Unexpected Emotional Cues and College Crime

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Abstract

This paper investigates how unexpected emotional cues influence crime in college towns. I use unanticipated outcomes of college football games as plausibly exogenous shocks to collective emotional states. Betting markets provide unbiased forecasts of game outcomes, generating quasi-random deviations from expectations that serve as emotionally salient shocks with both campus-wide and community-wide reach. To evaluate their impact, I compile administrative crime data from university police departments along with incident-level crime reports from the National Incident Based Reporting System (NIBRS). I employ generalized difference-in-differences (DiD) and Poisson frameworks to compare crime rates after games with unexpected outcomes to those with expected outcomes, conditioning on pregame expectations measured by the point spread.

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I Introduction

Emotional states influence decision making in ways that can have measurable economic and social consequences. Evidence shows that unexpected emotional or psychological shocks increase the likelihood of violence and impulsive actions (e.g. Jacob, Lefgren, and Moretti 2007, Joseph J. Doyle 2008, and Munyo and Rossi 2013). These unexpected or random cues may also influence outcomes beyond the individual.

Card and Dahl (2011) and Arnesen and Matsuzawa (2024) evaluate the effect of emotional distress caused by unexpected losses by NFL teams in their home city. This paper examines how unexpected emotional cues affect crime in college towns, similar to Rees and Schnepel (2009). College campuses provide a distinctive setting for three reasons. First, individuals on campus during game-days are more heavily invested in college football outcomes than residents of large metropolitan areas are in professional games. Second, fans are in close proximity to supporters of the opposing team, which creates opportunities for direct confrontation following a surprising outcome. Third, students and local residents attending college games are more likely to be under the influence of alcohol or other substances than the broader population of a NFL team's home city, which heightens the risk that emotional cues translate into criminal behavior (Ivandić et al. 2024). These features make the college campus setting particularly well suited to studying the consequences of sudden emotional distress.

Unlike Rees and Schnepel (2009), I use the point spread to determine unexpected outcomes rather than the team's rank and I include data from colleges' police departments.[1] My approach also differs from Lindo, Siminski, and Swensen (2018), who focus on the predictable timing of college football games and its effect on sexual assault through heightened party activity and general campus culture on game-days. By instead exploiting unanticipated outcomes, I separate the role of emotional shocks from the broader party environment that is known well in advance of game days. Moreover, whereas their analysis centers narrowly on sexual assault, I study a wider set of crimes recorded by both campus and municipal law enforcement, allowing me to assess whether emotional cues influence crime patterns more generally or if the effects are concentrated in particular types of offenses.

[1] The point spread provides an unbiased prediction of game outcomes and is available for every game, offering a cleaner source of quasi-random variation in treatment assignment and enabling analysis of the full set of games, unlike team rankings which only apply when exactly one team is ranked.

To generate plausibly exogenous variation in collective emotional states, I use unanticipated outcomes of college football games. Betting markets provide unbiased forecasts of game outcomes, generating quasi-random deviations from expectations (Pankoff 1968 and Gandar et al. 1988). Unexpected wins and unexpected losses can therefore be interpreted as emotional shocks with campus-wide or even community-wide salience. By focusing on how crime responds to these shocks, this paper contributes to the literature on the causal role of emotions in shaping criminal behavior.

I employ a generalized difference-in-differences and Poisson strategies that compare crime rates on days with unexpected outcomes to those with expected outcomes, conditioning on pregame expectations measured by the point spread. This framework isolates the effect of emotional shocks from confounding factors. I use administrative crime data from university police departments as well as the National Incident-Based Reporting System (NIBRS), which together provide coverage of both incidents on campus and those in the surrounding community.

The contribution of this paper is twofold. First, it extends the evidence on the behavioral effects of emotional distress beyond the household setting emphasized in Card and Dahl (2011) and Arnesen and Matsuzawa (2024). Second, it highlights college campuses as environments where the salience of emotional cues and dense social interaction produce measurable externalities. By leveraging a setting where emotional cues are both salient and plausibly exogenous, this study provides new evidence on how unexpected emotional shocks influence crime.

II Data

I aim to collect college crime report data from as many college police departments as possible. Per the Clery Act, all Title IX universities are required to maintain an up-to-date record of all daily crime reports covering the past sixty days to the public.[2] Additionally, universities must maintain the past seven years of daily crime log data and make it available upon request, although it need not be public.[3] Daily crime logs include all crimes reported to the college police department, and are required to include the crime type, date, time, location, and disposition of the alleged crime. These reports include all incidents that occur on the college campus as well as those adjacent to

[2]For example, Florida State University's Daily Crime Log can be found here.

[3]Universities may charge for this data.

the campus but within the college police department's jurisdiction. These data have been used in related literature in economics (e.g. Topper 2023).

In order to estimate the broader effect of such emotional cues on criminal behavior beyond the college campus, I use 2013-2024 data from the National Incident-Based Reporting System (NIBRS). These data include all incident level crime reports of participating agencies. Of the participating agencies, I use those who include a major college football program. The NIBRS allows me to observe many more crimes reported than the daily crime reports and extend further back in time. Crime reports are restricted to those on gameday which were reported to have occurred after the start of the football game. Importantly, university police departments may participate in NIBRS reporting. I exclude these departments from any analysis using the NIBRS to avoid double counting with reports in the daily crime logs.

I scrape college football outcomes for all universities from sports-reference.com, a leading sports statistics and history website which has been used in other economics research (e.g. Lindo, Siminski, and Swensen 2018). Historic closing point spreads come from from sportsoddhistory.com (Use covers.com as in Lindo, Siminski, and Swensen 2018?). Additionally, I get the date and time of the game, opponent and their rank, and the final score. Due to data limitations, I restrict my sample to Division I colleges in "Power Five" divisions for which daily crime logs are reasonably obtainable in terms of price.[4] The "Power Five" divisions in college football are the Atlantic Coast Conference (ACC), Big Ten Conference, Big Twelve Conference, Pac-12 Conference, and the Southeastern Conference (SEC). Universities in these conferences represent the most prominent universities in college football totaling sixty-five schools in the 2025 season.

Lastly, I obtain daily average weather data from the National Oceanic and Atmospheric Administration (NOAA) to be used as controls.

[4]This restriction does not bias the estimates if the price of obtaining daily logs is not correlated to the frequency of unexpected game outcomes and to how crime responds on days with unexpected outcomes relative to expected outcomes.

III Identification Strategy

III.A Difference-in-Differences Model

I use the generalized difference-in-differences (DiD) in equation 1 to estimate the effect of unexpected game outcomes on either college campus crime, using data from college police department reports, or on reported crime in the entire college town using the NIBRS. This gives me two measures of crime, allowing me to test whether aggregate crime rises or is merely relocated. Following Card and Dahl 2011 and Arnesen and Matsuzawa 2024, I am able to see the effect on crime in the entire city, including individuals not on the college campus, using the NIBRS.

$$\begin{aligned} Y_{cswt} = \alpha_0 &+ \alpha_1 \mathbb{1}\{S_{cswt} \leq -4\} + \alpha_2 \mathbb{1}\{S_{cswt} \leq -4\} \times (1 - \text{HomeWin}_{cswt}) \\ &+ \alpha_3 \mathbb{1}\{S_{cswt} \geq 4\} + \alpha_4 \mathbb{1}\{S_{cswt} \geq 4\} \times \text{HomeWin}_{cswt} \\ &+ \alpha_5 \mathbb{1}\{|S_{cswt}| < 4\} + \alpha_6 \text{HomeWin}_{cswt} \\ &+ \delta_i + \gamma_s + \phi_w + \tau_t + \text{Holiday}_{wt} + \rho X_{cswt} + \epsilon_{cswt} \end{aligned} \tag{1}$$

Where Y_{cswt} is the outcome of interest being the amount of either all crime, violent crime, or non-violent crime which occurred after the game concluded on college i's campus or home town, in state s, during the college football week w in year t. S_{cswt} is the point spread from the home team's perspective. For example, $S_{cswt} = -5$ implies the home team is favored to win the game by five points. HomeWin_{cswt} is an indicator for the home team winning the game. δ_c, γ_s, ϕ_w, and τ_t are a series of fixed effects for college, state, college football week, and year, respectively. Holiday_{wt} is an indicator for the Saturday the game is played on being a holiday. X_{cswt} is a vector of time-varying weather controls including temperature and precipitation. I cluster standard errors at the college level.

This generalized DiD specification compares outcomes on game-days with an unexpected loss or win to those with an expected result.[5] This gives α_2 as the average effect of unexpected emotional distress, caused by an unexpected loss, on crime in or around the college campus. α_3 is similar but of

[5]This is a deviation from Card and Dahl (2011) and Arnesen and Matsuzawa (2024) which compare Sundays with unexpected game outcomes to Sundays without any game.

an unexpected win. Since the point spread is an unbiased predictor of game outcomes, the treatment of unexpected game outcomes, determined by HomeWin_{cswt}, creates quasi-random variation in the emotional state on college campuses with greater salience than the outcome of an NFL game as in Card and Dahl (2011) and Arnesen and Matsuzawa (2024) (e.g. Pankoff 1968 and Gandar et al. 1988).

III.B Poisson Model

I estimate the Poisson model in equation 2 because reported crime counts often include many zeros, particularly when Y_{cswt} is restricted to subsets of all crime. This approach follows the estimation strategies in Card and Dahl (2011), Lindo, Siminski, and Swensen (2018), and Arnesen and Matsuzawa (2024).

$$\begin{aligned} log\left(E\left[Y_{cswt}|\cdot\right]\right) = \beta_0 &+ \beta_1 \mathbb{1}\left\{S_{cswt} \leq -4\right\} + \beta_2 \mathbb{1}\left\{S_{cswt} \leq -4\right\} \times (1 - \text{HomeWin}_{cswt}) \\ &+ \beta_3 \mathbb{1}\left\{S_{cswt} \geq 4\right\} + \beta_4 \mathbb{1}\left\{S_{cswt} \geq 4\right\} \times \text{HomeWin}_{cswt} \\ &+ \delta_i + \gamma_s + \phi_w + \tau_t + \text{Holiday}_{wt} + \rho X_{cswt} \end{aligned} \tag{2}$$

All variables are defined as in equation 1. Unlike in the DiD model, there is no indicator for a close game ($|S_{cswt}| < 4$) nor a home win. The close game category is omitted and serves as the reference group. For games with large spreads, the expected outcomes are the cases against which the unexpected outcomes are compared. This specification allows the coefficients on the unexpected outcome terms to be interpreted directly as log incidence rate ratios.

The Poisson specification is preferred given the prevalence of zeros in the outcome. Here, $exp(\beta_2) - 1$ represents the percentage change in crime attributable to emotional distress from an unexpected loss, while $exp(\beta_4) - 1$ captures the percent change in crime due to the positive emotional shock of an unexpected win.

IV Appendix

References

Arnesen, E. and K. Matsuzawa (2024). "Sports Betting Legalization Amplifies Emotional Cues & Family Violence". URL: %5Curl%7Bhttps://papers.ssrn.com/sol3/papers.cfm?abstract_id=4938642%7D.

Card, D. and G. B. Dahl (2011). "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior". *Quarterly Journal of Economics* 126.1, pp. 103–143. DOI: 10.1093/qje/qjr001. URL: https://davidcard.berkeley.edu/papers/card-dahl-family-violence.pdf.

Gandar, J. M. et al. (1988). "Testing Rationality in the Point Spread Betting Market". *The Journal of Finance* 43.4, pp. 995–1008. DOI: 10.2307/2328148.

Ivandić, R. et al. (Feb. 2024). "Football, Alcohol, and Domestic Abuse". *Journal of Public Economics* 230.C, p. 105031. DOI: 10.1016/j.jpubeco.2023.105031.

Jacob, B. A., L. Lefgren, and E. Moretti (2007). "The Dynamics of Criminal Behavior: Evidence from Weather Shocks". *Journal of Human Resources* 42.3, pp. 489–527. DOI: 10.3368/jhr.42.3.489.

Joseph J. Doyle, J. (2008). "Child Protection and Adult Crime: Using Investigator Assignment to Estimate Causal Effects of Foster Care". *Journal of Political Economy* 116.4, pp. 746–770. DOI: 10.1086/590216.

Lindo, J. M., P. Siminski, and I. D. Swensen (Jan. 2018). "College Party Culture and Sexual Assault". *American Economic Journal: Applied Economics* 10.1, pp. 236–265. DOI: 10.1257.

Munyo, I. and M. A. Rossi (2013). "Frustration, euphoria, and violent crime". *Journal of Economic Behavior & Organization* 89.C, pp. 136–142. DOI: 10.1016.

Pankoff, L. D. (1968). "Market Efficiency and Football Betting". *The Journal of Business* 41.2, pp. 203–214. DOI: 10.1086/295077.

Rees, D. I. and K. T. Schnepel (2009). "College Football Games and Crime". *Journal of Sports Economics* 10.1, pp. 68–87. DOI: 10.1177/1527002508327389.

Topper, M. (2023). "The Effect of Fraternity Moratoriums on Alcohol Offenses and Sexual Assaults". *Journal of Human Resources*. DOI: 10.3368/jhr.0722-12422R1. URL: https://jhr.uwpress.org/content/early/2023/05/01/jhr.0722-12422R1.