementation. We discuss potential policy strategies for reducing impacts of major planned events. Our results offer guidance on how to analyze and manage major events.

1. Data and method

We use a macro-simulation model (PTV-VISUM) to test effects of alternative mitigation strategies on highway performance. In VISUM, road segments are represented by links usable for specified modes of transport (Heyken Soares et al., 2021). Links are composed of two separate network objects, one for each travel direction. Each of these objects can have different attribute values, such as the allowed speed and capacity in terms of the number of vehicles. One-way streets can be represented by blocking one direction of a link to all modes. Nodes at the beginning and endpoints of each link define the positions of intersections and junctions in the network. Turning movement permissions can be defined in the properties of the nodes.

The second element of the traffic model is the demand model. The demand model reflects the number and arrival pattern of game attendees, estimated by game-day parking data and freeway traffic data. These data allow us to estimate the number of vehicles traveling to the Coliseum as well as traffic speed on different road segments on game-days.

Per standard practice, travel demand in VISUM is aggregated at the level of zones ($Z = \{z_1, z_2, \dots, z_i\}$) and given in the form of an origin-destination (O-D) matrix. We set zones as parking structures in the area. To estimate traffic conditions on freeways, we divided each freeway corridor into three segments: 0-3 mile, 3-6 mile, and 6-10 mile, and set the start point of each freeway segment as zones in the traffic model. Game-days generate additional demand on the network. In the absence of O-D data on game attendees, we assume they all travel at least 10 miles. Thus the origins are 10 mile points on the surrounding highways, and the destination are the parking structures. We generate three traffic mitigation scenarios:

1, Spreading traffic demand over a longer time period: We assume 50% of game traffic in the 0-3 hour time interval would move to the 3-6 hour time interval;

1. Increasing transit mode share: We assume that 50% of vehicles are removed from the network in the 0-3 hour time;
2. Increasing transit mode share: We assume that 20% of vehicles are removed from the network in the 0-3 hour time.

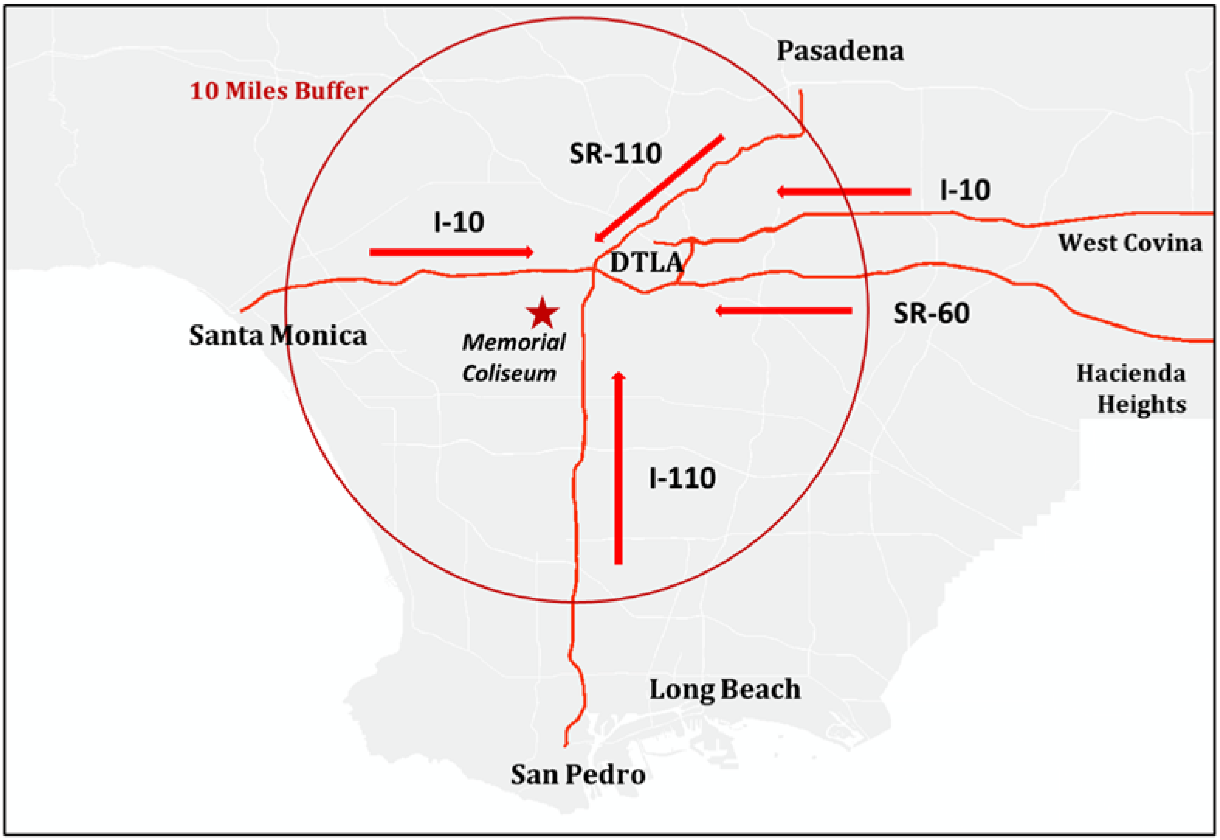
Scenario 2 is the comparable to Scenario 1 (e.g. would it be better to move a given share of traffic to another time interval or to shift it all to transit, which adds more transit vehicles to the traffic flow). Scenario 3 is a more realistic transit share target. These increases in transit mode are in addition to the existing transit mode share. Our baseline is the average game day traffic level observed in the prior analysis. Each scenario is compared to this baseline. We conducted the simulations in two time intervals: 0-3 hours before the game start and 3-6 hours before the game start for each football team and for two game start times.

Additionally, we use a micro-simulation model (PTV-VISSIM) to test effects of the scenarios on the arterial system. Our focus is the queuing around parking lots before the game. VISSIM allows for both meso and microscopic simulation. VISSIM requires detailed network data, including geometry of intersections, signal timing, lane configurations, etc. Like VISUM, demand is structured as an OD matrix, but the origins and destinations are specific locations on the network. We use the same baseline and the same scenarios as with the macro-simulation analysis

3.2 Study area and data

The study area is the Los Angeles Memorial Coliseum as described in Chapter 2. Figure 1 shows a map of the study area with the closest on and off ramp locations identified. There is a dense arterial road network that is part of the LADOT traffic management system. The signal system can be managed in real time.

Figure 1. Map of Study Area.

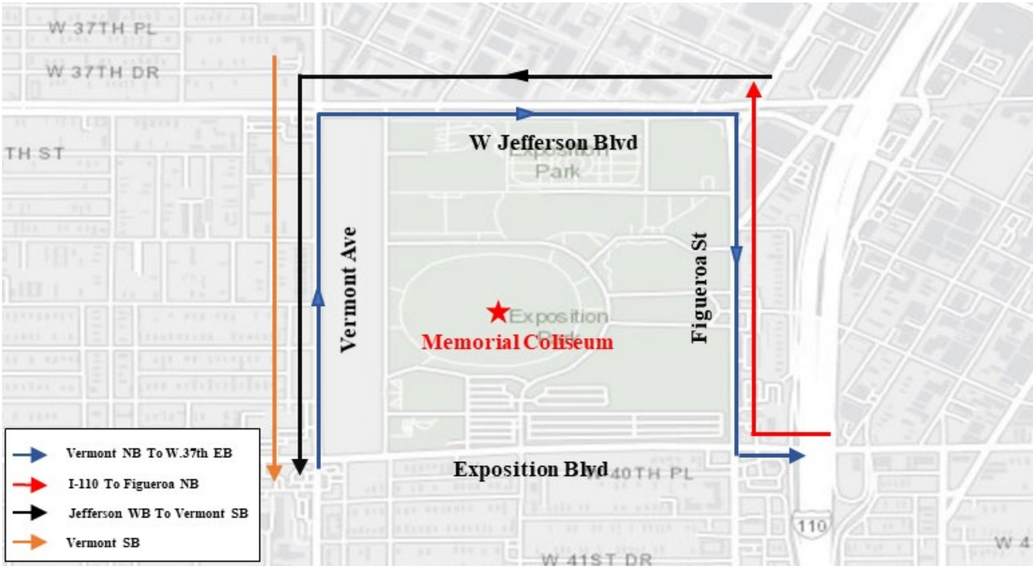


Traffic data for highways and arterial road system were obtained from the Archived Data Management System (ADMS) at USC (ADMS, 2022). ADMS gives directional volume, speed and occupancy for each highway segment at 30 second intervals. Midblock speed and volume at one minute intervals is available for each arterial segment. We aggregate the data to 15 minute intervals. The area of analysis includes 100 highway detectors and 4017 arterial detectors. Total number of observations is 34,548 for highways and 1,685,995 for arterials.

The highway and road network data were obtained from OpenStreetMap. OpenStreetMap is a collaborative mapping project that provides an accessible and publicly editable map of the world. OpenStreetMap is developed based on U.S. Census TIGER/Line roads (Zielstra et al., 2013), but many additions have been made, including pedestrian paths through parks, passageways between buildings, bike lanes and routes, and richer attribute data describing the characteristics of features, such as finer-grained codes for classifying arterial roads, collector streets, residential streets, alleys, parking lots, etc. (Boeing, 2017). OpenStreetMap data also includes detailed information for each road, such as road type, capacity, and speed limit.

We use the same four freeway corridors as in our previous analysis for the analysis of highway performance: I-110 North and South, I-10 West, and I-10/SR 60 East. The area for our arterial road analysis is shown in Figure 2. It is about 3.5 square miles. We examine four different travel routes from freeway off ramps to parking garages as shown in the figure. The selected parking garages tend to be the first to fill up on game days. There are three classes of vehicles: light duty, heavy duty, and buses. The VISSIM network includes 5 major intersections, 25 road links, and 30 connectors.

Figure 2. Simulated arterial routes.



4. Simulation Results

4.1.1 Results for highways

VISUM generates traffic volume for each highway segment. We calculate traffic speed and percentage change in traffic speed as our performance measure. Results are shown separately for Rams and USC games. Tables 1 and 2 give results for 1 PM Rams and USC games. Change in traffic speed is relative to the baseline described above.

For Rams games, the arrival smoothing scenario effectively reduces traffic between 0 and 3 hours before the game starts. Generally, traffic was reduced by 14.5% to 18.3% in the four studied highway corridors during 0 to 3 hours before the game kickoff compared to the benchmark model. Increasing the transit share by 20% has the least impact on game-day traffic; traffic speed increases range from 5.4% on I-10 East corridor to 8.6% on I-10 West corridor. To examine the impact of different strategies on game-day traffic, we also measure each mitigation strategy's impact on game-day traffic of earlier periods: 3 to 6 hours before the game start. Results show that the shifting to transit scenario has little effect on traffic between 3 to 6 hours before the game start. The arrival smoothing scenario reduces the traffic speed most during 3 to 6 hour time interval but with moderate reduction levels ranging from 5.3 to 6.9 miles per hour (Table 1).

For USC games, although the arrival smoothing scenario reduces traffic most between 0 and 3 hours before the game starts, a tremendous decrease in traffic speed can be found during 3 to 6 hours before the game starts. For example, when the arrival smoothing scenario is implemented, the traffic speed on I-10 East corridor increases from 61.0 to 69.9 miles per hour (+8.9) during the 0 to 3 hour period whereas traffic speed on the same corridor reduce from 61.5 to 44.2 miles per hour (-17.3) in the earlier three-hour period. When we examine the overall traffic change caused by different scenarios, we find that increasing the transit share by 50% has the greatest impact over the entire 6 hour period. Removing vehicles from the system will always have a greater net effect than shifting them across time periods.

Table 1. Highway simulation for Rams 1 PM games (unit: mile per hour)

Vehicle Travel Route	Baseline	Increase transit (20%)	% Change	Increase transit (50%)	% Change	Arrival Smoothing	% Change
0-3 hours							
I-10 E	62.5	65.9	5.4%	70.9	13.5%	72.9	16.5%
I-10 W	54.8	59.5	8.6%	64.3	17.4%	64.8	18.3%
I-110 N	52.1	55.1	5.9%	59.6	14.4%	60.0	15.3%
I-110 S	48.5	51.5	6.0%	55.3	14.0%	55.6	14.5%
3-6 hours							
I-10 E	63.5	63.0	-0.8%	63.0	-0.8%	56.6	-10.9%
I-10 W	62.0	62.2	0.4%	62.2	0.4%	55.1	-11.1%
I-110 N	61.1	60.0	-1.8%	60.0	-1.8%	55.3	-9.5%
I-110 S	59.9	59.7	-0.4%	59.7	-0.4%	54.6	-8.8%

Table 2. Highway simulation for USC 1 PM games (unit: mile per hour)

Vehicle Travel Route	Baseline	Increase transit (20%)	% Change	Increase transit (50%)	% Change	Arrival Smoothing	% Change
0-3 hours							
I-10 E	61.0	64.1	5.1%	67.9	11.2%	69.9	14.7%
I-10 W	37.8	41.1	8.6%	43.5	15.0%	43.2	14.2%
I-110 N	46.7	49.0	5.0%	51.5	10.3%	52.8	13.0%
I-110 S	43.5	45.7	4.9%	49.1	12.9%	49.8	14.3%
3-6 hours							
I-10 E	61.5	61.5	0.0%	61.5	0.0%	44.2	-28.0%
I-10 W	49.6	49.9	0.8%	49.9	0.8%	36.8	-25.7%
I-110 N	57.7	58.1	0.7%	58.1	0.7%	44.5	-22.8%
I-110 S	47.8	47.7	-0.1%	47.7	-0.1%	40.6	-15.1%

4.1.2 Results for arterial roads

VISSIM output includes vehicle travel time and vehicle speed; we use these as our performance measures. The VISSIM road network model was simulated across the 0-3 hour and the 3-6 hour time periods before USC and Rams games, with a start time of 1 PM. VISSIM was run twice across each scenario, resulting in a total of 32 simulation runs. The average performance measures of Vehicle Travel

Time and Travel Speed were collected and recorded for each of the simulation runs. Vehicle traffic behavior is measured in 15-minute increments. Three classes of vehicles were analyzed: cars, HDVs, and buses. Vehicles are randomly generated at the starting point of designated links within the traffic simulator across multiple time periods. USC Transportation closes specific streets and restricts turning movements during game-days. These restrictions are accounted for in the VISSIM network.

Tables 3 and 4 display results on average speed for the selected arterial road routes of 1 PM Rams and USC game-day during the 0-3 and 3-6 hour period, respectively. Results differ by route as well as time period and strategy. Increasing transit use leads to uniformly positive affect in traffic speed across the routes for the 0-3 hour period, but results in mixed results in the 3-6 hour period. Arrival smoothing for Rams games results in generally larger and consistently positive improvements in the 0-3 hour period that are not fully offset by added congestion in the earlier period. For USC games, shifting trips to the later period leads to a net increase in delay because the baseline arrival pattern is heavier in the earlier period. The 20% increase has a modest effect in all cases, and the 50% increase in transit has the greatest effect. As with the corridor analysis, removing vehicles from the network generates the most benefits.

Table 3. Arterial road simulation for Rams 1 PM games

Vehicle Travel Route	Baseline	Increase transit (20%)	% Change	Increase transit (50%)	% Change	Arrival Smoothing	% Change
0-3 hours							
Vermont NB To W. 37th EB	10.0	10.7	7.4%	11.6	16.4%	11.9	19.5%
I-110 To Figueroa NB	14.8	15.8	7.0%	17.8	20.5%	18.0	21.4%
Jefferson WB To Vermont SB	27.5	29.7	8.1%	31.5	14.7%	32.1	16.8%
Vermont SB	24.6	25.5	3.7%	27.1	10.2%	27.6	12.4%

3-6 hours							
Vermont NB To W. 37th EB	25.7	26.0	1.0%	26.0	1.0%	22.4	-12.9%
I-110 To Figueroa NB	26.3	26.6	1.1%	26.6	1.1%	22.2	-15.6%
Jefferson WB To Vermont SB	31.8	32.1	0.9%	32.1	0.9%	28.6	-9.9%
Vermont SB	30.6	31.0	1.4%	31.0	1.4%	26.6	-13.1%

Table 4. Arterial road simulation for USC 1 PM games

Vehicle Travel Route	Baseline	Increase transit (20%)	% Change	Increase transit (50%)	% Change	Arrival Smoothing	% Change
0-3 hours							
Vermont NB To W. 37th EB	10.5	11.3	7.3%	12.2	15.9%	12.5	18.7%
I-110 To Figueroa NB	19.3	21.1	9.3%	22.7	17.7%	22.8	17.8%

Jefferson WB To Vermont SB	23.7	24.7	4.4%	27.3	15.4%	28.4	20.0%
Vermont SB	22.7	23.9	5.4%	26.5	16.9%	26.9	18.5%
3-6 hours							
Vermont NB To W. 37th EB	25.7	25.2	-2.0%	25.2	-2.0%	17.3	-32.5%
I-110 To Figueroa NB	25.5	25.7	0.8%	25.7	0.8%	18.1	-29.0%
Jefferson WB To Vermont SB	29.7	27.9	-5.9%	27.9	-5.9%	18.6	-37.2%
Vermont SB	28.0	27.1	-3.2%	27.1	-3.2%	20.8	-25.6%

5. Conclusions

In this chapter, we utilize simulation modeling to estimate impacts of two mitigation strategies on regional and local traffic for weekend football games in Los Angeles Memorial Coliseum from 2016 to 2018: spreading arrivals and increasing transit use. Consistent with our earlier results, we find that strategies to smooth traffic should take into account the different spatial and temporal patterns the games generate. Rams attendees might be incentivized to arrive earlier with pre-game activities or preferential parking. USC volumes might be further spread by various parking policies. In all cases, travelers could benefit from information on anticipated traffic at the major nearby bottlenecks. The final chapter of this report presents our recommendations.

Chapter 7 Conclusions and Recommendation Policies on Game-day

Our results show that strategies for better management of major event traffic depend on the characteristics of the attendees, and in particular on arrival patterns. In the case of USC and Rams football games, we find that arrival patterns are very different. USC game arrivals are spread across many hours, hence simply adjusting arrival times alone does not reduce congestion. A better strategy for USC games is to greatly increase transit use. In contrast, Rams attendees tend to arrive within 1-2 hours of the game, generating a surge of demand that propagates through the network and increases in magnitude as it converges on the Coliseum area. In this case peak spreading makes sense.

There are many possibilities for better managing major planned events. In this chapter we offer a summary of a possible suite of strategies, as well as a more in depth discussion of parking policy.

7.1 Summary of management policies

In this section, we present a number of recommendations that reflect the findings of the study. Our recommendations are divided into six sections that aim to achieve six key outcomes: (1) A staggered arrival and departure pattern; (2) Better communication of game-day traffic; (3) better parking with differentiated pricing and improved communication; (4) more transit availability and encouragement; (5) and more car sharing.

Below is a detailed recommendation policy list: REDO THIS AS A SERIES OF BOXES

	Outcome		Recommendation
1	**Staggered arrival and departure pattern**	1.1	Share information on historic journey time and congestion levels with attendees well in advance of the game to enable attendee pre-planning
		1 .2	When parking is booked, provide a time when the vehicle should arrive. This could be combined with discounts and rebates – or hospitality vouchers - for those who arrive in early slots
		1.3	Consider expanding further the event so that the pre- or post- game attractions are more significant – such as children's performance or music mini-festival. (This could take up parking space which could be mitigated by parking recommendations below) Consideration should be given to changing the current business model. Games could be turned into more of a fair or festival – so there isn't just one key start time (kick off). So, children's attractions in one place and music venue elsewhere. This could bring opportunities to expand the hospitality offer
		1.4	To rival bring-your-own, provide early bird concession discounts and, especially, freebies (such as new food and drink products as part of product launch marketing)

			Realistically it would be hard to compete with low cost of BYO but catering with an ethical dimension (such as a partnership with Homeboy Industries) could persuade people to arrive early and spend
2	**Better Communication of Game-day Traffic**	2.1	Work with Caltrans to use electronic highway signs to give drivers advanced warning to avoid areas around congested time periods. This should be focused on all the identified bottlenecks in the weeks leading up to a game In the week before the game provide similar messages but with more urgent appeal
		2.2	Use electronic signage on roads approaching Metro stations to give live feeds on capacity status, such as *'Expo Metro parking full, use Sepulveda Expo/Bundy'*
		2.3	Establish a single, reliable, well-publicized, highly responsive Twitter feed for live information on congestion and on available parking spaces around the Coliseum and (especially) at Metro stations, but also traffic information and transit advice (such as 'Shuttle Bus from Union every 15 minutes. 10 minute wait time') Care needs to be taken to ensure it'd be delivered by a respected brand/ organization to which people would naturally turn (and delivered by a nimble team). All organizations involved in the game (including the team, Coliseum, transit agencies etc.) should have buy-in to the feed, direct their users to it for the duration of the game, and provide timely information and data to ensure it's the best it can be
		2.4	Partners responsible must share in-advance and real-time congestion data on road closures and other relevant actions - especially for Waze and Google Maps -
3	**Better Parking**	3.1	Differentiate parking pricing at structures to even out demand and discourage people from driving from one to the other
		3.2	Communicate expected and live parking availability (and cost) to avoid people driving from one to the other. Advanced booking should be a first resort
		3.3	Consider unified parking management on game-days between the parking providers (in this case USC and the Coliseum)
		3.4	Consider encouraging system of informal parking information by communicating links to information sources
4	**More Transit**	4.1	Double the frequency of the Silver Line on game-days
	Availability and Use	4.2	Offer game-day discounted Silver Line fare with ticket purchase. Link this offer to transit planner interface
		4.3	Consider expansion of the existing shuttle service from Union Station

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		4.4	Consider providing park and ride buses from locations where vehicles of longer distance travelers can be parked in large numbers.
		4.5	At ticket purchase, provide information about transit to the game before - and more prominently - than car parking. Consider providing link to a travel planner to show estimated time saves using transit
		4.6	Consider free transit pass with the game ticket. This would encourage transit use – including unplanned use (such as deciding to abandon a vehicle at a Metro station and take light rail without working out how to buy a ticket)
		4.7	Consider using Game Day signage at Metro stations such as, ‘Trains to USC Game every 10 minutes, 5 minute wait time’)
		4.8	Consider having tap out system to enable knowledge of system use at relevant sections of the transit network
5	**More car share**	5.1	Provide parking discount based on the number of people in the vehicle
		5.2	Consider ways to encourage car share such as competitions as run by Coachella
			https://2019.coachella.com/carpoolchella/
		5.4	Encourage pre-arranged ride-sharing – such as with messaging on tickets or working in partnership with a university or other to run a hackathon to arrange an app to provide such a service that mitigates risks associated with driving with strange

7.2 Parking policy

A manageable parking policy can help to stagger pre-game traffic patterns therefore reduce traffic congestion. The initial step in improving the game-day congestion problem surrounding the Coliseum is to collect improved data points on passenger vehicle activity exiting the parking structures and gates. A single transactional data point (for entry) cannot accurately serve as the basis for forecasting future demand patterns. The length of stay and passenger demographics are critical inputs for congestion optimization . Through the collection of these new data points, researchers will gain greater insights into the behaviors of drivers during congestion periods. We do not foresee the enhanced data collection effort to be a significant cost burden, because the hardware and software for passenger vehicle monitoring are already available .

We found that when parking demand reaches its peak, it does not meet the supply at the most popular parking structures during USC/Rams games. We recommend that parking demand be smoothed by establishing a method of detection to determine how full a car parking structure is and relaying live numbers to vehicle entrants. Our recommendation could be as simple as the installation of sensors in parking spaces (as already exists in some USC parking structures) and a dedicated twitter feed to relay the information from those sensors. Additionally, electronic signage on the exterior of the USC parking structures can display how many free parking spaces are available in any given parking lot (Figure 6.1).

Figure 6.1. Electronic signage along the exterior of the USC parking structures.

Image Source: https://images.app.goo.gl/ArRgZ5hHairyYiN77

Rams fans do not use USC parking structures due to prohibitive costs - they pay much more than USC patrons. Since there is insufficient parking at the Coliseum, Rams fans have to park elsewhere. USC could benefit from utilizing dynamic pricing so that USC Parking Garages are more attractive for Rams ticket holders. In addition, parking price is the same for all USC and Coliseum parking structures, but they are not equally attractive to game attendees. Drivers tend to park at locations most convenient to the entrance of the Coliseum. We recommend that event managers spread out the flow of passenger vehicles by differentiating the pricing scheme of USC/Coliseum parking garages, charging higher rates at parking structures closer to the Coliseum. Differential pricing should increase total parking revenue (Figure 6.2). We additionally recommend greater availability of advanced booking parking with incentives tied to advanced bookings. A more integrated parking system can result from the increased information through advanced bookings.

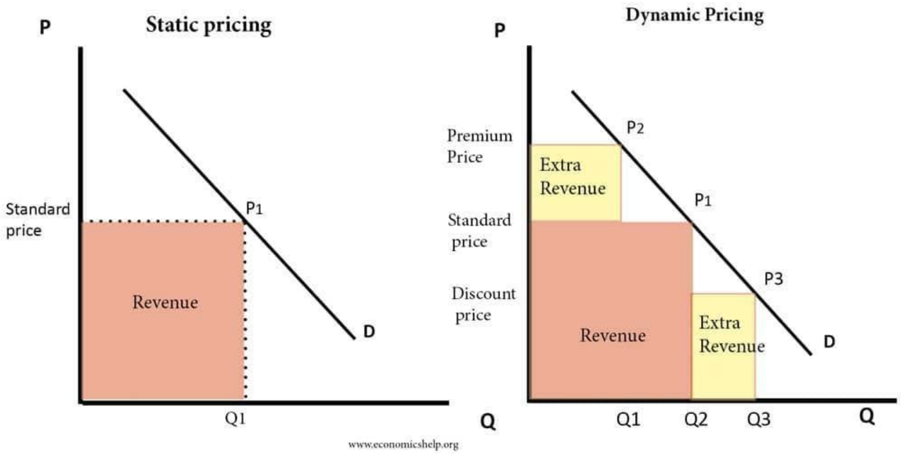

Figure 6.2. the fundamental economic concept of dynamic pricing as a method of maximizing revenue and thus, reducing congestion within our study area. Linear or fixed parking fees cause welfare loss.

Image Source: https://images.app.goo.gl/TtXspuDkMdhwMaJs7

Another parking strategy is to incorporate the informal parking market that exists on game days. A common practice in the neighborhoods surrounding the Coliseum is for local residents to park their own vehicles on the streets prior to the game in order to create off-street spaces within their lawns, driveways, and backyards. Private residents surrounding the Coliseum can then sell these spaces during peak parking demand periods on game-days. This market is quite fluid: spaces are offered depending on demand, and prices can vary from minute to minute. There is no data source for the size of this informal market. There are potential efficiencies in collaborating with this market.

Marketing-based partnerships between a collegiate sports organization and a city is not uncommon. Informal off-street parking markets have been transformed into solutions at the University of Michigan Stadium in Ann Arbor (Shoup, 2014) for example. This stadium, the largest in the United States, draws approximately 100,000 fans, on average, to each event. The city of Ann Arbor prohibits parking on lawns, but ordinances are purposely relaxed during game-days for the University of Michigan football team. Through the creation of a formal partnership with the informal off-street parking market, game managers could coordinate prices and reduce game-day congestion. Informal parking markets can be price mapped through the area to provide attendees with more information on parking options and reduce searching and queueing.

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