Emotional Cues and Crime: Spatial and Temporal Evidence from Brazilian Soccer Games*

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Abstract: This paper studies the effects of emotional cues and rational incentives on crime. Using police reports that provide granular information on vehicle robberies and thefts in the city of São Paulo, Brazil, we explore the impact of game outcomes of local soccer teams on crime and examine its spatial heterogeneity. Our estimates suggest that crime increase 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.

Keywords: emotional cues, crime, spatial distribution, regression discontinuity design
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1 Introduction

Seminal work by Becker (1968) theorizes a framework of rational crime, where the decision to commit a crime depends on whether the resulting expected economic benefit outweighs its cost. While Becker's model provides tremendous insights into the incentive aspect of criminal activities, its predictions do not hold well for many criminal behaviors, especially those triggered by emotions (Garoupa, 2003). Economists have understandably become interested in studying the behavioral attributes of crime, particularly regarding the role of emotional cues. Kőszegi and Rabin (2006) propose a reference dependent preferences framework with gain-loss utilities, where reference points are derived from consumers' recent rational expectations about outcomes and emotional cues are driven by deviations from expectations. Since sports games often provide well-defined outcomes and pre-game expectations based on betting odds, they offer an excellent field data source for testing for the empirical evidence of reference dependent preferences. Under the backdrop of this growing strand of literature,[1] there has been an increasing number of studies in the economics of crime literature that examine the impact of emotional cues as a result of upset sports game outcomes (e.g., Rees and Schnepel 2009; Card and Dahl 2011; Munyo and Rossi 2013; Marie 2016; Lindo et al. 2018).

Conditional on how fans react to sports game outcomes relative to their pre-game expectations, the empirical prediction of the impact of sporting events on crimes is still inherently ambiguous, as Marie (2016) points out, due to three potentially competing channels: 1) concentration of fans who could be prone to violence; 2) self-incapacitation of potential violent fans during the games; and 3) police displacement and re-positioning near the stadium. Additionally, congregation of fans may also present to perpetrators more targets for their criminal activities. Taken together, these potential mechanisms may lead to a disproportion-

[1]Recent examples of empirical evidence of reference dependent preferences using field data from sports include bunching of athlete performance (Allen et al., 2016), live game attendance (Coates et al., 2014), family violence (Card and Dahl, 2011), judge behavior (Eren and Mocan, 2018) and consumer tipping behavior (Ge, 2018).

ate spatial and temporal distribution of criminal activities relative to the stadium and game time. One would thus need to examine micro-level evidence of the spatial and temporal heterogeneity of criminal activities following the sports games in order to fully gauge the relative strength of these mechanisms. However, previous related studies either ignore the spatial aspects (e.g., Rees and Schnepel 2009; Munyo and Rossi 2013) or only consider limited aggregate-level evidence on the geographical heterogeneity of crimes (e.g., Marie 2016). In addition, other than considering the deterrence effect of police presence, existing literature also neglects to explore how perpetrators respond to the interaction between rational incentives for crimes and game-driven emotional cues. These are the major gaps that our study seeks to bridge.

Using a novel dataset of police reports that provides granular street- and vehicle-level information on vehicle robberies and thefts in the city of São Paulo, Brazil, we study the micro-level spatial and temporal distribution of both violent and nonviolent property crimes as a result of emotional cues. Specifically, consistent with a standard reference dependent preferences framework, the emotional cues that we consider are based on the home game outcomes relative to 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 also been plagued with vehicle thefts and robberies with its large underground car parts (chop shop) industry. The granular nature of our dataset provides the street location of each crime incident, from which we obtain the corresponding geocodes, determine the distance to the stadiums of interest and match with the data on game outcomes and betting spreads by game days. Moreover, the dataset contains the time stamp of each police report as well as the reported approximate time of the incident, both of which help one make reliable inferences regarding the timing of the crime incident relative to game time. Finally, our dataset also provides detailed characteristics of victims' vehicles, including year, model, make and color. This allows us to further explore how these emotion-driven vehicle thefts and robberies would respond to rational incentives for criminal activities due to the demand for popular car models in the underground chop shop market.

In addition to the granular and detailed nature of the 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 emotions due to upset game outcomes;[2] 2) each team that we consider has its own home stadium which again helps rule out confounding factors due to fans with shared facilities; 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 being played, which means that by pinpointing the exact location of the crimes, we are able to identify crime counts plausibly from fans who attended the live games.[3]

Our study focuses on vehicle thefts and robberies on game days within a tight three mile radius of each stadium.[4] We use a regression discontinuity design (RDD) similar to Davis (2008), Auffhammer and Kellogg (2011), and Carr and Packham (2018), that examines changes in crime immediately before and after the end of each game. We also identify the impact of game-driven emotional cues on crimes by exploiting the mismatch between pregame expectations and actual outcomes. Our estimates suggest that property crimes tend to increase after home games in streets that are within a two-mile radius from the stadiums. The effect is mostly driven by vehicle thefts with popular car models being more likely to be targeted and is particularly salient within the one-mile radius and after upset losses or derby games. For example, we find an over 60% increase in total property crimes within

[2]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).

[3]Each the 38 rounds of the Brazilian Football Championship has 10 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/`.

[4]Given the types of crimes we focus on in this study, we will use the phrase property crimes interchangeably with vehicle thefts and robberies.

the zero to one mile ring following the home team's upset loss. There is also evidence of heterogeneity in responses to upset losses across fan bases of different teams, with Corinthians home games being associated with most salient post-game property crimes. In addition, we find an increase in robberies targeting less popular cars within the two-mile radius upon upset losses. Our results are robust to a series of checks involving alternative distance rings, different cutoff points and placebo tests utilizing no-game days, reassigned stadiums and away games. Overall, our findings not only confirm the role of emotions in crime but also suggest that even when emotionally cued, perpetrators of nonviolent property crimes may still respond to rational incentives for crime compared to their violent crime counterparts.

Our study makes the following two contributions to literature. First, to our knowledge, we are the first to explore micro-level spatial and temporal heterogeneity in the impact of emotional cues on criminal activities. Munyo and Rossi (2013) are similar in scope to 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.[5] The spatial aspect of our study design allows us to more plausibly identify fans' reactions to emotional cues and disentangle the potential mechanisms and heterogeneity in their responses. Marie (2016) considers geographical variation in the distribution of crimes following soccer games in London. But their crime data are at much 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 crimes (see Levitt and Miles (2006) and Chalfin and McCrary (2017) for reviews of related literature) and tend to neglect the potential interactions between the two mechanisms. The granular nature of the police reports used in our study provides detailed information on victim's vehicle characteristics such as year, make and model, which can

[5] 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 the city of São Paulo between 2007 and 2017.

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., choosing between popular versus unpopular car models as targets). Indeed, our results suggest that emotionally cued theft perpetrators may respond more to rational incentives for crime than their robbery counterparts. Our research differs from and complements existing economics of crime literature that focuses on the gains from rational crime based on spot market prices for the target commodity, e.g., Reilly and Witt (2008), Brabenec and Montag (2014), and Brabenec and Montag (2014).

This paper is organized as follows. Section 2 outlines a conceptual framework for our study. Sections 3 and 4 present the data and empirical strategy employed in this study, respectively. We discuss our baseline findings and robustness checks in Section 5, followed by discussion of potential mechanisms in Section 6. Section 7 concludes.

2 Conceptual Framework

We consider a reference-dependent preferences framework similar to that in Kőszegi and Rabin (2006), where the reference points are based on recent rational expectations and consumers derive gain-loss utilities due to deviations from expectations. In our context, soccer fans derive emotional cues from the outcome of a given soccer game of their home team, relative to their pre-game expectation proxied by the betting odds published by sportsbooks.[6] 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 we focus on in our study tend to be the favorites in their home games and there are only limited occasions of upset wins in our sample, we focus on the impact of upset losses. Home team's losses, particularly upset losses, can result in frustration among supporters. Con-

[6] Pawlowski et al. (2018) show that there is a strong correlation between the average objective reference points derived from bookmakers' betting odds and individual fans' subjective reference points or perceived game uncertainty.

sistent 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 non-random 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 from a standard reference-dependent preferences framework would also predict an increase in crimes under upset losses.[7] Such loss aversion prediction on post-game criminal activities has been supported by recent empirical evidence from studies such as Card and Dahl (2011) and Munyo and Rossi (2013).

The crimes of interest in our study include both vehicle thefts and robberies. While a reference dependent preference framework may predict increases in crimes due to frustration over home team's upset losses, it does not offer predictions on whether and how perpetrators of violent and nonviolent property crimes may react differently. Compared to thefts (non-violent 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 emotions to differ for theft and robbery perpetrators. Since our granular crime data offer detailed accounts of victims' vehicle characteristics including year, make and model, we can shed more light toward such behavioral differences. Specifically, given the more emotionally susceptible nature of robberies compared to thefts, 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, although behavioral in nature, is consistent with existing empirical literature on how perpetrators respond to rational incentives of crime, i.e., the

[7]Previous studies tend to assume that perpetrators in post-game crimes are the fans who attended and were emotionally cued by the game outcomes. However, since congregation of fans on game days presents to perpetrators more potential targets for criminal activities, perpetrators may also come from criminals who did not actually attend the games but took advantage of additional supply of their criminal targets. Our study explicitly tests this assumption by utilizing variations of crime locations, timing of the crimes and game outcomes, and confirms that perpetrators in post-game crimes likely come from the fans who attended the games.

price-theft hypothesis. For example, Reilly and Witt (2008) confirm a correlation between price of audio-visual goods and domestic burglaries, and Brabenec and Montag (2014) and Sidebottom et al. (2014) both find a positive relationship between metal prices and volume of metal thefts.

Furthermore, reference dependence does not prescribe how crimes are *spatially* distributed, and the empirical prediction can be inherently ambiguous, as Marie (2016) points out, due to three potentially competing channels: fan concentration, police displacement and self-incapacitation. Sports games lead to a concentration of fans, which could result in an increase in criminal activities on game days. As police force is re-positioned close to the stadiums to avoid collisions between fans supporting different teams, locations in the city that are disproportionately unattended (i.e., due to the police displacement to the game venues) may see an increase in crime. Meanwhile, self-incapacitation predicts that if fans attending the games represent a subsample of the population that is more likely to be violent, then one should expect a decrease in crimes while they are watching the game. Thus, conditional on how fans respond to soccer game outcomes relative to their pre-game expectations, the number of *post-game* crimes near the stadium will depend on whether the police displacement or fan concentration effect dominates. In addition, if violent fans respond to police deterrence (despite their reception to emotional cues from game outcomes), they would also seek to commit crimes in areas with relatively low police presence. Thus, the interaction of these proposed channels essentially predicts that the spatial concentration of post-game crimes would depend on how perpetrators respond to deterrence and rational incentives for crimes. Combined with loss aversion, we expect the spatial heterogeneity to be particularly salient after an upset loss of the home team.

3 Data

3.1 Game Outcomes and Betting Spreads

In this study, we focus on the three most popular professional soccer teams in the city of São Paulo, including Palmeiras, São Paulo and Corinthians. For instance, in 2008, a survey conducted by DataFolha in the municipality of São Paulo showed that 33.3%, 22.2%, and 14.2% of the respondents considered themselves to be supporters of Corinthians, Palmeiras and São Paulo, respectively, making them the three most popular soccer teams based in São Paulo.[8] The selection of popular teams is in accordance with Edmans et al. (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. An additional advantage of our team selection is that these three teams play in their own home stadiums located in different neighborhoods across São Paulo, which helps us further explore the role of geographical heterogeneity in explaining how post-game property crimes may be affected by emotional cues from the games.

Our sample contains a total of 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.[9] For each game, we have detailed information about the game date, start and end time, final score, stadium played and attendance.[10] In addition, we collect information about the total number of red cards

[8]Santos FC is another popular local professional soccer team in São Paulo. 5.6% of the DataFolha survey respondents considered themselves to be Santos FC supporters. 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 the home games by Santos FC from our analysis. In addition, We also exclude Portuguesa, another professional football 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) the DataFolha survey suggests only a 0.3% local support for the team. For further detail, see the following link: `https://www.rsssfbrasil.com/miscellaneous/torcidassp08.htm`.

[9]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: 3 in Itu-SP; 2 in Londrina-PR; 1 in Presidente Prudente-SP; and 1 in Campo Grande-MS.

[10]The data on Brazilian Professional Football League game fixtures and outcomes are collected from `http://www.bolanaarea.com` and `www.worldfootbal.com`.

in a game as a proxy for the intensity of the game.

The pre-game expectations (or reference points) for game outcomes in our study are derived using betting odds published by a major sportsbook.[11] 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.[12] We define home team's upset loss as a loss when it is predicted to win the game. In Section 5.3, we also consider implications of incorporating draws into upset losses. For each of the 456 home games in our sample, we have both the opening spreads, which were posted at the start of each game day, and the game time spreads, which were posted approximately at the time when the actual game started. Following related literature, we choose to use the game time spreads because they provide the most updated information on the overall prediction of the game outcomes.

Table 1 provides the summary statistics of home 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 [13]. The average betting spreads show that home teams are more likely to win their games, and the last column suggests that an upset loss (relative to the pre-game betting spreads) of the home team is relatively uncommon.[14]

[11] We obtain our betting spread data on Brazilian soccer games from Pinnacle Sports.

[12] We also estimate our specifications using probability of winning derived from betting spreads and obtain identical results.

[13] São Paulo has more home games than Palmeiras and Corinthians because of two reasons: first, São Paulo rarely hosted a home game outside the municipality of São Paulo as Palmeiras did (see, for instance, footnote number 8). Second, Corinthians played in Serie B in 2008. However, there were no betting odds available for Serie B in 2008.

[14] Similar to Card and Dahl (2011) and Ge (2018), we also regress the realized score differentials between the home and away teams on the pre-game betting spreads and confirm a positive relationship ($\hat{\beta} = 0.111$, $p < 0.001$, $R^2 = 0.04$).

Table 1: Home Game 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.

3.2 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 major types of property crimes that we focus in this study are vehicle thefts and vehicle robberies, which account for close to 80% of all vehicle-related crimes in our sample.[15] Thefts are the most common crime in the state of São Paulo, followed by robberies. 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 dataset provides detailed information regarding the time of the police report, approximate time of the incident (in six-hour intervals), street location of the incident and characteristics of the stolen or robbed vehicle, including the vehicle type (car versus motorcycle), make, model, year, and color. With information on the street location of the incident, we are able to obtain the geocodes of each incident by utilizing the geocoding API platform from Google Maps, from which we also compute the straight line distance of each incident to the home stadiums of our three local soccer teams of interest.[16]

[15]The dataset also includes other types of vehicle-related property crimes, e.g., items being stolen from one's vehicle.

[16]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 Section 5.2.1 a robustness checking using walking distance as an alternative criteria for computing distance of each incident to stadiums.

In order to match with the dataset on game outcomes and betting spreads, we restrict our attention to vehicle-related property crimes from 2007 to 2017. After dropping observations of robberies and thefts that either do not have complete street locations or cannot be geocoded (approximately 7% of the raw dataset), we obtain 126,565 observations for property crimes that happened on game days in São Paulo. Table 2 provides the summary statistics of the city-wide game day property crime counts before and after the game as well as the distribution of crimes within a three-mile radius from our stadiums of interest. Both robberies and thefts seem to be 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 two to three miles 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.

Table 2: Game Day Vehicle Thefts and Robberies

Crime	Total	Before	After
Robberies	65,264	24,205	41,059
Thefts	61,301	25,922	35,379
0 to 1 mile ring			
Robberies	397	128	269
Thefts	886	313	573
1 to 2 miles ring			
Robberies	1,355	495	860
Thefts	2,208	925	1,283
2 to 3 miles ring			
Robberies	2,046	786	1,260
Thefts	3,032	1,314	1,718

Figure 1 plots the density distribution of the police report time of crime incidents by distance to the stadium. We focus on 10 hours before and after the game start. Relative to the 1–2 miles and 2–3 miles radius, we observe a clear rise in the relative distribution of crime incidents within the 0–1 mile radius. In addition, Table 3 presents the average daily frequency of vehicle related property crimes within 0–1 mile radius and shows more property crime counts on the game day than no-game day with the difference being statistically significant for Allianz and Corinthians Arena. This simple comparison suggests that in addition to a shift in the temporal distribution of criminal activities on game day as seen in Figure 1, there may actually be more property crimes on the game day. The comparison also implies a potential heterogeneity in the responses to game outcomes across different fan bases, which we will formally explore in Section 6.3.

Figure 1: Density Distribution of Property Crimes

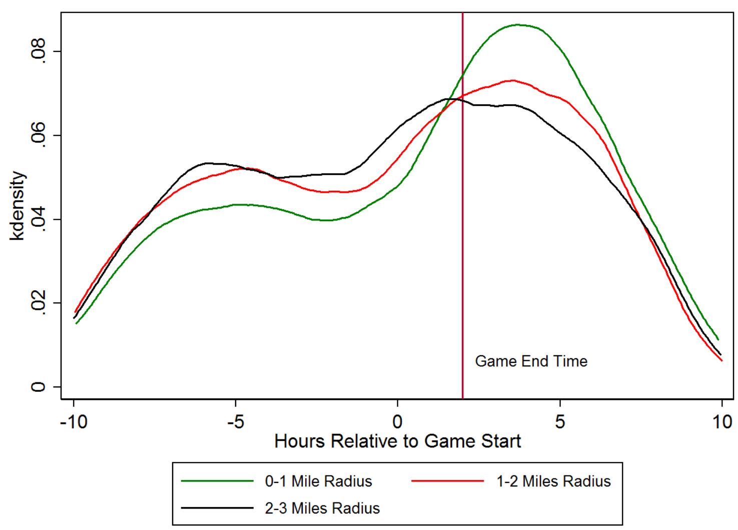


Table 3: Average Daily Frequency of Vehicle Thefts and Robberies 0–1 Mile Radius

	Pacaembu	Morumbi	Allianz	Corinthians Arena
Game Day	3.61	1.78	5.31	4.36
No-Game Day	3.48	1.75	4.61	3.1
Difference	0.13	0.03	0.7**	1.26***
p-value	0.62	0.82	0.046	0

As a further descriptive analysis in order to provide some intuition of our conceptual framework, we take advantage of the granular nature of our property crime dataset and utilize GIS tools to provide visual evidence of the geographical heterogeneity of property crimes as a result of upset losses. Figures 2 and 3 plot heat maps of all vehicle-related property crime incidents on game days before and after upset losses, respectively. The four stadiums of interest include Allianz Parque or Palestra (home stadium for Palmeiras before July, 2010 and after November, 2014), Arena Corinthians (home stadium for Corinthians since May, 2014), Morumbi (home stadium for São Paulo), and Pacaembu (home stadiums for Corinthians before 2014 and Palmeiras between July, 2010 and November, 2014).[17] As a visual reference, we also indicate a three-mile radius centered around each stadium with corresponding one-mile radius distance rings. While Figure 2 does not suggest any distributional patterns of vehicle-related property crimes, Figure 3 demonstrates a concentrations of robberies and thefts within a three-mile radius from the four stadiums of interest. While no causal inferences can be made from this visual inspection, there is overwhelming evidence suggesting a correlation between vehicle-related property crimes and upset losses with a heterogeneous spatial distribution. We will further explore this channel with a more formal empirical strategy described in the following section.

4 Empirical Strategy

Our objective is to identify the effects of emotional cues on property crimes. To achieve such goal, we adopt a regression discontinuity design similar to Davis (2008) and Carr and Packham (2018).[18] Our empirical model's running variable is the time-distance to the soccer games that we analyze. We construct this variable by aggregating the number of property crimes within a 30-minute interval of the running variable. We then restrict our analysis

[17]Corinthians historically played in Pacaembu until the opening of Arena Corinthians in 2014. Pacaembu also hosted Palmeiras while its original home stadium (Palestra) was overhauled and replaced with a new stadium (Allianz Parque) between 2010 and 2014.

[18]In Appendix A, we also present an alternative difference-in-differences empirical framework and discuss the corresponding results. The overall findings are qualitatively similar but we prefer RDD as our main empirical specification because it allows us to account for the rich time-distance relation provided in our novel property crime data.

Figure 2: Spatial Distribution of Game Day Property Crimes Before Upset Losses

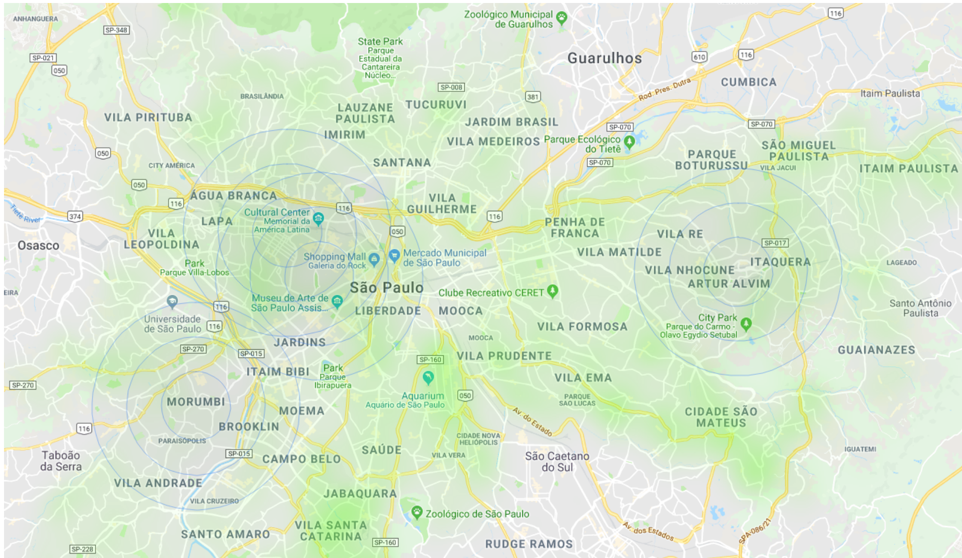
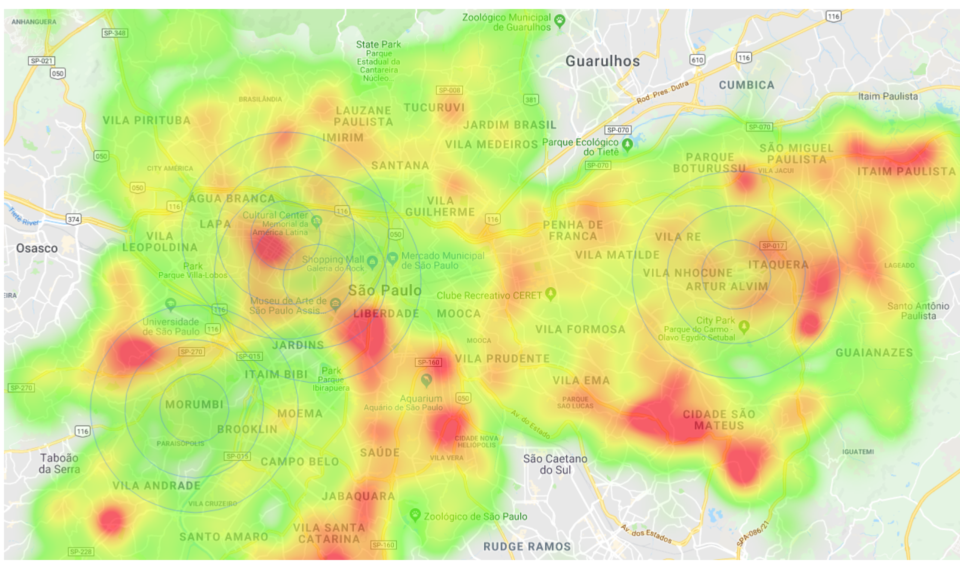


Figure 3: Spatial Distribution of Game Day Property Crimes After Upset Losses



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 3.2, our vehicle theft and robbery data contain the timestamp of the police report for each incident with reported approximate time of the incident (in six-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.[19] Finally, we identify the impact of emotional cues on property crimes by taking advantage of the variations in 1) the distance of the incident to the stadium; and 2) home game outcomes.

The variable measuring the distance to the stadium of interest helps us capture how exposure to games affect crimes, and the game outcome variable allows us to identify the effect of emotional cues on crimes due to deviations from pre-game expectations. Utilizing detailed information on the locations of crimes, we define three distance rings around the stadium: 0–1 mile; 1–2 miles; and 2–3 miles.[20] If crimes are related to soccer games, then we expect that fans attending the live games inside the stadiums, who are more exposed to the emotional cues provided by these games, are more likely to commit crimes after the end of each game. If this is the case, then crimes happening closer to stadiums will disproportionately increase after the end of the games. Furthermore, we measure the impact of loss aversion on crimes by using betting spreads to identify when game outcomes are upset losses. If frustration as a result of loss aversion affects crimes, we should expect an even larger increase in property crimes near stadiums following the end of a home team's upset loss.

More specifically, we measure the impact of soccer games on property crimes by running the following RDD, known interchangeably as the interrupted time series model as described by Carr and Packham (2018):

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

[19] Two features of the data mitigate concerns about not having the exact crime incident time in our data. 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 loss to the police in order to make their insurance claims, the crimes we studied are likely to be reported immediately once owners incur the losses. Second, even uninsured owners have an incentive to immediately report their loss to the police because they will otherwise be responsible for any incidents involving their stolen or robbed vehicles.

[20] The choice of distance rings up to three miles is based on the São Paulo police's maximum dispatch distance of five kilometers or approximately three miles. In addition, the size of each ring is based on the fact that the distance from the nearest subway station to three of the stadiums (except for Morumbi Stadium) is 1.5 kilometers or approximately one mile.

where $Crimes_{idt}$ is the total number of vehicles robbed or stolen on game day i, within the 1-mile distance ring d and 30-minute wide 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 is a dummy variable identifying the end of each game, and γ thus captures the impact of the end of the game on crimes. 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.[21] We apply this non-parametric estimation to better isolate the impact of game outcomes on crimes, and we estimate Equation 2 separately for each of the three 1-mile rings d. We allow the running variable to vary quadratically, cubically and quartically.[22] Finally, we also add game fixed effects (ω_i) and capture the error term in ϵ_{idt}.[23]

Although our bandwidth selection may seem discretionary, we justify our choice by plotting the optimal data-driven regression discontinuity plot using a fourth-order polynomial for each of the three 1-mile rings d.[24] Figure 4 displays these RD plots over a time interval of 20 hours (i.e., 40 30-minute intervals) before and after the game end. Here we observe the following three important characteristics of our data. First, the fourth order polynomial fits well the variability of our sample as previously discussed. Second, there is a clear discontinuity in the number of property crimes after the end of the games in the 0–1 and 1–2 mile rings, while the 2–3 mile ring is continuous around the cutoff, which reinforces the validity

[21] This is equivalent to 20 30-minute intervals before and after the end of each game since the crimes are aggregated in 30 minute-intervals.

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

[23] Following Auffhammer and Kellogg (2011), we also estimate the following modified specification of our main model:

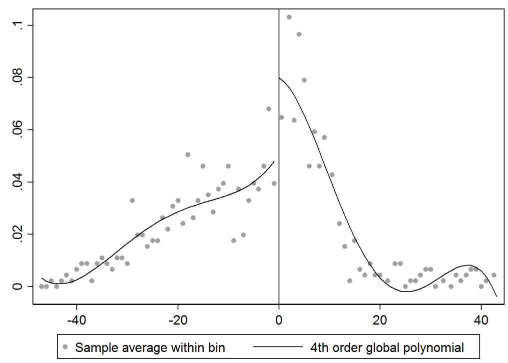
$$Crimes_{idt} = \alpha + \lambda Ring_1 + \gamma D + \sum_{n=1}^{4} \beta_n (r-c)^n + \rho Ring_1 * D + \kappa Ring_1 * \sum_{n=1}^{4} \beta_n (r-c)^n \omega_i + \epsilon_{idt}, \qquad (2)$$

where we compare the 0–1 mile ring to the 2–3 miles ring and find $\hat{\rho} = .54$ ($SE = .21$). When the 1–2 miles ring is compared to the 2-3 miles ring, we find $\hat{\rho} = .30$ ($SE = .15$). Both results are similar to our RDD estimation where we restrict the sample to each mile ring as presented on Table 4.

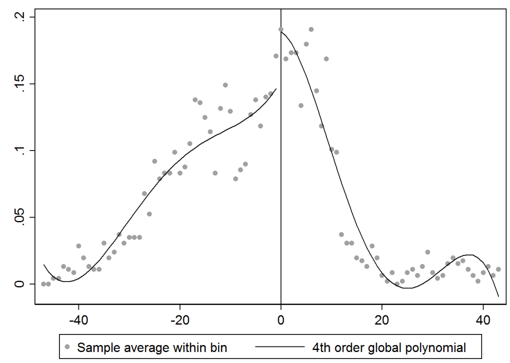
[24] The optimal data-driven RD plots are obtained by the Stata package `rdplot` by Calonico et al. (2015).

of our empirical strategy. Finally, we observe that 10 hours (i.e., 20 30-minute intervals) after the end of the games, the distributions start to stabilize across all three distance rings, which justifies our bandwidth choice of 10 hours before and after the game end.

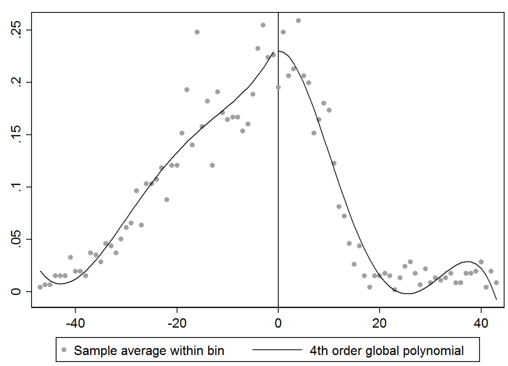
Figure 4: Regression Discontinuity Plots of Property Crimes



(a) Regression Function Fit 0–1 Mile



(b) Regression Function Fit 1–2 Miles



(c) Regression Function Fit 2–3 Miles

Note: The vehicle robbery and theft counts are fitted with a fourth-order polynomial using the optimal data-driven regression discontinuity plot (Calonico et al., 2015) over a time interval of 20 hours (in 30-minute intervals) before and after game end. Solid lines represent the 95% confidence intervals.

We then test the robustness of our results by adopting the optimal bandwidth selection and by using parametric estimation. We implement methods from both Imbens and Kalyanaraman (2012) and Calonico et al. (2014),[25] and the results suggest a bandwidth of 31 and 36 (29 and 27; 29 and 24) for the 0–1 mile ring (1–2 miles ring; 2–3 miles ring), respectively. Our results are not sensitive to the adoption of either non-parametric estimations using the

[25]The optimal bandwidth for our analysis is obtained by the Stata package `rdbwselect`.

optimal bandwidths discussed above or parametric estimations.[26] Finally, Card and Lee (2008) suggest that RD designs in applications with discrete running variables may suffer from the lack of independent observations. We address this potential problem by estimating our model using population average model and cluster-robust standard errors and find similar results to our baseline model.

Similar to Gonzalez-Navarro (2013), we estimate Equation 2 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 our model's choice as our findings are qualitatively similar when we use OLS or Poisson regression. Finally, we examine heterogeneous effects across games by adding to Equation 2 variables related to emotional cues and their interaction terms with dummy D. Specifically, we test separately for each variable whether upset losses and derby games accentuate the increase in crimes after the end of the game. We also investigate whether games' attendance affects the number of crimes.

The main advantage of employing a dataset that enables us to explore both distance and time 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 gives us flexibility to identify changes in crime that varies with the running variable. The ideal experiment to identify the (causal) impact of soccer games on crimes would require us to simultaneously observe the number of crimes close to each stadium for each time interval on a game versus no-game day. However, such experiment is clearly infeasible because any given day can either be a game day or a no-game day. Therefore, to empirically analyze the impact of soccer

[26] The increase of the magnitude of our results suggest that, if anything, we are reporting a lower bound estimate of the impact of soccer games on crimes. In addition, although the 2–3 miles ring becomes positive and statistically significant, the difference between each of the two first rings and the third ring is consistent with our model's choice and statistically significant.

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

games on crimes, we need to make the following two assumptions about 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 crime trends in neighborhoods surrounding the stadiums we analyze would not change abruptly after game end if there were no soccer games taking place in them. Second, we also need to assume that the confounding variables related to game days that affect crimes do not change discontinuously after the end of the games.

On the other hand, the advantage of our regression discontinuity design 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 crime trends varying smoothly across the cutoff on no-game days. In addition, our detailed crime report data, which measure the distance of each crime to the stadiums of interest, allow us to rule out the possibility that the confounding variables affecting crime 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 stadiums do not change discontinuously after the end of the games.

5 Baseline Results and Robustness Checks

5.1 Baseline Results

We first estimate Equation 2 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 all 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 0–1 and 1–2 miles radius rings but

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

not in the 2–3 miles rings. Specifically, the average number of property crimes increase *after* the game by 57.6% and 22.6% within the 0–1 and 1–2 radius rings, respectively.[29] The relatively large percentage responses in crimes are also expected in our context because most neighborhoods near the stadiums are comparatively safe and, as suggested in Table 2, only witness infrequent vehicle thefts and robberies.[30]

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 robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

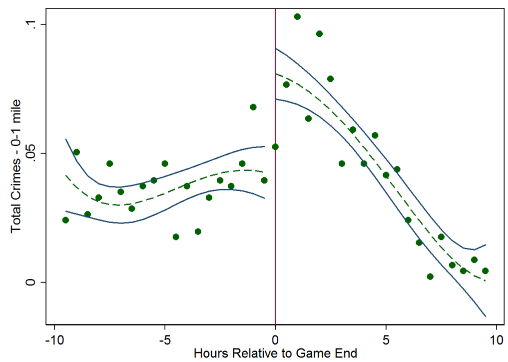
As an additional exercise, we also estimate our model using OLS with the same time interval of 10 hours before and after the game end and separately fit our property crime counts with a fourth-order polynomial for each of the distance rings. The corresponding RDD plots, presented in Figure 5 with solid lines representing the 95% confidence intervals, confirm our results in Table 4. Overall, the baseline results suggest that, even without considering the emotional cues due to departures from pre-game expectations, the soccer games can lead to an increase in post-game property crimes, and the effect is spatially

[29] Since our estimation is based on 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 0–1 mile ring is given by $e^{0.455} - 1$ or approximately 57.6%.

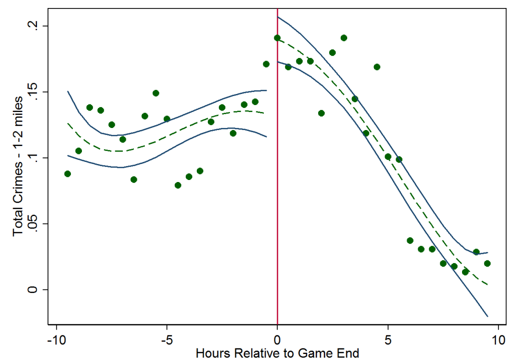
[30] For property crimes taking place within 10 hours prior to the end of each game, the average number of crimes, per 30 minutes, in the 0–1, 1–2, and 2–3 miles rings are 0.037, 0.12, and 0.18, respectively.

heterogeneous and attenuates as we move away from the stadium.

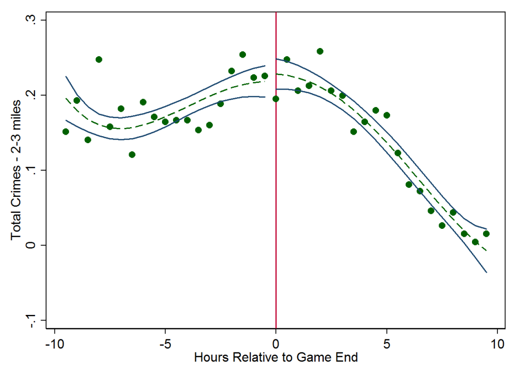
Figure 5: Impact of Games on Property Crimes



(a) 0–1 Mile Radius



(b) 1–2 Miles Radius



(c) 2–3 Miles Radius

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.

As we hypothesized in Section 2, the soccer game outcomes, particularly when being considered relative to pre-game expectations, 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 a crime. To investigate this possibility, we estimate a specification similar to Equation 2 but include a dummy variable for upset loss 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 two to three miles from the stadiums, property crime counts would increase on streets closer to the stadiums (within two miles from the stadium) after home teams' upset losses. Once again, the zero to one mile ring shows the largest impact with approximately 62.3% increase in post-game crimes upon upset losses.

Table 5: Impact of Upset Losses and Derby Games

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.205	0.086	-0.152
	(0.195)	(0.120)	(0.103)
Derby	0.281	-0.117	-0.354
	(0.856)	(0.319)	(0.263)
Post-Game × Derby	0.959***	0.495***	0.424***
	(0.250)	(0.146)	(0.133)
Upset Loss	-0.604	-0.148	-0.064
	(0.507)	(0.295)	(0.231)
Post-Game × Upset Loss	0.484**	0.247*	-0.086
	(0.234)	(0.141)	(0.118)
Derby × Upset Loss	0.334	13.565	-0.259
	(2.194)	(728.361)	(0.630)
Post-Game × Derby × Upset Loss	0.029	0.334	0.587*
	(0.656)	(0.446)	(0.338)
Observations	11,310	16,302	17,394
Number of games	290	418	446

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Additionally, we adopt a similar RDD specification and investigate the impact of derby games on crime counts. The results from Table 5 indicate that derby games may result in an increase in post-game criminal activities relative to non-derby games, and such effect is present throughout the three distance rings from the stadiums, with the largest impact again within the 0–1 mile ring (representing a drastic over 160% increase in post-game vehicle-related property crimes). On the other hand, the three-way interaction on post-game, derby and upset loss do not suggest statistically significant impact within the two-mile radius from the stadiums. This means that home fans' frustration over upset loss during derby games may not lead to increases in crimes close to the stadium, implying that part of the impact of derby games on crime counts could be driven by away fans from the rival team in São Paulo.

5.2 Robustness Checks

To assess the robustness of our baseline findings, we perform a series of robustness checks, including utilizing walking distance as an alternative measure for distance rings and conducting a number of placebo tests involving no-game days, reassigned stadiums and away games of the home teams. Moreover, we also consider winning probability as an alternative measure for pre-game expectations and draws as a separate realized game outcome.

5.2.1 Distance Rings Based on Walking Distance

One potential concern with our baseline findings is that the classification of distance to stadiums based on straight line distance may be restrictive. To that regard, we consider an alternative measure of distance to stadiums based on walking distance.[31] For each property crime in our sample, we utilize the Distance Matrix API from Google Maps to compute the walking distance of the crime location to the stadiums of interest. We then invoke the same distance rings from the stadiums using walking distance (e.g., a 0–1 mile radius would be based on a walking distance of up to one mile from the stadium) and re-estimate our main RDD specification that incorporates emotional cues due to upset losses and derby games (similar to Table 5). Table 6 reports the estimated coefficients of this robustness check. Although the magnitudes of the estimates are larger compared to Table 5, we observe qualitatively similar results in terms of the directions and statistical significance of the estimates. We also find a similar attenuation of the impact on crime as one moves away from the stadium. Overall, the results from this robustness check suggest that our baseline findings are

[31] In the Appendix, we also present results based on alternative ring size, including 1.5 kilometers and 2 kilometers.

not driven by our choice of straight line distances for the distance rings.

Table 6: Robustness Check Using Walking Distance

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.600**	0.205	-0.071
	(0.281)	(0.169)	(0.122)
Derby	12.076	0.567	0.107
	(904.198)	(0.667)	(0.340)
Post-Game × Derby	1.418***	0.575***	0.373**
	(0.414)	(0.201)	(0.150)
Upset Loss	-0.620	-0.133	-0.393
	(1.021)	(0.390)	(0.251)
Post-Game × Upset Loss	0.692**	0.396**	0.273*
	(0.350)	(0.189)	(0.140)
Derby × Upset Loss	-11.959	12.772	0.128
	(904.200)	(931.562)	(1.038)
Post-Game × Derby × Upset Loss	-1.124	0.389	0.477
	(0.970)	(0.580)	(0.419)
Observations	6,552	13,299	16,458
Number of games	168	341	422

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

5.2.2 Placebo Tests Using No-game Days, Reassigned Stadiums, and Away Games

To further test the robustness of our main empirical findings, we conduct a series of placebo tests on our main RDD specifications by simulating game times and stadium assignments on no-game days, reassigning stadiums to home teams, and examining crime responses near home stadiums following home teams' away games. Across all placebo tests, we do not find statistically significant responses in property crimes, particularly in neighborhoods within

0–1 or 1–2 miles radius from the stadium of interest, which again confirms the robustness of our main empirical findings. We describe in details the designs and findings from these placebo tests in Appendix C.

5.3 Alternative Pre-Game Expectation and Draws as Game Outcomes

Following related studies such as Card and Dahl (2011) and Ge (2018), we also convert our pre-game betting odds into winning probability and re-estimate all of our RDD specifications. The main findings, as expected, remain identical. In addition, one feature about soccer games that separates them from many other sports is the potential outcome of having a draw. In our baseline specification, we do not consider draws as part of the upset losses, i.e., if a team is expected to win but ends with a draw, the result is not considered to be an upset. As a robustness check, we redefine an upset loss as a game outcome that differs from the predicted outcome of winning by incorporating draws. We re-estimate our RDD specifications and we no longer observe statistically significance in our main findings.[32] Thus, findings from this robustness check reinforces the idea that home team's upset losses, but not draws, can result in strong emotional cues that potentially may lead to subsequent criminal activities.

6 Mechanisms and Discussion

6.1 Timing of the Crimes

In our main RDD specification, we utilize game end time as the cutoff and find an increase in the post-game crimes within the two-mile radius from the stadiums. Since our crime data only contain the time of the police report and the approximate time of the incident (in six-hour intervals), i.e., not the direct account of the actual time of the crime, we seek to

[32]Full results from specifications using alternative pre-game expectation and those incorporating draws as part of upset losses are available upon request.

make inference about the timing of the crimes relative to game end time by conducting a series of further checks on the cutoff choices. This would also shed further light on whether the perpetuators are fans attending the games.

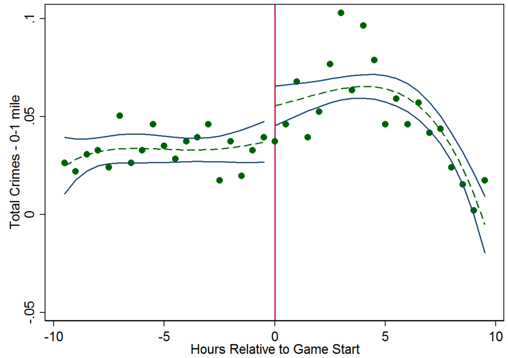
We first replace the cutoff with game start time, consider a time interval of 10 hours before and after the game start, and separately fit our property crime counts with a fourth-order polynomial for each of the distance rings similar to Figure 5. Figure 6 plots the estimates. Panels (a) and (b) respectively suggest that there are no significant changes in property crime counts within the 0–1 mile and 1–2 miles radius after the game start, which are in sharp contrast to Panels (a) and (b) in Figure 5. These results help confirm that the increase in criminal activities in our baseline results is indeed driven by game outcomes. On the other hand, Panel (c) of Figure 6 curiously suggests that there is a statistically significant increase in vehicle thefts and robberies within the 2–3 miles ring after game start. Specifically, after we separate the thefts from robberies, we find that the increase in the crime counts in the 2–3 miles ring is mostly driven by robberies.[33] Thus, it could be that fans are robbed on their way to the stadiums and, therefore, report to the police immediately, while vehicle thefts that happen during the game may only be recognized and reported by the owners after the game ends.

Additionally, we also experiment with changing the cutoff to four hours before, two hours before, and two hours after the end of the game and separately estimate Equation 2, but we find no statistically significant changes in vehicle thefts and robberies immediately following these cutoffs.[34] Overall, the findings based on alternative cutoff points support the hypothesis that property crimes respond to game outcomes (revealed at game end). Additionally, the fact that crimes only increase upon game end and in neighborhoods near the stadiums suggests that they are likely committed by fans attending the games.

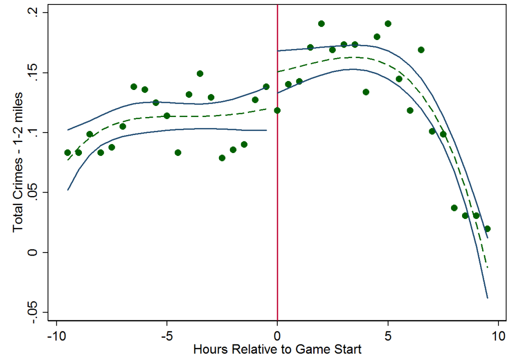
[33] These results are available upon request.

[34] Results from these additional robustness checks are available upon request.

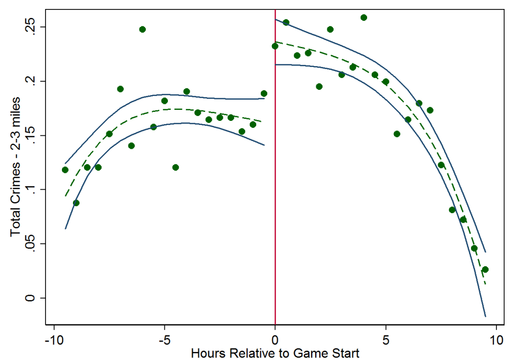
Figure 6: Impact of Games on Property Crimes: Game Start as Cutoff



(a) 0–1 Mile Radius



(b) 1–2 Miles Radius



(c) 2–3 Miles Radius

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 start. Solid lines represent the 95% confidence intervals.

6.2 Thefts versus Robberies

Our property crime data include both vehicle robberies and thefts. Since they are inherently different crime types with different criminal motives, required skills and legal punishments, we explore whether the impact of game outcomes elicits different responses from these crime types by estimating our main specification of emotional cues separately for thefts and robberies. Tables 7 and 8 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 Table 7 are similar to those in Table 5, whereas most of the coefficients in Table 8 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 lower legal punishment if caught. The stronger impact of game outcomes on thefts 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 as a result 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.[35]

6.3 Heterogeneity Across Fan Bases

So far we have shown an overall impact of soccer game outcomes on local property crimes. Our empirical evidence is drawn from three local soccer teams who play in four different home stadiums over our sample period. A natural next step is to examine the potential heterogeneity of the impact across different stadiums because teams such as Corinthians have anecdotal reputation of having more violent fans.[36] To this end, Table 3 seems to support such anecdotal reputation in that there is an increase in total number of robberies and thefts (rather than just a temporal shift) on game days in neighborhoods near Corinthians Arena. We investigate this possibility further by rerunning our main RDD specification on the impact of emotional cues on property crimes separately for each of our three teams of interest. The results do not show increases in vehicle thefts and robberies after home games of Palmeiras and São Paulo. However, there is a significant increase in vehicle-related property crimes within 2-mile radius of the stadium after Corinthians home games as shown

[35] Another possibility is that most of the vehicles stolen 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 game outcomes.

[36] We searched the State Court of Justice's online database of all lawsuits filed in the State of São Paulo and found that robberies and thefts 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/`.

Table 7: Impact of Upset Losses and Derby Games on Vehicle Thefts

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.504**	0.152	-0.096
	(0.234)	(0.150)	(0.130)
Derby	-1.379	0.198	-1.606***
	(1.051)	(0.972)	(0.501)
Post-Game × Derby	1.132***	0.626***	0.802***
	(0.308)	(0.178)	(0.167)
Upset Loss	-1.783**	0.104	-1.001**
	(0.795)	(0.704)	(0.480)
Post-Game × Upset Loss	0.637**	0.295*	-0.087
	(0.269)	(0.171)	(0.149)
Derby × Upset Loss	13.354	11.636	1.812
	(646.434)	(625.928)	(1.514)
Post-Game × Derby × Upset Loss	-0.551	0.051	0.384
	(0.703)	(0.507)	(0.394)
Observations	9,321	14,547	16,107
Number of games	239	373	413

Note: The dependent variable is the total number of vehicle thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

in Table 9. Again, the impact is most salient within the one mile ring from the stadium with an estimated increase in crime counts of approximately 120%.

On the other hand, Corinthians moved from their former stadium, Pacaembu, into their new stadium, the Corinthians Areana, in 2014. It is worth noting that these two stadiums are more than 15 miles apart. When further separating the Corinthians home games into those played in the old and new stadiums, we intriguingly find similar post-game increases in property crimes in the vicinity of the respective stadium.[37] In other words, these results

[37] We find that upset losses increase property crimes by 113% and 136% in the old and new stadiums, respectively. As the old stadium have more data points, the results for the new stadium are less precisely estimated. The separate estimates for Corinthians' new and old stadiums are available upon request.

Table 8: Impact of Upset Losses and Derby Games on Vehicle Robberies

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	-0.243	-0.154	-0.246
	(0.344)	(0.193)	(0.163)
Derby	1.384	0.131	0.136
	(1.221)	(0.369)	(0.329)
Post-Game × Derby	0.613	0.373	-0.245
	(0.431)	(0.252)	(0.218)
Upset Loss	-0.102	-0.341	-0.035
	(1.072)	(0.357)	(0.279)
Post-Game × Upset Loss	0.152	0.283	-0.081
	(0.465)	(0.244)	(0.190)
Derby × Upset Loss	-16.815	11.528	-0.772
	(962.305)	(803.334)	(0.847)
Post-Game × Derby × Upset Loss	14.153	1.210	1.046*
	(962.303)	(1.121)	(0.606)
Observations	5,694	11,973	14,586
Number of games	146	307	374

Note: The dependent variable is the total number of vehicle 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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

suggest that the post-game (particularly post-upset loss) property crimes seemed to have moved with Corinthians' home stadiums, which in turn suggests that there could exist a potentially violent Corinthians fan base that is likely to be suseptible to emotional cues and commit crimes.

6.4 Vehicles Models and Popularity

As discussed earlier, Brazil has a large underground car parts (chop shop) industry, and if property crime perpetrators do respond to rational incentives (benefits) for crime, we

Table 9: Heterogeneity of Impact: Corinthians Home Games

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.464	-0.122	-0.100
	(0.323)	(0.175)	(0.166)
Upset Loss	-1.231*	-0.271	0.102
	(0.685)	(0.431)	(0.378)
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

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

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 year, make and model of the vehicle being stolen or robbed. We divide the victim vehicles into popular versus unpopular types.[38] We then re-estimate our main specification separately based on distance to the stadiums, popularity of the car models, and the type of crimes (thefts vs. robberies), and Tables 10 and 11 report the estimated coefficients for the 0–2 miles and 2–3 miles radius, respectively.[39] While we do not find evidence for the impact of game outcomes on crimes across vehicle types in the 2–3 miles radius, interestingly, the interaction terms on *Post-Game* and *Upset Loss* in Columns (2) and (3) of Table 10 indicate that within the 0–2 miles distance ring, upset losses may lead to an increase of robberies of unpopular vehicles and

[38] The popular car models include: Fiat Palio, Volkswagen Gol, Volkswagen Fox, Fiat Siena, Opel 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, an Israeli company specializing in vehicle tracking services.

[39] Due to lack of property crime observations with vehicle characteristics, we combine incidents within 0–1 and 1–2 miles into one distance ring.

thefts of popular vehicles. These results 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, which may not be 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 vehicle models in the sample.

Table 10: Vehicle Robberies and Thefts within 0–2 Miles: Vehicle Popularity

	(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 robberies or thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

6.5 Discussion

Consistent with studies such as Card and Dahl (2011) and Munyo and Rossi (2013), our empirical findings that upset losses can result in significantly more property crimes provide support for the role of reference dependent preferences and loss aversion in criminal activities.

Table 11: Vehicle Robberies and Thefts within 2–3 Miles: Vehicle Popularity

	(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-related robberies or thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Marie (2016) finds that nonviolent property crimes increase in the boroughs that host games but not violent crimes. On the contrary, our granular street-level evidence suggests that upon home teams' upset losses, both nonviolent crimes such as vehicle thefts and violent crimes such as vehicle robberies can increase within a three-mile radius centered around the stadiums following local soccer games, with thefts and robberies targeting popular and unpopular vehicle models, respectively. This reflects different ways perpetrators react to emotional cues and rational incentives for crime. We also find a significant spatial heterogeneity of the impact of emotional cues within the three-mile radius. For thefts, the effect is most salient in street locations that are within one mile radius from the stadiums, attenuates as one moves to the 1–2 miles ring and disappears in the 2–3 miles distance ring. For robberies, the effect is not present within any of the distance rings unless one differentiates by vehicle popularity, where upset losses can result in a significant increase in unpopular cars being robbed within the 0–2 miles distance ring. We also find that derby games may result in emotional cues that can lead to increases in crimes, particularly thefts, across all three distance rings. And the derby effect on crimes does not depend on game outcomes.

It is worth noting that the magnitudes of our main empirical findings are noticeably larger compared to related studies.[40] For example, we find an over 62.3% increase in total property crimes upon upset losses within the zero to one mile ring. We attribute the contrast to the detailed and granular nature of our data that allows us to adopt a regression discontinuity design and explore 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 (e.g., Kalist and Lee 2016). Our findings thus suggest that previous studies may have underestimated the impact of games and the corresponding emotional cues on crimes to local communities, particularly those close to game venues.

In addition, previous related studies do not specifically investigate whether the game-driven increases in crimes are committed by fans attending the games or the perpetrators not at the games taking advantage of a larger supply of criminal targets during game time. The timing of the reported vehicle-related property crimes and heterogeneous effects in upset losses and derby games in our findings confirm that most of them are likely committed by fans who attended the home games. The spatial distribution of the crime counts suggests that the fan concentration effect seems to dominate police displacement near the stadium. This could be due to police displacement concentrating at the game venue to prevent collisions between home and away fans and thus neglecting even areas slightly away from the stadium. In this case, the strong impact of loss aversion is not subdued by external factors such as the deployment of law enforcement at game venues. Fans are frustrated about their home teams' upset losses, and they choose to commit crimes in areas close to the stadiums

[40]For example, we find that a home team's upset loss can lead to a 62.3% increase in post-game vehicle-related property crimes in within the 0–1 mile radius from the home stadium, which 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.

despite the heavy presence of police force at the stadiums. On the other hand, we also find evidence that perpetrators of different crimes may respond to emotional cues differently — while robbery offenders may commit the crimes 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. The behavioral aspects of our findings thus complement related empirical literature that focuses almost entirely on establishing evidence of how perpetrators respond to the gains from rational crime due to spot market prices for the target commodity, e.g., Reilly and Witt (2008); Brabenec and Montag (2014); Brabenec and Montag (2014).

7 Conclusion

In this paper, we utilize a novel dataset of police reports that provide detailed street-level information on vehicle-related property crimes in the city of São Paulo, Brazil, which we then matched with game outcomes and betting odds of three major local soccer clubs. Using a regression discontinuity design with time as the running variable, we explore the impact of game outcomes on post-game vehicle robberies and thefts and explore its spatial and temporal heterogeneity. We find that crime incidents tend to congregate within a two-mile distance ring from the stadiums, particularly within the one mile radius. After home teams' upset losses, we observe significantly more car thefts in streets that are in the 0–1 mile and 1–2 miles radius from the stadiums compared to the 2–3 miles distance ring, with most of the thefts targeting popular car models. There is evidence of heterogeneous responses across fan bases of different teams, with Corinthians home games resulting in most salient increases in post-game property crimes. There is also a derby game effect that leads to increases in crimes, particularly thefts, across all three distance rings. In addition, we find an increase in robberies targeting unpopular cars within the two-mile radius. Our results not only provide empirical support toward reference dependence and loss aversion in the context of economics of crime but also suggest that emotionally cued perpetrators may still react to rational incentives for crime.

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 (even within one mile radius from the stadiums) and commit violent and non-violent crimes. The effect is even more salient following derby games. This calls for a more strategic positioning of police force, particularly during high-stakes games such as derby games or games with potentially unexpected outcomes.

Our study also opens up several avenues for future research. For instance, detailed records of police deployment during sporting events could help further parse the police displacement effect. A structural model incorporating demand shocks of vehicle models could also help uncover more direct estimates of how cued perpetrators respond to rational incentives for crime. Lastly, there is anecdotal evidence of targeted incidental emotions where frustrated sports fans would vandalize properties containing visual hints of the opponent team, e.g., 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 emotional cues from home teams' game outcomes.

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Appendix A: Difference-in-Differences Specifications and Results

Difference-in-Differences Specification

As an alternative empirical strategy to the RDD specifications, we employ a spatial difference-in-differences model that compares crimes at various distances from the stadiums, before and after upset losses, by leveraging the exogenous variation generated by the outcome of a game conditional on the pre-game betting spreads similar to Card and Dahl (2011), taking into account confounding unobserved neighborhood attributes (Diamond and McQuade, 2016; Cui and Walsh, 2015; Pope and Pope, 2015; Linden and Rockoff, 2008) arising from the non-random locations of soccer stadiums, and focusing within a small radius of each stadium (3 miles). Specifically, we estimate the following equation:

$$Crimes_{gtj} = (\beta_0 D_j^1 + \gamma_0 D_j^2) \times Post \times Upset\,Loss + \theta X + \Psi_{gymd} + u_{gtj} \tag{3}$$

where $Crimes_{gtj}$ denotes the total number of vehicle thefts or robberies in a game day (g) at time (t) near stadium (j). Notice that the distance to the stadium (j) also indicates the location (or street) where the crime took place. D_j^1 and D_j^2 are indicators for whether the crime took place within a 0 to 1 mile ring or 1 to 2 miles ring from stadium j, respectively. *Post* indicates whether the incident took place after the game, and *Upset Loss* indicates if the game was an upset loss. X is a vector that summarizes all single and double interactions that complete the triple difference-in-differences and also contains all control variables related to each game (i.e., number of red cards, attendance and difference between home and away teams number of scored goals). Finally, the term Ψ_{gymd} adds game, year, month and day of the week fixed effects. Similar to our RDD specification, we estimate Equation 3 using a negative binomial model.

The main advantage of using a difference-in-differences empirical design while controlling for spatial fixed effects and comparing the number of crimes before and after the game, within a three-mile radius of each stadium, is that we can isolate the impact of the game on crimes. Our results only need to rely on the assumption that the crime trend would be identical in areas close to the stadium, and those farther away had no soccer games played on that day. We then take advantage of the empirical evidence documented in existing literature that emotions may induce crimes in order to construct a triple difference, in which our outcome variable is expected to be determined by time, location and whether the home team had an upset loss. By using this methodology, we can identify and measure the impact of an upset loss on the number of crimes committed in neighborhoods close to the stadium after the game ends. On the other hand, compared to our main RDD specification (Equation 2), a spatial difference-in-differences model will not be able to account for the detailed time-distance relationship provided in our unique property crime data.

Difference-in-Differences Findings

We estimate Equation 3 and present the estimated coefficients in Table A1. The dependent variable is the number of all vehicle-related property crimes that combine thefts and robberies. Similar to the discussions on the RDD estimates, we consider the impact of games per se (regardless of outcomes) and emotional cues including upset losses of home teams and derby games. Column (1) presents a difference-in-differences model, without taking into account the emotional cues from upset losses. Similar to findings in Table 4 based on the RDD specification, we find statistically significant increases in post-game property crime counts in the 0–1 and 1–2 miles distance rings from the stadium relative to the 2–3 miles ring with a larger magnitude of responses in the 0–1 mile ring. In Columns (2) and (3), we investigate the impact of upset losses and derby games, respectively. Similar to results in Table 5, we once again find increases in property crimes in the 0–1 mile and 1–2 miles rings relative to the 2–3 miles, following home team's upset losses, with more salient impact in the inner ring closer to the stadium. In contrast to Table 5, however, we only observe an increase in property crimes within the 0–1 mile distance ring following a derby game.

Table A1: Impact of Upset Losses and Derby Games: Difference-in-Differences

	(1) Crime	(2) Crime-Upset Loss	(3) Crime-Derby
Post × D_j^1	0.408***	0.320***	0.341***
	(0.082)	(0.090)	(0.089)
Post × D_j^1 × Upset Loss		0.521**	
		(0.222)	
Post × D_j^2	0.143**	0.097	0.131**
	(0.059)	(0.064)	(0.064)
Post × D_j^2 × Upset Loss		0.292*	
		(0.158)	
Post × D_j^1 × Derby			0.432*
			(0.234)
Post × D_j^2 × Derby			0.052
			(0.163)
Observations	27,360	27,360	27,360
Number of games	456	456	456

Note: The dependent variable is the number of vehicle thefts and robberies. Standard errors are reported in parenthesis. *Post Game* is a dummy variable that represents hours after the end of the game. D_j^i is a dummy variable for being in the i-mile distance ring from the stadium. All regressions use game, year, month and day of the week fixed effects and control for number of red cards, attendance and the difference between home and away teams number of scored goals. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Additionally, to access the robustness of the difference-in-differences model, we follow the distribution of the actual game times on game days and randomly assign game times and stadiums to neighboring no-game days. We rerun our main difference-in-differences specification (Equation 3 and Column (1) of Table A1) 1,000 times using these simulated no-game day game times and stadiums. Table A2 presents the distribution of the estimated difference-in-differences interaction coefficients, without upset losses (i.e., Post × $D_j^1 = \hat{\beta}_0$ and Post × $D_j^1 = \hat{\gamma}_0$ in Equation 3) for each of the distance rings relative to the 2–3 miles ring. We observe that on average, the coefficients on the interaction terms for both inner rings are not statistically significant, and the magnitudes are much smaller compared to the corresponding coefficients presented in Column (1) of Table A1.[41] These results thus confirm the robustness of the findings from our difference-in-differences specifications.

Table A2: Distribution of Estimated Three-Way Interaction Terms from No-Game Days

	Mean	SD	Min	Max
0–1 Mile				
$\hat{\beta}_0$	0.090	0.056	-0.091	0.258
SE	0.067	0.001	0.064	0.070
1–2 Miles				
$\hat{\gamma}_0$	0.024	0.039	-0.091	0.149
SE	0.047	0.000	0.455	0.476

Overall, we conclude that the findings from the difference-in-differences specifications are similar to those from the RDD specifications, which help further confirm their robustness.

[41] The likelihood of observing a larger magnitude on the coefficient for the three-way interaction term for the 0–1 mile and 1–2 miles radius is 0% and 0.3%, respectively.

Appendix B: Impact of Game Attendance

To further investigate the mechanisms of how emotional cues affect crimes, we consider the role of game attendance. A larger attendance implies not only more fans (and perpetrators) aggregating at or near game venues but also potentially a larger supply of vehicles from fans attending the games. We run an RDD specification similar to Equation 2 but include an interaction term of game attendance (measured in 10,000 fans) with the *Post-Game* dummy to capture the additional impact of attendance on post-game property crimes. We again estimate the specification separately based on the distance rings to stadiums, and the estimates are reported in Table A3. The results suggest that attendance is only positively correlated with post-game property crimes within the one-mile distance ring, with an estimated increase of 30.9% of property crime per 10,000 additional fans. Given the spatial distribution and the timing of the crime incidents, this finding thus provide further evidence that the perpetrators of the property crimes are likely from the fans attending the games.

Table A3: Impact of Game Attendance

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	-0.196	0.084	-0.228*
	(0.265)	(0.159)	(0.132)
Attendance	-0.165	-0.155	-0.092
	(0.194)	(0.106)	(0.074)
Post-Game × Attendance	0.269***	0.051	0.055
	(0.078)	(0.046)	(0.037)
Observations	11,310	16,302	17,394
Number of games	290	418	446

Note: The dependent variable is the total number of vehicle robberies and thefts. *Post Game* is a dummy variable that represents hours after the end of the game. *Attendance* is measured in 10,000 fans. All specifications follow an RDD that uses time as a quartically varying running variable with the cutoff point being game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Appendix C: Placebo Tests Using No-game Days, Reassigned Stadiums, and Away Games

No-Game Days

We first perform a placebo test similar to that described in Appendix A. We again follow the distribution of the actual game times on game days and randomly assign game times and stadiums to neighboring no-game days. We then estimate our main RDD specification (Equation 2 and Table 4) 1,000 times using these simulated no-game day game times and stadiums. Table A4 presents the distribution of the estimated RDD coefficient ($\hat{\gamma}$ in Equation 2) for each of the distance rings. We observe that on average, the coefficients on *Post-Game* for all three rings are not statistically significant, and the magnitudes are much smaller compared to the corresponding coefficients presented in Table 4.[42] These results thus offer further support for the robustness of the findings based on our RDD specificationss.

Reassigned Stadiums

Next, we consider a placebo test by switching the home stadium locations but keeping the same game time. In our sample, we observe the following distribution of stadiums: Morumbi (37%), Pacaembu (34%), Allianz (16%) and Arena Corinthians (13%). We then reassign the home stadiums on game days in the following way: Morumbi becomes Pacaembu and vice versa; Allianz becomes Arena Corinthians and vice versa. For example, for a particular property crime that took place after a game in Morumbi, its relative distance to the stadium will now be computed relative to Pacaembu (even though the actual game was played at Morumbi). The intuition behind this placebo test is that if the property crimes are really induced by game outcomes, then we should expect no impact of games on crimes in neighborhoods near the reassigned stadiums because the games were not in fact

[42]The likelihood of observing a larger magnitude on the coefficient for *Post-Game* in the 0–1 mile and 1–2 miles radius is less than 0.5% and 2.2%, respectively.

Table A4: Distribution of Estimated Coefficients on *Post-Game* from No-Game Days

	Mean	SD	Min	Max
0–1 Mile				
$\hat{\gamma}$	0.071	0.152	-0.452	0.648
SE	0.158	0.004	0.146	0.169
1–2 Miles				
$\hat{\gamma}$	0.021	0.092	-0.337	0.295
SE	0.095	0.001	0.091	0.100
2–3 Miles				
$\hat{\gamma}$	-0.006	0.081	-0.329	0.208
SE	0.081	0.001	0.078	0.084

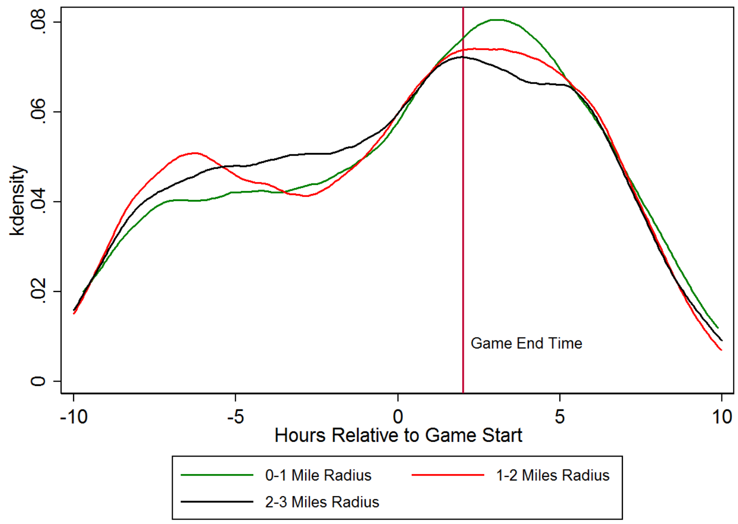
played at these stadiums. Figure A1 plots the density diagram of the temporal distribution of the crimes as a result of reassigned stadiums. While the overall distribution of property crimes in each distance ring is similar to that in Figure 1 which is based on the actual home game stadiums, the gap among the three distributions following game end is much smaller, confirming the setup of this placebo test.

We then seek to replicate a series of RDD analyses similar to those presented in Figure 5 and Table 5. Across both Figure A2 and Table A5, we do not observe systematic impact of games on property crimes regardless of the presence of emotional cues. There is also no evidence on the spatial distribution of the impact. Overall, the results from this placebo test lend further support for our empirical findings presented in the main text.

Away Games

Finally, we consider another placebo test where we focus on the crimes in neighborhoods near the home stadiums but following home teams' away games. Here, we only consider

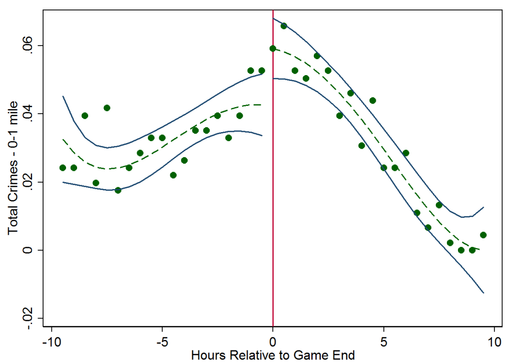
Figure A1: Density Distribution of Property Crimes: Reassigned Stadiums



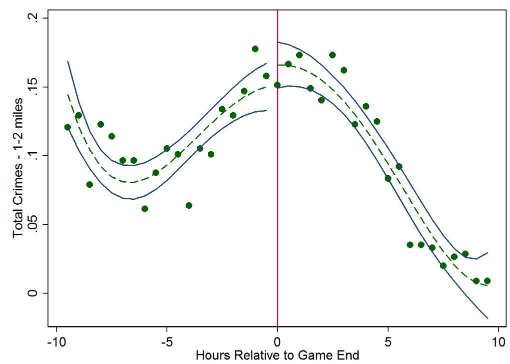
away games played outside São Paulo, i.e., we exclude derby games in this placebo test. If the findings presented in the main text are indeed induced by home games as well as the associated emotional cues, then we would not be able to observe crime responses near the home stadiums following away games because the home teams did not actually play in the stadiums. We re-estimate Equation 2 and incorporated emotional cues from upset losses. Table A6 presents the estimated coefficients, and indeed, none of the coefficients on the interaction term between *Post-Game* and *Upset Loss* are statistically significant.[43] Thus, similar to the other placebo tests, the results based on away games confirm the robustness of our main findings.

[43]The small sample size is because in this placebo test we also only focus on the away games on the days that we already have the geocodes of the property crime locations.

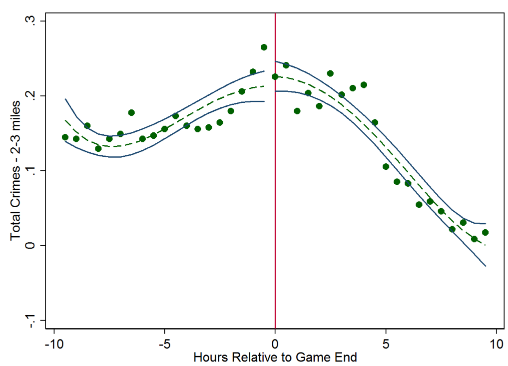
Figure A2: Impact of Games on Property Crimes: Reassigned Stadiums



(a) 0–1 Mile Radius



(b) 1–2 Miles Radius



(c) 2–3 Miles Radius

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.

Table A5: Placebo Test Using Reassigned Stadiums

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.022	-0.127	-0.054
	(0.214)	(0.122)	(0.105)
Derby	-0.668	0.114	-0.166
	(0.559)	(0.387)	(0.248)
Post-Game × Derby	0.228	0.512***	-0.075
	(0.285)	(0.157)	(0.135)
Upset Loss	0.003	-0.506*	0.007
	(0.707)	(0.285)	(0.281)
Post-Game × Upset Loss	-0.005	0.156	0.118
	(0.311)	(0.154)	(0.125)
Derby × Upset Loss	0.980	-0.858	-0.305
	(3.248)	(0.678)	(0.566)
Post-Game × Derby × Upset Loss	0.918	0.143	0.260
	(0.713)	(0.406)	(0.324)
Observations	10,062	15,795	17,004
Number of games	258	405	436

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Table A6: Placebo Test Using Away Games

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.224	0.360	0.039
	(0.497)	(0.362)	(0.285)
Upset Loss	-1.421	-0.168	1.287
	(1.014)	(0.980)	(2.809)
Post-Game × Upset Loss	-0.287	-0.556	0.470
	(0.502)	(0.446)	(0.334)
Observations	1,599	2,028	2,496
Number of games	41	52	64

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Appendix D: Additional Robustness Checks

In this section, we present a number of additional robustness checks where we re-estimate our main emotional cue specification by 1) using alternative distance rings; 2) excluding games played in Morumbi Stadium; 3) excluding afternoon games.

Alternative Distance Rings

We assess the robustness of our main findings by also considering alternative distance rings measured in kilometers. Here, we consider distance rings in the sizes of 1.5 kilometers and 2 kilometers. Table A7 presents the estimates for both distance ring sizes. These results show that the post-game and post-upset loss impacts on crime remain in the distance ring closest to the stadiums, with larger magnitude being within 0–1.5 km. Note that other than Morumbi Stadium, the closest subway station to each stadium is within 1.5km. Overall, our main findings are robust to alternative distance ring sizes.

Excluding Morumbi Stadium

There may be concerns that the increase in post-property crimes may be due to the influx of vehicles parked in the neighborhoods near the stadium on game days, which could cloud the role of emotional cues in activating criminal activities. We argue that such concern is less likely since most fans are likely to take public transit to games with all stadiums except Morumbi having nearby subway stations within 1.5 kilometers. Morumbi is less conveniently connected by public transit, which means that fans are more likely to drive their personal vehicle to attend the games in Morumbi. Therefore, we perform a robustness test by re-estimating our RDD specification but excluding games that took place in Morumbi. Table A8 presents the estimates. The coefficients on *Post-Game* and *Post-Game* × *Upset Loss* for 0–1 mile radius are largely similar to our main results on emotional cues. This confirms the idea that the increase in post-game property crimes, particularly after upset losses, are

Table A7: Robustness Check: 1.5 Kilometer Radius

	(1) Crime 0–1.5 Km	(2) Crime 1.5–3 Km	(3) Crime 3–4.5 Km
Post-Game	0.573***	0.151	-0.005
	(0.205)	(0.127)	(0.105)
Upset Loss	-0.562	-0.112	-0.358*
	(0.590)	(0.319)	(0.208)
Post-Game × Upset Loss	0.444*	0.239*	0.100
	(0.236)	(0.143)	(0.113)
Observations	10,374	15,717	17,355
Number of games	266	403	445
	Crime 0–2 Km	Crime 2–4 Km	Crime 4–6 Km
Post-Game	0.342**	0.217	-0.096
	(0.163)	(0.143)	(0.129)
Upset Loss	-0.113	0.079	-0.552**
	(0.436)	(0.390)	(0.241)
Post-Game × Upset Loss	0.351**	0.241	0.190
	(0.179)	(0.164)	(0.137)
Observations	13,182	15,054	16,692
Number of games	338	386	428

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

unlikely to be drive by an increase in the supply of vehicles on game days but more likely due to perpetrators being emotionally cued by (upset) game outcomes and committing crimes as a result.

Table A8: Robustness Check: Excluding Morumbi

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.414**	0.080	-0.049
	(0.203)	(0.129)	(0.118)
Upset Loss	-1.019**	-0.010	-0.181
	(0.518)	(0.357)	(0.267)
Post-Game × Upset Loss	0.599**	0.345**	0.056
	(0.237)	(0.149)	(0.129)
Observations	8,736	11,193	11,310
Number of games	224	287	290

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.

Excluding Afternoon Games

We also check on the heterogeneous impact due to game schedules. Specifically, we re-estimate our emotional cue specification by focusing on evening games (i.e., excluding afternoon games) as an effort to alleviate the concerns regarding the potential discrepancy between actual crime time and police report time. Tables A9 present the estimates. We observe similar but larger estimates compared to those in Table 4, which confirms the robustness of our main findings.

Table A9: Robustness Check: Excluding Afternoon Games

	(1) Crime 0–1 Mile	(2) Crime 1–2 Miles	(3) Crime 2–3 Miles
Post-Game	0.822***	0.565***	0.240*
	(0.234)	(0.145)	(0.125)
Upset Loss	-1.148	0.663	-0.065
	(0.792)	(0.559)	(0.301)
Post-Game × Upset Loss	0.629**	0.211	-0.169
	(0.300)	(0.169)	(0.150)
Observations	8,736	11,193	11,310
Number of games	224	287	290

Note: The dependent variable is the total number of vehicle robberies and thefts. *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 game end time. All specifications are estimated using negative binomial model and use game fixed effects. Standard errors are reported in parenthesis. The 1%, 5% and 10% level of significance are represented by ***, ** and * respectively.