Economic Inquiry

SPORTING EVENTS, EMOTIONAL CUES, AND CRIME: SPATIAL AND TEMPORAL EVIDENCE FROM BRAZILIAN SOCCER GAMES

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Utilizing a novel data set of police reports that provides granular street- and vehicle-level information on vehicle thefts and robberies in the city of São Paulo, Brazil, we explore the impact of soccer games and their outcomes on crime and study its spatial heterogeneity. Estimates from a regression discontinuity design suggest that crime increases immediately after home games in streets that are within a tight radius from the stadiums. The effect is driven by vehicle thefts with popular car models being more likely to be targeted and is particularly salient after upset losses and derby games. (*JEL* D91, R12, Z2)

I. INTRODUCTION

The impact of sporting events on crime has generated a lot of attention and debates among scholars and policy makers. Recent literature draws upon a variety of empirical contexts and generally documents increases in criminal activities following sports games (Card and Dahl 2011; Kalist and Lee 2016; Marie 2016; Munyo and Rossi 2013; Rees and Schnepel 2009). On the other hand, the empirical prediction of the impact is inherently ambiguous due to potentially competing underlying mechanisms, and these channels tend to be underexamined in existing literature.

Marie (2016) theorizes three competing channels in explaining the game-day crime patterns, including (1) concentration of fans who could be prone to violence; (2) self-incapacitation of fans during the game; and (3) police displacement and re-positioning near the stadium. Taken together, these channels may lead to a disproportionate spatial and temporal distribution of criminal activities relative to the stadium and game time. One would need to examine microlevel evidence of such spatial and temporal heterogeneity in order to gauge the relative strength of these mechanisms. However, previous related studies either ignore the spatial aspects (Munyo and Rossi 2013; Rees and Schnepel 2009) or only consider limited aggregate-level evidence on the geographical heterogeneity of crimes (Marie 2016). Meanwhile, large concentration of fans also presents to perpetrators outside the stadium more potential targets, which raises a competing explanation as to who may have committed the post-game crimes, but prior studies are unable to explicitly test such possibility and instead assume that it is the fans attending the games who committed post-game crimes. Lastly, other than considering the deterrence effect of police presence, existing literature neglects to explore how perpetrators may also respond to the rational incentives for crime. These are the major gaps in the literature that our study aims to bridge.

Using a novel data set of police reports that provides granular street- and vehicle-level information on vehicle thefts and robberies in the city of São Paulo, Brazil, we study the microlevel spatial and temporal distribution of property crimes

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ABBREVIATIONS

DID: Difference-In-Differences
HDI: Human Development Index
RDD: Regression Discontinuity Design

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as a result of local soccer games.[1] We leverage the granular nature of our data to explore the above mentioned potential mechanisms in shaping the post-game crime patterns, with a particular interest in examining upset losses as a source of emotional cues in helping parse the channels.[2] To this end, we consider the home game outcomes relative to the pre-game expectations of three major professional soccer teams in São Paulo, including Palmeiras, São Paulo, and Corinthians, who play in their respective home stadiums located across the city. We draw our empirical evidence from soccer games in Brazil because (1) soccer is the most popular sport in Brazil, whose outcomes can plausibly result in significant emotional cues among fans; and (2) Brazil has been plagued with vehicle thefts and robberies with its large underground car parts (chop shop) industry. Our granular data set provides the street location of each crime incident, from which we obtain the corresponding geocodes, determine its distance to the stadium of interest, and match with the data on game outcomes and betting spreads by game days. Moreover, the data set contains the timestamp of each police report as well as the reported approximate time of the incident, both of which help us make reliable inferences regarding the timing of the crime incident relative to the game end. Finally, our data set also provides detailed characteristics of victims' vehicles, including make, model, and year. This allows us to further explore how perpetrators would respond to rational incentives due to the demand for popular car models in the underground chop shop industry.

Besides the granular property crime data, our empirical setting is also unique because (1) alcoholic beverages are not allowed in Brazilian stadiums, which helps isolate the impact of games and game outcomes[3]; (2) each team that we consider has its own home stadium, which again helps rule out confounding factors due to shared facilities[4]; and (3) most Brazilian soccer games do not have free live broadcasting, and there is no live broadcast in the city where the game is played,[5] which means that by pinpointing the exact locations of the crimes, we are able to identify the crime counts plausibly related to fans attending the live games.

Our study focuses on game-day vehicle thefts and robberies within a tight 3-mile radius of each stadium. We utilize a regression discontinuity design (RDD), similar to Davis (2008), Auffhammer and Kellogg (2011), and Carr and Packham (2019), that examines changes in crime distributions immediately before and after the end of each game. Our estimates suggest that property crimes tend to increase after home games in streets that are within a 2-mile radius from the stadiums, with particularly salient effect within the 1-mile radius and after upset losses or derby games. For instance, we find an over 60% increase in total property crimes within the zero to 1-mile distance ring following the home team's upset loss. We find the impact mostly driven by thefts with popular car models being more likely to be targeted. There is also evidence of heterogeneity in responses to upset losses across fan bases of different teams, through which we deduce that these incidents are likely committed by fans attending the games. Our results are robust to a series of sensitivity tests involving alternative distance rings, different cutoff points and placebo tests utilizing nongame days, reassigned stadiums and away games. Overall, our findings lend strong support toward the dominance of the fan concentration effect and provide suggestive evidence that emotionally cued perpetrators of nonviolent property crimes could still respond to rational incentives for crime compared with their violent crime counterparts.

Our paper makes the following two contributions to the literature. First, to our knowledge, we are the first to explore microlevel spatial and temporal heterogeneity in the impact of sporing events and the resulting emotional cues on crime. Munyo and Rossi (2013) are similar in scope to

1. We will use the phrase property crimes interchangeably with vehicle thefts and robberies. In addition, the vehicle thefts and robberies in our study are defined as thefts and robberies of vehicles, that is, carjacking, which do not include thefts and robberies of possessions in the cars.

2. It is worth noting that although not formally modeled in related literature, derby games, where teams from the same city play against each other, can often generate intense animosity among rival fans and affect their behaviors. Our study also explores derby games as a separate source of emotional cues.

3. Since June 15, 2008, vendors in the vicinity of the stadiums in the municipality of São Paulo have been further banned from selling alcoholic beverages during game time (for detailed information, see the São Paulo city law number 14726).

4. It is also rare for stadiums in Brazil to hold other events, such as concerts, during the soccer season.

5. Each of the 38 rounds of the Brazilian Professional Football League has ten games, and only two of them are selected to have free live broadcasting. However, there is no live broadcast in the city where the game is being played (except for pay-per-view). See the following link for a more detailed explanation: https://rodrigomattos.blogosfera.uol.com.br/2016/10/16/emissoras-rivais-explicam-por-que-nao-concorrem-com-globo-pelo-brasileiro/.

our study as they consider the impact of upset wins and losses from two major Uruguayan soccer teams on local property crime counts. However, their focus is on the temporal aspect of the crime while we study both the temporal and spatial heterogeneity in crime responses.[6] The spatial aspect of our study design allows us to more plausibly identify fans' reactions to games and game outcomes, disentangle the potential mechanisms and heterogeneity in their responses, and explicitly test whether the crimes are committed by fans at the games as opposed to perpetrators outside the stadium strategically taking advantage of the games and attendance. Marie (2016) considers geographical variation in the distribution of crimes following soccer games in London. But the involved crime data are at much more aggregated borough level (ranging from 6 to 33 square miles in sizes) and thus do not pinpoint the exact location of the crime.

Second, previous empirical studies within the economics of crime literature seek to document evidence from the field for either the rational incentive-based or the behavioral emotion-based explanations for crime (see Levitt and Miles (2006) and Chalfin and McCrary (2017) for reviews of the related literature). The police reports employed in our study provide detailed information on victims' vehicle characteristics including make, model, and year, which can be linked to the demand for popular vehicle models in the underground chop shop industry. This offers a unique opportunity to explore whether and how *emotionally cued* perpetrators would respond to incentives for crime, particularly in terms of their reactions to expected benefits of crime (e.g., targeting popular versus unpopular car models). Indeed, our results offer suggestive evidence that following upset losses, theft perpetrators, who we demonstrate are likely the fans attending the games, tend to respond more to rational incentives for crime than their robbery counterparts. Our research thus complements and provides additional evidence toward a growing strand of economics of crime literature that explores gains from rational crime based on spot market prices for the target commodity, for example, Reilly and Witt (2008), Brabenec and Montag (2014), Shoukry (2016), Draca, Koutmeridis, and Machin (2018), and Kirchmaier et al. (2019).

6. In addition, Munyo and Rossi (2013) only consider a total of 86 games over an 8-year span, while our sample includes 456 games from three major teams in São Paulo between 2007 and 2017.

II. CONCEPTUAL FRAMEWORK

In this section, we outline a conceptual framework that will guide our empirical investigation. We first follow Marie (2016) and characterize the overall impact of soccer games on crime into the following three potentially competing channels: (1) concentration of fans who could be prone to violence; (2) self-incapacitation of fans during the games; and (3) police displacement and repositioning near the stadium. Specifically, concentration of potentially violent fans would unequivocally predict an increase in crimes in the areas where fans congregate. Self-incapacitation effect implies a decrease in crimes while fans are watching the game. Lastly, the displacement effect entails that as police force is re-positioned closer to or at the stadium to avoid collisions between fans of different teams, locations that are subsequently disproportionately unattended will likely see an increase in crimes. Therefore, we expect that the number of *post-game* crimes on a home game day near the home team's stadium will not be affected by the self-incapacitation effect and will instead depend on whether the police displacement or the fan concentration effect dominates.[7] An increase in post-game crimes in the immediate vicinity of the home stadium would imply the dominance of the fan concentration effect—congregation of fans leads to post-game criminal activities in areas close to the stadium despite the heavy presence of police *at* the stadium.

While the temporal and spatial variations of crime incidents relative to the game time and home stadium of interest can help establish the baseline evidence of the underlying channels, game characteristics such as game outcomes and derby games can act as emotional cues to fans and potential perpetrators, which can not only corroborate but also offer additional insights toward the baseline mechanisms.[8] In our context, we first adopt a reference-dependent preferences framework similar to Köszegi and Rabin (2006),[9] where soccer fans derive emotional cues from the

7. On an away game day, both the lack of fan concentration and self-incapacitation (e.g., fans travel to away city to support their team) would predict no increase in post-game crimes in areas near the home stadium. We test such prediction in Appendix F since our main empirical analysis focuses on post-game crime patterns on home game days.

8. In Appendix D, we also discuss the role of game attendance as a way of corroborating the fan concentration effect.

9. Recent studies adopting a similar reference-dependent preference framework have considered bunching of athlete performance (Allen et al. 2016), live game attendance

outcome of a given soccer game of their home team, relative to their pre-game expectation proxied by the betting odds published by sports books.[10] The game outcome may disagree with the expectation, resulting in an upset win (i.e., unexpected win) or an upset loss (i.e., unexpected loss). Since the three teams that our study focuses on tend to be the favorites in their home games, our data set only affords three upset wins during the sample period and thus does not allow us to precisely test loss aversion.[11] We will instead focus on upset losses as a source of emotional cues and compare their impact to wins (regardless of pre-game expectations) as well as all other game outcomes. Additionally, home team's losses, particularly upset losses, can result in frustration among supporters. Consistent with the frustration-aggression hypothesis that links frustration with violence and the impact of incidental emotions, frustrated fans may be more likely to commit violent crimes (Munyo and Rossi 2013), especially since soccer fans may already represent a nonrandom sample that is more prone to violence (Marie 2016). If (some) fans respond to these game outcome-triggered emotional cues by committing crimes, loss aversion together with frustration-aggression hypothesis would predict an increase in crimes under upset losses. Such prediction on post-game criminal activities upon upset losses is supported by recent empirical evidence from studies such as Card and Dahl (2011) and Munyo and Rossi (2013) and will corroborate the fan concentration effect.

Although not formally modeled in prior literature, our study also exploits derby games as a separate (albeit secondary) source of emotional cues. In soccer, derby games refer to games that are played by teams from the same city. As teams from the same city often represent different neighborhoods and potentially different socioeconomic classes of the fan bases, derby games can generate intense animosity among both players and rival fans. Given the importance and intensity of derby games, we expect an even larger concentration of home team supporters and potentially away team supporters as well around the home stadiums on derby-game days, which will in turn magnify the fan concentration effect.

It is worth noting that prior studies tend to assume that perpetrators responsible for post-game crimes are the fans attending the games. Since the congregation of fans on game days presents to perpetrators more potential targets for criminal activities, a competing hypothesis is that the perpetrators may possibly come from criminals who did not actually attend the games but took advantage of additional supply of their criminal targets and game outcomes, for example, criminals outside the stadium may anticipate crimes to be easier to conduct after upset losses when victims are more distracted. As a result, congregation of fans can positively affect post-game crimes through concentration of potentially violent fans and potential victims at the same time, and either channel would predict the impact to be stronger in areas closer to the home stadium. By examining the heterogeneity of the impact across different stadiums and variations in the socioeconomic characteristics of the relevant neighborhoods, our study aims to explicitly test whether the crimes are committed by fans at the games as opposed to perpetrators outside the stadiums strategically taking advantage of the games and attendance. This will shed further light toward the validity of the fan concentration effect.

Lastly, crimes of interest in our study include both vehicle thefts and robberies. Compared to thefts (nonviolent property crimes), vehicle robberies (violent property crimes) presumably require less careful planning and may be more susceptive to offenders' impulses. We thus expect the impact of games and game outcomes to differ for theft and robbery perpetrators. Since our granular crime data offer detailed accounts of victims' vehicle characteristics including make, model, and year, we can shed more light toward such behavioral differences. Specifically, we hypothesize that robbers may be less selective in terms of the popularity of victims' vehicle models while theft perpetrators may have specific targets of car models based on their popularity in the underground chop shop industry. Our prediction is consistent with existing empirical literature on how perpetrators respond to rational incentives of crime, that is, the price-theft hypothesis. As examples, Reilly and Witt (2008) confirm a correlation between the price of audiovisual goods and domestic

(Coates, Humphreys, and Zhou 2014), family violence (Card and Dahl 2011), judge behavior (Eren and Mocan 2018), and consumer tipping behavior (Ge 2018).

10. Pawlowski, Nalbantis, and Coates (2018) show that there is a strong correlation between the average objective reference points derived from bookmakers' betting odds (e.g., money line or point spread) and individual fans' subjective reference points or perceived game uncertainty (e.g., as solicited in survey questions like "how likely do you think there will be a home win in the upcoming game?").

11. Loss aversion refers to the idea that people may react more to losses than to similarly sized gains. In our setting, this would mean that fans may react more (in terms of post-game crime incidents) to upset losses compared to upset wins.

TABLE 1
Home Game Attendance, Outcomes, and Betting Spreads

Teams	Attendance	Games	Win	Tie	Loss	Spread	Upset Loss
Corinthians	28,350.47	145	88	36	21	−3.98	14.5%
Palmeiras	20,806.22	143	79	33	31	−3.97	19.5%
São Paulo	23,261.27	168	100	40	28	−4.25	16.1%

Note: Attendance and *Upset Loss* columns are based on the average attendance and betting spreads, respectively. *Upset Loss* is defined as a loss when the home team is predicted to win. Proportion of *Upset Loss* games are relative to all games.

burglaries, and Brabenec and Montag (2014) and Sidebottom, Ashby, and Johnson (2014) both document a positive relationship between metal prices and metal theft volumes.

III. DATA

A. Game Characteristics and Betting Spreads

In line with Edmans, Garcia, and Norli (2007) who suggest that in order to conduct an effective study using sporting event outcomes as an instrument for emotions, the sports team of interest must enjoy a large fan base, our study focuses on the three most popular professional soccer teams in the city of São Paulo, including Palmeiras, São Paulo and Corinthians.[12] Another advantage of our team choices that helps rule out confounding factors due to shared stadiums is that the three teams play in their own home stadiums located in different neighborhoods across São Paulo. Additionally, Corinthians completed a stadium move from Pacaembu to the Corinthians Arena in 2014, offering a potential natural experiment to further study the impact of soccer games on local crimes.

Our sample contains 456 home games in the Brazilian Professional Football League (Campeonato Brasileiro) from three major soccer clubs in São Paulo from 2007 to 2017, including 444 Serie A games and 12 Serie B games.[13] For each game, we have detailed information about the game date, start and end time, final score, stadium played and attendance.[14] The pre-game expectations for game outcomes are derived using betting odds published by Pinnacle Sports, a major sports book. Following related literature, we choose to utilize the game time betting odds, which were posted approximately at the time when the actual game started, because they provide the most updated information on the overall prediction of the game outcomes. Unlike betting data utilized in Card and Dahl (2011) or Ge (2018) that rely on predicted point spreads, the betting spreads in our study are calculated by subtracting the amount of dollars paid for each dollar bet on the away team winning from the amount paid for each dollar bet on the home team winning.[15] We define home team's upset loss as a loss when it is predicted to win the game. In Appendix G, Supporting information, we also consider the implication of incorporating draws into upset losses.

Table 1 provides the summary statistics of home game attendance, game outcomes, and the corresponding pre-game betting spreads. Here, we observe that Corinthians, Palmeiras and São Paulo share similar likelihood of winning a home game with Corinthians edging the other two teams in terms of attendance. The average betting spreads show that the home teams are more favored to win their games, and the last column

12. Santos FC is another popular local professional soccer team in São Paulo. However, the club is based and plays its home games in the city of Santos, approximately 50 miles away from São Paulo. We therefore exclude Santos FC from our analysis. In addition, We also exclude Portuguesa, another professional soccer team based in São Paulo, from our analysis because (1) the team mostly played in the second division league (Campeonato Brasileiro Serie B) during our sample period; and (2) a survey conducted by DataFolha in the municipality of São Paulo suggests only 0.3% local support for the team.

13. Palmeiras played in Serie B in 2013 for a total of 19 home games, with 12 of them played in the municipality of São Paulo. The remaining home games were distributed across four municipalities: three in Itu-SP; two in Londrina-PR; one in Presidente Prudente-SP; and one in Campo Grande-MS.

14. The data on Brazilian Professional Football League game fixtures and outcomes are collected from http://www.bolanaarea.com and www.worldfootball.com.

15. We also re-estimate our empirical specifications using probability of winning derived from the betting spreads and obtain identical results. Similar to Card and Dahl (2011) and Ge (2018), we regress the realized game outcomes (using a dummy for wins) on the pre-game predicted probability of winning and confirm a positive relationship ($\hat{\beta} = 0.820$, $p < 0.001$, $R^2 = 0.03$). The coefficient is also statistically indistinguishable from 1 ($p = 0.404$).

suggests that an upset loss of the home team is relatively uncommon.[16]

B. Vehicle Thefts and Robberies

We obtain police reports on vehicle-related property crimes in the city of São Paulo from *Secretaria de Segurança Pública de São Paulo*. The two types of property crimes that our study focuses on are vehicle thefts and vehicle robberies, which account for close to 80% of all vehicle-related crimes in our sample. Note that the vehicle thefts and robberies in our study are defined as thefts and robberies of cars, that is, carjacking, which do not include thefts and robberies of possessions in the cars. Compared to thefts, robberies involve criminals interacting with victims who were at the scene using force, intimidation and coercion. Criminals also often employ guns, knives or other weapons in robbery incidents.

Our vehicle theft and robbery data are at hourly- and street-level. For each vehicle robbery or theft, the data set provides detailed information regarding the time of the police report, the approximate time of the incident (in 6-hour intervals), the street location of the incident, and the corresponding vehicle characteristics, including make, model, and year. We are able to obtain the geocodes of each incident's street location by utilizing the geocoding API platform from Google Maps, from which we compute the straight line distance of each incident to the home stadiums of our three local soccer teams of interest.[17]

In order to match with the data set on game characteristics, we restrict our attention to vehicle-related property crimes from 2007 to 2017. After dropping observations of thefts and robberies that either do not have complete street locations or cannot be geocoded (approximately 7% of the raw data set), we obtain 126,565 observations for property crimes that happened on home game days in São Paulo. Figure 1 presents a choropleth map of game day vehicle-related property crimes in the city center (aggregated to neighborhood-level) over our sample period as well as the stadium locations with the corresponding closest metro stations, where darker shades indicate higher neighborhood-level crime counts. Overall, our stadiums of interest are located in relatively safe neighborhoods and are well served by the São Paulo Metro, with the exception of Morumbi Stadium.

Figure 2 provides a visualization of the summary statistics of the city-wide game day property crime counts before and after the games as well as the distribution of crimes within a 3-mile radius from our stadiums of interest.[18] Both thefts and robberies seem more likely to take place after, rather than before, the games, possibly because most games take place in the evenings. We also observe that compared to the 2- to 3-mile ring, the increase in crimes is more accentuated in areas closer to the stadium. It is worth noting that although there are more robberies overall, thefts outnumber robberies in each of the three distance rings before and after the games.

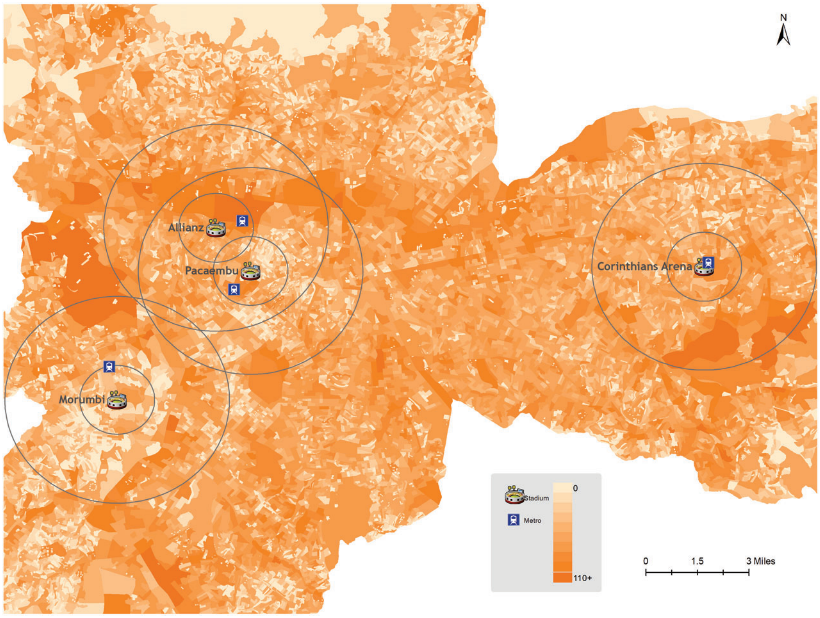
Figure 3 plots the kernel density distribution of the police report time of crime incidents by distance to stadium. We focus on 10 hours before and after the game start. Relative to the 1–2 miles and 2- to 3-mile radius, we observe a clear rise in the relative distribution of crime incidents within the 0- to 1-mile radius. In addition, we utilize detailed data on socioeconomic outcomes at the neighborhood (census tract) level from the 2010 Brazilian census to assess the neighborhoods surrounding our stadiums of interest. The relevant average neighborhood characteristics, including the average monthly per-capita income, Gini coefficient, life expectancy, schooling, and Human Development Index (HDI), are presented in Table 2. Overall, we find that all three teams have their stadiums located in relatively wealthy neighborhoods, with the exception of Corinthians' new stadium (Corinthians Arena), where Corinthians played since 2014. In Section VI.C, we will formally explore the potential heterogeneity in the responses to game outcomes across different fan bases given their local neighborhood socioeconomic characteristics.

16. In our sample, the home team is predicted to win 445 games and lose 11 games with no predicted ties. Our main empirical specifications compare local crime impact from upset losses (76 games in total) against all other game outcomes (380 games in total including 11 predicted losses). Out of the 369 nonupset loss games where the home team is predicted to win, the distribution of the realized game outcomes is as follows: home team won 264 games (71.5%) and tied 105 games (28.5%) with fairly even distribution of game outcomes across all three teams.

17. As a robustness check, we also compute the walking distance of each crime incident to the home stadiums utilizing the Distance Matrix API from Google Maps. We present in Appendix G a robustness check using walking distance as an alternative criteria for computing the distance of each incident to the stadiums.

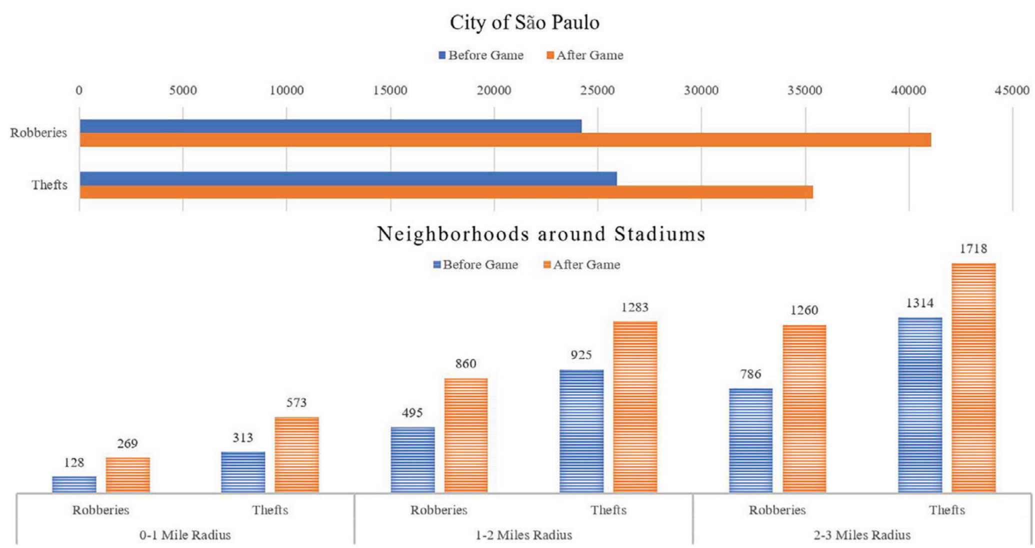
18. The choice of distance rings up to 3 miles is based on the São Paulo police's maximum dispatch distance of 5 km or approximately 3 miles. In addition, the size of each ring is based on the fact that the distance from the nearest metro station to three of the stadiums (except for Morumbi Stadium) is well within 1.5 km or approximately 1 mile.

FIGURE 1
Game Day Property Crimes, Stadium Locations, and Metro Stations.



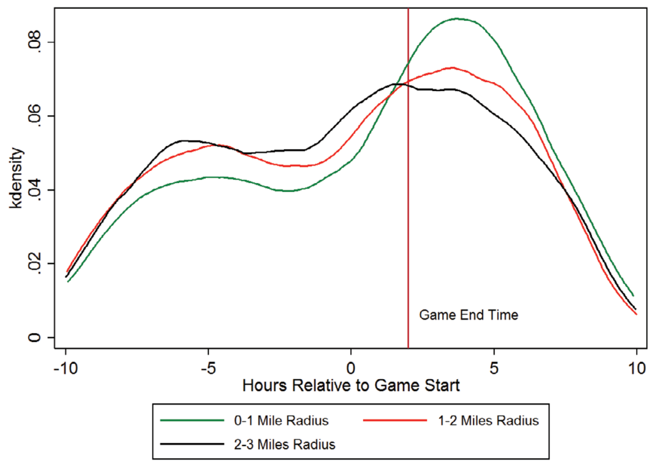
Note: The choropleth map focuses on the city center of São Paulo and is based on the home game day neighborhood/census tract-level aggregated counts of vehicle-related property crimes from 2007 to 2017. Each stadium of interest is presented with the closest metro station and the corresponding 1-mile and 3-mile distance rings. Neighborhood-level crime count thresholds are determined using geometric interval classification

FIGURE 2
Game Day Vehicle Thefts and Robberies.



Note: The figure presents the city-wide game day property crime counts before and after the game as well as the distribution of crimes within a 3-mile radius from our stadiums of interest

FIGURE 3
Density Distribution of Property Crimes.



Note: The figure plots the kernel density distribution of the police report time of crime incidents by distance to stadium, focusing on 10 hours before and after the game start

TABLE 2
Neighborhood Characteristics by Stadiums

	Pacaembu	Morumbi	Allianz	Corinthians Arena
Monthly per capita income (in BR-reals)	6,312.68	13,802.96	5,108.69	576.5
Gini coefficient	0.55	0.72	0.49	0.44
Life expectancy	81.91	82.41	81.59	74.19
Schooling	12.25	10.46	11.55	9.83
HDI	0.96	0.93	0.94	0.71

Note: Data for neighborhood-level socioeconomic outcomes are from the 2010 Brazilian census. Neighborhood is defined based on the census tract surrounding a given stadium of interest.

IV. EMPIRICAL STRATEGY

A. Motivation

To motivate the discussion of our empirical strategy, we first examine the effect of distance to stadium on crime by comparing home game days against away game days and nongame days. Specifically, we aggregate crime incidents to daily-level and consider the following difference-in-differences (DID) model:

$$(1)\quad Crimes_{id} = \beta_0 Ring_d^1 + \beta_1 Home_i + \beta_2 Away_i + \beta_3 Ring_d^1 \times Home_i + \beta_4 Ring_d^1 \times Away_i + \Psi_{ymw} + u_{id}$$

where $Crimes_{id}$ denotes the total number of vehicle thefts or robberies on a given day i relative to distance ring d from the home stadiums of the local soccer teams. We focus on the area in the immediate vicinity of our stadiums of interest, proxied by a 1-mile distance ring, and $Ring_d^1$ is an indicator variable for whether the crime took place within the 0- to 1-mile distance ring from the stadiums with the baseline being the rest of the city. $Home_i$ and $Away_i$ indicate whether a given day sees any of the local soccer teams in São Paulo having a home and away game, respectively.[19] The term Ψ_{ymw} adds year, month, and day of the week fixed effects. Given that our dependent variable contains counts of daily crimes, we estimate Equation 1 using a negative binomial model and present the results in Table 3.

19. Note that for nongame days, we randomly assign a stadium of interest to each of the nongame day and consider the crime patterns in the corresponding distance rings.

TABLE 3
Impact of Game and Distance-to-Stadium on Property Crimes: Full Sample

	(1) Crime	**(2) Crime**	**(3) Theft**	**(4) Robbery**
Ring_d^1	−4.380***	−4.439***	−4.111***	−4.822***
	(0.017)	(0.026)	(0.032)	(0.041)
Home	0.024**	0.019	0.057***	−0.009
	(0.012)	(0.012)	(0.015)	(0.016)
$\text{Home} \times \text{Ring}_d^1$		0.099**	0.126***	−0.038
		(0.039)	(0.048)	(0.066)
Away	0.017	0.012	0.056***	−0.023
	(0.013)	(0.013)	(0.016)	(0.017)
$\text{Away} \times \text{Ring}_d^1$		0.111***	0.087*	0.076
		(0.041)	(0.051)	(0.069)
Observations	1,343	1,343	1,343	1,343

Note: The dependent variable is the total number of vehicle robberies or thefts. $Ring_d^1$ is an indicator variable for whether the crime took place within the 0- to 1-mile ring from the stadiums (versus the rest of the city). *Home* and *Away* indicate whether there is a home and away game, respectively, on a given day. All specifications are estimated using negative binomial model and use year, month, and day of the week fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

Overall, the positive and significant coefficients on the interaction terms suggest that crimes, especially thefts, increase on home and away game days within 1 mile around the stadium compared to nongame days. Curiously, the results in Table 3 suggest that home game days do not necessarily show larger effects than away game days as the relevant coefficients are not statistically different from each other, despite the larger concentration of fans and the supply of vehicles surrounding the stadiums. In addition, the results also point to an increase in crimes on away game days. We believe that these counterintuitive DID estimates can be explained by the fact that the nongame days in our full sample have a more balanced distribution across different days of the week, while the home and away game days center on Saturdays and Sundays. As presented in Appendix A, once we restrict all game and nongame days to weekend days during the soccer season, crimes surrounding the stadiums are no longer affected on away game days.[20]

In order to further investigate whether home game days have a differential impact on vehicle thefts and robberies compared to away game days, we take advantage of the granular nature of our data and aggregate crime counts based on 30-minute intervals and consider crimes taking place within the 0- to 1-, 1- to 2-, and 2- to 3-mile distance rings surrounding the stadiums of interest. We restrict our data to a small interval surrounding the end of the game on game days (home and away) and estimate the following generalized DID equation separately for each ring:

$$(2)\quad Crimes_{idt} = \alpha + \sum_{t=-6}^{6} \lambda_t Time_{it} + \beta Home_i + \sum_{t=-6}^{6} \omega_t (Time_{it} \times Home_i) + \epsilon_{idt},$$

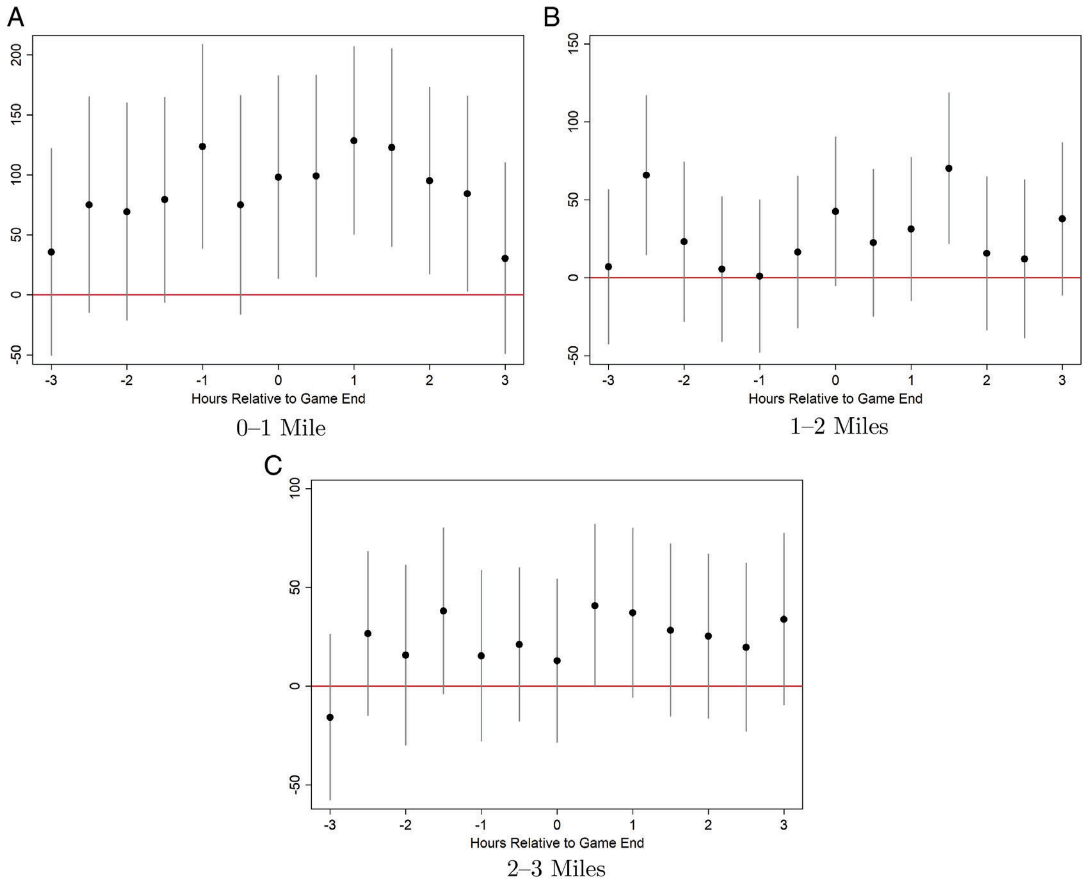
where $Crimes_{idt}$ is the total number of property crimes in ring d within a 30-minute interval t on game day i. $Home_i$ is a dummy variable that identifies whether game day i sees a game played in São Paulo or an away team city. $Time_{it}$ identifies each 30-minute interval t within 3 hours before and after the game end on game day i. Finally, ω_t identifies the DID effect for each interval t, that is, it compares the difference in crimes between home and away game days at each 30-minute interval t relative to the baseline $t = -7$.

We plot the estimated coefficients on ω_t in Figure 4, where time 0 denotes the game end time. We notice from these coefficient difference plots a larger increase in crimes committed following the end of home games compared to the end of away games. Interestingly, this result is driven by thefts, which is consistent with the results presented in Table 3 related to the 0- to

20. In addition, we present in Appendix A a similar daily-level DID analysis and compare the crime counts in each of the 1-mile distance rings within a 3-mile radius from the stadiums of interest. The results confirm that compared to away game or nongame days, game days see more crimes within the 0- to 1-mile distance ring from the stadiums of interest, and they are primarily driven by thefts.

FIGURE 4

Differential Impact of Home vs. Away Game Days on Property Crimes.



Note: The figure plots the estimated coefficients on ω_t in Equation (2), where the dependent variable is the total number of vehicle thefts and robberies. The presented confidence intervals are at 90% level. Time interval is 3 hours (in 30-minute intervals) before and after the game end

1-mile ring.[21] Overall, as we further explore the temporal and spatial dimensions of our granular crime data, we learn that there is a larger increase in crimes on home game days compared to away game days, and the impact is driven by crimes taking place within a small time interval surrounding the game end and within the immediate vicinity of the stadiums. Both results suggest that the increase in crime counts is likely due to a large concentration of fans and a large supply of vehicles surrounding the stadiums during home games. These stylized findings have thus motivated us to focus on a small time interval close to the end of each game on home game days to parse the impact of games and their outcomes on crime. In the next subsection, we describe our main econometric specifications that allow crime to vary flexibly across time in order to better identify the impact of home games and their outcomes on crime and test potential mechanisms in explaining the observed impact.

21. Additional coefficient difference plots for thefts versus robberies are available upon request.

B. Econometric Specifications

In order to identify the effects of home games on property crimes, we adopt a RDD, known interchangeably as an interrupted time-series model, similar to those employed in recent studies including Davis (2008), Auffhammer and Kellogg (2011), Anderson (2014), Schneider (2018), and Carr and Packham (2019).[22] Our empirical model's running variable is the time distance to the soccer games. We construct the running variable by aggregating the number of property crimes within a 30-minute interval of the running variable. We then restrict our analysis to a 10-hour window around the end of each game, which we define as the cutoff point of our model. As discussed in Section III.B, our vehicle theft and robbery data contain the timestamp of the police report for each incident with reported approximate time of the incident (in 6-hour intervals). In order to identify post-game crimes, we thus restrict our attention to those incidents that were reported to the police after the games with the reported approximate incident time in the same evenings as the games.[23] Lastly, we identify the impact of home games on property crimes by taking advantage of the variation in (1) the distance of the incident to the stadium; and (2) home game outcomes.

Utilizing detailed information on the locations of crimes combined with the descriptive evidence presented in Section IV.A, we define three distance rings around the stadium: 0–1 mile; 1–2 miles; and 2–3 miles. If crimes are related to soccer games, then we expect that fans attending live games, who are more exposed to the emotional cues due to the games, are more likely to commit post-game crimes. If this is the case, then crimes happening closer to stadiums will disproportionately increase after the games end. Furthermore, if frustration as a result of upset losses affects crimes, we should expect an even larger increase in property crimes near the stadium following the home team's upset loss compared to other game outcomes.

Specifically, following Carr and Packham (2019), we measure the impact of soccer games on property crimes by estimating the following baseline RDD:

(3)

$$Crimes_{idt} = \alpha + \gamma D_{it} + \sum_{n=1}^{4} \beta_n (r-c)^n + \omega_i + \epsilon_{idt},$$

where $Crimes_{idt}$ is the total number of vehicles robbed or stolen on game day i, within a given distance ring d from the stadium of interest and a 30-minute interval t of the running variable r, which is defined as the minutes (combined into half-hour slots) around the cutoff point c based on the game end time. D_{it} is a dummy variable identifying the end of each game, and γ thus captures the impact of the end of the game on crime. We weigh the time distance to the end of each game by including β_n, which captures closeness to the threshold, and we restrict our sample such that $r \in [-20, 20]$. Our RDD specification, therefore, captures how a time-varying function of crimes changes within two time intervals: 10 hours before and 10 hours after the end of each game, which is equivalent to 20 30-minute intervals before and after the end of each game since the crimes are aggregated based on 30-minute intervals.[24] We apply this nonparametric estimation to better isolate the impact of games on crime, and we estimate Equation 3 separately for each of the three distance rings d, that is, 0 to 1-mile, 1- to 2-mile, and 2- to 3-mile rings, where we allow the running variable to vary quadratically, cubically and quartically.[25] Finally, we also add game fixed effects (ω_i) and capture the error term in ϵ_{idt}.[26]

22. In Appendix A, we present an alternative spatial DID model and discuss the corresponding results. The overall findings are qualitatively similar, but we prefer RDD for our main empirical specifications because it allows us to account for the rich time-distance relation provided in our granular property crime data.

23. Two features of our data mitigate the concerns about not having the exact crime incident time. First, we examine thefts and robberies involving vehicles, which, compared to other types of properties, are more likely to be insured. Therefore, as insurance companies demand owners to immediately report their losses to the police in order to make the insurance claims, the crimes we study are likely to be reported immediately once the owners incur losses. Second, even uninsured owners have an incentive to immediately report their losses to the police because they will otherwise be responsible for any future incidents involving their stolen or robbed vehicles.

24. Note that our time intervals are of 30 minutes across the cutoff by construction, and we therefore have a balanced sample and manipulation around the cutoff is less of a concern. The evidence against manipulation around cutoffs is also confirmed by the density test that we conduct which rejects the possibility of manipulation with 99% level of confidence. We discuss in details about the robustness of our bandwidth and cutoff choices in Appendices B and C, respectively.

25. All specifications yields statistically significant results. We choose to have our running variable varying quartically because in this setting our estimation yields the best fit based on adjusted R^2.

26. Following Auffhammer and Kellogg (2011), we also estimate the following modified specification of our main RDD model:

(4)

$$Crimes_{idt} = \alpha + \lambda Ring_d^j + \gamma D_{it} + \sum_{n=1}^{4} \beta_n (r-c)^n + \rho Ring_d^j \times D_{it} + \sum_{n=1}^{4} \kappa_n \left(Ring_d^j \times (r-c)^n \right) + \omega_i + \varepsilon_{idt},$$

Similar to Gonzalez-Navarro (2013), we estimate Equation 3 using a negative binomial regression rather than a Poisson regression model because our dependent variable contains the counts of crimes that are nonnegative but also with a large amount of zeros, implying that the variance of the number of crimes is larger than its average.[27] However, our results are not driven by the model choice as our findings are qualitatively similar when we use ordinary least squares (OLS) or Poisson regression. Lastly, we examine the heterogeneous effects across games by adding to Equation 3 variables related to emotional cues and their interaction terms with the post-game indicator variable D. Specifically, we test separately for each distance ring whether upset losses and derby games accentuate the increase in post-game crimes. In Appendix D, we also investigate whether games' attendance affects the number of crimes by interacting the game attendance measure with the post-game indicator variable D.

The main advantage of employing a data set that enables us to explore both spatial and temporal dimensions is that the former allows us to rule out confounding variables related to the timing of games, while the latter permits us to adopt an RDD that offers us flexibility to identify the changes in crime that vary with the running variable. The ideal but infeasible experiment to identify the treatment effect of soccer games on crime would require us to simultaneously observe the number of crimes close to each stadium for each time interval on a game day versus a nongame day. Therefore, to empirically analyze the impact of soccer games on crime, we need to make the following two assumptions about the crime trends and confounding variables and acknowledge that there may be some caveats to the interpretation of our results. First, we need to assume that the crime trends in neighborhoods surrounding the stadium of interest would not change abruptly after the counterfactual game end time if there were no soccer games taking place. Second, we also need to assume that the confounding variables related to game days that affect crime patterns do not change discontinuously after the game end.

On the other hand, the advantage of our RDD is that it allows us to analyze a small time interval surrounding the end of the game so that we can relax the strength of our assumption on the crime trends varying smoothly across the cutoff on nongame days. In addition, our detailed police report data, which measure the distance of each crime to the stadium of interest, allow us to rule out the possibility that the confounding variables affecting crimes that are changing simultaneously with the end of each game are driving our results. To do so, we show that crimes taking place farther from the stadium do not change discontinuously after the game end.

V. BASELINE RESULTS AND ROBUSTNESS CHECKS

A. *Baseline Results*

We first estimate Equation 3 for each of the distance rings from the stadiums and present the estimated coefficients in Table 4.[28] Here, we consider the overall evidence of property crimes that combine vehicle-related thefts and robberies. Since our RDD specification is estimated using negative binomial model, the coefficients thus indicate the natural log of the expected count as a function of the independent variables. We find statistically significant increases in the post-game property crime counts in the 0- to 1- and 1- to 2-mile distance rings but not in the 2- to 3-mile rings. Specifically, the average number of property crimes increases *after* the game by 57.6% and 22.6% within the 0- to 1- and 1- to 2-radius rings, respectively.[29] The relatively large percentage responses in crimes are also expected in our

where $Ring_d^j$ equals one if the 1-mile distance ring d corresponds to the 0–1 mile ($j = 1$) or 1- to 2-mile ($j = 2$) ring, and zero otherwise (i.e., the 2- to 3-mile distance ring). We then separately estimate Equation (4) for each of the distance ring j and deliver the following findings. First, when comparing the 0- to 1-mile ring to the 2-to 3-mile ring, we find $\hat{\rho} = .54$ ($SE = .21$). Second, when comparing the 1- to 2-mile ring to the 2- to 3-mile ring, we find $\hat{\rho} = .30$ ($SE = .15$). Both results are similar to our baseline RDD results as presented in Table 4 where we restrict the sample to each distance ring.

27. Given the large number of zeros in our crime count data, we also consider using a zero-inflated negative binomial model with the post-game dummy variable as the predictor of the excess zeros. However, results from the Vuong (1989) test suggest that we adopt the negative binomial model instead.

28. The differences in the number of games across different distance rings are due to the fact that there may not be post-game vehicle thefts or robberies in neighborhoods near the stadiums on some game days. We perform a robustness check by restricting all distance rings to those 290 games with robbery and theft incidents within the 0- to 1-mile ring and the results are similar.

29. Since our estimation is based on a negative binomial model, similar to Gonzalez-Navarro (2013), the interpretation of our coefficients in terms of percentage terms is given by $e^{\hat{\beta}} - 1$. For example, in Table 4, the coefficient on *Post-Game* for the 0- to 1-mile ring is given by $e^{0.455} - 1$, or approximately 57.6%.

TABLE 4
Impact of Games on Property Crimes

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-game	0.455**	0.204*	−0.098
	(0.188)	(0.116)	(0.100)
Observations	11,310	16,302	17,394
Number of games	290	418	446

Note: The dependent variable is the total number of vehicle thefts and robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

context because most neighborhoods near the stadiums are comparatively safe and generally witness infrequent vehicle thefts and robberies.[30]

As an additional exercise, we also estimate our model using OLS with the same time interval of 10 hours before and after the game end and separately fit our property crime counts with a fourth-order polynomial for each of the distance rings. The corresponding RDD plots, presented in Figure 5 with solid lines representing the 95% confidence intervals, confirm our results in Table 4. Overall, our baseline results suggest that, even without considering the emotional cues due to upset losses or derby games, soccer games can lead to an increase in post-game property crimes, and the effect is spatially heterogeneous and attenuates as we move away from the stadium. These baseline findings thus confirm the dominance of the fan concentration effect—congregation of fans leads to post-game criminal activities in areas close to the stadiums despite the heavy presence of police *at* the stadium.

As hypothesized in Section II, home teams' upset losses may also be relevant in explaining crimes near the stadiums. Specifically, we believe that upset losses may trigger emotional cues that frustrate supporters who, in response to their anger, become more prone to committing crimes. To investigate this possibility, we estimate a specification similar to Equation 3 but include a dummy variable for upset losses and its interaction term with the post-game indicator variable. The results presented in Table 5 indeed corroborate our hypothesis and suggest that compared to locations between 2 to 3 miles from the stadiums, property crime counts would increase on streets closer to the stadiums (within 2 miles from the stadium) after home teams' upset losses.[31] Once again, the 0- to 1-mile distance ring shows the largest impact with approximately 62.3% increase in post-game crimes upon upset losses. Note by construction, our specification here compares the local crime impact from upset losses against all other game outcomes, rather than testing loss aversion (i.e., comparing upset losses against upset wins). In Appendix E, we formally test loss aversion and discuss the implications and limitations, where we also document more crime counts within the 2-mile radius of the stadiums following upset losses compared to wins (mostly wins as predicted). In Appendix F, we show that upset losses from away games do not result in more post-game crimes near the home stadiums, confirming that the game outcome-driven emotional cues lead to increases in local crimes likely through the concentration of home team supporters during home games.

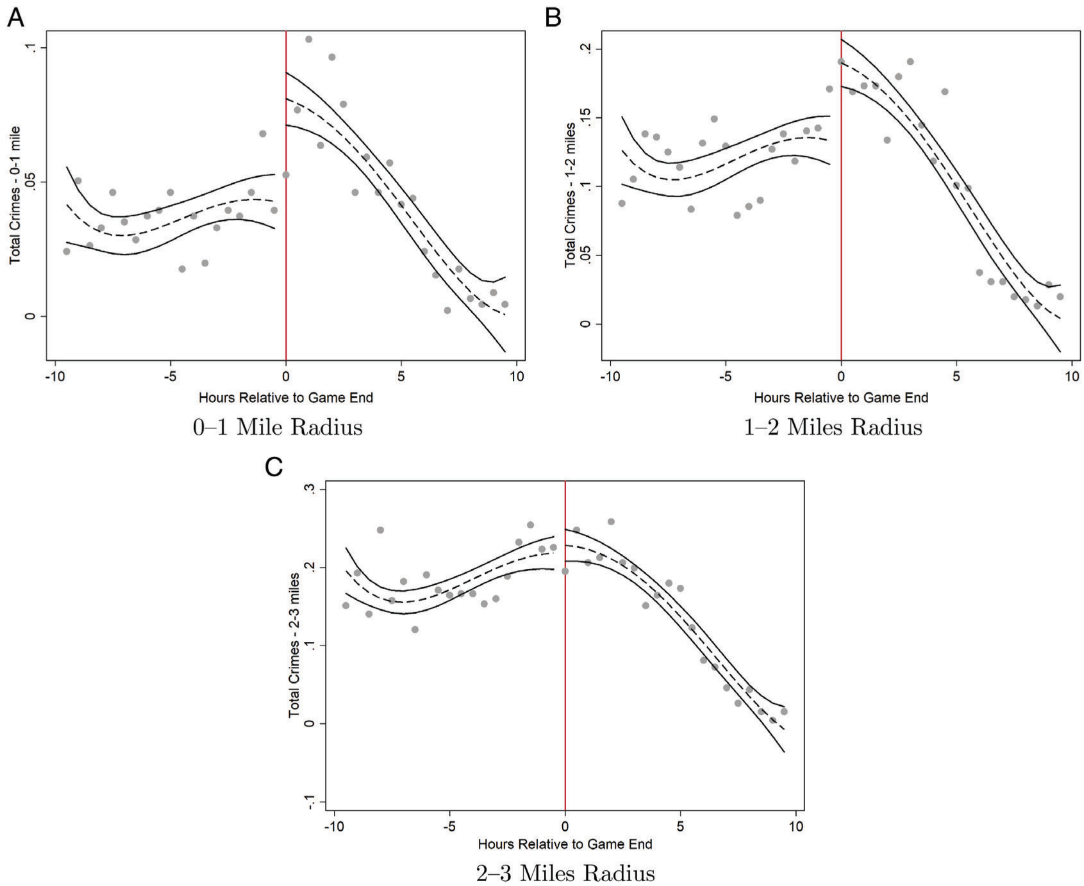
B. Robustness Checks

To assess the robustness of our baseline findings, we conduct a number of sensitivity and placebo tests. First, since our crime data only contain the time of the police report and the approximate time of the incident (in 6-hour intervals), that is, not the direct account of the actual time of the crime, we seek to make inferences about the timing of the crimes relative to the game end time by conducting several further checks on the cutoff choice. We then consider a series of placebo tests involving nongame days, reassigned stadiums, and away games of the home teams. Lastly, we perform a range of additional robustness checks including utilizing walking distance as an alternative measure for distance rings and considering probability of winning as an alternative measure for pre-game expectations and draws as a separate realized game outcome. To streamline the presentation in the main text, we describe in details

30. For property crimes taking place within 10 hours prior to the end of each game, the average number of crimes, per 30 minutes, in the 0- to 1-, 1- to 2-, and 2- to 3-mile rings are 0.037, 0.12, and 0.18, respectively.

31. It is worth noting that the findings on upset losses still cannot rule out the possibility that perpetrators outside the stadium strategically take advantage of game outcomes and commit thefts and robberies on fans distracted by home teams' upset losses. We will further test this possibility in Section VI.C.

FIGURE 5
Impact of Games on Property Crimes.



Note: The vehicle robbery and theft counts are fitted with a fourth-order polynomial using OLS over a time interval of 10 hours (in 30-minute intervals) before and after game end. Solid lines represent the 95% confidence intervals

the designs and findings from these robustness checks and placebo tests in Appendices C, E, and F, respectively. Overall, the results from the robustness checks are similar to our main findings and become insignificant under all placebo tests.

VI. MECHANISMS

A. Thefts versus Robberies

Our property crime data include both vehicle thefts and robberies. Since they are inherently different crime types with different criminal motives, required skills, and legal punishments, we explore whether the impact of upset losses elicits different responses from these crime types by estimating our main specification of emotional cues separately for thefts and robberies. The upper and lower panels of Table 6 report the estimated coefficients with the dependent variable for each specification being the counts of vehicle thefts and robberies, respectively. The overall directions and statistical significance of the coefficients in the upper panel are similar to those in Table 5, whereas most of the coefficients in the lower panel are not statistically significant. This suggests that much of the impact of game outcomes and the resulting emotional cues is driven by crimes related to vehicle thefts.

Compared to robberies, thefts can be more discreetly committed as they require no direct interactions with the victims and entail a relatively

TABLE 5

Impact of Upset Losses on Property Crimes

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-game	0.373*	0.163	−0.094
	(0.191)	(0.118)	(0.101)
Upset loss	−0.581	−0.027	−0.083
	(0.485)	(0.301)	(0.214)
Post-game × Upset loss	0.472**	0.256*	−0.021
	(0.216)	(0.132)	(0.109)
Observations	11,310	16,302	17,394
Number of games	290	418	446

Note: The dependent variable is the total number of vehicle thefts and robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

TABLE 6

Impact of Upset Losses on Vehicle Thefts versus Robberies

Thefts	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-game	0.666***	0.252*	0.019
	(0.229)	(0.147)	(0.127)
Upset loss	−1.424*	0.293	−0.592
	(0.750)	(0.781)	(0.390)
Post-game × Upset loss	0.548**	0.267*	−0.046
	(0.247)	(0.159)	(0.135)
Observations	9,321	14,547	16,107
Number of games	239	373	413
Robberies	**Crime 0–1 Mile**	**Crime 1–2 Miles**	**Crime 2–3 Miles**
Post-game	−0.133	−0.097	−0.278*
	(0.337)	(0.189)	(0.161)
Upset loss	−0.885	−0.393	−0.112
	(0.849)	(0.352)	(0.263)
Post-game × Upset loss	0.320	0.333	0.033
	(0.440)	(0.234)	(0.179)
Observations	5,694	11,973	14,586
Number of games	146	307	374

Note: The dependent variable is the total number of vehicle thefts or robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

lower legal punishment if caught. The stronger impact of upset losses on thefts compared to robberies is thus consistent with our hypothesis that perpetrators respond to rational incentives. The spatial and temporal distributions of the impact also confirm that the response is likely as a result

TABLE 7

Impact of Derby Games on Property Crimes

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-game	0.289	0.127	−0.169*
	(0.191)	(0.117)	(0.101)
Derby	0.304	0.017	−0.390
	(0.757)	(0.324)	(0.239)
Post-game × Derby	0.959***	0.517***	0.519***
	(0.230)	(0.137)	(0.122)
Observations	11,310	16,302	17,394
Number of games	290	418	446

Note: The dependent variable is the total number of vehicle thefts and robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. *Derby* is a dummy variable that indicates if a game is played by two of the three local soccer teams in São Paulo. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

of the game outcomes, implying that thefts were likely committed by fans who were at the games because we would otherwise expect more thefts being reported when the games are in session.[32]

B. Derby Games

We also consider derby games as a separate source of emotional cues (apart from upset losses) and examine their impact on local crimes.[33] In our context, we classify derby games as those played by two of the three local soccer teams in São Paulo, and we adopt an RDD specification similar to that presented in Section V.A to investigate their impact on post-game crime counts. The estimates from Table 7 indicate that derby games result in an increase in post-game criminal activities relative to nonderby games, and curiously, such effect is present throughout the three distance rings from the stadiums, with the largest impact again within the 0- to 1-mile ring (representing a drastic over 160% increase in post-game vehicle-related property crimes).[34] While our derby game findings suggest that post-game crimes can correlate with emotional cues

32. Another possibility is that most of the stolen vehicles belong to the fans and they do not realize the thefts until after the game. This explanation however is not supported by the finding that the theft counts are related to upset losses.

33. In Appendix E, we explore the interaction between game outcomes and derby game status and find that the impact of derby games does not depend on game outcomes.

34. Corroborating findings from Section VI.A, we also find that the derby game effect is mainly driven by thefts rather than robberies. These results are available upon request.

TABLE 8
Heterogeneity across Fan Bases: Impact of Games

Corinthians	**(1) Crime 0–1 Mile**	**(2) Crime 1–2 Miles**	**(3) Crime 2–3 Miles**
Post-game	0.607*	−0.028	−0.105
	(0.318)	(0.173)	(0.163)
Observations	4,407	5,616	5,577
Number of games	113	144	143
Palmeiras	**Crime 0–1 Mile**	**Crime 1–2 Miles**	**Crime 2–3 Miles**
Post-game	0.474*	0.239	0.041
	(0.257)	(0.190)	(0.166)
Observations	4,251	5,421	5,577
Number of games	109	139	143
São Paulo	**Crime 0–1 Mile**	**Crime 1–2 Miles**	**Crime 2–3 Miles**
Post-game	−0.578	0.684**	−0.298
	(0.614)	(0.276)	(0.194)
Observations	2,652	5,265	6,240
Number of games	68	135	160

Note: The dependent variable is the total number of vehicle thefts and robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

generated through the importance and intensity of the games, the increase of crimes in the 2- to 3-mile ring contradicts the results presented in Tables 4 and 5. One possible explanation is that derby games, regardless of their outcomes, can evoke strong emotions and animosity among fans from both sides, who live in different neighborhoods in São Paulo. This could lead to increases in post-game crimes even in neighborhoods further away from the game venues.[35]

C. Heterogeneity across Fan Bases

So far we have shown an overall impact of soccer games and their outcomes on local property crimes, which suggests that changes in crime patterns may be driven by supporters attending the games according to the fan concentration effect. On the other hand, a competing explanation can be that criminals outside the stadiums (who do not attend the games) adapt their strategies to game outcomes, for example, criminals outside the stadiums may anticipate that crimes are easier to conduct after upset losses when victims are more distracted. To test such possibility, we examine the potential heterogeneity of the impact across different stadiums and variations in the socioeconomic characteristics of the relevant neighborhoods since our empirical evidence is drawn from three local soccer teams who play in four different home stadiums over our sample period.

To this end, we first re-estimate our baseline specification on post-game property crimes separately for each of our three teams of interest with the estimates presented in Table 8. Compared to the baseline results from Table 4, these estimates suggest that the increases in post-game property crimes within the 1-mile radius of the stadiums are reflected in both Corinthians and Palmeiras games, and for São Paulo's games, the effect is mostly seen in the 1- to 2-mile distance ring. In other words, the baseline impact does not seem to be driven by games of a specific team. We then re-estimate our RDD specification individually for each team, taking into account the impact of upset losses. The results presented in Table 9 do not show increases in vehicle thefts and robberies after upset home games of Palmeiras and São Paulo. However, we do observe a significant increase in vehicle-related property crimes within the 2-mile radius of the stadium after Corinthians' upset losses. Again, the impact is

35. Another potential explanation for the observed derby game effect could be due to the influx of away team fans' cars surrounding the stadium despite the strict capacity control on away team fans during derby games. Unfortunately, we do not have the relevant supporting data to test these explanations.

TABLE 9
Heterogeneity across Fan Bases: Impact of Upset Losses

Corinthians	**(1) Crime 0–1 Mile**	**(2) Crime 1–2 Miles**	**(3) Crime 2–3 Miles**
Post-game × Upset loss	0.776**	0.645***	−0.024
	(0.352)	(0.211)	(0.186)
Observations	4,407	5,616	5,577
Number of games	113	144	143
Palmeiras	**Crime 0–1 Mile**	**Crime 1–2 Miles**	**Crime 2–3 Miles**
Post-game × Upset loss	0.422	0.045	0.125
	(0.321)	(0.217)	(0.181)
Observations	4,251	5,421	5,577
Number of games	109	139	143
São Paulo	**Crime 0–1 Mile**	**Crime 1–2 Miles**	**Crime 2–3 Miles**
Post-game × Upset loss	−0.282	−0.073	−0.169
	(0.576)	(0.293)	(0.203)
Observations	2,652	5,265	6,240
Number of games	68	135	160

Note: The dependent variable is the total number of vehicle thefts and robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Separate estimates on the baseline terms *Post-Game* and *Upset Loss* are available upon request. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

most salient within the 1-mile ring from the stadium with an estimated increase in crime counts of approximately 120%. Overall, our results here indicate that while the baseline results on post-game crime responses may be generalized to teams across the city, the impact of upset losses is likely driven by Corinthians fans. We will thus focus on Corinthians fans to continue the investigation regarding the identity of the perpetrators.

We next explore a natural experiment during our sample period—in 2014 Corinthians moved from their former stadium, Pacaembu, into their new stadium, the Corinthians Arena. It is worth noting that these two stadiums are more than 15 miles apart. When further separating Corinthians home games into those played in the old and new stadiums, we intriguingly find similar post-upset loss increases in property crimes in the vicinity of the respective stadium.[36] In other words, these results suggest that the post-game (particularly post-upset loss) property crimes seemed to have moved with Corinthians' home stadiums.

Moreover, we utilize detailed data on socioeconomic outcomes at neighborhood level from the 2010 Brazilian census to assess the average income levels for the neighborhoods surrounding our stadiums of interest. As noted in Section III.B and Table 2, all three teams have their stadiums located in wealthy neighborhoods, with the exception of Corinthians' new stadium (Corinthians Arena). Thus, the similar post-upset loss impact from Corinthians' new and old stadiums, despite their different neighborhood socioeconomic characteristics, make us deduce that it is more likely to be the emotionally cued fans who committed crimes rather than distracted fans being targeted by (rational) criminals outside the stadiums. The cued supporter explanation is further supported by the anecdotal reputation of Corinthians fans being particularly zealous about their team and potentially more prone to violence.[37] Our findings thus far imply that the

36. We find that upset losses increase property crimes by 113% and 136% in the old and new stadiums, respectively. The separate estimates for Corinthians' new and old stadiums are available upon request.

37. For example, we searched the State Court of Justice's online database of all lawsuits filed in the State of São Paulo and found that thefts and robberies involving members of the most famous organized supporters of each club add to 16 for Corinthians fans (i.e., "Gaviões da Fiel"); 6 for Palmeiras fans (i.e., "Mancha Verde"); and 2 for São Paulo fans (i.e., "Torcida Independent"). The database can be accessed at https://www.tjsp.jus.br/. In addition, in a 2012

observed increase in post-game crimes may result from a potentially violent fan base likely to be susceptible to emotional cues and commit crimes.

Finally, if it were perpetrators outside the stadium targeting distracted fans, then we would expect a larger impact in stadiums where there is a larger influx of vehicles parked in nearby neighborhoods on game days, which could cloud the role of upset losses in instigating criminal activities. In our case, all stadiums except for Morumbi (the home stadium of São Paulo soccer club) have nearby metro stations within 1.5 km, which makes it easier for fans to take public transit to games. The fact that Morumbi is less conveniently connected by public transit implies that São Paulo fans are more likely to drive their personal vehicles to attend the games in Morumbi. As seen in Table 9, we do not observe statistically significant increases in property crimes following São Paulo's upset losses in Morumbi stadium,[38] which provides further evidence suggesting that large supply of vehicles from potentially distracted fans (from upset losses) does not seem to attract additional car thefts or robberies.[39]

D. Vehicle Models and Popularity

Brazil suffers from a large underground car parts (chop shop) industry, and if property crime perpetrators respond to rational incentives (benefits) for crime, we would expect a larger proportion of victims' vehicles belonging to models popular in the underground car parts market. Our data allow us to explore the make, model, and year of the vehicle being stolen or robbed. We divide the victims' vehicles into popular versus unpopular types.[40] We then re-estimate our RDD specification separately based on distance to stadium, vehicle popularity, and crime type (thefts versus robberies), and Tables 10 and 11 report the estimated coefficients for the 0–2 miles and 2- to 3-mile radius, respectively.[41] While we do not find evidence for the impact of game outcomes on crime across vehicle types in the 2- to 3-mile radius, interestingly, the interaction terms on *Post-Game* and *Upset Loss* in columns 2 and 3 of Table 10 indicate that within the 0- to 2-mile distance ring, upset losses may lead to an increase of thefts of popular vehicles. In addition, although we do not observe an overall response of robbery incidents to upset losses as discussed in Section VI.A, once we explore the underlying heterogeneity by decomposing the cases by vehicle popularity, results from Table 10 in fact indicate an increase in robberies of unpopular cars following home teams' upset losses. These results thus suggest that while both crime types may be driven by emotional cues, vehicle thieves appear to act "rationally" by responding to incentives from the underground chop shop industry and targeting popular car models, whereas robbers are more likely to be impulsive and would consider unpopular vehicles as their targets that are not as valuable in the underground chop shop market. It is also worth noting that 55% of vehicle related crimes in our sample involve popular cars, which means that our results are unlikely driven by the dominance of either popular or unpopular models in the sample. On the other hand, there could still be rational explanations for perpetrators' preference toward popular cars even when emotionally cued. For instance, robberies may be more difficult to carry out for specific car models compared to thefts. Our data unfortunately do not allow us to further parse between the behavioral and rational explanations.

VII. DISCUSSION AND CONCLUSIONS

Our paper aims to leverage the granular nature of our property crime data to study the impact of soccer games and their outcomes on the spatial and temporal distributions of local crimes. Our baseline empirical results lend strong support toward a disproportionate increase in post-game property crimes in neighborhoods closest to

survey by Pluri Consultoria, Corinthians was rated as having the most "fanatic" fan base in the state of São Paulo. See the following link for details: https://www.otempo.com.br/superfc/futebol/segundo-pesquisa-atletico-tem-a-terceira-torcida-mais-fanatica-do-brasil-1.730338.

38. In Table A13 in Appendix G, we also present a similar analysis that excludes Morumbi stadium and reach identical conclusions.

39. It is worth noting that if criminals were targeting distracted fans, there would also be a stronger effect for teams whose supporters are on average wealthier. Unfortunately, we could not obtain systematic information on fans' purchasing power, particularly that of Corinthians fans', because Corinthians is the most popular team across almost all neighborhoods in São Paulo, that is, Corinthians supporters do not necessarily come from a narrow set of neighborhoods where we can confidently identify the average socioeconomic characteristics of the fans.

40. The popular car models include: Fiat Palio, Volkswagen Gol, Volkswagen Fox, Fiat Siena, Chevrolet Corsa, Chevrolet Celta, Fiat Strada, Volkswagen Voyage, Ford Fiesta, and Fiat Uno. This list is based on a 2015 study conducted in São Paulo by Ituran, a company specializing in vehicle tracking services in Brazil.

41. Due to lack of property crime observations with vehicle characteristics, we combine incidents within 0–1 mile and 1–2 miles into one distance ring (i.e., 0- to 2-mile ring).

TABLE 10
Vehicle Thefts and Robberies by Vehicle Popularity: 0−2 Miles

	(1) Robbery Popular	(2) Robbery Unpopular	(3) Theft Popular	(4) Theft Unpopular
Post-game	0.016	−0.228	0.173	0.866***
	(0.331)	(0.240)	(0.202)	(0.306)
Upset loss	−0.777	0.844	−0.497	−1.443
	(1.857)	(1.827)	(1.120)	(1.866)
Post-game × Upset loss	0.396	0.657**	0.454**	0.141
	(0.424)	(0.324)	(0.224)	(0.345)
Observations	5,889	9,516	11,037	7,722
Number of games	151	244	283	198

Note: The dependent variable is the total number of vehicle thefts or robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

TABLE 11
Vehicle Thefts and Robberies by Vehicle Popularity: 2−3 Miles

	(1) Robbery Popular	(2) Robbery Unpopular	(3) Theft Popular	(4) Theft Unpopular
Post-game	0.027	−0.001	0.259	−0.194
	(0.327)	(0.240)	(0.211)	(0.327)
Upset loss	0.318	2.673	−0.696	0.549
	(1.254)	(8.239)	(0.967)	(2.319)
Post-game × Upset loss	0.123	−0.053	−0.326	0.268
	(0.379)	(0.271)	(0.228)	(0.332)
Observations	6,318	9,750	11,193	7,254
Number of games	162	250	287	186

Note: The dependent variable is the total number of vehicle thefts or robberies. *Post-Game* is a dummy variable that represents hours after the end of the game. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being the game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis.
***Significant at 1%; **significant at 5%; *significant at 10%.

the home stadiums. A leading explanation is through the dominance of the fan concentration effect over police displacement near the stadium, possibly due to police deployment concentrating at the game venue to prevent collisions between home and away fans and thus neglecting areas even slightly away from the stadium. The timing of the reported vehicle-related property crimes and the heterogeneous effects of upset losses across fan bases of different teams further confirm that the crimes are likely committed by fans who attended the home games, rather than the perpetrators not at the games taking advantage of the game outcomes and a larger supply of targets.

Our study further explores upset losses as a source of emotional cues in instigating post-game crimes and finds suggestive but somewhat inconclusive evidence. We document a significant spatial heterogeneity of property crime incidents upon home teams' upset losses. For thefts, the effect is most salient in street locations that are within the 1-mile radius from the stadiums, attenuates as one moves to the 1- to 2-mile distance ring, and disappears in the 2- to 3-mile ring. For robberies, the effect is not present within any of the distance rings unless one differentiates by vehicle popularity. On the other hand, much of the upset loss effect seems to be driven by Corinthians fans and may not be generalized to other fan bases, which is consistent with Corinthians fans' reputation of being particularly zealous about their team. Additionally, we consider derby games as a separate source of emotional cues and find them to result in increases in crimes, particularly thefts, across all three distance rings. Such finding is in contrast to the spatially concentrated impact of upset losses, which we attribute to the strong emotions and animosity generated by derby games for both home and away fans living across different neighborhoods of São Paulo.

Moreover, we also find suggestive evidence that perpetrators of different crimes may respond to upset losses differently—while robbery offenders may commit crime due to impulses, vehicle thieves seem to nonetheless respond to rational incentives for crime by targeting popular car models that are highly sought after in the underground car parts market. Yet, it remains an open ended question as to why emotionally cued fans, primarily Corinthians fans, would steal cars to vent out their frustration and still behave rationally to target popular car models. One possible explanation based on anecdotes could be the presence of organized crime group members among Corinthians fans. Although our data limitations admittedly do not allow us to test such possibility or further rule out other potential rational explanations, the behavioral aspects of our findings complement related empirical literature that focuses on establishing evidence of how perpetrators respond to the gains from rational crime due to spot market prices of the target commodity, for example, Reilly and Witt (2008), Brabenec and Montag (2014), Shoukry (2016), Draca, Koutmeridis, and Machin (2018), and Kirchmaier et al. (2019).

It is worth noting that the magnitudes of our main RDD estimates seem to be noticeably larger compared to several related studies. For example, we find an over 62.3% increase in total property crimes upon upset losses within the 0- to 1-mile distance ring.[42] We attribute the contrast to the detailed and granular nature of our data that allows us to examine the impact of games at street- and hourly-level, whereas previous studies rely on much more aggregated crime data at borough (e.g., Marie 2016), jurisdiction (e.g., Munyo and Rossi 2013; Rees and Schnepel 2009), or city level (Kalist and Lee 2016). In fact, the estimates from our DID analysis as shown in Table 3, where we aggregate all crimes to daily-level and compare the 0- to 1-mile ring against rest of the city, suggest that relative to a nongame day, home game days see an overall 10.4% increase in property crimes (14.4% increase in thefts) within the 0- to 1-mile radius from the home stadium. With an average home game attendance of approximately 25,000 supporters in our sample, our aggregated daily-level evidence is in fact in line with the findings from studies such as Marie (2016). On the other hand, the contrast also implies that by only considering aggregate daily-level data, previous studies may have underestimated the localized crime impact of sporting events and their outcomes in areas close to the game venues.

Our findings provide important policy implications regarding the distribution of law enforcement during mega events. While police concentration at the game venues may help prevent fan collisions during and following the games, frustrated fans may travel to areas with lower police presence, including unattended areas within a tight radius from the stadiums, and commit crimes. The effect can be even more salient and spread out following derby games. This calls for a more strategic positioning of police force, particularly during high-stakes games such as derby games, games with potentially unexpected outcomes, or games involving teams known for their violent fans.

Lastly, our study also opens up several avenues for future research. For instance, detailed records of police deployment during sporting events could help precisely identify the police displacement effect. Additional data on police reports of vandalism and assaults as well as explorations of exogenous shocks to perpetrators' rational incentives, for example, the introduction of Lojack to select car models and geographic regions as in Gonzalez-Navarro (2013), will offer further opportunities to parse the rational and behavioral channels behind our findings. Finally, there is anecdotal evidence of targeted incidental emotions where frustrated sports fans would vandalize properties containing visual hints of the opponent team, for example, a car that shares the same color as the opponent's team color. One could thus extend our study design to explore such kind of more nuanced behavioral changes following the emotional cues due to sporting events and their outcomes.

42. This is in contrast to studies such as Marie (2016) who finds an approximately 7% increase in property crimes in the game-hosting borough in London for every 10,000 additional soccer fans on a game day, or Kalist and Lee (2016) who also document approximately 7% increase in vehicle thefts following an NFL home game. On the other hand, our findings are consistent with Munyo and Rossi (2013) that study the temporal impact of soccer game outcomes in hourly intervals using an event study design and document a 70% jump in crimes 1 hour after the game end.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1: Supporting information