Sports Betting Legalization's Impact on Child Maltreatment: Evidence from Child Protective Services Reports*

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Abstract

This study explores the unintended consequences of sports betting legalization on child maltreatment. Using administrative Child Protective Services case data and a staggered difference-in-differences framework, I estimate the causal effect of sports betting on cases of child maltreatment and find that following legalization, states experience around a six-percent higher rate of cases. The effect is largely driven by states that legalize mobile sports betting and is slightly more prominent in rural areas relative to urban areas. Based on previous literature, I outline two potential pathways for these effects: an amplification of emotional cues from bad sports betting outcomes, and the family stress of accumulated financial hardship. While reports of child maltreatment generally increase following unexpected losses of local football teams, I do not find that this is amplified by legal betting. Instead, the long horizon over which effects emerge suggests a financial hardship pathway.

JEL Codes: J13, K42, Z28

Keywords: sports betting, child abuse

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1 Introduction

Child maltreatment remains a pervasive public health concern in the United States, with nearly four million referrals and over 600,000 confirmed victims each year (U.S. Department of Health & Human Services 2024). The social costs of adverse childhood experiences are immense: victims face elevated risks of mental illness, chronic disease, substance abuse, and premature death (Hughes et al. 2017; Vinnerljung, Brännström, and Hjern 2015; Widom et al. 2012). Maltreatment also disrupts education, increases contact with the criminal justice system (Berger et al. 2016), and can perpetuate cycles of disadvantage across generations (Font and Maguire-Jack 2020; Currie and Spatz Widom 2010). Economic hardship and parental conflict, including intimate partner violence, are among the strongest predictors of abuse and neglect (Sedlak et al. 2010; Renner and Slack 2006). Economic strain can magnify stress and instability within households, reducing parents' capacity to provide consistent care and supervision (Conger and Donnellan 2007; Conger and Conger 2002). Given these established links, policies that affect household finances or stress may have unintended consequences for child welfare. This paper investigates one such policy change—the recent legalization of sports betting.

In 2018, the United States Supreme Court effectively struck down the Professional and Amateur Sports Act, paving the way for states to legalize sports betting for the first time since 1992. Since then, 38 states have legalized some form of sports betting and 31 have allowed sports betting from the internet. Sports betting, especially online or mobile betting, coincided with rapid growth in interest and participation with more than $100 billion wagered in 2023 (Hoffer 2024; Hollenbeck, Larsen, and Proserpio 2024; Baker et al. 2024; American Gaming Association 2023). The growing popularity of sports betting raises concerns about the prevalence of "problem gambling" and its impact on families.

For most, betting is a harmless form of entertainment that leads to small financial losses on average. However, some "problem gamblers" may experience far more severe outcomes, such as household financial stress and the disruption of family dynamics (Gabellini, Lucchini, and Gattoni 2022; Dowling et al. 2016; Griffiths, Hayer, and Meyer 2009; Shaffer and Korn 2002). Previous work on sports betting legalization has shown increases in the size of the population that experiences these more severe betting-related outcomes. For example, states that legalize sports betting, particularly mobile sports betting, exhibit a greater number of help-seeking posts on online betting support groups (Van Der Maas, Cho, and Nower 2022), worsening consumer financial health specifically through lower credit scores, increased rates of bankruptcy, and lower rates of investing (Baker et al. 2024; Hollenbeck, Larsen, and Proserpio 2024), and the amplification of sports outcome-related intimate partner violence (Matsuzawa and Arnesen 2024). Both financial stress and intimate partner violence are known risk factors for child maltreatment, and they both appear to increase in response to the legalization of sports betting, yet the impacts of this policy change on child abuse and neglect remain unexplored.

This paper seeks to fill this gap in the literature; I explore the causal effect of legal sports betting on the reporting of child maltreatment. To estimate this relationship, I use Child Protective Services (CPS) case data retrieved from the National Child Abuse and Neglect Data System (NCANDS), and leverage variation from the staggard adoption of legal sports betting across states. Using two-way fixed effects Poisson models, and pooling all law changes that legalize sport betting in some form, I find that on average states experience between a 5-7% increase in the number of screened-in reports of child maltreatment (more details on the report handling and screening process are in Section 3). When I split out the legalization of mobile (online) sports betting and in-person sport betting, I find that the overall effects are driven almost entirely by the former. I explore the heterogeneity of this effect in terms of county characteristics, child demographics, report source, and type of alleged abuse.

Other work suggests two likely pathways through which these effects could manifest. One is an amplification of the impact of sports-related emotional cues following upset losses, akin to the analysis done by Card and Dahl (2011). I find that while child maltreatment reports appear to increase in the two weeks following upset losses that this effect was not exacerbated by legal sports betting. Another pathway is long-run financial hardship, which the family stress model suggests creates frictions in family dynamics leading to increased chance for the occurrence of abuse or neglect (Conger, Ge, et al. 1994). Indeed, the effect of these policies is slow to emerge and grows over time, showing very similar patterns to existing findings on sport betting and consumer financial health (Baker et al. 2024; Hollenbeck, Larsen, and Proserpio 2024).

The rest of this paper is structured as follows. Section 2 provides a brief history of sports betting in the United States and background on child abuse and neglect. Section 3 outlines each data source used. Section 4 the empirical strategy for the paper. Section 5 provides results and Section 6 concludes.

2 Background

2.1 History of Legal Sports Betting

In 1992, the Professional and Amateur Sports Protection Act (PAPSA), or "Bradley Act" effectively banned sports betting in most of the United States. Oregon, Delaware, and Montana were exempt due to their existing sports lottery systems, along with Nevada's licensed sports pools.[1] The challenge that ultimately led to the repeal of the federal sports betting ban began when New Jersey passed legislation to remove its own state-level bans. The NCAA and several professional sports leagues quickly sued, arguing that New Jersey's actions violated the Professional and Amateur Sports Protection Act (PASPA). The case reached the U.S. Supreme Court, which in May 2018 issued its decision in Murphy v. National Collegiate Athletic Association, striking down PASPA and overturning the federal prohibition on sports betting. The Court ruled that PASPA's ban on state sports betting violated the anticommandeering doctrine of the 10th Amendment by preventing states from making their

[1] The law also allowed states with established betting industries a one year window to legalize sports betting and become exempt from the ban, but no states elected to do so.

own laws. This decision didn't legalize sports betting nationwide, rather, it gave each state the power to decide for itself.

Delaware became the first state to legalize sports betting following this decision, soon followed by New Jersey. As of June 2025, 38 states and the District of Columbia have legalized some form of sports betting. There are two main ways that such laws permit people to bet on sports. First, retail or in-person betting takes place in a licensed physical space within the state, often at casinos, bars, or stadiums. Second, people can bet using the internet, either on a computer or mobile device. Often called mobile or online betting, this form of betting can happen anywhere within a state.[2] Sports betting laws govern the location where a bet is placed, rather than the state residency of the bettor. Online sportsbooks enforce this by checking the GPS location of the device used to access the platform. While there are a sophisticated set of tools available to sportbooks to prevent illegal use (e.g. via a virtual private network), there is still some potential for spillovers via bettors taking their phones across state lines, or betting through proxy individuals in other states.

Table 1: U.S. Sports-Betting Adoption Timeline

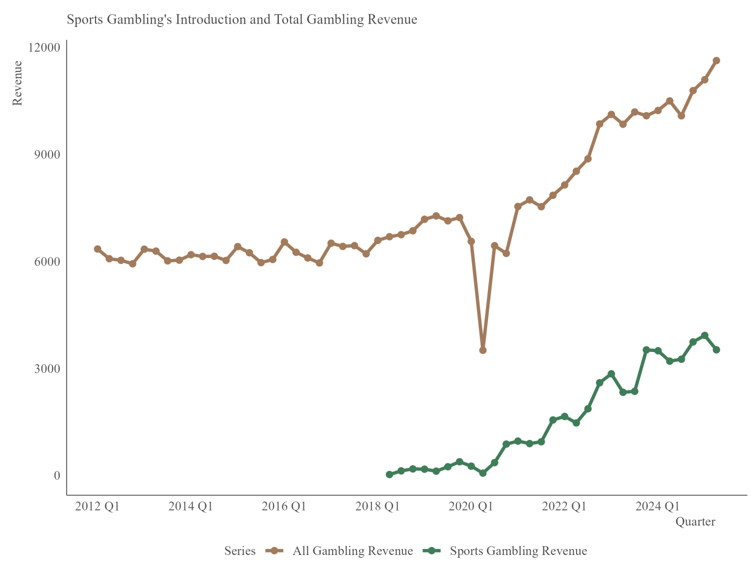
State	Online	Retail	Online Launch	Retail Launch	State	Online	Retail	Online Launch	Retail Launch
Arizona	YES	YES	9/9/2021	9/9/2021	Nevada	YES	YES	1/1/2010	1/1/1949
Arkansas	YES	YES	3/6/2022	7/1/2019	New Hampshire	YES	YES	12/30/2019	8/12/2020
Colorado	YES	YES	5/1/2020	6/17/2020	New Jersey	YES	YES	8/1/2018	6/14/2018
Connecticut	YES	YES	10/19/2021	9/30/2021	New Mexico	NO	YES	—	10/16/2018
Delaware	YES	YES	12/27/2023	6/5/2018	New York	YES	YES	1/8/2022	7/16/2019
Florida	YES	YES	11/7/2023	12/7/2023	North Carolina	YES	YES	3/11/2024	3/18/2021
Illinois	YES	YES	3/5/2022	3/9/2020	North Dakota	NO	YES	—	6/23/2021
Indiana	YES	YES	10/3/2019	9/1/2019	Ohio	YES	YES	1/1/2023	1/1/2023
Iowa	YES	YES	8/15/2019	8/15/2019	Oregon	YES	YES	8/27/2019	8/27/2019
Kansas	YES	YES	9/1/2022	9/1/2022	Pennsylvania	YES	YES	5/1/2019	11/15/2018
Kentucky	YES	YES	9/28/2023	9/7/2023	Rhode Island	YES	YES	9/14/2019	11/26/2018
Louisiana	YES	YES	1/28/2022	10/6/2021	South Dakota	NO	YES	—	9/9/2021
Maine	YES	YES	5/2/2022	5/2/2022	Tennessee	YES	NO	11/1/2020	—
Maryland	YES	YES	11/23/2022	12/9/2021	Vermont	YES	NO	1/11/2024	—
Massachusetts	YES	YES	3/10/2023	1/31/2023	Virginia	YES	YES	1/21/2021	1/21/2021
Michigan	YES	YES	1/22/2021	3/11/2020	Washington	NO	YES	—	9/9/2021
Mississippi	NO	YES	—	8/1/2018	District of Columbia	YES	YES	5/28/2020	8/31/2020
Montana	NO	YES	—	3/11/2020	West Virginia	YES	YES	12/1/2018	9/1/2018
Nebraska	NO	YES	—	6/22/2023	Wisconsin	NO	YES	—	11/31/2021
					Wyoming	YES	YES	9/1/2021	9/1/2021

Table 1 shows the market open date for both in-person and/or mobile betting in each

[2]Some states restrict online betting to specific areas. For example, Washington only allows mobile betting while on tribal lands. Such laws are considered in-person betting for the sake of this study as they do not enable betting at all times and locations for the vast majority of a state's residents.

state. Typically, states legalize in-person betting prior to mobile betting, and the timing between opening the markets for these different modalities is often close. However, 8 states have legalized in-person betting with no mobile betting during the sample period January 2012 - December 2022. Several of these states—New Mexico, North Dakota, Washington, and Wisconsin—only legalized sports betting on tribal lands.

Figure 1: Trends in Sports Betting Revenue



Regardless of the type of legalization, one question remains important: Does the legalization of sports betting actually change how people engage in the behavior or is it just a new substitute for other gambling? Figure 1 shows the trends in sports betting revenue (green) versus total revenue for all gambling industries (brown) collected from Legal Sports Report and the Federal Reserve Bank of St. Louis, respectively. This figure suggests that following sports betting legalization the total amount of money flowing into sports-books, casinos, and other pools has increased as a result.

2.2 Background on Child Maltreatment

Child abuse and neglect are critical public health issues in the United States. In 2020, approximately 3.9 million child maltreatment referrals were made, involving about 7.1 million children. Of these, 618,000 children were confirmed victims of abuse or neglect, and 1,750 children died as a result (U.S. Department of Health & Human Services 2024). The majority of confirmed cases are of neglect, but physical, sexual, and emotional abuse cases are also prominent (Wildeman et al. 2014). Official reports likely under-count the actual prevalence of abuse, as many cases go unreported. By age 18, 25% to 37% of U.S. children will experience a CPS investigation for abuse or neglect, with higher rates for some groups, such as Black children (Kim, Wildeman, et al. 2017).

The prevalence of cases varies spatially and over time within the United States. Panel A of Figure 2 shows how the number of cases investigated in a state has changed over the last 11 years. The variation across states does not appear to be cleanly aligned with geography. Panel B shows the number of CPS cases over the same 11 year window. Child populations in the U.S. are falling which coincides with a falling number of investigations. [3] The bottom-most panel shows the rate of investigations per 10,000 children which also indicates a return to a rate of investigations similar to 2010. While progress is being made to reduce the number of children impacted my maltreatment, the improvements are not uniform and we still have a long way to go. Table 2 shows the quarterly pre-treatment prevalence of child maltreatment across states. Additionally, it includes information about the distribution of report targets (alleged victims) in terms of their race and age. On average, more than 20,000 cases make it into the hands of CPS professionals in each state each quarter of the year.

The social costs of adverse childhood experiences are immense. Children who are found to be victims of abuse or neglect are more likely to experience developmental delays, mental health disorders (such as depression, anxiety, and Post-Traumatic Stress Disorder), chronic physical conditions (like heart disease and diabetes), and substance abuse (Hughes et al. 2017; Widom et al. 2012). Victims of abuse are more likely to receive disability pensions, be incarcerated, and experience preventable deaths (Berger et al. 2016; Vinnerljung, Brännström, and Hjern 2015). They also face disruptions in education, and juvenile offenders with abuse

[3] You can find maps similar to Panel A for 2012 - 2018 and 2018 - 2022 in the Appendix which provides more context into the periods of expansion and contraction of caseloads shown in Panel B.

Figure 2: Trends in Child Maltreatment Reporting

Panel A: Change in CPS Cases by State 2012 - 2022

Panel B: CPS Cases over Time 2012 - 2022

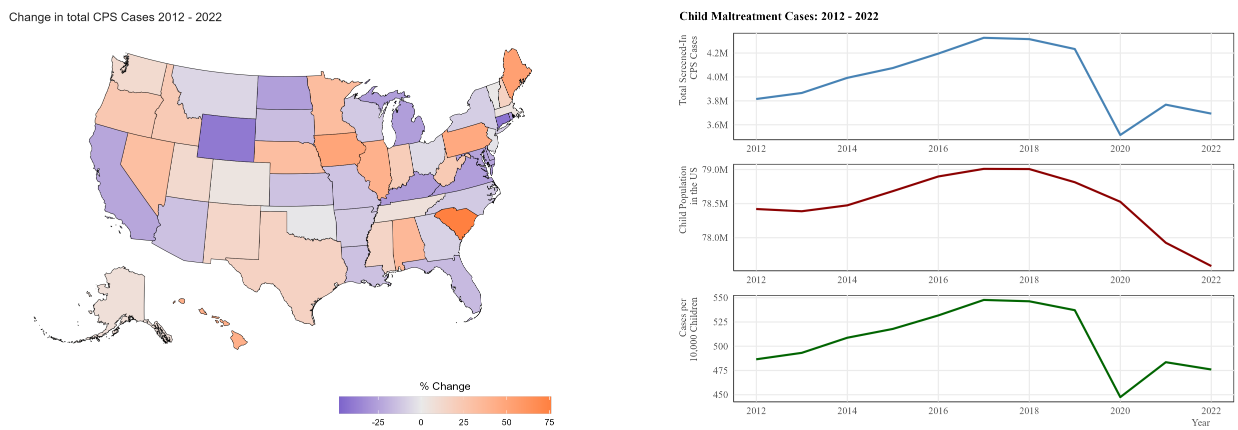


Table 2: Pre-Treatment Summary Statistics by Case Type, Child Age, and Race/Ethnicity

Category	**Mean**	**Min**	**1st Qu.**	**Median**	**3rd Qu.**	**Max**
By Case Type						
All Cases	20,258	818	4,574	11,053	24,776	122,303
Abuse Cases	4,448	66	941	2,676	4,528	27,787
Neglect Cases	12,600	33	2,452	6,462	15,757	74,123
By Child Age						
<1 year old	1,637	66	382	968	2,086	9,021
1–5 years old	6,192	240	1,426	3,462	7,170	35,874
6–11 years old	7,024	235	1,649	3,848	8,674	43,252
12–17 years old	5,258	148	1,197	2,748	6,750	35,138
By Child Race						
Asian	192	1	19	62	159	4,216
Black	4,393	1	271	1,976	5,006	31,063
Other	2,986	7	377	927	2,081	66,343
White	11,607	1	2,987	7,127	14,486	63,811

histories are at greater risk of continued involvement with the criminal justice system (Font and Maguire-Jack 2020; Currie and Spatz Widom 2010). Beyond individual impacts, maltreatment often sticks with the victim throughout their life which in many cases can impact their success in raising their own kids leading to generational consequences.

Child maltreatment researchers often use the family stress model developed by Conger, Ge, et al. (1994) to guide their understanding about the mechanisms which cause child abuse and neglect. The Family Stress Model (FSM) posits that economic hardship undermines family functioning through a cascading sequence of stress processes. [4] Economic hardship takes many forms including general low income, poverty which qualifies for welfare assistance, job loss, negative financial events, or excessive debt. These constraints on a family's ability to meet their basic needs creates emotional distress among one or both parents (Slack et al. 2011). This can destabilize the couple's relationship via inter-parental conflict, and erodes the quality of parenting—often manifesting as harsher, less responsive interactions with children (Conger and Donnellan 2007; Conger and Conger 2002). Harsh, inconsistent parenting undermines the development of children's non-cognitive skills like self-control, emotional regulation, and cooperation (Neppl, Senia, and Donnellan 2016), which increases the likelihood of conflict between parents and children. Originally formulated during the 1980s farm crisis (Conger and Conger 2002), there is now a large body of evidence across different cultures and income levels supporting the causal chain of events described by the FSM (Zietz et al. 2022; Masarik and Conger 2017; Repetti, Taylor, and Seeman 2002; Brooks-Gunn and Duncan 1997). Overall, children from low socioeconomic status (SES) families face maltreatment rates five times higher than their more affluent peers (Sedlak et al. 2010), and aggregate changes in child poverty are associated with changes in maltreatment reports (Kim and Drake 2023).

Intimate partner violence (IPV) can amplify the risk factors outlined by the FSM. Economic hardship escalates partner conflict, and abusive relationships can exacerbate financial

[4] See Figure 3 for a diagrammatic view of this model.

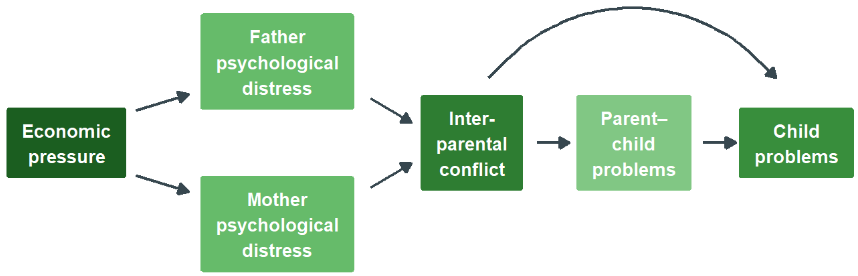


Figure 3: Family Stress Model Diagrammed

instability (Stylianou 2018). Families facing both poverty and IPV are often at the highest risk of maltreatment, as multiple stressors converge to undermine family stability. Part of this relationship is mechanical since children being exposed to domestic violence among adults in their household is considered a form of emotional abuse in its own right (Kitzmann et al. 2003). Approximately 30-60% of child maltreatment cases involve domestic violence in the home (Renner and Slack 2006; Edleson 1999). IPV can directly harm children or lead to emotional and physical abuse as a result of the trauma experienced by the non-abusive parent. It also impairs parental capacity, as a parent experiencing abuse may struggle to care for or protect their children (Hamby et al. 2010). Chronic IPV often co-occurs with child abuse, and the dynamics of power and control in these situations can exacerbate maltreatment (Renner and Slack 2006).

2.3 Sports betting and maltreatment risk factors

Together, financial hardship and violence among adults are the two significant risk factors for child maltreatment that motivate this study. This is because past literature has identified direct effects of sports betting on both. First, sports betting can create the economic hardship central to the FSM. One time large losses can create moments of economic hardship, particularly those that occur immediately following a payday, thus causing households to more strictly budget until the next. In the longer-run, repeated losses lead households to have worsening credit scores, and increased rates of bankruptcy (Hollenbeck, Larsen, and

Proserpio 2024; Baker et al. 2024). Second, emotional shocks in high-stakes situations often translate into real-world violence, and this pathway is heightened with the addition of sports betting. Using National Football League data, Card and Dahl (2011) found that unexpected (upset) home-team losses increased male-on-female partner assaults in the hours immediately after the game. [5] The results match the frustration–aggression mechanism that links anger from violated expectations to violence (Berkowitz 1989). Matsuzawa and Arnesen (2024) find that the legalization of sports betting amplifies the effects of game outcomes on IPV following NFL games, driven by states that legalized mobile betting.

3 Data

3.1 Child Protective Services Case Data

I obtain child protective services (CPS) case-level data from the National Child Abuse and Neglect Data System (NCANDS). NCANDS is a federally-sponsored collection and analysis of state child abuse and neglect data mandated under the 1988 amendments to the Child Abuse Prevention and Treatment Act (CAPTA). Data are submitted voluntarily by all 50 states, Washington D.C. and Puerto Rico. NCANDS reporting follows the federal fiscal calendar (October - September) and culminates into two files each year: the Agency File and the Child File. The agency file provides aggregate information at the state level regarding the total number of reports, the number of screened in reports, and aggregated information about services rendered. I use data from the FY2012 to FY2023 child files to measure child maltreatment reports from January 2012 to December 2022.[6]

The child file provides biweekly case-level data which includes information about the

[5] Data from England following soccer matches shows a similar pattern; during the world cup domestic-abuse calls climb roughly 25% after national-team wins or draws and 38% after losses (Kirby, Francis, and O'Flaherty 2014).

[6] Each row in the data is a child-report pair. This means that every time a child is reported, it contributes towards the overall count, reports featuring multiple children are already disaggregated for proper counting. Children can be linked across multiple reports during the sample period.

characteristics of screened-in reports. The exact report date for each report is suppressed for privacy and recoded as either the 8th or the 23rd depending on which date is closer. In my main specification, I aggregate the data up to the quarter level to better capture the expected long-run evolution of effects.

The file also contains information about the county of the offense, types of alleged maltreatment, the final result (known as disposition) of CPS investigation, and characteristics about the children, caregivers, and perpetrators of the report. Only counties which have more than 700 cases in a fiscal year are identified. Otherwise, data from a county with fewer than 700 cases in a fiscal year is identified only at the state level for that entire year. When conducting analysis at the county level, I remove counties which are not consistent reporters during my sample period; counties which report for less than two years in the pre-period and less than two years in the post-period are dropped from the sample.

Exact statutes regarding valid reasons for reporting and how to report cases of child abuse and neglect varies across states. In general, the process of reporting starts with a concerned adult or mandatory reporter (e.g. schoolteacher) encountering information that leads them to suspect that a child is experiencing maltreatment. When a report comes in, an intake worker first gathers basic facts and determines whether the allegations fall within a state's statutory definition of maltreatment and whether the child's caregiver is the alleged perpetrator. This triage step is called screening. If the report lacks jurisdiction or alleges concerns that do not meet legal criteria, it is "screened out" and closed or referred to other services. If it meets all basic criteria, it is screened in and assigned a response priority.[7] The case is then either routed to a traditional investigation or in some states to a family-assessment/alternative-response track. Next, a caseworker begins an investigation and determines appropriate course of actions. Once the investigation is complete and the child is deemed safe the report is given a disposition or outcome. Substantiated and indicated dispositions mean that a CPS investigator determined that a child in the report is a victim

[7] Usually "immediate" (within 24 hours), or "non-emergency" (within 72 hours).

of abuse or neglect. Unsubstantiated and alternative response dispositions mean that either the alleged act did not occur, or the evidence did not meet the legal definition required for a formal intervention.

3.2 NFL Game Data

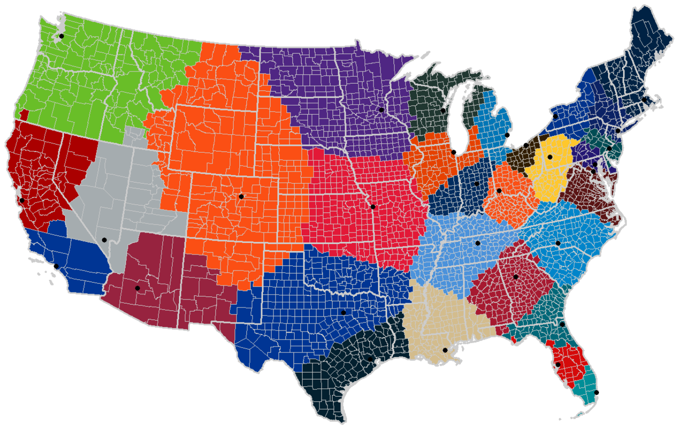
To determine the role of emotional cues, I use spread (*ex-ante*expected difference in points scored between the teams in a game) data on the predicted outcome of each regular season NFL game during my sample period from NFLOddsHistory.com. The sign of the spread indicates which team is favored (negative indicating the favored team) and the magnitude of the spread provides information about how close the game should be. A larger magnitude spread indicates less uncertainty about the winner.

Akin to Card and Dahl (2011) and Matsuzawa and Arnesen (2024), I match spread data to the outcome of each game to create an indicator for games where the favored team ended up losing –an event likely to cause a negative emotional response. Again following the above authors, I define an upset loss for a team that lost but was favored by four or more points according to the spread. Upset wins are defined symmetrically.

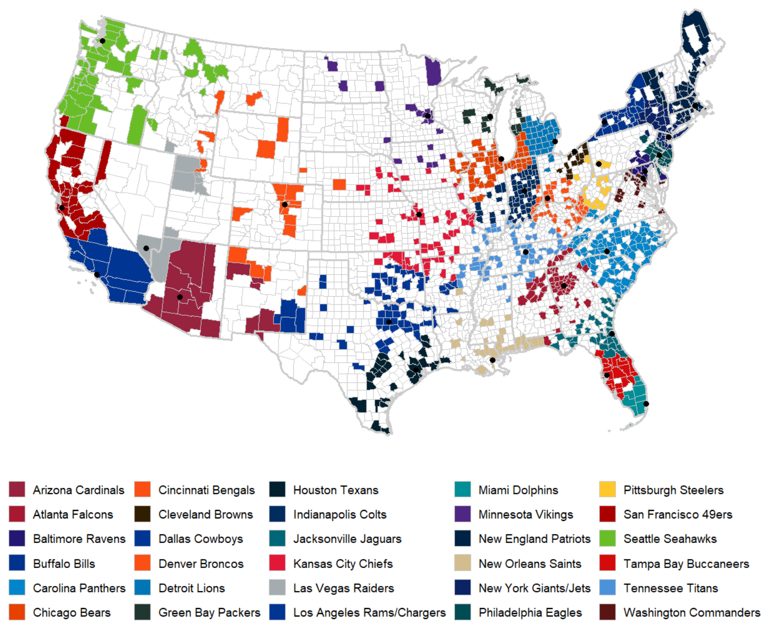
Determining where sports fans reside and which counties favor specific teams is a challenge. Some states have multiple NFL teams, during the sample period three teams move, and in two areas of the country, Los Angeles and New York, two teams play in the same stadium or relatively close to one another. I adopt an approach similar to Matsuzawa and Arnesen (2024), who determine a county's home team as the team whose stadium is closest linear distance to that county's centroid. I use the linear distance from a stadium to a county's nearest edge. This is because there are several large, oddly shaped counties which are between two cities with NFL teams but touch only one of those cities, the county edge approach better deals with this. Panel A of Figure 4 shows the team to which each county in the contiguous U.S. is assigned. Panel B shows the counties in which NCANDS data is available at some point during the sample period.

Figure 4: Home Team for Each County based on Distance to Nearest Stadium

(a) All U.S. Counties



(b) U.S. Counties Identifiable in NCANDS Data



Notes: (A) Map of the contiguous United States showing the "home team" that each county should be assigned based on the linear distance to the nearest stadium. (B) takes the map of all counties and subsets it to only include the counties which are consistent reporters in the data.

3.3 Population, COVID School Closures, and Debt to Income

In addition to the above sources of data, I retrieve county-level population data from the Surveillance, Epidemiology, and End Results (SEER) Program. The SEER population files provide annual July 1 mid-year estimates for every U.S. county stratified by single year of age, sex, bridged race, and Hispanic origin. Using these data, I find the size of the population in each state or county which would be eligible for any type of CPS investigation.

COVID-19 impacted many of the institutions which were most likely to identify child maltreatment, such as schools and daycare facilities (Brown et al. 2022; Rapoport et al. 2021). In order to control for the time varying state specific policies enacted to reduce the spread of COVID, I collect school closure policy severity information from the Oxford Covid-19 Government Response Tracker (OxCGRT). School closure severity ranges from 0 (normal operation) to 3 (schools are prevented from operating in-person) and is reported at the onset of COVID through 2022.

To proxy for a households financial health, I use Debt-to-Income ratios collected from the Federal Bank of New York Consumer Credit Panel. Data is collected at the county level and represents a DTI ratio for each quarter of the year.

4 Empirical Strategy

My empirical strategy exploits the staggered adoption of sports betting between 2018 and 2022. My baseline specification uses state-level counts of child protective services cases to estimate a two-way fixed effects (TWFE) difference-in-difference model. To adjust for the use of count data in the dependent variable, I estimate a Poisson pseudo–maximum likelihood model with two-way fixed effects:

$$\mathbb{E}[\text{Cases}_{st} \mid Policy_{st}, X_{st}, \alpha_s, \lambda_t] = \exp\left(\tau\, Policy_{st} + \alpha_s + \lambda_t + \beta' X_{st} + \ln(\text{Population}_{st})\right) \quad (1)$$

where $Cases_{st}$ is the count of cases of child maltreatment started in state s in time period t. $Policy_{st}$ is a dummy variable indicating whether sports betting was legalized for more than 50% of the time period t in state s and X_{st} represents co-variates such as COVID school closure controls. (α_s) denotes state fixed effect and (λ_t) time fixed effects. When estimating rates, I include $\ln(\text{Population}_{st})$ as an "offset" term with its coefficient fixed at one, allowing the model to account for differences in exposure across observations without estimating its effect. In this case, the offset converts the model from counts to rates by scaling reports by the child population in each state and year. Under this specification, $\exp(\tau) - 1$ is the proportional change in the expected number of reports per child associated with the implementation of $Policy_{st}$.

Recent literature shows that in the presence of a staggered treatment with heterogeneous effects, TWFE regressions can result in biased estimates. To address this concern, I also estimate my main results using methods proposed by Sun and Abraham and Borusyak et al. Additionally, I report OLS TWFE estimates comparable to the Poisson specification from equation 1. The TWFE OLS specification uses logged number of investigated cases as the outcome variable.

Equation 1 identifies a causal effect of sports betting legalization on child maltreatment under the assumption that in the absence of a policy change, treated states would have experienced similar time trends in child maltreatment reports as non-treated states. In Section 5 I present event-study figures that lend support to this parallel trends assumption. We must also assume that policy adoption is not driven by unobserved factors affecting reporting trends. News reporting and commentary from state legislatures suggests legalization timing is not correlated with trends in child maltreatment. Most reporting around sports betting legalization focuses on tax revenues for states and the expansion of individual rights.

I consider two possible treatments regarding sports betting legalization. In the first, I consider the first quarter in which any market (online or in-person) opens as the moment of treatment. In the second, I consider mobile betting as an independent treatment from in-person betting which is determined by the first quarter in which the respective market first begins operation.

To test the mechanisms underlying the relationship between sports betting and child maltreatment, I use an alternative specification to consider the impact of sports-related emotional cues on child maltreatment(Matsuzawa and Arnesen 2024; Card and Dahl 2011). To take advantage of within state variation of sports team loyalty and the higher frequency of games, I create a panel of child maltreatment data at the county–biweekly level. I Specifically, I estimate:

$$
\begin{aligned}
ln(Cases_{ct}) = \quad & \gamma_1 ExpWin_{ct} + \gamma_2 ExpLoss_{ct} + \gamma_3 UpsetLoss_{ct} + \gamma_4 UpsetWin_{ct} + \\
& +\tau_0 Policy_{ct} + \tau_1 \big(ExpWin_{ct} \times Policy_{ct}\big) + \\
& \tau_2 \big(ExpLoss_{ct} \times Policy_{ct}\big) + \tau_3 \big(UpsetLoss_{ct} \times Policy_{ct}\big) + \\
& \tau_4 \big(UpsetWin_{ct} \times Policy_{ct}\big) + \\
& \alpha_c + \lambda_t + \beta X_{ct} + \epsilon_{ct}
\end{aligned} \tag{2}
$$

where $ExpWin_{ct}$ is a variable indicating the number of games a county's home team won as expected –with a pregame spread of -4 or better– within two-week period t. $ExpLoss_{ct}$ is the equivalent for games lost as expected –a pregame spread of +4 or worse– $UpsetWin_{ct}$ is the equivalent for games unexpectedly won –with a pregame spread of +4 or worse– $UpsetLoss_{ct}$ is the equivalent for games unexpectedly lost –with a pregame spread of -4 or better– and the omitted game outcome category is thus close games and weeks with no games. Equation 2 identifies the causal effect of wins vs. losses under the assumption that holding fixed the pregame expectation, the realization of the outcome is as-good-as-random. This assumption underpins a substantial literature on sports outcomes in economics, and has been supported in past work (Card and Dahl 2011; Gandar et al. 1988).

5 Results

5.1 Legalization increases reports of child maltreatment

To analyze the impact of sports betting on child maltreatment investigations, I estimate Equation 1 using a state-by-quarter panel of child protective services cases. Table 3 shows the DiD estimates of Equation 1 when treatment is considered to be the legalization of any type of sports betting (in-person or online). Column (3) shows the basic Poisson specification from equation 1 without covariates. The coefficient suggests that the legalization of sports betting results in a ~ 7 percentage point increase in the rate of cases of child maltreatment. The inclusion of COVID School Control and the use of OLS instead of Poisson attenuates the size of this effect slightly as shown in columns (1), (2), and (4). The smallest estimate still suggests that the rate of investigations increases by 6.1 percentage points in response to legalized sports betting.

Table 3: OLS and Poisson Estimates of Any Betting

	(1)	(2)	(3)	(4)
	OLS	OLS	Poisson	Poisson
Any Betting	0.0652	0.0612	$0.0701^{\cdot}$	0.0668
	(0.0399)	(0.0380)	(0.0431)	(0.0415)
N	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Control		X		X

${}^{\cdot}p < 0.1$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$

Notes: Columns (1) and (3) exclude COVID School Control. Columns (2) and (4) include them. OLS estimates are weighted by child population and include log(`child population`) as a covariate. Poisson estimates include log(`child population`) as an offset. All specifications include state and quarter fixed effects. Standard errors are clustered at the state level.

Table 4 separates treatment into the legalization of mobile and in-person betting. Nine of the thirty-nine states in the U.S. have legalized only in-person forms of sports betting, but only Tennessee restricts sports betting to mobile only. Mobile betting leads to an increase access or lower time cost of betting. It is for this reason that mobile sports betting has recently garnered so much interest. I find qualitatively similar results to the literature finding that access to mobile betting has a slightly larger effect than in-person betting on the rate of investigations. The legalization of mobile betting alone contributes to a 6.9 percentage point increase in the rate of cases.

Table 4: OLS and Poisson Estimates of Mobile and In-Person Betting

	(1)	(2)	(3)	(4)
	OLS	OLS	Poisson	Poisson
Mobile Betting	$0.0654^{\cdot}$	$0.0606^{\cdot}$	$0.0677^{\cdot}$	$0.0630^{\cdot}$
	(0.0344)	(0.0325)	(0.0346)	(0.0325)
In-Person Betting	0.0308	0.0300	0.0340	0.0340
	(0.0332)	(0.0327)	(0.0333)	(0.0333)
N	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Control		X		X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Columns (1) and (3) exclude COVID School Control. Columns (2) and (4) include them. OLS estimates are weighted by child population and include log(`child population`) as a covariate. Poisson estimates include log(`child population`) as an offset. All specifications include state and quarter fixed effects. Standard errors are clustered at the state level.

5.2 Pre-Trends and Dynamic Effects

Before further investigating the estimated effects of the policy, it is important to verify that treated and control units were on similar trajectories prior to adoption and to understand how outcomes evolve over time following treatment. Because TWFE estimates can be biased in the presence of heterogeneous treatment effects (De Chaisemartin and D'Haultfœuille 2020;

Sun and Abraham 2021; Callaway and Sant'Anna 2021; Goodman-Bacon 2021) I re-estimate the main specification of the paper using methods developed by Sun and Abraham (2021) and Borusyak, Jaravel, and Spiess (2024). Since Borusyak, Jaravel, and Spiess (2024)'s estimator uses not-yet-treated units as the comparison, I believe that in the context of sports betting it is the more applicable method.[8]

Borusyak, Jaravel, and Spiess (2024)'s estimator uses a two-step imputation method that predicts counterfactual untreated and not-yet-treated outcomes using unit and time fixed effects and then computes treatment effects as the difference between actual and imputed outcomes. While flexible and efficient for unbalanced panels, their approach offers limited diagnostic tools relative to regression-based methods. The results in Table 5 and Figure 5 show the DiD Imputation estimates and event study, respectively.

Table 5: DiD Imputation Estimates

	Without COVID Controls		With COVID Controls	
	(1)	(2)	(3)	(4)
Any Betting	$0.0526^{\cdot}$		$0.0485^{\cdot}$	
	(0.0300)		(0.0292)	
Mobile Betting		0.0673^{***}		0.0626^{***}
		(0.0206)		(0.0200)
In-Person Betting		0.0289		0.0288
		(0.0251)		(0.0246)
N	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Notes: Imputation-based DiD estimator (Borusyak et al.). Entries are treatment effects with state-clustered SEs in parentheses. Columns (1)–(2) exclude COVID school-related controls, while Columns (3)–(4) include them. Columns (1) and (3) report "Any" legalization; Columns (2) and (4) stack Mobile and In-Person estimates in the same specification. All use the same state-by-quarter panel (2,200 obs.).

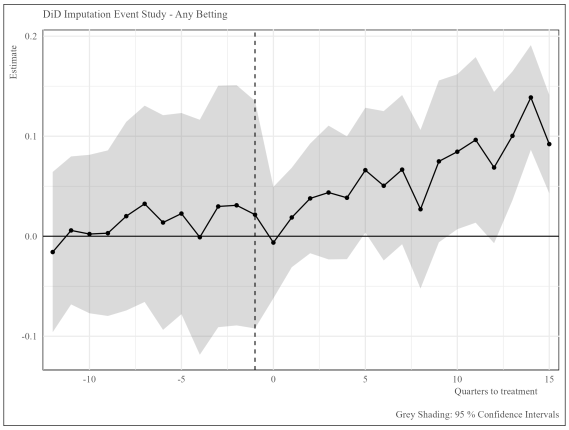
The estimates in Table 5 show results which closely match those in the main specification found in Table 4. The coefficient estimates of any betting and in-person betting are smaller, but the effect of mobile betting become more precise. Figure 5 shows the dynamic effects

[8] You can find results for the Sun and Abraham (2021) estimator in the Appendix.

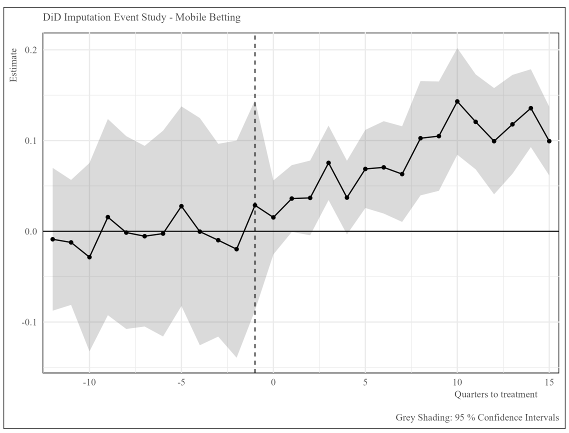
of the policy broken down by legalization type. Across both in-person and mobile betting, the pre-trend estimates are near and not statistically different than zero. In the post period, the effect of mobile betting occurs quickly while in-person betting appears delayed and relatively small. Taken together, the size of the DiD Imputation estimates and the lack of a concerning pre-trend provides robustness for the continued use of Poisson TWFE as the main specification of this paper.

Figure 5: DiD Imputation Event Studies

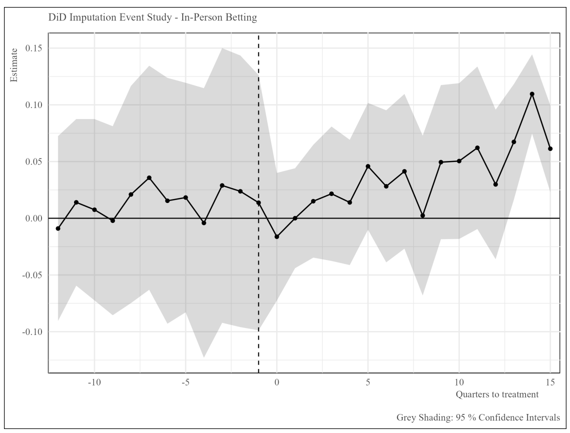
Panel A: Overall



Panel B: Mobile Betting



Panel C: In-Person Betting



Notes: This figure plots the estimated dynamic treatment effects of sports betting legalization relative to the quarter of adoption (period 0). Estimates prior to treatment indicate pre-trends are likely not present. The imputation approach ensures that estimates are not contaminated by inappropriate comparisons across units with different treatment timings. Shaded areas denote 95% confidence intervals.

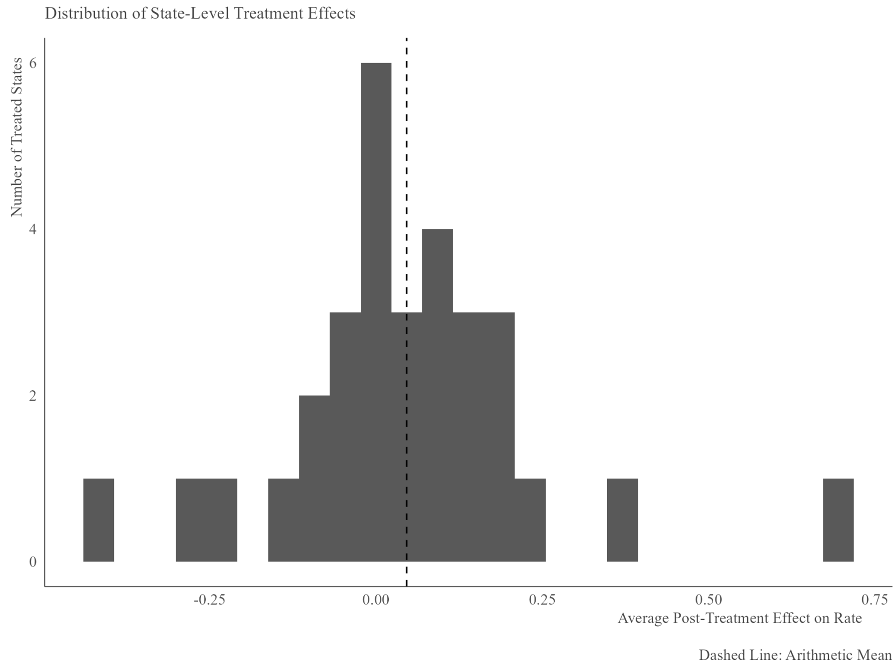
Effects do appear to emerge over time. There are two possible explanations for the gradual emergence of effects following legalization. The first is that uptake into betting is slow. When betting markets first opened they were a fraction of the size they are today. This suggests that either less people were betting when they first opened, bettors were betting less money a year, or both. As more people engage in this activity and spend more money, possible negative effects may appear in other social domains. The second is the dynamics of family stress. When a family member, who is also a problem gambler, engages in sports betting they are putting income at risk that is needed to pay for rent, food, and other child expenses. Each consecutive loss of income has the possibility to lead to arguments between partners and the use of savings or loans to make up the difference. As resources get depleted and conversations remain unresolved, Conger, Ge, et al. 1994 suggests that these problem increasingly trickle down to children. It takes time for this to occur and then be detected by the reporting adult. Both of these explanations suggest a financial motive as the driving explanation of the increase in child maltreatment reports following sports betting legalization.

5.3 Synthetic Controls Methods

As an alternative approach to using staggered difference-in-difference estimators, I use various synthetic control methods (SCM) to characterize the full distribution of effect sizes. These analyses should be taken as exploratory and aimed at providing understanding at the underlying differences in effects across states. SCM, originally introduced by Abadie, Diamond, and Hainmueller (2010), constructs a weighted average of control units to approximate the counterfactual outcome trajectory of a treated unit. However, the classic synthetic control method was developed for a single treated unit and does not directly accommodate multiple units with staggered adoption. One strategy for multiple treated units involves computing separate synthetic controls for each treated unit and then averaging their estimated effects. (Dube and Zipperer 2015; Donohue, Aneja, and Weber 2019)

Figure 6 shows the distribution of ATTs of sports betting on the log rate of child maltreatment reports. ATTs were calculated as the difference in mean outcomes between the treated and synthetic unit in the post-period. The dashed-line is at 0.045 and represents the average ATT across all units when equal weight is applied to each treated unit. This estimate aligns closely with the DiD Imputation estimate, but is smaller than the OLS and Poisson specifications. Because these results do not include placebos or confidence intervals, the figure should be interpreted as descriptive evidence of the cross-state distribution of estimated effects rather than a formal inference result. One limitation of this approach, generally, is that the fit of SCM varies by adoption state and it doesn't use any information across units. When each treated unit's weights are estimated independently, some units have poor donor fits and are matched on noisy pre-treatment paths. This produces high variance in unit-level ATT estimates and a potentially biased average if poorly fit units receive extreme weights or idiosyncratic shocks. (Ben-Michael, Feller, and Rothstein 2021)

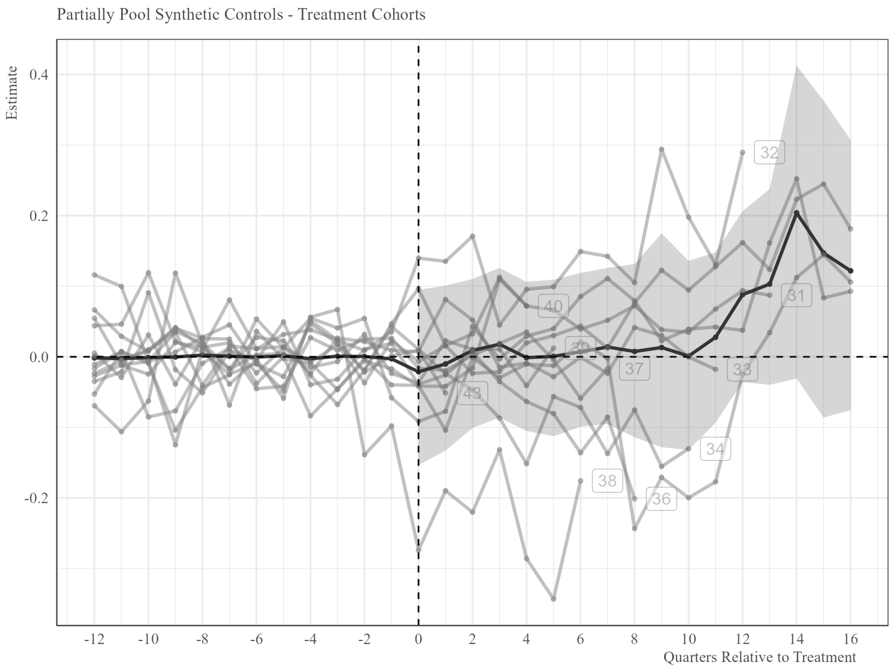
Figure 6: Distribution of Synthetic Control ATTs



Notes: The histogram summarizes state-level average treatment effects (ATTs) from separate synthetic control estimates. For each treated state i, a synthetic counterfactual of the log rate of reports is constructed using pre-treatment weights determined by rolling means of the log rate of reporting for the three half years prior to adoption. The ATT for state i is calculated as the mean post-t_0 difference $\overline{(y^{\text{real}} - y^{\text{synth}})}$ across all post-treatment periods, where positive values indicate higher post-treatment outcomes relative to the synthetic counterfactual. The dashed vertical line denotes the arithmetic mean ATT across treated states, while the dispersion of the histogram illustrates heterogeneity in treatment effects.

At the other extreme, pooled synthetic control estimates a single set of weights that minimizes the average pre-treatment imbalance across treated units. When all treated units share one common set of weights, the method targets the average treated trajectory rather than each unit. This reduces variance but risks bias if units differ in their underlying outcome dynamics or treatment timing. But instead, I follow the partially pooled synthetic control approach introduced by Ben-Michael, Feller, and Rothstein (2021) which minimizes a weighted average of the pooled and unit-specific imbalance measures. By tuning the degree of pooling, the partially pooled estimator helps mitigate the bias–variance trade-off that arises when estimating heterogeneous treatment effects across staggered adoption settings.

Figure 7: Partially Pooled Cohort Synthetic Control Method



Notes: This figure presents dynamic treatment effects estimated using a partially pooled synthetic control framework. The pooling parameter nu is selected flexibly to minimize variance and bias. SCs are estimated for each legalization cohort.

Figure 7 shows the evolution of the average, and cohort, effect of sports betting legalization on the log rate of child maltreatment reports. Cohorts which adopted sports betting later appear to see reductions in reports of child maltreatment, but poorer fit, while early adopters appear to see an increase in reports.

5.4 Financial Health and Emotional Responses to Betting

Beyond the financial pathway outlined above, the existing literature suggests another possible explanations for the connection between child maltreatment and sports betting: increases in intimate partner violence rates (IPV) following sports matches with unexpectedly poor outcomes. In fact, in most jurisdictions, the act of a child watching a display of intimate partner violence is in an of itself an act of maltreatment. For this reason, increased rates of IPV may lead to increase rates of child maltreatment if the increases in IPV occur in families with children. However, most reports of child abuse and neglect are from trusted adults (teachers, doctors, police, etc.) in the community. This means that many acts of maltreatment go unreported as they are never directly or indirectly observed by a reporter. This could especially be true for child maltreatment via witnessed IPV or co-incident with IPV. To explore this channel I estimate Equation 2 leveraging the variation in NFL game outcome conditional on the pregame expectations to measure emotional responses following unexpected losses.

Table 6 looks at the impact of sports betting legalization on cases of abuse and neglect separately. Cases of abuse would be best associated with an emotional response mechanism while neglect would likely follow from financial insecurity. Both cases of neglect and abuse appear to increase on average following legalization. Mobile betting in particular seems to exacerbate cases of abuse. Focusing on this abuse, I investigate a model of upset losses akin to Card and Dahl 2011 to provide better clarity on the emotional state of bettors following games.

Table 6: Poisson Estimates for Types of Maltreatment Investigations

	(1) Abuse	(2) Abuse	(3) Neglect	(4) Neglect
Mobile Betting	0.1276^{**}		0.0563	
	(0.0633)		(0.0503)	
In-Person Betting	-0.0466		0.0394	
	(0.0754)		(0.0492)	
Any Betting		0.0649		0.0595
		(0.0687)		(0.0596)
N	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Control	X	X	X	X

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: All models are Poisson regressions with an offset for child population. Specifications include state and quarter fixed effects. Standard errors clustered at the state level. Columns (1)–(2) present results for **abuse**, while Columns (3)–(4) present results for **neglect**. Models (2) and (4) use a combined treatment indicator (`TREAT_ALL`). Models include a control for COVID-19 school closures.

In Table 7, I find little evidence that emotional cues from sports games influence child maltreatment investigations. Most estimates are close to zero, and interacting betting with the upset loss measure produces signs that do not align with the expected direction. One important limitation is that my analysis is aggregated at the biweekly level because of how the NCANDS data are structured. In contrast, earlier studies (e.g., Card and Dahl 2011; Matsuzawa and Arnesen 2024) looked at outcomes just hours after a game, when any emotional effects are likely to be strongest. By aggregating over two weeks, where multiple games occurred of varying outcomes, any short-term spikes in reports are likely to be smoothed out, making them harder to detect. This wider time window also captures unrelated events and shocks, adding noise and pushing the estimates toward zero. As a result, the lack of observed effects may reflect the limits of the data's timing, rather than evidence that no relationship exists.

Investigating how sports betting impacts child maltreatment through household financial constraints poses interesting challenges. Due to the sensitive nature of child maltreatment data, it is not possible to try to identify or link any household specific information to individual incidences of abuse or neglect. For this reason, I use the 2018 county-level Debt-to-Income ratio as a proxy for the average financial health of households.

Table 8 shows treatment effects by county debt-to-income quintile. Column 1 consists of counties with the lowest debt-to-income ratio and column 5 consists of the highest. Effects appear to be driven by counties which fall in the middle of the distribution of financial health. One possible explanation is that this grouping includes households which have enough disposable income to initiate widespread adoption of sports betting increasing the possible number of households which may then later experience problem gambling as a result.

Table 7: Poisson Estimates of Treatment Effects by Local NFL Team Game Outcomes

	(1)	(2)
Upset Loss	0.0061	0.0081
	(0.0065)	(0.0067)
Exp. Loss	$0.0095^{\cdot}$	0.0076
	(0.0053)	(0.0052)
Upset Win	-0.0085	-0.0068
	(0.0054)	(0.0060)
Exp. Win	0.0004	-0.0016
	(0.0040)	(0.0037)
Mobile Betting		0.0925^{*}
		(0.0469)
Upset Loss × Mobile Betting		$-0.0255^{\cdot}$
		(0.0154)
Exp. Loss × Mobile Betting		0.0039
		(0.0156)
Upset Win × Mobile Betting		-0.0187
		(0.0196)
Exp. Win × Mobile Betting		0.0198
		(0.0168)
Observations	71,024	71,024
County FE	X	X
Fortnight FE	X	X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Poisson regression with offset for child population. Standard errors are clustered at the state level.

Table 8: Poisson Estimates of Betting Effects by County Debt-to-Income Quintile

	(1) (Lowest)	(2)	(3)	(4)	(5) (Highest)
Mobile Betting	0.0743	0.0178	$0.0636^{\cdot}$	0.0832^{**}	0.0097
	(0.0472)	(0.0295)	(0.0350)	(0.0313)	(0.0440)
In-Person Betting	0.0352	-0.0275	0.0937^{*}	0.0182	0.0475
	(0.0455)	(0.0346)	(0.0471)	(0.0225)	(0.0392)
Observations	8,622	8,622	8,622	8,622	8,591
County FE	X	X	X	X	X
Quarter FE	X	X	X	X	X

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Notes: Each column reports results from a separate Poisson regression within quintiles of county debt-to-income ratio. All models include an offset for child population, county (FIPS) and quarter fixed effects. Standard errors are clustered at the state level.

5.5 Case and Child Heterogeneity

Baseline reporting rate differences by race is well documented. For example, black children are persistently more likely to be reported than white children as a percentage of the population (Kim, Wildeman, et al. 2017). For this reason, I conduct heterogeneity analyses by child race. Table 9 shows the estimates of Equation 1 subset by child race. These estimates suggest that sports betting is impacting all communities, but that some are being impacted more than others. The largest increase in investigations appears to be in Asian Households. By proportion to the population, Asian children hold the fewest number of investigations overall in the data. White children represent the largest number of investigations by magnitude. They experience a mobile and in-person betting relationship that closely matches the main specification.

Table 9: Poisson Estimates of Treatment Effects by Race

	White	Black	Latino	Asian
Mobile Betting	0.0721$^{\cdot}$	0.0871	0.0592	0.0948
	(0.0401)	(0.0580)	(0.0605)	(0.0590)
In-Person Betting	0.0411	0.0683	0.0555	0.1211**
	(0.0504)	(0.0646)	(0.0475)	(0.0613)
Observations	42,928	41,100	41,840	22,700
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Control	X	X	X	X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$

Notes: Each column reports estimates from a separate Poisson regression subset by child race. All models include an offset for child population, county (FIPS) fixed effects, fortnight fixed effects, and a control for COVID school closures. Standard errors are clustered at the state level. Sample period: 2012–2022.

Cities have more resources to detect, address, and prevent child abuse and neglect (Maguire-Jack, Smith, and Spilsbury 2022). For this reason, I investigate whether treatment effects are heterogeneous by urban vs. rural counties. Table 10 shows the differential effects of legalization for urban and rural counties. Column (1) uses a binary indicator variable for whether a county is rural based on a simplified version of the USDA Rural-Urban Continuum Code for the year the data was collected. I find that rural counties in general experience a one percentage point higher rate of investigations following legalization than their urban counterparts. Column (2) breaks down counties into finer groups by population size to better understand which types of rural counties are most impacted by betting. I find that the most populated (> 20k) rural areas are driving the rural-urban differences. Column (3) looks at rurality in yet another way –is this county next to a metro area or not. I find that rural areas not adjacent to metro areas experience the largest impact from sports betting legalization. These results together suggest that rural counties which are large and/or not next to a metro areas experience the greatest increase in the rates of child abuse and neglect following sports betting legalization.

Table 11 provides estimates by age group and suggests that the relationship between betting legalization and child maltreatment may vary with children's developmental stage. Data is subset to represent a rough categorization into infants, pre-school age, elementary school, and middle/high school. For mobile betting, the largest and most precisely estimated increase appears among children ages 1–5. The estimates are also positive and large for children ages 6–11 and 12–17. In-person betting appears to increase reports of younger groups and essentially no effect for adolescents. These results suggest that younger children, that are not infants, experience the greatest increase in investigated cases following the legalization of sports betting.

Table 10: Poisson Estimates of Betting Effects by Rurality: County-Level

	(1)	(2)	(3)
Any Sports Betting	0.038092	0.064274	0.064294
	(0.045369)	(0.041705)	(0.041697)
Rural	0.006532		
	(0.014848)		
Rural pop $\geq$ 20k		-0.014108	
		(0.048239)	
Rural pop 5k–20k		-0.016104	
		(0.046922)	
Rural pop $<$ 5k		-0.037986	
		(0.076162)	
Rural Area Adj.			-0.025531
			(0.044100)
Rural Area Not Adj.			0.021788
			(0.051147)
Betting $\times$ Rural	0.015368^{**}		
	(0.006018)		
Betting $\times$ Rural pop $\geq$ 20k		0.063986^{***}	
		(0.014129)	
Betting $\times$ Rural pop 5k–20k		0.011368	
		(0.020059)	
Betting $\times$ Rural pop $<$ 5k		$0.102920^{\cdot}$	
		(0.059712)	
Betting $\times$ Rural Adj.			0.033951^{**}
			(0.016102)
Betting $\times$ Rural Not Adj.			0.083693^{***}
			(0.027094)
Observations	43,156	43,156	43,156
County FE	X	X	X
Quarter FE	X	X	X
COVID School Control	X	X	X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: All models are Poisson regressions with an offset for child population. Column (1) includes a binary rural indicator interacted with treatment. Column (2) includes three rural population categories: $\geq$ 20,000 people, 5,000–20,000 people, $<$ 5,000 people, each interacted with sports betting legalization. Column (3) includes indicators for *Rural Area Adjacent* to Metro Areas and *Rural Area Not Adjacent* to Metro Areas. All specifications include county (FIPS) and time (fortnight) fixed effects, and a control for covid school closures. Standard errors are clustered at the state level.

Table 11: Poisson Estimates of Treatment Effects by Child Age Group

	(1)	(2)	(3)	(4)
	<1 year old	1–5 years old	6–11 years old	12–17 years old
Mobile Betting	0.0396	0.0764*	0.0638$^{\cdot}$	0.0635$^{\cdot}$
	(0.0300)	(0.0358)	(0.0345)	(0.0363)
In-Person Betting	0.0314	0.0495$^{\cdot}$	0.0510	−0.0011
	(0.0361)	(0.0299)	(0.0339)	(0.0447)
Observations	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Control	X	X	X	X

$^{\cdot}p < 0.1$, $^{*}p < 0.05$

Notes: Each column reports a separate Poisson regression with an offset for child population log(child population). Models include state and quarter fixed effects and a COVID school-closure control. Standard errors are clustered at the state level.

Table 12: Poisson Estimates of Treatment Effects by Child Sex

	(1) Boys	(2) Girls
Mobile Betting	0.0602$^{\cdot}$	0.0621$^{\cdot}$
	(0.0339)	(0.0320)
In-Person Betting	0.0387	0.0323
	(0.0331)	(0.0338)
Observations	2,200	2,200
State FE	X	X
Quarter FE	X	X
COVID School Control	X	X

$^{\cdot}p < 0.1$

Notes: Each column reports a separate Poisson regression with an offset for child population log(child population). Models include state and quarter fixed effects and a COVID school-closure control. Standard errors are clustered at the state level.

The estimates by child sex in Table 12 show small and marginally significant increases for both boys and girls, with little evidence of differences between the two groups. Investigating several of the largest sources of reports, shown in Table 13, increases in the cases caused by mobile betting appear to be detected largely by therapists and other mental health providers which account for 5% of cases. For in-person betting, there appears to be large increases in common sources of reporting. The largest changes in reporting behavior comes in through reports that did not receive a clear source listed which is reported in column 6. These reports which account for 7% of all reports increase overall following legalization mostly driven by states which legalize mobile betting.

Table 13: Poisson Estimates of Treatment Effects by Report Source

	(1) Medical	(2) Mental Health	(3) Legal / CJ	(4) Education	(5) Daycare	(6) Other
Mobile Betting	-0.0569	0.0979	0.0035	-0.0390	0.0218	0.3604^{*}
	(0.1233)	(0.0678)	(0.0626)	(0.0994)	(0.0982)	(0.1820)
In-Person Betting	0.1441	0.0924	$0.0937^{\cdot}$	0.0919	0.0768	-0.1721
	(0.1148)	(0.0965)	(0.0528)	(0.0930)	(0.0816)	(0.1667)
Observations	2,200	2,112	2,200	2,200	2,112	2,163
State FE	X	X	X	X	X	X
Quarter FE	X	X	X	X	X	X
COVID School Control	X	X	X	X	X	X

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Notes: Each column reports a separate Poisson regression by primary report source of child maltreatment (Medical Personnel, Mental Health Personnel, Legal / Criminal Justice, Education Personnel, Child Daycare Provider). Column (6) shows the aggregate regression specification. All models include an offset for child population, state and quarter fixed effects, and a COVID school-closure control. Standard errors are clustered at the state level. Two states do not report Mental Health or Day Care report sources.

6 Conclusion

Legislation regarding the legal status and regulation of sports betting is still active in many states. Missouri, Georgia, and Minnesota among others have recently proposed bills to legalize sports betting. Bills proposed in North Carolina and New York look to add regulation on the the age at which people can bet and what types of bets people can engage in and the SAFE Bet Act introduced into the U.S. congress proposes regulations on advertising and a ban on college sports prop bets. New Jersey, which played a central role in overturning PASPA, is now advancing new regulations to address problem gambling. The proposals would require operators to designate a Responsible Gaming Lead, implement monitoring systems to identify potentially risky behavior, and use a tiered intervention process ranging from education to direct outreach. In addition, pending legislation seeks to prohibit micro-betting, reflecting concern over the potential for impulsive wagering in real time. It is crucial to policymakers in this evolving environment to have ample information regarding the negative externalities caused by sports betting.

This paper provides causal estimates of the impact of sports betting legalization on reports of child maltreatment. Overall, I find that sports betting increases reports of maltreatment by 5-7%. A 6% increase corresponds to a 1,215 case increase per quarter per state that legalizes sports betting. Since thirty-two states, and the District of Columbia, legalized during the sample period of this study, this amounts to a 40,095 case increase in the United States each quarter. This number does not represent the number of victims, but about 15.8% of all cases are substantiated as abuse. A back of the envelope calculation, assuming the cases generated by the policy follow the substantiation rate of the overall sample, puts the costs of sports betting legalization at $1,330,428,120 per quarter.[9]. The increase in cases also has implications on the constraints of case workers and their ability to adequately investigate cases as well as municipal budget planning for FTE allocation.

The increase in cases is driven by reporting in rural areas and for children ages 1 to 11 years old. Given that the sports-outcome specifications find results that are opposite those for IPV, and that the event studies show the effect growings over time, I speculate that the mechanism driving the connection between sports betting and maltreatment reporting appears to be one of resource constraint.

My paper adds to the existing literature of the negative externalities caused by sports betting legalization (Matsuzawa and Arnesen 2024; Baker et al. 2024; Hollenbeck, Larsen, and Proserpio 2024; Van Der Maas, Cho, and Nower 2022). While many states have chosen to legalize sports betting for the possible benefits related to state tax revenues or personal freedoms, these benefits may be offset by the growing number of unintended costs now including child abuse/neglect.

[9]Fang et al. (2012) estimate of the cost of nonfatal incidents of child maltreatment at $210,012 per victim

An important avenue for future research concerns the ways in which legalized sports betting, especially through mobile apps, integrates gambling into the home environment. Unlike casinos or racetracks, mobile platforms allow betting to occur during family time, often while parents are simultaneously watching sports with their children. This shift raises questions about how gambling in the household may compete with time, attention, and financial resources devoted to children. Future studies could examine whether parental engagement decreases when gambling is embedded in leisure activities at home, and whether children's exposure to betting behaviors shapes their own attitudes toward risk and gambling. Investigating these intergenerational and household-level effects would provide valuable insights into how sports betting legalization influences family well-being beyond direct financial strain.

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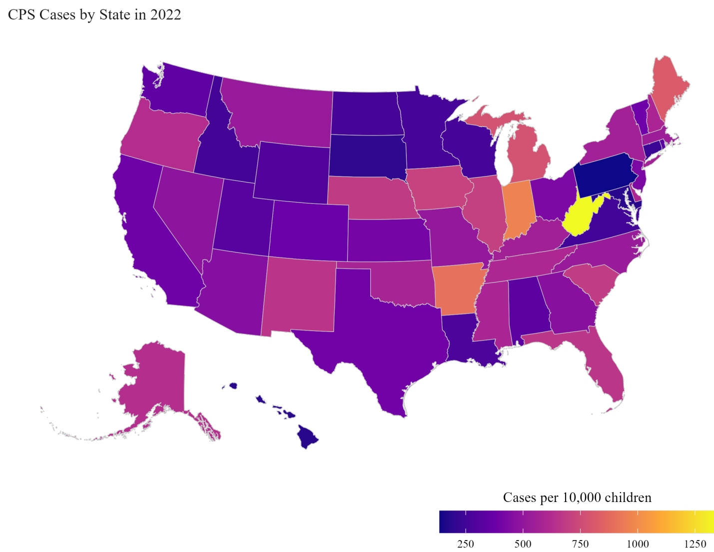
A Appendix

A.1 Child Maltreatment Cases Trends

Figure A.1: Spatial Distribution of Child Abuse Cases

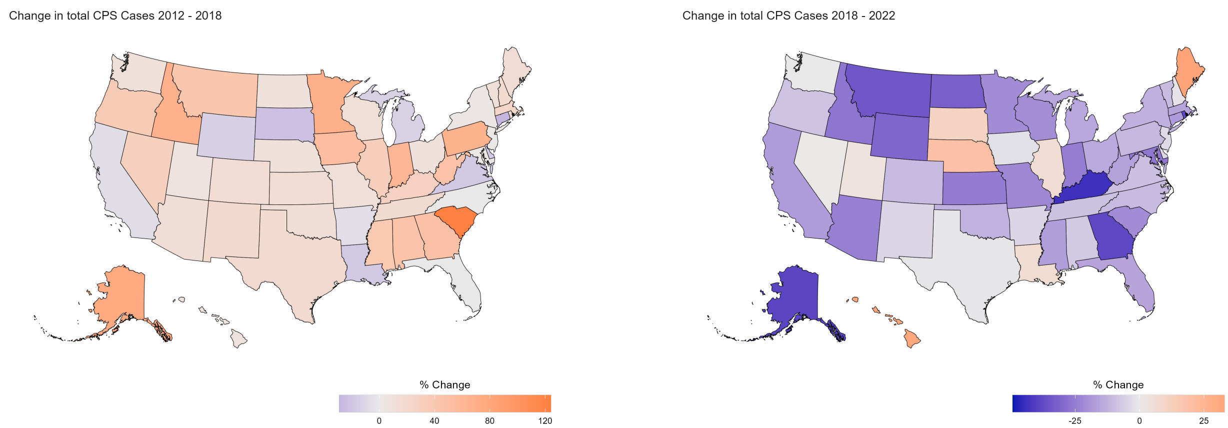


Notes: This map shows the number of cases of child abuse and neglect cases per 10,000 children across the United States in 2022. It shows variation in the severity of child maltreatment and that the prevalence is not directly connected to the change in cases.

Figure A.2: Spatial Distribution of the Change in Child Abuse Cases

Panel A: Percent Change in Cases from 2012 to 2018

Panel B: Percent Change in Cases from 2018 to 2022



Notes: Panel A and B aim to decompose the percentage change in cases of abuse and neglect across the U.S. shown in Figure 2. Panel A shows that from 2012 to 2018 most states saw an increase in the number of cases of child maltreatment. Panel B shows that most states saw a decrease in the number of cases from 2018 to 2022 largely driven by the height of the COVID pandemic and it's impacts on reporting. Though, this decrease in case volume is less homogeneous than the increases seen prior to 2018.

A.2 Main Specification by Fortnight

The main specification of this paper uses data aggregated to the quarter-level. This aggregation helps to compare the results to the literature and to reduce noise and seasonality seen at lower aggregations. To show that this decision does not dramatically impact the results, Table A.1 and A.2 provide the results to my main results if a fortnight panel is used instead of a quarterly panel.

Table A.1: OLS and Poisson Estimates of Treatment Effects: Any Sports Betting

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson
Any Sports Betting	0.0683$^{\cdot}$	0.0658$^{\cdot}$	0.0724$^{\cdot}$	0.0702$^{\cdot}$
	(0.0392)	(0.0378)	(0.0420)	(0.0407)
N	13,200	13,200	13,200	13,200
State FE	X	X	X	X
Biweekly FE	X	X	X	X
COVID School Closure Control		X		X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Models (1) and (2) are OLS regressions weighted by state population under 18 years old. Models (3) and (4) are Poisson regressions with an offset for child population. All specifications include state and time fixed effects. Standard errors are clustered at the state level. Model (2) and Model (4) include a COVID-19 school closure indicator. All models control for child population either as a covariate (OLS) or as an offset (Poisson).

Table A.2: OLS and Poisson Estimates of Treatment Effects: Mobile vs In-Person

	(1) OLS	(2) OLS	(3) Poisson	(4) Poisson
Mobile Betting	0.0604$^{\cdot}$	0.0568$^{\cdot}$	0.0648$^{\cdot}$	0.0614$^{\cdot}$
	(0.0336)	(0.0324)	(0.0345)	(0.0331)
In-Person Betting	0.0362	0.0361	0.0371	0.0372
	(0.0328)	(0.0325)	(0.0314)	(0.0314)
N	13,200	13,200	13,200	13,200
State FE	X	X	X	X
Biweekly FE	X	X	X	X
COVID School Closure Control		X		X

$^{\cdot}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

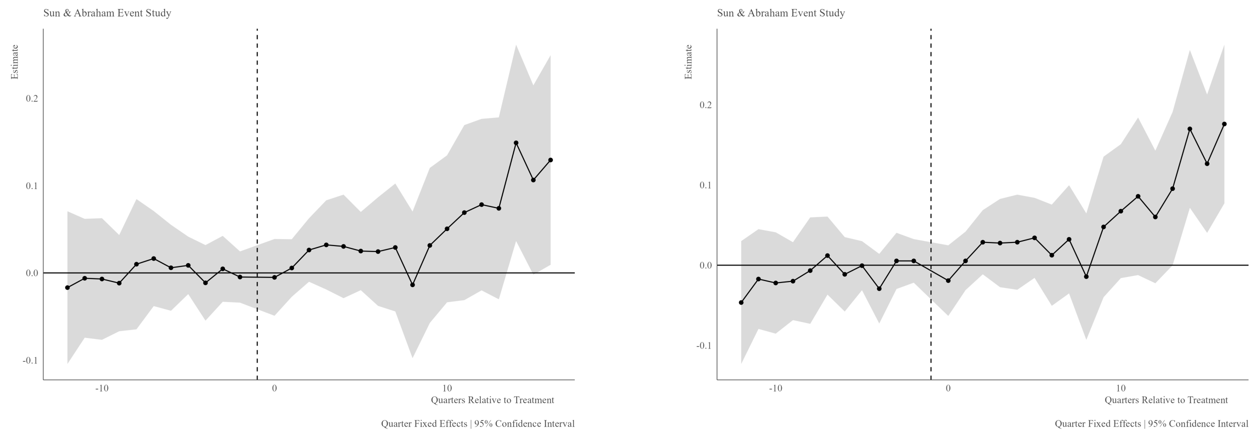
Notes: Models (1) and (2) are OLS regressions weighted by state population under 18 years old. Models (3) and (4) are Poisson regressions with an offset for child population. All specifications include state and time fixed effects. Standard errors are clustered at the state level. Model (2) and Model (4) include a COVID-19 school closure indicator. All models control for child population either as a covariates (OLS) or as an offset (Poisson).

A.3 Staggard Adoption Robustness Check

The Sun and Abraham (2021) estimator identifies treatment effects by interacting cohort and relative-time indicators, estimating cohort-specific event-study coefficients, and aggregating them using non-negative weights based on untreated comparison groups. This approach corrects the bias and negative-weight issues inherent in traditional two-way fixed effects estimators, but requires sufficient untreated comparisons in each period. Panels A and B of Figure A.3 show the event study estimates for the Sun & Abraham estimator. It shows that pre-treatment coefficients remain near and are not statistically different from zero, supporting the parallel trends assumption. The effect of treatment is delayed in these figures becoming statistically significant in the third year following legalization.

Figure A.3: Sun & Abraham Event Study Estimates

Panel A: Poisson Model **Panel B: OLS Model**



Notes: The plots show Sun and Abraham (2021)-style event-study estimates for the effect of any form of sports-betting legalization on child maltreatment reports.

Since the effects evolve over time, this may bias the pooled TWFE coefficients reported in the main table. To address this concern, I re-create the main effects of any gambling legalization treatment using the average treatment effect on treated units. Table A.3 shows qualitatively similar effects to Table 3, with an increase in the number of investigations post-legalization, but the effects are smaller. The Sun & Abraham estimator reported uses only never-treated units as the comparison group. This may be unreasonable given the large number of adopters leaving only about twelve never treated units in the sample.

Table A.3: Sun and Abraham ATTs

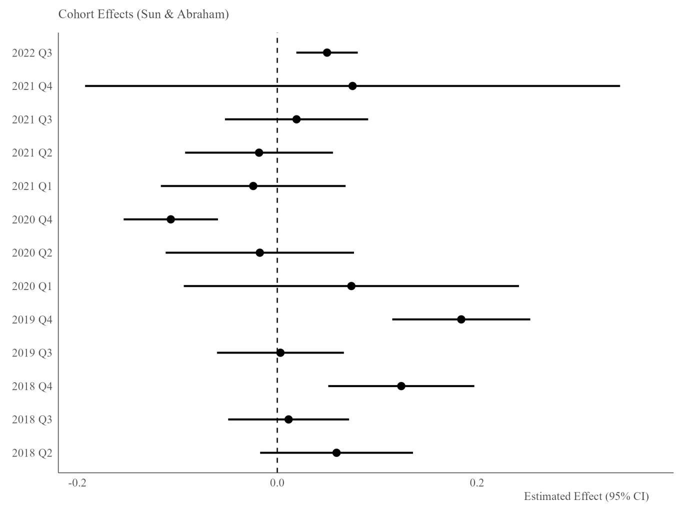
	Poisson		OLS	
	(1)	(2)	(3)	(4)
Any Sports Betting	0.0352	0.0328	0.0365	0.0334
	(0.0274)	(0.0260)	(0.0259)	(0.0246)
N	2,200	2,200	2,200	2,200
State FE	X	X	X	X
Quarter FE	X	X	X	X
COVID School Controls		X		X

${}^{*}p < 0.1$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

Notes: Columns (1)–(2) report Poisson estimates; Columns (3)–(4) report OLS estimates. Each pair contrasts models with and without COVID school-related controls. Poisson specifications include an offset for the child population. All models include state and quarter fixed effects. Standard errors are clustered at the state level.

Heterogeneous effects may in-part explain why the Sun and Abraham (2021) ATT effects are smaller in magnitude than the TWFE main effects. Figure **??** shows the Sun and Abraham (2021) ATT estimate separately for each policy change cohort. These results suggest that some states are experiencing disproportionate impacts from sports betting. The cohort which legalized in the fourth quarter of 2020 is a notable standout. It is the only cohort to shows a negative, statistically significant impact of sports gambling legalization on child maltreatment investigations. This estimate is likely heavily influenced by reporting difficulties brought on by the COVID-19 pandemic and not fully captured by controls. Additionally, this only consists of one state, Tennessee.

Figure A.4: Cohort Effects (Sun & Abraham)



Notes: Points show cohort-level ATT estimates; bars are 95% confidence intervals. The horizontal dashed line denotes zero.

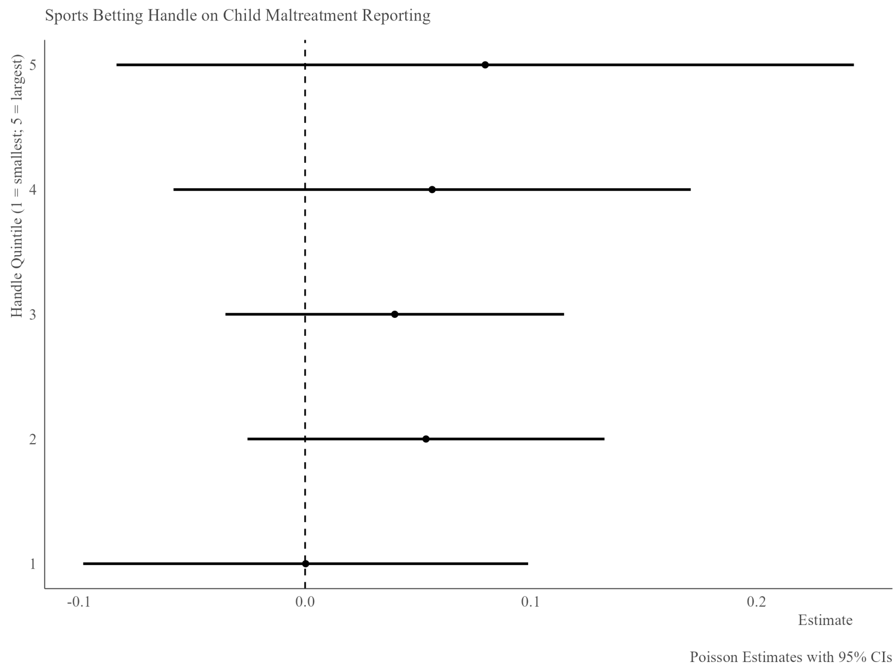
A.4 Betting Handle As Treatment

Sports betting legalization was a binary treatment in accordance to the law, but it's popularit has grown over time. This popularity can be gauged by the amount of money that people collectively wager (handle) each quarter. Specifically, per capita handle is one way to view how states that legalized sports betting may experience heterogeneous treatments. States with higher per capita handle may experience broader social or economic effects if betting activity leads to problem gambling and negative outcomes such as child maltreatment.

Figure A.5 plots estimates from a Poisson model which breaks per capita handle into quintiles and interacts it with treatment status. In the smallest quintile, the coefficient is near zero. The magnitude of the coefficients, more or less, increase as states spend more on sports betting. This is suggestive evidence that as more people engage in sports betting the more likely that negative outcomes may occur.

Table A.4 reports results from a Poisson model which adds per capita betting as a continuous treatment alongside the dummy treatment indicators. The estimated coefficient on per capita betting handle accounts for about a three percent increase in the number of reports per $100 spent per person per quarter on sports betting. More interestingly, it appears that

Figure A.5: Treatment Effects by Betting Handle Quintile



Notes: Bars are 95% confidence intervals. The horizontal dashed line denotes zero.

the availability of betting in any capacity may have an impact on child maltreatment reports. One possible explanation for this relationship is a change in time use following sports betting legalization that reallocates time away from parenting towards sports betting.

Table A.4: Poisson Estimates of Combined and Separate Betting Treatments

	(1)	(2)
Per Capita Betting Handle	0.0003	0.0002
	(0.0003)	(0.0003)
Any Betting	0.0480	
	(0.0358)	
Mobile Betting		$0.0494^{\cdot}$
		(0.0254)
In-Person Betting		0.0329
		(0.0328)
N	2,200	2,200
State FE	X	X
Quarter FE	X	X

${}^{\cdot}p < 0.1$, ${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$

Notes: All specifications show Poisson estimates with a child population offset which include state and quarter fixed effects.