Sports Betting Legalization Amplifies Emotional Cues & Intimate Partner Violence

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Abstract

This study explores the relationship between legalized sports gambling, unexpected emotional cues stemming from NFL home team upset losses and reported intimate partner violence (IPV). Using 2011–2022 crime data from NIBRS and extending Card & Dahl (2011)'s model, we find that legalized gambling increases the impact of upset losses on IPV by 10 percentage points. The effect is larger in states with mobile betting, where higher bets were placed, around paydays, and for teams on a winning streak. These results suggest that financial losses from gambling amplify emotional reactions to unexpected team losses.

JEL Codes: D01; J12; Z28

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1 Introduction

Family violence or intimate partner violence (IPV) is a huge problem both in the United States and worldwide, as approximately 41% of women in the United States and 26% of women worldwide have experienced some form of IPV in their lifetime (Centers for Disease Control and Prevention 2024; National Domestic Violence Hotline n.d.; UN Women 2023). Previous studies have demonstrated that experiencing family violence victimization can lead to adverse effects on mental health, resulting in lower cognitive ability scores, reduced employment opportunities, and diminished earnings (Adams-Prassl et al. 2023; Bhuller et al. 2022). Peterson et al. 2018 estimate that the lifetime cost of a female victim of IPV – from health, lost productivity, and criminal justice costs– is approximate $137,000 in 2024 dollars. Finally, research has documented that family violence victimization can generate negative externalities affecting other peers (Carrell & Hoekstra 2010; Carrell & Hoekstra 2012; Carrell et al. 2018).

One explanation for increased IPV is the role of emotional cues stemming from various causes and unexpected events. Card & Dahl (2011) leverage a potential emotional cue with pre-game NFL spreads and find that an upset loss (a team lost when they were predicted to win by more than 3.5 points) increases male-to-female IPV by up to 11.2 percentage points. Cardazzi et al. (2022) find similar patterns when examining the NBA, suggesting that Card & Dahl (2011)'s findings do not pertain to the NFL, where the nature of sports is more violent than other sports and the games are played only once a week. Arenas-Arroyo et al. (2021) and Beland & Brent (2018) find that negative emotional cues outside of sports, such as the COVID-19 pandemic or traffic congestion, also contribute to increased family violence. Conversely, Collins (2022) finds that positive emotional cues, such as voting for the winning presidential candidate, can reduce IPV.

Household finances can also influence family violence, although the direction of this relationship remains unclear. Several studies have found an increase in family violence during periods of negative economic shocks, such as the Great Recession (Schneider et al.

2016), COVID-19 pandemic (Arenas-Arroyo et al. 2021), mass layoffs (Lindo et al. 2018), and stock market losses (Lin & Pursiainen 2023). These findings are consistent with the possibility of increases in the likelihood of conflicts arising from household finances (Carr & Packham 2021). In contrast, a signaling model by Anderberg et al. (2016) and empirical analysis using data from the UK suggest that a higher risk of unemployment and lower wages decrease male IPV rates. Their findings suggest that factors like fear of job loss, the economic incentive to avoid divorce, and the associated loss of spousal insurance may play significant roles. This finding is also consistent with Aizer (2010)'s household bargaining model, which finds that decreases in the female-to-male wage gap reduce violence against women.

Participation in gambling can also impact the probability of committing IPVs.[1] Gambling participation can result in unexpected outcomes where individuals will feel more negative emotional cues. Moreover, the gambling market will lead to lower expected but larger variations in household finances due to potential short-term gains and losses but the casinos making profits in expectation.

In 2018, a United States Supreme Court decision allowed states to legalize sports gambling for the first time since 1992.Following this ruling, 38 states and the District of Columbia legalized sports gambling. This legalization led to vastly increased interest and participation in sports gambling (American Gaming Association 2023; Baker et al. 2024; Hollenbeck et al. 2024; Huble 2023; Oxford Economics 2017). Thus, in theory, sports gambling legalization can lead to changes in emotional cues and IPV. However, to our knowledge, no studies have investigated such causal relationships. In this paper, we are the first to fill this gap in the literature.

Using data from the 2011-2022 National Incident-Based Reporting System (NIBRS) and extending Card & Dahl (2011)'s model, we document that in states where sports betting has

[1] Several papers document a strong association between problem gambling and IPVs. For example, Dowling et al. (2016) conduct a meta-analysis of six studies and find that 36.5% of problem gamblers are perpetrators of IPVs. Korman et al. (2008a) find that 55.6% of problem gamblers had perpetrated IPV.

been legalized, the effect of upset losses on IPV is about 6 to 7 percentage points larger than in states without sports betting. Supplemental tests examining the effect on Sunday morning crimes, bar fights, or other non-IPV assaults confirm that changes in crime reporting or crime displacements do not drive this estimate. Furthermore, we find that the effects are driven by home teams on a winning streak, states with legal mobile betting, Sundays right after paydays, and states with a larger betting market. The pattern of these findings confirms that the reaction to gambling loss explains our results.[2] Together, our paper sheds some light on one of the unintended consequences of legalized sports betting: Legalized sports betting can amplify negative emotional cues.

The remainder of the paper is organized as follows. Section 2 provides a brief history of sports betting in the United States. Section 3 explains each of the data sources used. Section 4 discusses the methodology used in our analysis. Section 5 provides results. Section 6 concludes.

2 Background

Sports gambling's availability was regulated by the Professional and Amateur Sports Protection Act of 1992 (PASPA). Before then, some states offered betting for big games such as the Super Bowl and considered legalizing sports betting in the 1980s. In 1992, the federal government stopped sports betting in all states except Nevada through the PASPA. For the next 26 years, Nevada was the only state where sports betting was legal. Delaware, Oregon, and Montana also offered some types of sports betting before PASPA, so what they had legalized before PASPA was grandfathered into the law. Delaware had legal parlay bets for football on three teams or more but stopped offering it in 1976. Oregon also offered parlay betting before PASPA but ceased offering it in 2007. Montana had legal sports pools,

[2] Another potential mechanism noteworthy that may be at play is that sports gambling legalization can increase emotional attachments to the fans' favorite team. This heightened attachment can lead to a larger adverse reaction to an upset loss of their favorite team. However, we do not directly test this hypothesis in this paper due to data limitations.

fantasy sports leagues, and sports tab games. However, the advent of the internet introduced new challenges. Online betting has become popular regardless of the state in which a person lives. The Unlawful Internet Gambling Enforcement Act of 2006 was passed, which did not ban online gambling, but banned the collection of credit, checks and electronic fund transfers to gambling websites in the United States.

On May 14, 2018, in a court case *Murphy v. National Collegiate Athletic Association,* the U.S. Supreme Court overturned the PASPA. After this ruling, 38 states plus Washington D.C. made some form of sports gambling legal, and the sports betting market began growing with an estimated annual total revenue of $10 billion. There are two distinct ways in which people can bet on sports. Retail or in-person betting occurs within a physical building that a state's government has approved. These places are usually casinos; however, in some states, bars and stadiums have been approved to facilitate sports gambling. The other way people can bet on sports is through online (sometimes called mobile) betting. In most states where online betting is allowed, people can place bets from anywhere in the state as long as they have access to the internet.[3] A majority of states who have legalized some form of sports gambling legalized retail betting first. Figure 1a and Figure 1b show the month and year when each state launched retail and online sports gambling.

3 Data

3.1 Crime Data

We obtain our crime data from the National Incident-Based Reporting System (NIBRS). The NIBRS collects incident-level crime data reported by around 8,500 local law enforcement agencies, covering approximately 146.5 million people in the U.S.[4] The NIBRS data has several attractive features that we can utilize. First, we can observe the number of incidents

[3]There are some states, such as Washington, which only allow online sports gambling on tribal land.
[4]Our NIBRS data comes from Kaplan (2023) and can be downloaded from ICPSR.

rather than arrests.[5] Because the probability of arrest may be a function of police discretion, using arrest may underestimate the actual crime rate. Second, it permits the identification of the date and time of offense, which we can leverage to estimate the hourly crime rates during the game day. Finally, the rich set of information provided in the NIBRS data allows us to identify whether a crime was an IPV.

Following Card & Dahl (2011), our primary variable of interest is defined as any male-to-female simple assault, aggravated assault, or intimidation that occurred against a spouse or partner at home during a 12-hour time window (12 pm to 11:59 pm Eastern Time) centered around game and post-game window.[6] Because the rate of violence varies substantially across the days of the week and most NFL games occur during Sundays, we restrict our sample to the 17 Sundays during the regular NFL season.[7] To match the length of Card & Dahl (2011)'s 12-year sample window, we focus our sample on the years 2011-2022.

One limitation of the NIBRS data is that agencies may not consistently report across the year. For instance, an agency may report all the incidents in January but not February. Thus, interpreting zero crime can pose a challenge because we cannot distinguish whether the crime rate is truly zero or not reported in the data. To address this concern, we follow Card & Dahl (2011) and restrict our agencies where they report any crime during 13 out of 17 game-days during a season.[8] By restricting the sample to agencies that report any crime during most game-days, we can be more confident that zero family violence reports reflect an actual absence of crime rather than a reporting artifact.

Another limitation of the NIBRS is that agencies will enter the NIBRS sample and, in some rare cases, stop reporting at different points in time. Hence, the changes we observe in county-level crime rate may be driven by changes in the agencies reporting to the NIBRS. To circumvent this issue, we follow Lindo et al. (2022) and aggregate our sample to the agency

[5] Approximately only half of reported incidents result in an arrest.

[6] Approximately half of the NFL have a start time of 1 pm Eastern Time.

[7] Because NIBRS data is not available for 2023, for the 2022 season, we restrict our sample to 16 Sundays.

[8] We also follow Card & Dahl (2011) and exclude college or special agencies. Our estimates are robust to different samples, such as including these agencies and using different numbers of days reported.

level rather than a more aggregate level such as the county level.

3.2 Game Spread Data

NFLOddsHistory.com provides a final pre-game point spread for each NFL game, which measures the likelihood that a team will win a game using an algorithm.[9] A negative spread favors the team to win, and a larger absolute value implies a higher likelihood of winning or losing. For example, a point spread of -9 implies that the team must win by more than 9 points for a bet on that team to pay off, and that the team is favored to win by a quite large margin. Previous research has shown that the point spread is an unbiased predictor of game outcomes (Gandar et al. 1988; Pankoff 1968).

We match the pre-game point spread with the actual outcome of the game to create a measure of unexpected wins and losses. Following Card & Dahl (2011), we define an unexpected loss (upset loss) if a team had a point spread of -4 or more (favored to win), but lost the game; unexpected win (upset win) if a team had a point spread of 4 or more (favored to lose), but won the game; and close loss if a team had a point spread between -4 and 4 (close game) and lost the game. In Appendix Table 1, we present the total count and percentage of unexpected outcomes for each NFL teams. On average, each team experiences an unexpected loss about once per season (approximately 27% of the predicted to win games), close loss about 3 times per season (approximately half of the predicted close games), and upset win about once per season (approximately 28% of the predicted to lose games).

3.3 Mapping Home Team

Mapping each NIBRS agency to an NFL franchise can be challenging because not all large cities with an NFL stadium have data for NIBRS. This sample limitation can result in loss of power or generalizability of our treatment effects. To address this issue, Card & Dahl (2011) focus only on states with a single NFL team (or nearby team) with at least four

[9]Data can be obtained from https://www.sportsoddshistory.com/nfl-game-odds/

years of crime data, and assign all jurisdictions within a state to a team in the same state.[10] Panel a of Appendix Figure 1 shows the states with at least one NIBRS agency with an NFL team. However, a limitation of this approach is that the estimated treatment effects only apply to jurisdictions with exactly one NFL team.

To extend upon Card & Dahl (2011)'s model, our preferred approach of defining a "home" NFL team is to map each county with at least four years of crime data based on NFL fandom. Our preferred method of defining NFL fandom is based on proximity. Specifically, we find the closest NFL stadium in linear distance from its centroid for each county.[11] Panel a of Figure 2 presents the "home team" for every county in the U.S. Using this approach, our total selection includes 2447 police agencies within 831 counties across 40 states (see panel b).

Figure 3 plots the mean IPV rate per 100,000 when mapping the home team using our preferred method. Panel (a) suggests that relative to when a home team wins as expected, the mean IPV rate is 5% higher (0.412 vs. 0.439) when the team experiences an upset loss. However, when comparing close wins vs. close losses or losses as expected vs. upset wins, the difference in the mean is not stark. Strikingly, panel (b) shows that these differences in mean IPV rates across upset loss days vs. non-upset loss days are higher when sports betting is legal (19% vs. 3.6% increase).

Because proximity may not fully capture the intensity of the fanbase, we also experiment with supplemental definitions of the fanbase. Specifically, we obtain information for the most favored team for each county using data from Seatgeek and Facebook. These measures are based on the total number of ticket searches and Facebook likes.[12] We also combine both these datasets to obtain the temporal changes in fandom and to estimate the intensity of

[10] For nearby teams, they assign South Carolina to the Carolina Panthers and New Hampshire and Vermont to the New England Patriots.

[11] Two stadiums have two home teams: Los Angeles Rams and Chargers, and New York Jets and Giants. Since California is not in our sample, we ignore the former stadium. We use the New York Giants for the New York teams since they are a more popular franchise with a larger fanbase. However, our results are robust to (1) mapping counties to Jets instead of Giants or (2) excluding Giants from our analysis.

[12] The data for SeatGeek is for the year 2018, and the data for Facebook is for the year 2013.

fans based on different definitions of fans.[13] The advantage of such a method is that we can examine a more precise fanbase. Appendix Figure 1 panels (b) and (c) show the fandoms for each county with at least one NIBRS agency. A caveat with combining both sources for fanbase is that because these datasets measure fanbase differently, our estimated effect can be driven by changes in fanbase because of changes in the actual measurement. For this concern, we also experiment with restricting the counties where the fanbase is consistent across both data sources.

4 Empirical Strategy

Our main empirical strategy builds off Card & Dahl (2011), but the main difference is that we also include interaction between unexpected game outcomes and sports betting legalization. More specifically, we estimate the following model:

$$\begin{aligned} IPV_{isw} = &\beta_1 \text{Exp Win}_{isw} + \beta_2 \text{Exp Loss}_{isw} + \beta_3 \text{Exp Close}_{isw} \\ &+ \beta_4 \text{Upset Loss}_{isw} + \beta_5 \text{Upset Win}_{isw} + \beta_6 \text{Close Loss}_{isw} + \alpha_0 \text{ Policy}_{isw} \\ &+ \alpha_1 \text{Exp Win}_{isw} * \text{Policy}_{isw} + \alpha_2 \text{Exp Loss}_{isw} * \text{Policy}_{isw} + \alpha_3 \text{Exp Close}_{isw} * \text{Policy}_{isw} \\ &+ \alpha_4 \text{Upset Loss}_{isw} * \text{Policy}_{isw} + \alpha_5 \text{Upset Win}_{isw} * \text{Policy}_{isw} + \alpha_6 \text{Close Loss}_{isw} * \text{Policy}_{isw} \\ &+ \delta_i + \gamma_s + \phi_w + \rho \text{Holiday}_{sw} + \rho X_{isw} + \varepsilon_{isw}. \end{aligned} \tag{1}$$

In Equation (1), IPV_{isw} is the count of intimate partner violence (IPV) in agency (i), season (s), and NFL week (w). Exp Win_{isw} is a dummy variable indicating whether a "home" team in agency i is expected to win; Exp Loss_{isw} is a dummy variable indicating whether a "home" team is expected to lose; and Exp Close_{isw} is a dummy variable indicating whether a "home" team is expected to have a close game. Upset Loss_{isw}, Upset Win_{isw}, and Close Loss_{isw} are dichotomous variables indicating whether a game resulted in upset loss,

[13] This may be important because three teams (Rams, Chargers, and Raiders) moved cities during our sample period, which may change who they root.

upset win, or close loss, respectively. We also include agency (δ_i), season (γ_s), and week of the season (ϕ_w) fixed effects. We also include controls for whether a Sunday is a holiday or not.[14] X_{isw} is a vector of time-varying weather controls (daily average temperature and total precipitation). Finally, Policy_{isw} is a dichotomous policy treatment variable indicating if a state had launched any in-person or online sports betting.[15]

Following Card & Dahl (2011), we restrict our counterfactual to any Sundays where there are no "home" games.[16] To account for zero counts, we estimate Equation (1) using a poisson with agency population as the exposure variable. Finally, because our policy treatment variable varies across states and our game outcome varies by team and season, we cluster our standard errors for Equation (1) at the state-by-game-by-season level.

One underlying assumption for Equation (1) to produce an unbiased estimate is strict exogeneity. Formally, we require that the unexpected outcome we observe is as good as random, conditional on our observables. Under strict exogeneity assumption, we can still recover the causal α_4, α_5, and α_6 in Equation (1) even if sports betting legalization is endogenous to the error term (Nizalova & Murtazashvili 2016).[17] This assumption is likely to be valid because after controlling for the pre-game spread, the outcome of the game is random (Card & Dahl 2011; Pankoff 1968; Gandar et al. 1988).

Another assumption necessary for Equation (1) is the stable unit treatment value assumption (SUTVA), which requires no spatial spillovers to states that did not legalize sports betting. Justifying this assumption is challenging because individuals can travel to nearby jurisdictions to gamble on sports or use VPNs for mobile betting. However, in the event of a violation of SUTVA, our estimate will be attenuated towards zero, and our estimated effect will serve as

[14] Holiday includes Labor Day weekend, Columbus Day weekend, Halloween, Veteran's Day weekend, Thanksgiving day weekend, Christmas Eve and Day, and New Year Eve and Day.

[15] If Policy_{isw} is a constant, then Equation (1) will be identical to the model estimated by Card & Dahl (2011).

[16] A team can have no home games if they have a bye-week or play a game on a different day of the week (i.e., Thursday or Monday night). We document that approximately 20% of our sample has no game on a given Sunday.

[17] Because our interests are in the changes in behavior when a fan experiences an unexpected shock rather than a baseline shift as result of implementing a policy, we will not be arguing whether sports gambling policy is exogenous to our outcome of interest.

a lower bound and not a spurious relationship.

One potential threat to our identification is that our treatment turns on and off (i.e., unexpected game outcomes change heterogeneously across jurisdictions). This feature of our treatment can lead to each treated observation receiving unequal (and sometimes negative) weights. Consequently, it can lead to biased (and even different in sign) estimates than the true average treatment effects Chaisemartin & d'Haultfoeuille (2020). We note that this concern is minimal for two reasons. First, when we calculate the negative weights in our main specification, we find no observations receiving negative weights, suggesting that the sign of our estimated effect is the same as the sign of the true treatment effect. Second, when we experiment with Chaisemartin & d'Haultfoeuille (2020) estimator, which allows the treatment to turn on and off, we find contemporaneous effects of 0.071 per 100,000 (or 16.1 percent relative to the baseline mean of 0.44 with SE=0.039 and p-value=0.070) for our upset loss times betting coefficient, which is qualitatively similar to our estimated treatment effects.[18]

Our last assumption is the first-stage assumption. We assume that the intensity of sports gambling participation increased following the legalization of sports gambling. This assumption can be violated, for instance, if the legalization of sports gambling just moved individuals from the black market to the legal market. While the total count of individuals participating in the legal and illegal sports gambling cannot be directly measured, we believe this assumption is justified for three reasons. First, several reports and papers document evidence suggesting that the intensity of sports gambling, both in the extensive and intensive margins, has increased. For example, two recent working papers by Baker et al. (2024) and Hollenbeck et al. (2024) use household-level transaction data and consumer credit data, respectively, and find causal evidence that sports betting expenditure increased and overall consumers' financial health deteriorated after the legalization of sports gambling. Moreover, van der Maas et al. 2022 find that the legalization of online sports gambling led to an

[18] Because these estimations and diagnostics do not allow for Poison estimation, we conduct these using OLS where the outcome is IPV per 100,000. Our main model using OLS shows qualitatively similar results.

increase in the activity in online gambling message board. Another paper by Humphreys (2021) finds that sports betting legalization had a cannibalism effect where the amount of money wagered in video game lottery decreased by $900 million in West Virginia, suggesting a potential change in gambling behavior as a result of sports gambling legalization. Finally, reports from American Gaming Association (2023) and Huble (2023) suggest that the number of adults in the U.S. who are interested in sports gambling increased by 24 million between 2019 and 2023 and that calls into the National Problem Gambling Helpline increased by 45% between 2021 and 2022.[19]

Next, we validate our first-stage assumption in panel (a) of Figure 4 by showing that the monthly money wagered on sports by average individuals over the age of 21 has been rising following the 2018 U.S. Supreme Court Case.[20] This figure confirms that legalized sports gambling indeed increased the size of the sports betting market, especially following the COVID-19 pandemic recovery, as the amount wagered increased by approximately 68 percent from $1,026 per person (in 2019) to $1,729 per person (in 2022). Moreover, we also show that participation in sports gambling spikes during football season (September to January). This pattern is consistent with the fact that the NFL is one of the most popular sports to bet on and that the NFL is an appropriate setting for our study.[21]

Finally, we validate our assumption by examining if interest in sports gambling, as measured by data from Google Trends, increased after sports betting legalization. More specifically, we estimate the following model:

$$Searches_{it} = \sum_{j=-23}^{24} \beta_j D_{i,t}^{j} + \delta_i + \gamma_t + \varepsilon_{it} \tag{2}$$

[19]In the intensive margin, an online consumer survey data by EY noted that illegal sports bettors responded that the average amount wagered significantly increases when sports gambling is legal (Oxford Economics 2017).

[20]In panel (b), we show that the trend pattern is similar when we examine monthly revenue from sports gambling.

[21]We acknowledge that for more than half of the NFL season, the NBA is also in season, which will also increase betting revenue. While we cannot distinguish how much money is wagered per sport, it is estimated that the NFL is the most betted sport, with 81% of sports bettors placing an NFL wager (Walsh 2023).

In Equation (2), $Searches_{it}$ is the total Google search for the keywords "sportsbook" or "sports betting" in state i for each month-year t.[22] We denote $D_{i,t}^{j}$ as our treatment leads and lags indicator, representing j months before or after sports betting became legal. δ_i and γ_t are our state and month-by-year fixed effects. We weight our estimates using state-level population and cluster our standard errors at the state level (Bertrand et al. 2004). We also experiment with using Sun & Abraham (2021) estimator using states that did not legalize sports betting by December 2022 as our counterfactuals to guard against negative weights arising from staggered treatment and dynamic treatment effects (Chaisemartin & d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun & Abraham 2021).

In the top row of Figure 5, we present our TWFE event study estimates of Google Trends search for the keywords "sports betting" (panel a) and "sportsbook" (panel b). Though there may be some anticipatory effect in the pre-treatment period, which may be correlated with the announcement of the sports betting legalization, there is an apparent post-treatment reaction to the policy enactment. We find that around the month of the policy enactment, people are significantly more likely to search for the keyword "sports betting". Furthermore, the search for the term "sportsbook" rose and persisted immediately following the policy enactment. The magnitude of the effect for the latter keyword suggests an approximately 0.37 percentage point increase (or 197 percent relative to the baseline mean of 0.189) in the post-treatment period. In the bottom row, we continue to find similar patterns of results when we use a different difference-in-differences technique. In summary, these estimates establish the first stage effect of sports betting legalization on interest in sports gambling.

[22] Sportsbook is a physical or online platform where one can place bets.

5 Results

5.1 *Sports Gambling, Emotional Cues, & IPVs*

In Table 1, we present our estimates when we interact our indicators for various game outcomes with an indicator for whether a state legalized sports gambling. We first document that our estimates are robust to the inclusion of various control variables and whether we use population as our exposure variable (i.e., weighted vs. unweighted). Our estimates imply that legalizing sports gambling increases the effect of upset loss on IPVs by 4.1 to 6.31 percentage points ($\alpha_0 + \alpha_4$). The magnitude of our point estimates suggests that when sports betting is legal, IPVs increase by 8.5 to 9.6% (or by 0.035 to 0.040 per 100,000 relative to the mean).[23] We also document a statistically significant change in individual's response to a home team's close loss when sports gambling is allowed. These findings support the possibility that an unexpected loss may lead to additional emotional cues and fans may express their frustration and anger towards other people (Hing et al. 2022; Korman et al. 2008b; Suomi et al. 2013).

While this estimated effect is large (over 100 percent increase relative to when states did not legalize sports betting), this magnitude is plausible for several reasons. First, when we examine the estimated effect of upset loss on only the states that legalized sports gambling, we find a beta coefficient of 9.1 percentage points, similar to that reported by Card & Dahl (2011). Second, there are several anecdotal examples of fans being upset about Fantasy Football, another form of sports gambling, or losses from their favorite team, and taking out their frustrations directly against players.[24] Third, the fact that problem

[23]To derive the percent change, we add our upset loss coefficient, betting coefficient, and upset loss times betting coefficient, then we take the exponential and subtract one from it. For instance, column (1) implies exp(0.0263+0.0996-0.0406)-1=0.0890. To calculate level change, we multiplied our percent change by our baseline mean IPV rates of 0.417 per 100,000.

[24]Two recent examples from the 2023 NFL season include Alexander Maddison and Tyler Bass. When Maddison was underperforming and fans were losing their Fantasy Football game, some fans messaged Maddison on Instagram, calling racial slurs. In the latter example, Bass missed a critical play, leading to his team missing the playoffs. Consequently, he had to deactivate his social media because he received many online harassment and death threats.

gambling has adverse effect on IPVs (i.e., 36.5 to 55.6 percent of gamblers who commit IPVs (Dowling et al. 2016; Korman et al. 2008a) and the fact that sports gambling legalization has significant adverse effects on problematic gambling behavior (i.e., 45 percent increase in calls to gambling hotline (Huble 2023) imply that the risk of increased IPVs may be significant. Fourth, a conservative estimate suggests about 22 million dollars wagered per NFL game (Edelstein 2021).[25] If we assume that, on average, the bets are placed evenly across both teams, then this estimate suggests that one game, in expectation, leads to approximately 11 million dollars lost.

In Appendix Table 2, we present the sensitivity of our findings to different definitions of "home team" and the inclusion of different geographic regions. In column 1, we follow Card & Dahl (2011)'s mapping strategy, focusing on the entire state with one NFL team. In columns 2 to 5 of Table 2, we experiment with different sources to define the fanbase and map home teams to the county level.[26;27] Our results for upset losses remain qualitatively similar when we use different geographies or definitions of a home team. We note that the coefficient on close loss interacted by sports betting loses precision, though the magnitude is still large and meaningful (3.5 to 6.8 percentage points).

To further assess the robustness of our estimates and address concerns about data cleaning and empirical choices, we present the results of sensitivity analyses in Appendix Table 3. In column 1, we present our main coefficient for comparison. In columns 2 and 3, we demonstrate that our estimates remain robust when we require each agency to report data for multiple years. These findings imply that the changes in sample composition over time are not driving our results. Column 4 shows that our estimated effect is robust even when we exclude 2020, a period marked by the COVID-19 pandemic and potential issues with crime reporting. In column 5, we restrict our comparison to the treatment state and analyze

[25]They estimate $350 million per week, which we divided by 16 games to estimate our per game number.

[26]Due to the relocation of the Rams, Raiders, and Chargers during our sample period, we are unable to identify the fanbase for these teams either before or after the move, so we exclude them from our analysis.

[27]For columns 5 and 6, we use Facebook likes to define our home team for 2010-2015 (pre-Rams move) and Seatgeek ticket searches for 2016 onwards.

the differences between the pre- and post-betting periods. The consistent patterns of results confirm that heterogenous treatment effects across states that legalized sports gambling vs. those that did not are not driving our results. Moreover, the result from column 5 implies that spatial spillovers and SUTVA violations are not much of a concern. Finally, in columns 6 and 7, we employ alternative specifications: negative binomial (column 6) and OLS estimates using the rate of IPVs per 100,000 (column 7). Despite these changes, we find qualitatively similar results, suggesting that our findings are robust to different modeling approaches. In addition to Appendix Table 3, we also experiment with excluding each state and team in Appendix Figure 2. The results from this exercise confirm that a particular state or team does not drive our estimated effect. Collectively, these sensitivity analyses provide reassurance that our estimated effect is not an artifact of specific data cleaning procedures or empirical choices but rather a robust finding in our study.

In Table 2, we extend our analysis to examine the effect of upset losses at various times of the day and on different types of assaults. Columns 1 to 4 focus on the timing of intimate partner violence (IPV) incidents: Sunday morning (before the game), Sunday afternoon (around or immediately after most games), Sunday night (around or immediately after the Sunday night game), and Monday mornings (the morning after). The findings in column (1) indicate no evidence of a change in IPVs during the "pre-treatment" period, suggesting that there may be no spurious relationship between treatment (upset loss) and the rate of IPVs. These findings provide some evidence that our treatment may be orthogonal to IPV outcomes. Columns 2 and 3 show larger effects on IPVs occurring between noon and 5:59 pm compared to those occurring between 6 pm and midnight, although the 95% confidence intervals of these estimates overlap. In column 4, we find no evidence of IPVs increasing on Monday mornings following an upset loss by a home team. These findings support the hypothesis that reactions to emotional cues and potential financial losses may be temporal and immediate rather than persisting over an extended period.[28]

[28] When we conduct our exercise focusing on just the morning games, we continue to find similar patterns of findings.

In columns 5 and 6 of Table 2, we estimate the effect on other types of assaults: bar fights and non-IPV assaults. This exercise aims to detect any crime displacement resulting from NFL games. For example, if sports gambling creates an incapacitation effect, causing more people to stay home and watch the game instead of going out to bars, we might expect to see a negative effect on bar fights and other assaults. The point estimates show no negative decline in these types of assaults. Instead, we find a positive effect on upset loss, which is consistent with the idea that unexpected emotional cues can lead to more violent behavior beyond just IPVs, especially in locations where alcohol people consume alcohol and watch sports. The findings in columns 5 and 6 suggest that displacement of the location where violence occurs is not a predominant channel.

5.2 Heterogeneity

Two potential mechanisms may explain why we observe the adverse effect of legalized sports gambling on the relationship between upset loss and IPVs. The first channel is the financial loss from betting on one's favorite team, who is favored to win but ends up losing. The second channel is increased emotional attachment toward one's favorite team from participating in sports gambling. While the latter mechanism is more complex to tease out due to not having data on the intensity of the fanbase, we conduct several heterogeneity estimates to confirm that the former is a predominant channel that is driving our results.

In Table 3, we present our treatment effects after restricting our sample based on the home team's previous performance and by week of the month. To ensure consistency in our comparison group within our main specification, we restrict our primary sample to game days when a home team was expected to win.[29] As a result, our estimated effect can be interpreted as the effect relative to game days when a team won as expected.

In column 1 of Table 3, we present our estimates using the restricted sample and show that our estimated effect is qualitatively similar to our main specifications. Next, we further

[29]For example, if a home team does not have a bye week or non-Sunday games on a winning streak, that team will have no counterfactuals.

narrow down our sample based on whether a team lost the last game (column 2), won the last game (column 3), or won the last two games (column 4). We find that the estimated effect becomes larger (0.2025 vs. 0.1257) when a home team is on a winning streak, though we cannot precisely rule out whether these coefficients are statistically different. In columns 5 to 7, we find similar patterns of results when we focus on whether a spread was covered or not.[30] These findings are consistent with the hot hand fallacy or recency bias. An individual who observes their team recently winning may perceive their team as "good", leading them to place more bets on their team and experience stronger adverse reactions to an unexpected loss.

In columns 8 and 9 of Table 3, we restrict our sample based on whether the Sunday coincided with the payday week.[31] Notably, we find that the upset loss coefficients are qualitatively similar between the two groups. However, the upset loss times betting coefficient is large and statistically significant during Sundays following payday (column 8) but small and insignificant on other Sundays (column 9). These findings align with the hypothesis that individuals may allocate more of their funds to sports betting activities when they receive their paychecks, resulting in more pronounced adverse reactions to monetary losses (Dobkin & Puller 2007; Stephens Jr 2006).

In Table 4, we examine for heterogeneous treatment effects between in-person vs. mobile betting as well as the size of the betting market. In column 1, we find no evidence of a worsening reaction to upset loss when states legalize in-person betting. Instead, we find that states that legalized mobile betting drive our results. These findings are consistent with the theory that mobile betting has a larger impact on sports gambling participation than in-person betting due to its lower opportunity cost (Hollenbeck et al. 2024).[32] In

[30] Covering a spread is slightly different from winning because a team who lost but had a point difference smaller than the spread will cover its spread. For example, if a home team's spread was +5 (lose by 5 points), then a home team can cover the spread if they lose by less than 5 points.

[31] Since most paydays in the U.S. typically occur on the first day, 15th, and/or last day of the month, we define the "week of payday" as any Sunday falling within the 1st to 7th or 15th to 21st of the month.

[32] Another possibility worth noting is that in-person betting may lead to less time at home during NFL games, which could also explain why the effect on family violence at home is smaller.

column 2, we document that states with large handles primarily drive our overall treatment effect. This finding demonstrates that the financial loss resulting from an upset may be one crucial mechanism through which individuals react more strongly to unexpected NFL game outcomes.

6 Conclusion

Policymakers and legislatures are advocating for the legalization of sports betting due to its potential tax benefits. Sports betting can generate large tax revenues from displacing the black market, and increase in the number of people who gamble in the state due to the creation of a new market or people deciding to place a bet in that state rather than Nevada. In 2022, total taxes collected among states with legalized sports betting totaled almost $1.5 billion.[33] On the other hand, sports gambling legalization can generate negative externalities, such as displaced tax revenues in other gambling markets (Humphreys 2021; Can et al. 2023)

Another potential negative externality arising from sports gambling legalization is the amplification of emotional cues. In this paper, we are the first to investigate the causal relationship between legalized sports gambling and IPV. Using data from the 2011 to 2022 NIBRS, we document that legalized sports betting amplifies emotional cues, as evidenced by increased IPV when a fan's home team unexpectedly loses.

Although we shed light on some potential consequences of allowing sports gambling, we do not necessarily conclude that states should reverse such legalization. Following a similar line of thought as Humphreys (2021), who suggests that states should carefully examine how legalizing sports betting impacts tax revenues to "mitigate the fiscal consequences of legalization," we suggest that states should examine how they can use state tax revenues from sports betting to mitigate these negative externalities.[34] For instance, states can

[33]This data does not include tax revenue in Montana or Oregon.

[34]While doing back-of-the-envelope calculations to estimate whether the net social costs from emotional

fund advertising campaigns—perhaps during commercial breaks during sporting events—to raise public awareness of the potential consequences of participating in sports gambling or committing family violence. Moreover, states can also invest their tax revenues in domestic violence shelters or hotlines to assist the victims or in counseling services to offer support for potential offenders.

7 References

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cues outweigh the tax revenue from sports gambling is intriguing, we cannot perform such calculations for several reasons. First, we need to determine the temporal and spatial distribution of IPVs in the U.S. While the NIBRS provides helpful information about IPVs, they are not necessarily nationally representative because some states and counties do not report to the NIBRS. Second, our estimates are specific only to NFL; thus, any derivations of costs will only be specific to September to December. Finally, we do not know the severity of each IPV to measure the total costs. While we find compelling evidence that the number of IPVs is increasing, we need to figure out whether these IPVs lead to physical injury or hospitalization.

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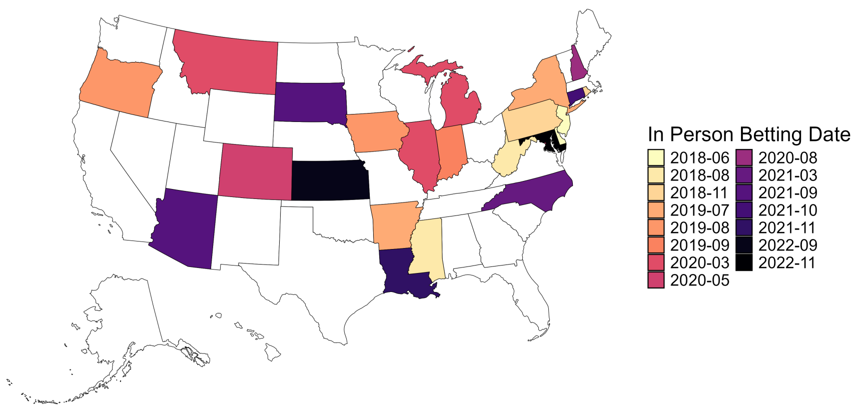
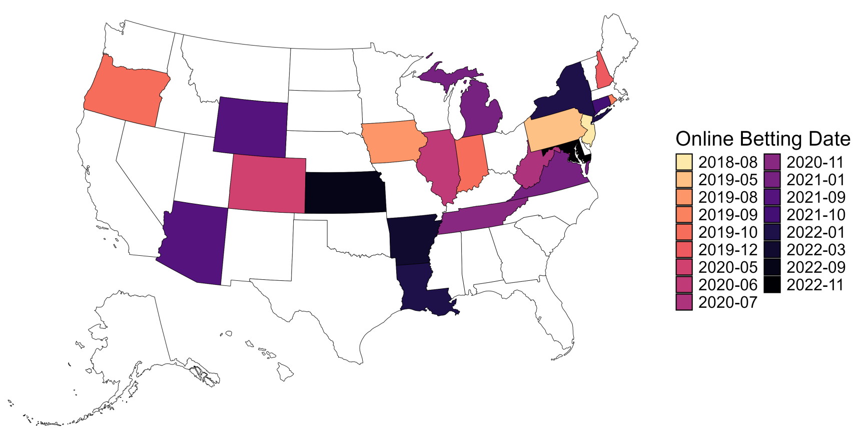
8 Tables and Figures

Figure 1. Sports Gambling Launch Date

(a) Retail Gambling



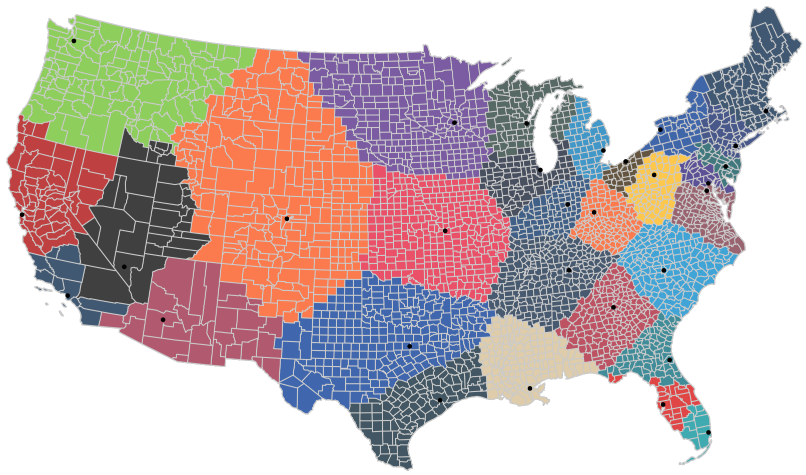
(b) Online Betting



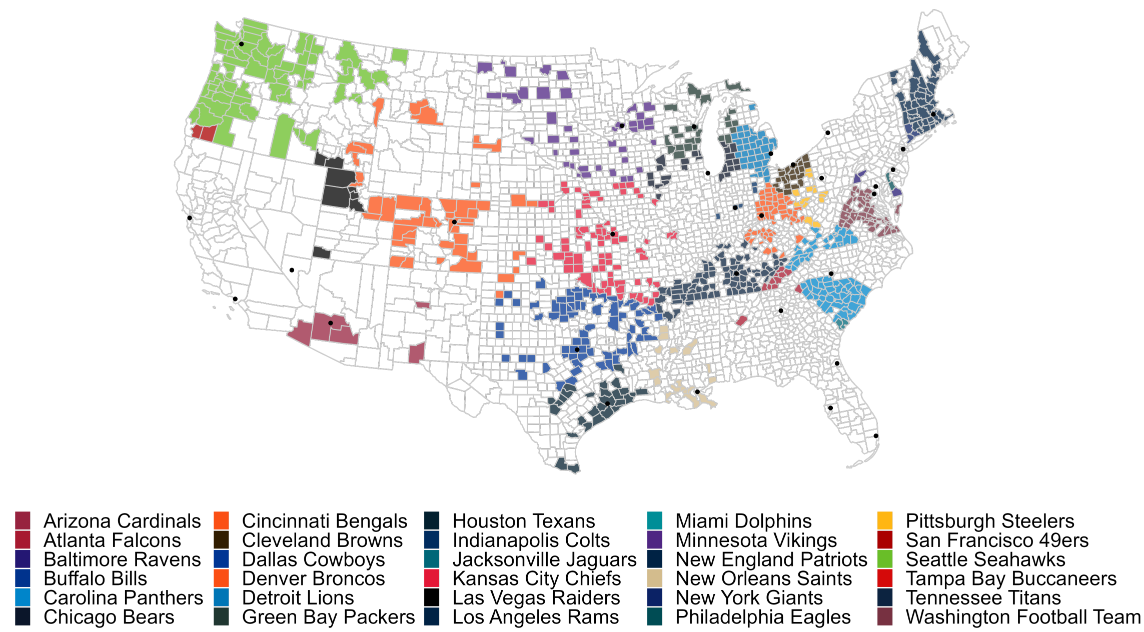
Notes: These figures show the month and year when each state launched legalized retail or online (mobile) sports gambling between 2018 and 2022. We exclude NM, ND, WA, and WI, which legalized sports gambling only on tribal land.

Figure 2. Home Team for Each County Based on Proximity

(a) All U.S. Counties



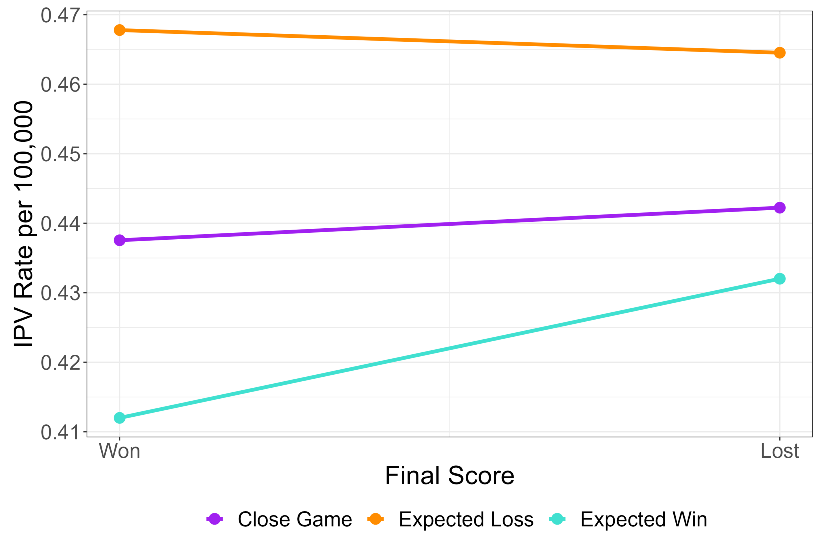
(b) All Counties Covered Under NIBRS



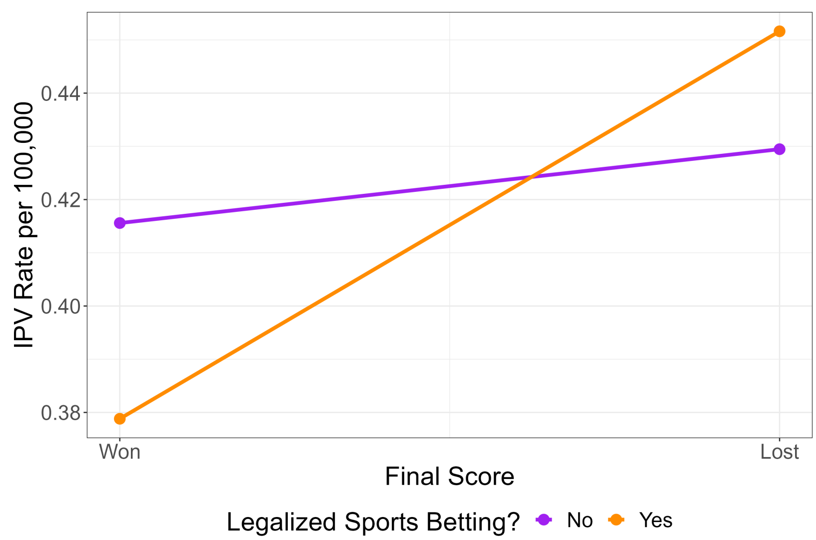
Notes: These figure show the closest NFL team based on linear distance for each continental U.S. county. These data are based on stadiums open on 2021. Panel a presents home team for all counties, and panel b presents home team for all counties in our NIBRS sample. Black dot represents location where each NFL stadium is located.

Figure 3. Weighted Mean IPVs

(a) By Expected Game Outcome & Actual Game Outcome



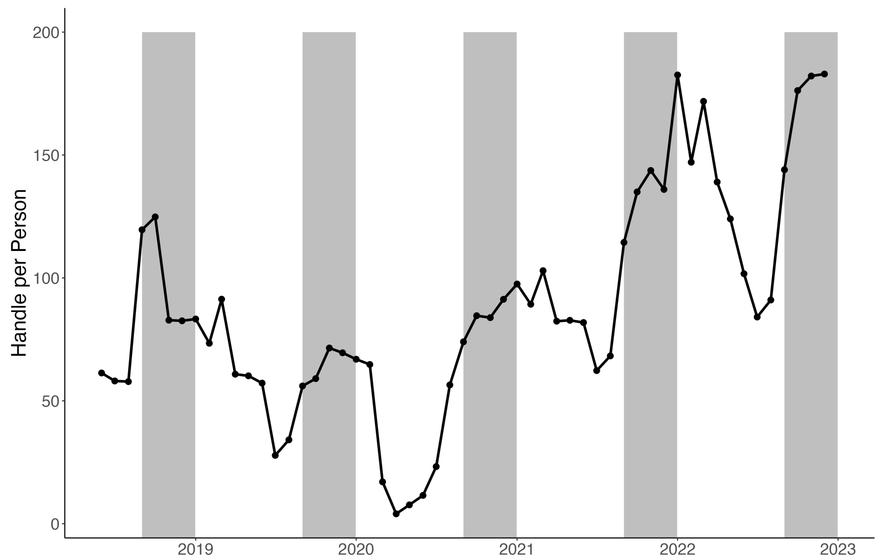
(b) By Sports Betting Legalization & Actual Game Outcome



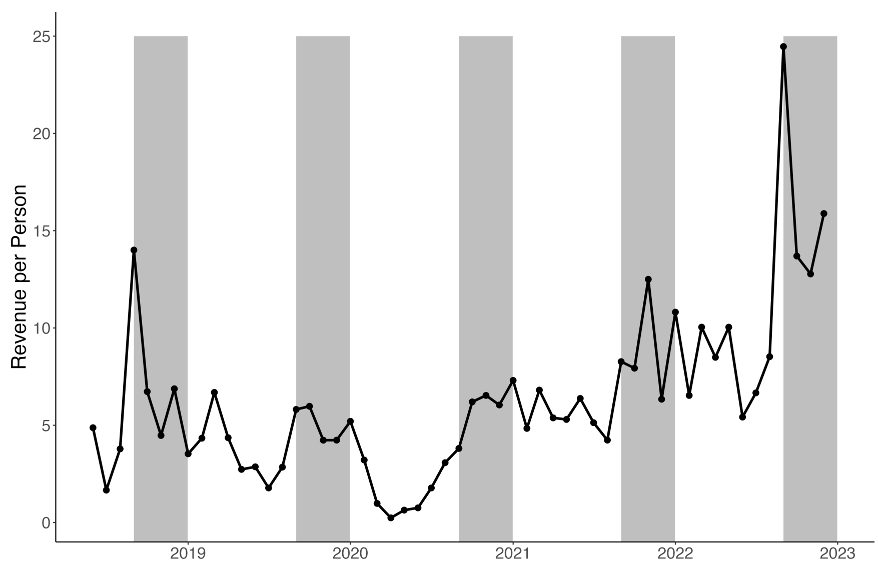
Notes: These figures show population weighted IPV rates per 100,000. Panel (a) plots the weighted mean by expected game outcome and actual game outcome. Panel (b) restricts sample to teams that were expected to win and plots the mean by actual game outcome & sports gambling legalization.

Figure 4. Total Handle & Revenue per Adults from Sports Betting

(a) Monthly Handle



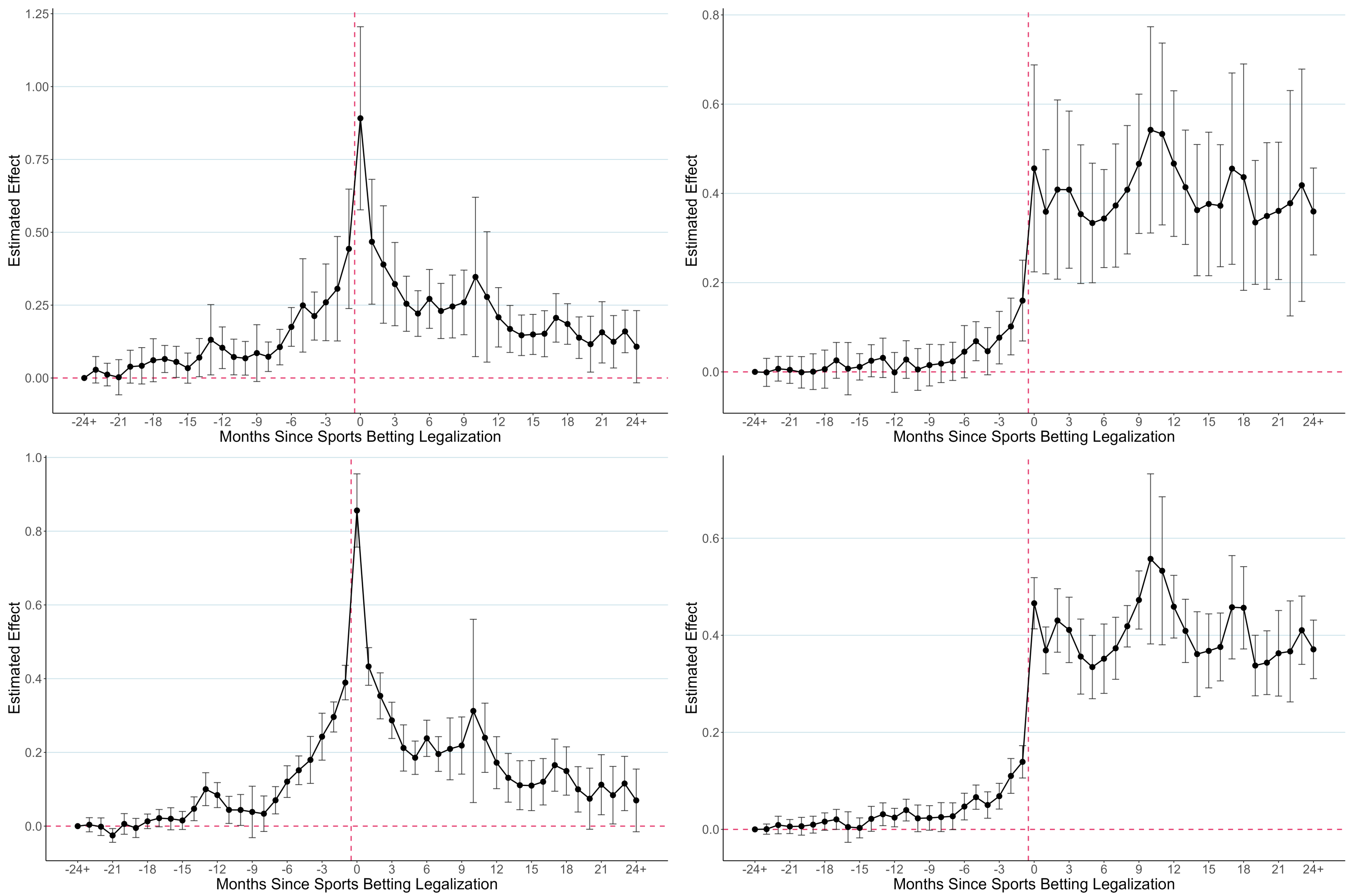
(b) Monthly Revenue



Notes: These figures show monthly U.S. handle (panel a) and revenue (panel b) from sports betting. The data is derived from Legal Sports Report. The y-axis is scaled by dividing total amount by total adult (21 years or older) population in states that allowed sports gambling. The gray shaded area in panel b represents NFL season.

Figure 5. TWFE & Sun & Abraham Event Study Estimates of Google Trends Search

(a) "Sports Betting" *(b) "Sportsbook"*



Notes: These figures show two way fixed effects (top row) and Sun & Abraham (bottom row) event study estimates of the impact of sports gambling legalization on total google searches between January 1, 2015 to December 31, 2022, for the keywords "sports betting" (left column) and "sportbook" (right column). All estimates include state and month-by-year fixed effects and weighted by state-level population. The bar line represent 95%

confidence interval generated using standard errors clustered around the state-level.

9 Tables

Table 1. Heterogeneous Treatment Effects of Legalized Sports Betting

	(1)	(2)	(3)	(4)	(5)
Upset Loss	0.0263	0.0298	0.0289	0.0303	0.0342*
	(0.0202)	(0.0198)	(0.0199)	(0.0198)	(0.0197)
Upset Loss*Betting	0.0996*	0.0969*	0.0993*	0.1000*	0.0975*
	(0.0509)	(0.0506)	(0.0508)	(0.0511)	(0.0513)
Close Loss	-0.0158	-0.0159	-0.0151	-0.0135	-0.0140
	(0.0128)	(0.0127)	(0.0126)	(0.0125)	(0.0124)
Close Loss*Betting	0.0783**	0.0825**	0.0811**	0.0764*	0.0772**
	(0.0384)	(0.0393)	(0.0393)	(0.0394)	(0.0387)
Upset Win	0.0236	0.0260	0.0256	0.0264	0.0259
	(0.0203)	(0.0201)	(0.0201)	(0.0199)	(0.0197)
Upset Win*Betting	0.0147	0.0126	0.0120	0.0095	0.0157
	(0.0641)	(0.0673)	(0.0670)	(0.0668)	(0.0653)
Betting	-0.0406	-0.0350	-0.0362	-0.0390	-0.0504
	(0.0350)	(0.0348)	(0.0347)	(0.0349)	(0.0341)
N	301,854	301,854	301,854	301,854	301,854
Agency FE?	Yes	Yes	Yes	Yes	Yes
Season FE?	Yes	Yes	Yes	Yes	Yes
Week FE?	No	Yes	Yes	Yes	Yes
Holiday FE?	No	No	Yes	Yes	Yes
Weather Control?	No	No	No	Yes	Yes
Unweighted?	No	No	No	No	Yes

* P-val < 0.1; ** P-val < 0.05; *** P-val < 0.01

Notes: Estimate is estimated via Poisson model using population as an exposure variable. Control variables include agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the state-by-season-by-team level.

Table 2. Estimated Effect on Other Time, Day, & Assaults

	(1)	(2)	(3)	(4)	(5)	(6)
Upset Loss	-0.0218	0.0578**	0.0115	0.0062	0.0693	0.0111
	(0.0233)	(0.0272)	(0.0281)	(0.0288)	(0.0923)	(0.0121)
Upset Loss*Betting	0.0744	0.1198	0.0807	-0.0537	0.4122*	-0.0010
	(0.0612)	(0.0767)	(0.0746)	(0.1006)	(0.2448)	(0.0248)
N	300,543	285,836	294,540	262,132	135,010	310,180
Outcome	IPV	IPV	IPV	IPV	Bar Fights	Non IPV Assaults
Day	Sun	Sun	Sun	Mon	Sun	Sun
Time	0to12	12to18	18to23	0to12	12to23	12to23

* P-val $<$ 0.1; ** P-val $<$ 0.05; *** P-val $<$ 0.01

Notes: Estimate is estimated via Poisson model using population as an exposure variable. Control variables include agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the state-by-season-by-team level. Bar fights are defined as any assaults occurring between 12 to 23 pm on Sundays at a bar or nightclub. Non IPV assaults are defined as any assaults occurring between 12 to 23pm on Sundays that is not classified as IPV.

Table 3. Heterogeneity Estimates by Home Team Winning Record and Week Day

		Won?			Covered Spread?			Payday?	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Upset Loss	0.0297	-0.0094	0.0499*	0.0546	0.0274	0.0233	0.0184	0.0273	0.0535*
	(0.0205)	(0.0337)	(0.0264)	(0.0338)	(0.0310)	(0.0289)	(0.0404)	(0.0327)	(0.0304)
Upset Loss*Betting	0.1261**	0.1283	0.1737**	0.2085**	0.0946	0.2085**	0.2464**	0.2428***	-0.0533
	(0.0506)	(0.0991)	(0.0707)	(0.0909)	(0.0807)	(0.0876)	(0.1208)	(0.0855)	(0.0807)
N	64,056	18,664	37,945	22,008	25,108	31,306	14,069	24,502	31,653
Sample Cut	None	Lost	Won Last	Won Last 2	Not Covered	Covered Last	Covered Last 2	Pay Week	Non-Pay Week

* P-val < 0.1; ** P-val < 0.05; *** P-val < 0.01

Notes: Estimate is estimated via Poisson model using population as an exposure variable. Control variables include agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the state-by-season-by-team level. The sample is restricted to game-days where a home team is expected to win (spread less than -4). Columns 2 to 4 further restricts the sample based on whether a team won or lost the previous week. Columns 5 to 7 further restricts the sample based on whether the home team covered the spread (actual score less than the pre-game spread). Columns 8 and 9 further restricts the sample based on Sundays after paydays (1st to 7th and 15th to 21st) or other Sundays.

Table 4. Sensitivity of Our Estimates to Type & Size of Betting Markets

	(1)	(2)
Upset Loss	0.0374*	0.0303
	(0.0199)	(0.0198)
Upset Loss* Mobile Betting	0.1667***	
	(0.0611)	
Upset Loss* In-person Betting	-0.0712	
	(0.0679)	
Upset Loss*Betting*$<$ Median per capita handle		0.0748
		(0.0717)
Upset Loss*Betting*$\geq$ Median per capita handle		0.1356**
		(0.0665)
N	301,854	301,854

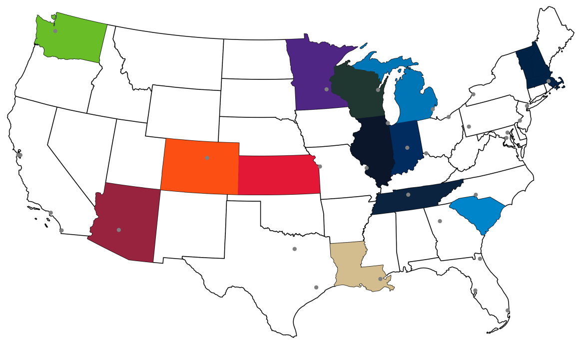
* P-val $<$ 0.1; ** P-val $<$ 0.05; *** P-val $<$ 0.01

Notes: Estimate is estimated via Poisson model using population as an exposure variable. Control variables include agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the state-by-season-by-team level. Column (1) examines if the state allows online or in-person sports betting. Column (2) examines heterogeneity by whether a state had larger sports gambling market, as measured by average amount wagered. The median handle used for cutoff is 26 per person.

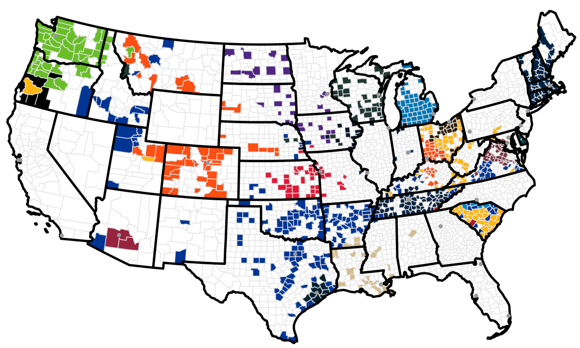
Appendix

Appendix Figure 1. NIBRS Coverage by Home Team

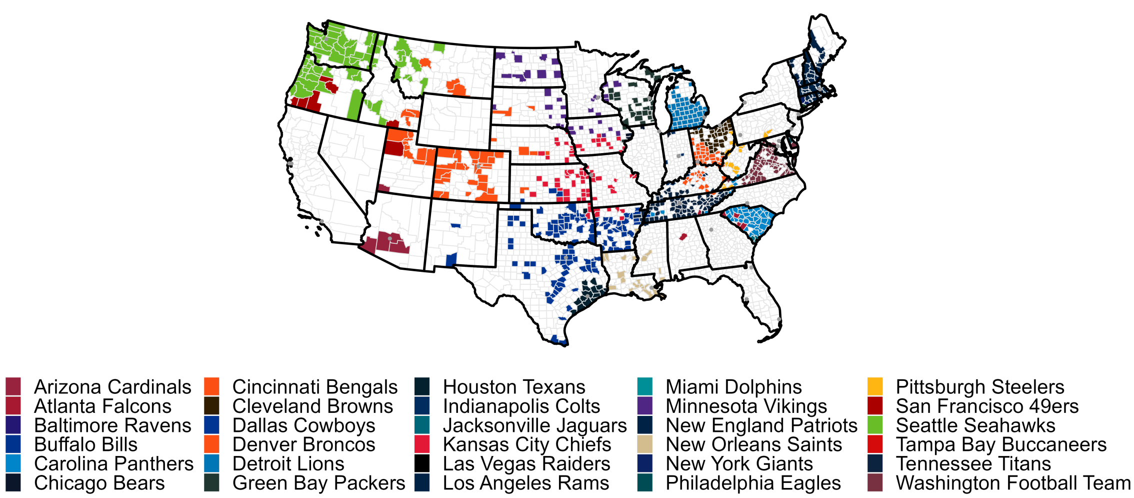
(a) State



(b) Facebook

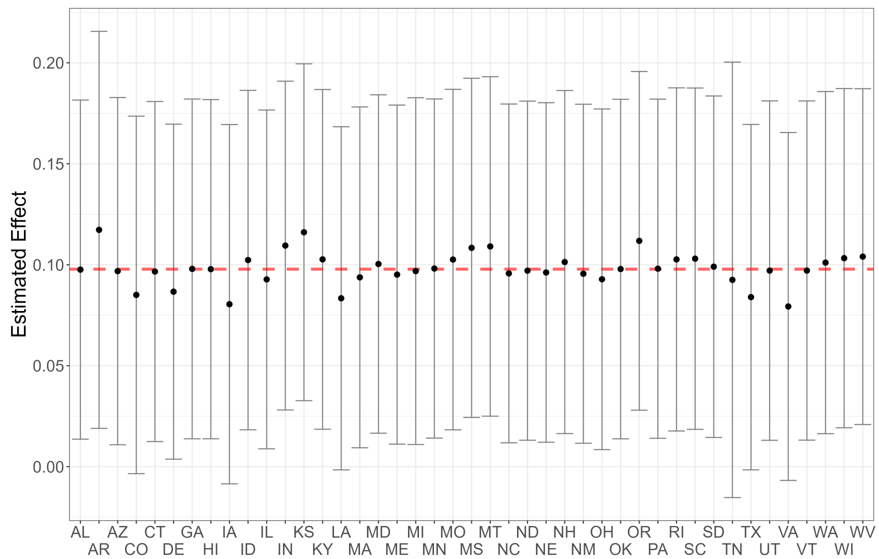


(c) Seatgeek

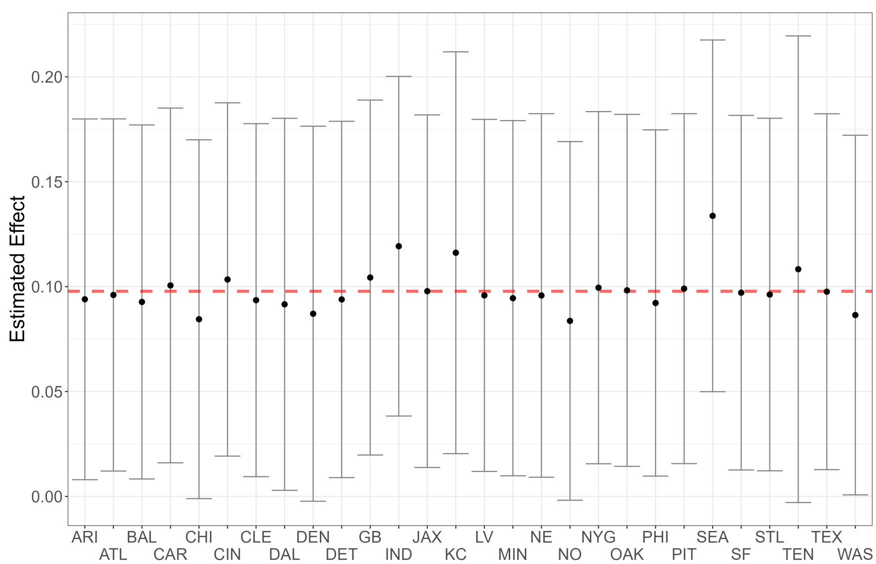


Appendix Figure 2. Sensitivity of Betting∗Upset Loss Coefficient to Excluding Each State/Team

(a) Exclude Each States



(b) Exclude Each Teams



Notes: These figures show sensitivity of our betting∗upset loss coefficient when we exclude each state or team. The gray bar line represents 95% confidence intervals generated using standard errors that are clustered at the state-by-team-by-season level. The red dashed line represents the overall treatment effect from our preferred estimate using the full sample.

Appendix Table 1. Game Outcomes by Teams

	Upset Loss		Close Loss		Upset Win	
	Count	% Expected Win	Count	% Expected Close	Count	% Expected Lose
Arizona Cardinals	11	30.6	32	40	13	25
Atlanta Falcons	9	23.1	51	56	9	25.7
Baltimore Ravens	19	28.4	33	44	2	11.8
Buffalo Bills	12	28.6	33	43.4	14	31.1
Carolina Panthers	7	23.3	45	50.6	13	26.5
Chicago Bears	8	25	35	53.8	10	17.2
Cincinnati Bengals	5	14.3	38	42.7	8	18.2
Cleveland Browns	9	36	41	59.4	7	9.5
Dallas Cowboys	10	20	38	49.4	9	33.3
Denver Broncos	7	14	39	54.2	11	28.9
Detroit Lions	12	42.9	43	48.9	10	21.7
Green Bay Packers	14	17.3	30	47.6	5	33.3
Houston Texans	14	31.1	30	45.5	6	11.3
Indianapolis Colts	10	24.4	40	54.1	20	41.7
Jacksonville Jaguars	8	50	47	65.3	14	15.7
Kansas City Chiefs	16	21.1	24	40	8	30.8
Miami Dolphins	7	28	39	45.9	15	26.8
Minnesota Vikings	8	24.2	36	39.1	7	18.9
New England Patriots	16	16.3	24	46.2	3	42.9
New Orleans Saints	22	31.4	27	40.3	9	47.4
New York Giants	6	27.3	36	52.2	22	32.8
New York Jets	1	7.7	41	54.7	17	23.3
OAK/LV Raiders	6	37.5	45	56.2	18	26.9
Philadelphia Eagles	16	27.1	37	52.1	7	26.9
Pittsburgh Steelers	13	23.2	34	42.5	10	43.5
SD/LA Chargers	12	23.5	46	57.5	8	27.6
STL/LA Rams	10	23.8	37	52.9	15	30
San Francisco 49ers	16	27.1	24	46.2	9	19.1
Seattle Seahawks	18	25.7	34	47.2	8	47.1
Tampa Bay Buccaneers	10	33.3	53	58.9	12	25.5
Tennessee Titans	9	28.1	48	54.5	16	34
Washington Commanders	5	31.2	40	48.2	11	19.3

Notes: Data is from the 2011 to 2022 season. Upset loss is defined as losing when the team is expected to win (pre-game spread under -4). Close loss is defined as losing when the team is expected to experience a close matchup (pre-game spread between -4 to 4). Upset win is defined as winning when the team is expected to lose (pre-game spread over 4).

Appendix Table 2. Robustness Check of Our Estimates to Various Definitions of Home Team & Geography

	(1)	(2)	(3)	(4)	(5)
Upset Loss	0.0143	0.0206	0.0112	0.0116	0.0155
	(0.0257)	(0.0184)	(0.0182)	(0.0179)	(0.0212)
Upset Loss*Betting	0.1213*	0.1055**	0.0794	0.1145**	0.1321**
	(0.0632)	(0.0493)	(0.0535)	(0.0493)	(0.0616)
Close Loss	-0.0123	-0.0171	-0.0043	-0.0113	-0.0116
	(0.0173)	(0.0126)	(0.0132)	(0.0127)	(0.0160)
Close Loss*Betting	0.0358	0.0538	0.0697	0.0481	0.0578
	(0.0553)	(0.0456)	(0.0456)	(0.0455)	(0.0501)
Upset Win	0.0264	0.0254	0.0146	0.0182	0.0146
	(0.0274)	(0.0203)	(0.0209)	(0.0200)	(0.0240)
Upset Win*Betting	-0.0508	0.0262	0.0086	0.0332	0.0604
	(0.0826)	(0.0682)	(0.0674)	(0.0681)	(0.0785)
Betting	-0.0366	-0.0525	-0.0682**	-0.0591	-0.0260
	(0.0508)	(0.0381)	(0.0348)	(0.0381)	(0.0391)
N	160,653	301,854	299,987	301,854	217,601
Home Team Definition	State	County	County	County	County
Source	N/A	Seatgeek	Facebook	Both	Both
Restrict to Same Fans	No	No	No	No	Yes

* P-val < 0.1; ** P-val < 0.05; *** P-val < 0.01

Notes: Estimate is estimated via Poisson model using population as an exposure variable. Control variables include agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the season-by-team level.

Appendix Table 3. Robustness Check of Our Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upset Loss	0.0303	0.0282	0.0293	0.0246	0.0240	0.0317	0.0140*
	(0.0198)	(0.0201)	(0.0216)	(0.0202)	(0.0273)	(0.0199)	(0.0084)
Upset Loss*Betting	0.1000*	0.1019*	0.1483***	0.1396**	0.1093**	0.1018**	0.0374*
	(0.0511)	(0.0533)	(0.0571)	(0.0580)	(0.0548)	(0.0513)	(0.0225)
Close Loss	-0.0135	-0.0164	-0.0068	-0.0161	-0.0050	-0.0140	-0.0060
	(0.0125)	(0.0126)	(0.0137)	(0.0131)	(0.0162)	(0.0125)	(0.0058)
Close Loss*Betting	0.0764*	0.0700*	0.0857**	0.0771*	0.0677*	0.0808**	0.0325**
	(0.0394)	(0.0388)	(0.0413)	(0.0453)	(0.0395)	(0.0405)	(0.0164)
Upset Win	0.0264	0.0275	0.0183	0.0262	0.0224	0.0283	0.0116
	(0.0199)	(0.0217)	(0.0246)	(0.0204)	(0.0283)	(0.0197)	(0.0096)
Upset Win*Betting	0.0095	0.0181	0.0661	0.0007	0.0185	0.0063	-0.0022
	(0.0668)	(0.0702)	(0.0784)	(0.0841)	(0.0685)	(0.0670)	(0.0298)
Betting	-0.0390	-0.0421	-0.0368	-0.0583	-0.0463	-0.0243	-0.0133
	(0.0349)	(0.0355)	(0.0395)	(0.0424)	(0.0386)	(0.0345)	(0.0150)
N	301,854	284,582	228,545	272,515	187,176	301,854	311,837
Agency Cut?	No	4 Years	8 Years	No	No	No	No
Exclude 2020?	No	No	No	Yes	No	No	No
Sample States?	All	All	All	All	Policy	All	All
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Neg Binom	OLS

* P-val < 0.1; ** P-val < 0.05; *** P-val < 0.01

Notes: Estimates for columns 1 to 5 are estimated via Poisson model using population as an exposure variable. Estimate for column 6 is estimated via Negative Binomial model using population as an exposure variable. Estimate for column 7 is estimated via OLS using population as the weight variable. Every regression includes controls for agency fixed effects, season fixed effects, week of the season fixed effects, indicator for holiday, average temperature and total precipitation. Standard errors are clustered at the state-by-season-by-team level.