The Financial Consequences of Legalized Sports Gambling

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Abstract

Following a 2018 ruling of the U.S. Supreme Court, 38 states have legalized sports gambling. We study how this policy has impacted consumer financial health using a large and comprehensive dataset on consumer financial outcomes. We use data from the University of California Consumer Credit Panel, containing credit rating agency data for a representative sample of roughly 7 million U.S. consumers. We exploit the staggered rollout of legal sports betting across U.S. states and evaluate two treatment effects: the presence of any legal sports betting in a state and the specific presence of online or mobile access to betting. Our main finding is that overall consumers' financial health is modestly deteriorating as the average credit score in states with legalized sports gambling decreases by roughly 0.8 points. When states introduce access to online sports gambling, average credit scores decline by nearly three times as much (2.75 points). The decline in credit score is associated with changes in indicators of excessive debt. We find a substantial increase in average bankruptcy rates, debt sent to collections, use of debt consolidation loans, and auto loan delinquencies. Together, these results indicate that the ease of access to sports gambling is harming consumer financial health by increasing their level of debt.

1 Introduction

In 2018, the U.S. Supreme Court ruled that the Professional and Amateur Sports Protection Act (PASPA), which prohibited states from authorizing and regulating sports gambling, was unconstitutional. Since the ruling, 38 states have legalized some form of sports gambling. Before this, almost all legal gambling in the U.S. came in the form of tribal casinos with limited gaming options, commercial casinos in a small number of jurisdictions, and state lotteries (Kearney, 2005). In this environment, survey data suggested that roughly 75-80% of Americans engaged in some gambling over a year, with roughly 10% gambling twice per week or more (Welte et al., 2015). The new availability of legal sports betting and growth in mobile accessibility represent a substantial increase in gambling accessibility. Between 2018 and 2023, nearly $300 billion has been wagered via newly legalized sports gambling markets, with most bets flowing through online channels.[1]

While for many, gambling is a relatively inexpensive and generally harmless form of recreation, there is a fraction of so-called "problem gamblers," for whom gambling is associated with a range of serious harms (Meyer et al., 2009). These include financial stress, disruption of family life and relationships, health problems, worsening of job performance, criminal activity, and even suicide (Clarida, 2020; Gabellini et al., 2023; Shaffer & Korn, 2002). The bulk of prior research into the factors associated with problem gambling comes from the period before legalized sports gambling and, therefore, has focused on either commercial casino gambling or illegal gambling (Gabellini et al., 2023). In addition, it's unclear whether to view negative correlations between gambling and health from prior research as causal, as unobserved underlying factors, such as psychological or environmental factors, could drive both.

This paper studies the causal impact of legalized sports gambling on consumer financial health using the variation in legalization across states and time following the state-by-state legalization of sports gambling during the period 2018–2023. To do so, we leverage data

[1] See: https://www.legalsportsreport.com/sports-betting/revenue/

from the University of California Consumer Credit Panel (UC CCP), which contains detailed financial information from a nationwide credit bureau for a sample of roughly 7 million U.S. adults. This data includes credit scores, credit card balances, loan delinquency information, and many other measures of financial health.

We study the impact of sports gambling on a set of key financial health indicators. We first test for consumer credit score changes, an overall summary indicator of a person's financial health or creditworthiness. Next, we measure changes in indicators associated with consumers taking on problematic levels of debt: bankruptcies, total debt collections, use of debt consolidation loans, credit card delinquencies, and auto loan delinquencies.

We consider two definitions of treatment. First, we focus on all states that implemented legalized sports gambling, with the treatment date being the first month in which any type of sports gambling became legal (online or offline). Next, we differentiate between sports gambling that occurs offline, at specified retail locations such as casinos, and sports gambling that occurs online, typically via mobile apps. In doing so, we define an additional treatment focused on online accessibility and consider states that legalized online gambling at some point (some time in addition to offline gambling) and use the first date when betting was available online as the treatment start date.

Our empirical strategy leverages the staggered state-by-state rollout of legal sports gambling and compares how financial outcomes evolve in treated states compared to states that did not implement legal sports gambling or did so at a later date. The primary challenge in isolating the causal effect on consumer financial outcomes is the possibility that the decision by state policymakers to legalize sports betting is correlated with unrelated state-level trends in economic conditions, budgetary conditions, or other policies that also correlate with our financial outcomes of interest.[2] We use fixed effects to control for state-level time-invariant features and national time trends. Because treatment is staggered and treatment

[2]For example, a state may implement legal sports betting because of revenue shortfalls and a need for the additional tax revenue that it may generate, and these states may also be more susceptible to economic shocks.

effects are potentially heterogeneous in time and across groups, we follow best practices in the estimation by employing the estimator proposed in Callaway and Sant'Anna, 2021. This estimator aggregates comparisons of treated and not-yet-treated states and allows us to easily estimate dynamic treatment effects and test for parallel trends across states in the pre-treatment data.[3]

We then separately estimate each treatment's average treatment effect for the full population. We find that for all states that implemented legal sports betting, we observe a small but significant decrease in the average credit score. In states that allow online/mobile gambling, the decrease is roughly three times larger, suggesting that legal sports gambling worsens consumer financial health, especially when mobile access is allowed. Next, we turn to signs of problematic debt loads. For the full set of treated states, we find that only one of our measures (auto loan delinquencies) increases by a statistically significant amount. By contrast, when we focus on the effects of online access to gambling, we find a roughly 10% increase in bankruptcy likelihood and an 8% increase in debt collection amounts, both of which are statistically significant. These effects generally appear roughly two years after when online gambling became legal.[4]

Next, we examine the heterogeneous impact of legal sports betting access. We use the highly granular consumer credit data to examine effects separately for men and women, old and young male panelists, high- vs. low-income male panelists. We find relatively few significant differences in outcomes across these groups, although we find a pattern suggesting that effects are directionally strongest for low-income younger men. Finally, we test for heterogeneous treatment effects across pre-treatment credit score categories (sub prime, prime,

[3]In addition, we test for differences between treatment states and control states for whether they offered different levels of financial assistance or social insurance programs like unemployment insurance before, during, or after the 2020 COVID pandemic. We find no differences except that legalized gambling states offer persistently more generous unemployment insurance. We also show that local trends in economic conditions or state government fiscal conditions are not significantly related to the timing of gambling legalization.

[4]We also test two robustness checks. In both cases, these are designed to account for differences in economic trends or demographic composition between treated and control states. The first explicitly matches counties on these variables and the second compares adjacent counties that lie on opposite sides of state borders between treated and control states. We find that the effects remain significant with a similar magnitude under both.

and super prime) for changes in credit scores and bankruptcies. We find that the negative effects on financial health are overwhelmingly concentrated among the subprime category, that is, among those who were financially precarious prior to access to legal gambling.

2 Literature: Sports Gambling and Financial Health

We contribute to the study of causal effects of gambling on financial outcomes as well as to the growing literature specifically studying the impact of the introduction of widespread legal sports betting in the United States.

A large body of previous research finds that gambling is associated with negative outcomes including financial difficulties, debt accumulation, and mortgage delinquencies (Clarida, 2020; Griffiths, 2009; Wardle et al., 2011). Prior economic research on gambling has placed a particular emphasis on studying the relationship between gambling and personal bankruptcies. Using county-level bankruptcy results, existing economic literature has generally found that access to casinos and state lotteries lead to increasing bankruptcy rates (Barron et al., 2002; Daraban & Thies, 2011; Goss et al., 2009; Grote & Matheson, 2014). This research has also shown that the associations between gambling and negative outcomes are more common among specific demographic groups, such as young adults and individuals with lower socioeconomic status (Binde, 2009; Hahmann et al., 2021; Hing, Lamont, et al., 2015), as well as other risk factors like impulsivity and psychological distress (Hing, Cherney, et al., 2015; Wood & Williams, 2007). Past research has also found that ease of access may exacerbate gambling-related financial harm, as individuals can place bets anytime and anywhere, leading to increased gambling frequency and expenditure (Gainsbury et al., 2015; LaPlante et al., 2011; Nordmyr et al., 2014; Wood & Williams, 2007). Relatively little research is able to find causal associations between financial outcomes and gambling access, however. We contribute to the broad literature on gambling by studying causal links between access to gambling and a range of financial outcomes using the state-by-state rollout of legal sports

betting.

Closely related to our work are two working papers studying different impacts of the spread of legal sports betting on financial outcomes.[5] First, our work complements work by Baker et al., 2024, who use customer-level credit and debit transactions provided by a financial institution to identify who is transferring money to sports gambling apps and how their credit card debt and consumption patterns change when they do so. In a sample of 230,000 households, they find that about 8% use sports betting apps, and that conditional on doing so, lose an average of $1,100 per year. They find that those who bet on average invest less and see their credit card debt increase.

Second, a recent working paper (Taylor et al., 2024) estimates the causal effect of sports gambling legalization on irresponsible gambling behavior. Using an individual-level credit card panel dataset, they find that legalization increases gambling and irresponsible gambling behavior, particularly among those who were previous gamblers. While, unlike these papers, our sample does not identify which specific individuals adopt gambling, we are able to use a much larger sample that is representative of U.S. consumers to measure average effects in the population. We complement their findings on gambling adoption by studying the impacts on a broad range of financial health outcomes such as excessive debt usage and bankruptcy.

3 Background and Data

This section provides an overview and history of state-level legal sports gambling regimes. We then introduce our primary data source, the University of California Consumer Credit Panel (UC CCP), and provide some high-level summary statistics for this data.

[5]Other research explores the impact of the rollout of sports betting in the U.S. on intimate partner violence (Matsuzawa & Arnesen, 2024) and mental health outcomes (Couture et al., 2024).

3.1 Background on Legal Gambling

In May 2018, the Supreme Court overturned the Professional and Amateur Sports Protection Act (PAPSA), deeming it unconstitutional and infringing on states' rights. This opened the door for individual states to legalize and regulate sports betting. Before this ruling, only Nevada had the ability to offer legal sports betting. Within just one month of this ruling, Delaware and New Jersey launched retail sports betting at casinos and racetracks, with many states following in the years since. As of February 25, 2025, 39 states and the District of Columbia have legalized some form of sports betting.[6]

There are a wide variety of different state-level regulations and tax structures for sports betting. Perhaps most notable is the decision of whether to allow online (typically mobile) betting or require bets to be placed in person at a qualified location. Currently, 33 states and DC choose to allow some form of online betting accessibility. As shown in Supplementary table 14 in Appendix A, many states in our data legalized retail betting before mobile betting, though time lags between the two types of legalization are often small. Other policy choices faced by states include whether advertising is allowed and how, what types of entities are licensed to offer sports betting, what tax rate is levied, and on what tax base. In Figure 1, we show how the total amount bet on sporting events (dark series) has grown over time along with the number of states with legal sports gambling (gray series).[7] In Supplementary table 15 in Appendix A, we report handle amounts by state and for both online and retail channels during our data period (2018 to June 2023).

3.2 Consumer Credit Data

Our primary dataset is the University of California Consumer Credit Panel (UC-CCP). It contains anonymized individual-level records of a nationally representative 2% sample of U.S. adults with a credit report (i.e., roughly 7 million panelists). Data is tracked from 2004

[6]See: https://www.americangaming.org/research/state-gaming-map/.

[7]We obtained sports betting handles data in June 2023 from https://www.legalsportsreport.com/sports-betting/revenue/.

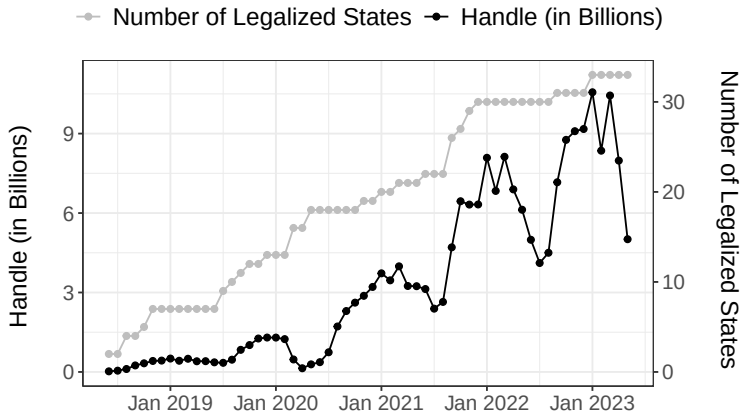


Figure 1: Monthly sports handle in billions and the number of legalized states. The left axis is the sports handle, and the right axis is the number of legalized states. Our data does not contain handles for states where tribal lands run the offline sports gambling market.

to the present day. For each year, we observe records from March, June, September, and December.[8] We observe demographic characteristics for nearly all individuals. This includes information such as age, gender, and ethnicity. The panel also contains modeled and/or self-reported information such as occupation, if the individual owns a home, marital status, and if the individual has children.[9]

We observe account information across all open and closed accounts for each individual-month combination. This includes mortgages, student loans, auto loans, credit cards, secured and unsecured loans, debt consolidation loans, debt buyer accounts, and collections. Information includes when the account was opened, most recent account balance, most recent payment amount, amount past due, if the account is delinquent, what type of business the account is associated with, and, in the case of loans, various loan categories such as personal or medical.

We restrict our panel to individuals who maintain at least one active account and are not deceased. We also remove any individual who moved across states to prevent treatment-

[8]We refer to these observations as quarterly observations or quarters.

[9]See https://www.capolicylab.org/data-resources/university-of-california-consumer-credit-panel/ for additional discussion of data.

control spillovers and any individual whose demographic information is missing, particularly location and gender. Our final dataset contains observations for $4,382,529$ unique individuals and 90 million quarterly observations over seven years, from March 2016 to June 2023.

3.3 Types of Gambling Access

We study the causal impact of gambling access on financial health using the treatment effects framework, and consider two types of treatment definitions. The first is meant to capture the overall effect of any type of gambling legalization and defines a state as treated after the first month a state begins reporting state tax revenue from any sports gambling operations. In our analysis, we call this group "General Access." Note that states may offer online, offline, or both gambling channels. The rollout of channels may occur at different times. For example, in Pennsylvania, casinos began accepting offline wagers in November 2018, with online channels beginning in May 2019. In this case, we define Pennsylvania's treatment status to begin in January 2019 (the first month in our dataset after November 2018).

Our second treatment status is meant to capture the specific effects of the legalization of online gambling. In our analysis, we call this group "Online Access." In our data, 23 states and DC legalized online sports betting as of June 2023.[10] Treatment begins in the first month after the state collects tax revenue from online channels. Additionally, we removed states that exclusively offer offline gambling venues. This removes nine states (Delaware, Mississippi, Montana, New Mexico, North Carolina, South Dakota, Washington, and Wisconsin), leaving us with 40 states and DC that are either eventually treated with online sports gambling access or are never treated. In some cases, states introduce offline gambling before online gambling (10 states). The lags between offline and online rollout are small for most states, excluding Arkansas and New York. No states with both online and offline access implemented online access before offline access. Lastly, three states in our data

[10]Since beginning the project, ten more states have introduced online betting access. For example, Delaware introduced online betting at the end of 2023. However, we treat it as offline-only because our data does not go that far.

only offered online access (Tennessee, Wyoming, and Virginia).

A full list of treated states and their legalization timing can be found in Supplementary table 14 in Appendix A. Start dates are calculated based on the first month the state began collecting tax revenue.[11]

3.4 Primary Outcomes of Interest

We focus our analysis on six outcomes designed to capture overall financial health and the presence of excessive debt.

Overall financial health A credit score is a numerical expression based on a level analysis of a person's credit files, representing the creditworthiness of an individual. Essentially, it is used by lenders to evaluate the risk of lending money to consumers and to mitigate losses due to bad debt. Decreases in consumer credit scores represent lower consumer creditworthiness. Our data observes a consumer's credit score for a given quarter.

Indicators of excessive debt Next, we consider five measures of excessive debt. The first is bankruptcy, which captures instances where consumers do not think they can reasonably repay outstanding debts and need to manage or restructure their finances to pay off debts over time. Filing for bankruptcy is a serious financial decision that requires a consumer to go to bankruptcy court. It seriously harms a consumer's credit score and is a significant indicator of financial stress.

The second is the total amount of debt on an account that has been sent to collections. This is a measure of how much unpaid debt the consumer's creditors have assigned to collection agencies. When a consumer misses payments, or a lender does not think it will receive payment on a debt, the lender may coordinate with a collections agency to manage the debt collection process or sell the debt to a collections agency. Any missed debt can be sent to collections. A debt going to collections can seriously harm a consumer's credit score. In

[11] We do not include Nevada in our analysis because it offered sports betting prior to 2018.

our data, we observe each consumer's collection amounts on file. Unfortunately, we do not observe which specific debts the collections come from. We only know the collection amount and whether it is on the consumer's account.

The second is the use of debt consolidation loans, a financial strategy for managing and reducing debt by combining multiple debts into a single, more manageable loan. This approach is often used by individuals with high debt levels with various creditors, particularly if they face high interest rates from loans or credit cards. Prior survey and observation work finds that gamblers with high levels of debt may use debt consolidation loans (Downs & Woolrych, 2009). Given their low usage rate and the association between the loan product and problem gambling, we focus on changes in the likelihood that individuals take on debt consolidation loans.

Finally, we study credit card and auto loan delinquencies, which indicate missed payments and are a strong sign of financial distress. Delinquencies for credit cards and auto loans will typically be reported if a consumer has missed 1-2 monthly payments. We analyze changes to the number of actively delinquent credit card accounts and auto loans on file to measure failing payments.

In Table 1, we present summary statistics from the pre-legalization period for our six dependent variables.

Table 1: Pre-treatment summary statistics.

Dependent Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Credit Score	300	649	731	714.657	798	850
Pr(Bankruptcy)	0	0	0	0.00072	0	1
Collections	0	0	0	365.071	0	2,084,548
Pr(CC Delinquency)	0	0	0	0.0185	0	1
Pr(Auto Loan Delinq.)	0	0	0	0.014	0	1
Pr(Consol. Loan)	0	0	0	0.00066	0	1

4 Empirical Strategy

We exploit the staggered legalization of sports gambling across states to measure its impact on consumer financial health. We do so by implementing a difference-in-differences (DD) identification strategy that compares changes in average outcomes before and after legalization relative to the changes in these outcomes for states that did not yet legalize sports gambling or that never legalized it over the same period. While DD is typically implemented using a Two-Way Fixed Effect (TWFE)—county and year-quarter in our case—recent literature has pointed out some shortcomings of this estimator (Borusyak et al., 2024). In particular, in cases where there is treatment heterogeneity by treatment groups or time, TWFE can generate biased estimates. To avoid this issue, econometricians have developed a set of alternative estimators (Borusyak et al., 2024; Callaway & Sant'Anna, 2021; Gardner, 2022). In this paper, we rely on the proposed method by Callaway and Sant'Anna, 2021, which we refer to as CS estimator. For computational tractability, we aggregate our data to the county-level and weight county-level observations by the average number of individuals present in the data in 2015. The estimated Average Treatment on the Treated (ATT) can be interpreted as the average change in treated individuals' financial outcomes.

4.1 Identification Checks

Since states decide whether to legalize sports gambling, the primary concern is that unrelated trends in consumer financial outcomes correlate with state-level decisions to implement legalization. Of particular concern would be if states that choose to legalize sports betting to generate revenue do so because they have budgetary problems and, consequently, when economic shocks such as the COVID pandemic arise, are less able to provide social assistance.

We test for this possibility in two ways. First, we test for cross-sectional differences between treated and control states across various social assistance programs and COVID-19 fiscal responses. We compare states across 13 policies, as shown in table 2. We find no

significant differences in these policies except for the duration of unemployment insurance, which is consistently higher among treated states both pre- and post-pandemic. There is little time variation in unemployment insurance duration across the periods studied among treated states. Nevertheless, any declines in consumer financial health observed among treated states could be understated due to those states' more generous unemployment policies.

Table 2: Fiscal policies of treated and control states.

Policy	Treated	Control	t
2020 UI maximum amount ($)	471.4	490.85	.467
COVID Expanded eligibility for UI (high-risk individuals)	.2333	.1905	-.359
COVID Expanded eligibility for UI (lost childcare/school)	.4333	.2857	-1.064
COVID Expanded eligibility for UI (quarantined or caregiver)	.8333	.8095	-.215
COVID Extended UI duration	.0667	.0476	-.279
2021 UI maximum duration (weeks)	**25.73**	**23.85**	**-2.348**
January 2020 UI maximum duration (weeks)	**25.2**	**22.67**	**-2.238**
July 2020 UI maximum duration (weeks)	**25.73**	**23.52**	**-2.255**
Reinstated one week waiting period for UI	.5	.6190	.829
Reinstated work search requirement for UI	.4667	.6667	1.413
Stopped Participating in Federal UI Programs	.4	.4762	.531
Waived work search requirement for UI	.9333	.9524	.279
Weekly UI maximum amount with extra stimulus ($)	1071.4	1090.9	.467
Cumulative State Fiscal Debt 2015-2017 log($)	17.56	17.33	0.702

The second test we perform relates to the timing of gambling legalization. We estimate the relationship between state rollout timing and local economic indicators that likely impact our dependent variables, including weekly wages, quarterly unemployment rates, COVID cases within counties, and measures of state fiscal capacity, namely the one-year and three-year net budget position and the log of cumulative state debt. We use a Cox Hazard model with all 49 states and DC in our data to see if these variables correlate with the timing in which a state first introduces LSG. We present these results in Table 3. We find no significant relationships between these variables and the timing of legalization, alleviating concerns that such factors may plausibly correlate with treatment timing and our dependent variables.

5 Aggregate Effects

This section presents aggregated (across all consumers) event study estimates covering eight quarters before and 16 quarters after the treatment. By doing so, we can validate the parallel counterfactual trends assumption and observe the evolution of the treatment over time. At the end of the section, we present ATT estimates for our treatment conditions and all consumers.

5.1 Overall Consumers' Financial Health

Credit score The first outcome we study is the average consumer credit score. As we discussed in Section 3, a credit score is a measure of the overall financial health of a consumer. It is designed to summarize a consumer's creditworthiness by predicting their future default risk based on all the data observed in credit reports. In Figure 2, we present the event study estimates for changes in the average credit score by treatment status.

First, it is worth noting that we observe largely zero pre-treatment period estimates. This suggests that before the treatment, treated and control states' average credit scores evolved similarly, supporting the validity of our identification strategy.[12]

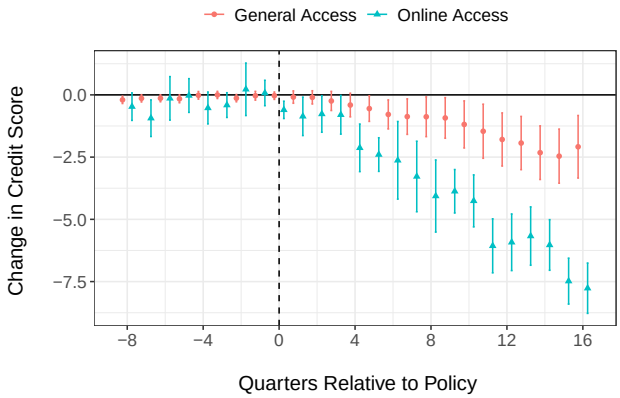


Figure 2: The effect of sports gambling legalization on consumer credit score.

In the post-treatment period, we see that general access to sports betting decreases the

[12]This is the case for all our study outcomes.

average credit score among consumers by a modest 0.8 points. This negative effect is stronger for Online Access treatment as shown in Table 4. During the same time window, the average credit score drops by roughly 2.74 points with access to online gambling, or close to three times the decline we observe for general access to sports gambling. In the next section we provide more discussion of the interpretation of the magnitude of these effects.

5.2 Indicators of Excessive Debt

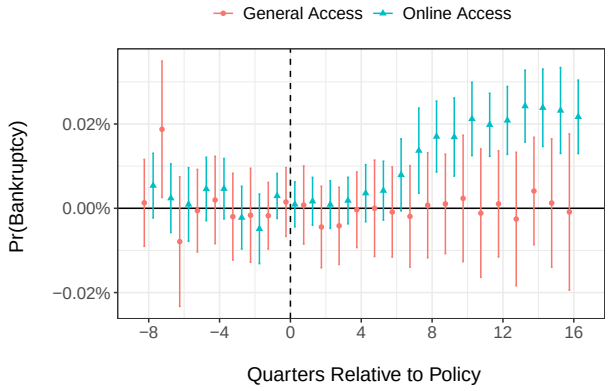
Next, we analyze changes in indicators of excessive debt. This analysis can help us better understand the reasons behind the decrease in the average credit score we observe.

Bankruptcies To measure bankruptcy filing likelihood, we create a binary indicator that takes on the value of 1 when a consumer has filed a bankruptcy (Chapter 7, 11, 12, 13) in any of the months since the previous quarter observation, and 0 otherwise.[13] In Figure 3a, we present event study estimates for bankruptcies by treatment conditions. We find that while the general accessibility to sports betting leads to insignificant changes to bankruptcy filing, online access significantly increases the likelihood of bankruptcy filing. We also see that the increase in bankruptcy filings occurs only after a lag of roughly two years. This is expected given that bankruptcies are often a last-resort option for consumers, and they would likely occur only after consumers experience significant financial stress.

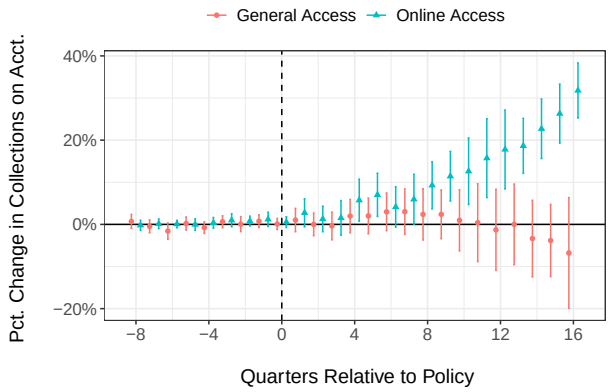
Our ATT estimate in Table 4 translates to roughly 10% increase, or nine more individuals per $100,000$ filing for bankruptcy in states with access to online sports gambling. Considering the pre-treatment population among online treated states, we estimate that this increase leads to about $7,000$ more bankruptcies a quarter, or roughly $30,000$ more bankruptcies a year.[14]

[13] The last three months is due to our sample being the months of March, June, September, and December.

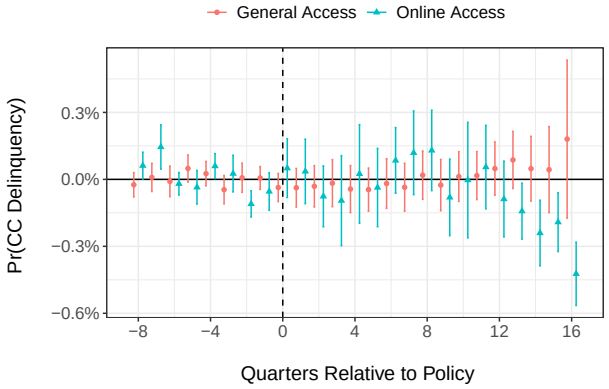
[14] Personal bankruptcies in the US are around $400,000$ a year. See https://www.uscourts.gov/data-news/judiciary-news/2024/11/07/bankruptcy-filings-rise-162-percent?utm_source=chatgpt.com



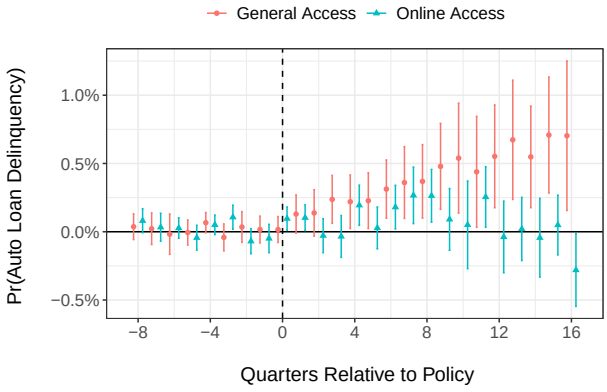
(a) The effect of sports gambling legalization on bankruptcy filing likelihood.



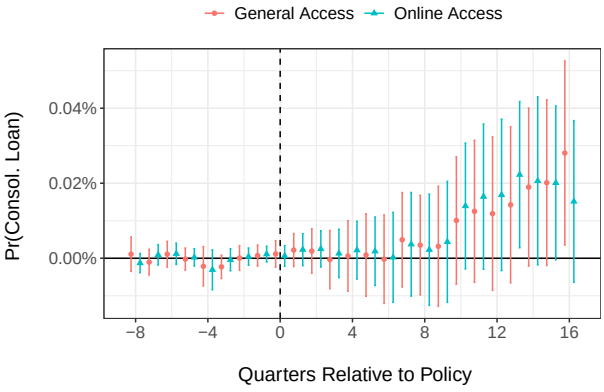
(b) The effect of sports gambling legalization on collections on account amount.



(c) The effect of sports gambling legalization on the likelihood that an individual has a credit card delinquency.



(d) The effect of sports gambling legalization on the likelihood of having an auto loan delinquency on file.



(e) The effect of sports gambling legalization on the likelihood of having an open debt consolidation loan.

Figure 3: Changes in bankruptcies, collection on account, credit card delinquency likelihood, auto loan delinquency likelihood, and debt consolidation usage.

Collections In Figure 3b, we present the event study estimates for changes in the amount of debt in collection on account. We observe a significant increase in collections when focusing on online accessibility, translating to a roughly 7.5% average increase. Given that the pre-treatment period average collection amounts were about $360, our estimate translates to a roughly $30 increase in the average amount of debt in collections per consumer due to sports betting.

A natural question is whether the increase in collections on account with online accessibility is coming from extensive or intensive margins. It could be the case that more unique individuals are generating collections (extensive), or individuals with collections are generating more collections (intensive). To test for extensive margins, we analyze the likelihood that an individual has a collection on file. We find that there is a statistically significant increase ($p < 0.01$) of about 1.3% in the likelihood an individual has a collection on file, suggesting that the rate of consumers with debt sent to collections is increasing across individuals in states with online sports gambling access relative to states that don't. To analyze intensive margins, we then conditioned our dataset to individuals that had any collections on file in the pre-legalization period (January 2016 to March 2018) and re-estimated changes in collection amounts on account among those consumers. We find a statistically significant increase of close to 15% among these consumers ($p < 0.001$). These findings suggest that legalized online sports gambling is leading to both extensive and intensive margin changes in collections on account. More consumers are taking on collections, and those who have existing collections are taking on greater amounts of debt.

Credit card delinquency In Figure 3c, we present event study estimates for changes in the probability of an individual having a credit card delinquency on file. While both series are quite noisy, there is no clear trend (upward or downward) in credit card delinquencies.

These findings suggest that sports gambling does not appear to affect consumers' financial health through credit card debt directly but through harder forms of loan accessibility. This

complements work by (Baker et al., 2024), who find that financially constrained households increase their credit card balances by about $368 relative to less constrained households, or an 8% increase in credit card debt. We find that this increase in credit card balances does not translate into delinquencies but is instead associated with other adverse outcomes, such as bankruptcies, collections, or auto loan delinquencies, as we discuss next.

Auto loan delinquency In Figure 3d, we present event study estimates for changes in the probability of an individual having an auto loan delinquency on file. For both forms of treatment, we see that auto loan delinquency likelihoods are significantly increasing. Compared to pre-treatment averages, this leads to a roughly 20% (6%) increase in delinquency likelihood with General Access (Online Access) treatment.

In contrast to credit cards, auto loans are fairly fixed lending agreements that generally require higher payments. This is consistent within our data, where average cumulative amount spent on credit cards is roughly $123 while cumulative auto loan payments are roughly $530. These are larger loans that have significantly less flexibility compared to credit cards that consumers could access to avoid delinquency. We reason that these differences in lending structures are why we see auto loan delinquencies rise but not credit card delinquencies.

Debt consolidation Finally, we measure the impact on the use of debt consolidation loans, which are used to consolidate and manage high-interest forms of debt (e.g., credit cards). Given that these types of loans are last-resort measures to manage debt, similar to bankruptcies, we expect to see a delayed effect post-introduction of sports gambling. In Figure 3e, we present the event study estimates for the likelihood of an individual having an open debt consolidation loan. We see rates increase after roughly two years (eight quarters), but because of this long lag the average ATT in the post-perid is a statistically insignificant average ATT of roughly 0.01%. In both of the robustness checks described in the next section, the increase in use of debt consolidation is statistically significant.

5.3 Overall ATTs and Summary of Results

In Table 4, we report ATT estimates for all our dependent variables across the event study time windows (eight periods before and 16 periods after treatment).[15] Given that we analyzed several dependent variables, we use the Benjamini-Hochberg procedure to maintain a 5% false discovery rate and account for multiple hypothesis testing (Benjamini & Hochberg, 1995).

While sports betting accessibility appears to be financially harming consumers, online access drives most of the effect we observe. Access to legal sports betting is associated with a modest decrease in consumer financial health and, in particular, causes an increase in signs of excessive debt, such as consolidation loans, debt sent to collections agencies, auto loan delinquencies, and bankruptcies.

While some of these effects are small, it is important to remember that we do not observe which members of the credit panel are actively engaged in sports betting. Therefore, we can only estimate the average effect across the full population. Because most residents of treated states are unlikely to be problem gamblers, it suggests that the average effect on the gambling population is much larger than the effects we find here. Different data sources find that the proportion of treated states' populations who adopt sports betting is in the range of 13-20%.[16] Assuming that sports betting does not impact financial outcomes for the non-betting population, it implies that the average effect on actual bettors is 5-10 times larger than our estimates.

5.4 Robustness Checks

Coarsened Exact Matching While our hazard model in Table 3 does not show that various economic and demographic measures correlate with the timing of sports betting legalization, we may still worry that they could correlate with some confound that impacts

[15] In Appendix B we present TWFE estimates that are consistent and control for additional economic factors that are present in Equation 3.

[16] Baker et al., 2024 find that in their bank account transactions data, 13.9% of those in treated states adopt legal betting. A survey by Siena finds 19% adoption in 2024 (see https://scri.siena.edu/2025/02/18/22-of-all-americans-half-of-men-18-49-have-active-online-sports-betting-account/).

both adoption and our dependent variables. For example, if Covid-19 affects states and counties at particular income thresholds, and this impacts both sports betting adoption and our outcome variables, then our results could be confounded by the interaction between income and Covid-19. To strengthen the causal interpretation of our results, we consider matching counties on the economic and demographic characteristics captured in our hazard model.

Because of the inherent staggered setting and the lack of a post period for never-treated units, we elect to match on pre-period observations that exist for all counties. Specifically, we take 2015-2017 (inclusive) observations for each of our economic and demographic variables and take the average for each county. A county is defined as treated if it is eventually treated, otherwise it is deemed a control unit (i.e., never treated). We then use coarsened exact matching (Iacus et al., 2012) with one-to-one restriction within bins to match control counties to (eventually) treated counties based on 2015-2017 average observable characteristics. Since we drop states with only retail access to sports betting for the Online Access treatment, we run two separate matching procedures for each treatment status (General Access and Online Access). In Table 5, we present differences in observable characteristics between treated (General Access) and control counties before and after matching for the 2015-2017 time period. Matching leaves us with 696 eventually treated counties and 696 never-treated control counties. (1141 treated counties and 571 control counties are dropped).

Similarly, in Table 6, we present differences in observable characteristics between treated (Online Access) and control units for the 2015-2017 time period. This leaves us with 509 treated and 509 control counties. (758 control counties are dropped and 830 treated counties are dropped).

The challenge with matching using only 2015-2017 observable characteristics is that it does not necessarily guarantee similar observable characteristics in the periods just before treatment.[17] One can view our matching as a "light" matching.

[17]We elect to match on only the 2015-2017 observable characteristics due to the staggered setting varying the underlying post-period for treated and control units, making traditional pre-treatment matching

This strategy works if county observable characteristics evolve similarly and do not "drift" apart after the 2015-2017 time periods. If this holds, then we should observe that the matched counties share similar observable characteristics just before treatment occurs. This is testable with our data. Taking the period just before treatment (-1), we can look at the differences in observable characteristics between the matched counties. In Table 7 we show that without matching counties do show observable differences right before treatment. However, once matched, these differences are insignificant, as shown in Table 8. We find insignificant differences across variables, suggesting that counties do not "drift" apart from one another with our given matching strategy.

After matching, we re-run our primary CS estimator using this subset of counties. Results are presented in Table 9. We find results that are consistent with our main unmatched specification, suggesting that differences in financial outcomes between treated and control states are not driven by differences in observable economic or demographic factors between states. In addition, the positive treatment effect on the use of debt consolidation loans, which was statistically insignificant in our main specification, is now significant.

CS Border counties As an additional robustness check, we restrict our analysis to counties along the border and re-estimate our CS model. Restricting comparisons to residents of counties on opposite sides of state borders acts as a robustness check under the assumption that these residents are more similar to one another than average state residents are, and that trends over time in economic conditions are otherwise similar for these groups, with the exception that one group gains access to online gambling and the other does not.[18] If this is the case, there should not be significant differences across counties in observables prior to treatment. This is testable and we show in Table 3 comparisons of observables in the period just before treatment (-1). We see that there are no observable differences across eventually

infeasible.

[18]There is no legal restriction on crossing state borders to place bets, so in theory residents of control states could adopt sports betting after neighboring states legalize it. In that sense, this robustness check presents a conservative estimate of treatment effects.

treated and never treated counties.

In Table 11, we then present results using the CS estimator with the border county units. We find results that are consistent with our primary model specification. In addition, the positive treatment effect on use of debt consolidation loans which was statistically insignificant in our main specification is now significant.

iGaming Lastly, one potential concern could be that the results of online access are driven by the introduction of iGaming, not sports betting. iGaming refers to online or mobile access to a general class of gambling formats besides betting on sporting events, including lotteries, slots, and casino games like poker. In our time window, six states had some form of legalized iGaming accessibility (Pennsylvania, West Virginia, New Jersey, Michigan, Delaware, and Connecticut). The market for iGaming is smaller than online sports betting but still generates substantial revenue. In November 2024, iGaming company revenue was over $800 million. [19] To test the robustness of our Online Access results, we drop the six states with iGaming accessibility and re-estimate the same models used to generate results in Table 4. In Table 12 we present ATT estimates over the time period. We find that our Online Access results continue to hold, which suggest these findings are not driven by iGaming accessibility, but by online sports gambling.

5.5 Heterogeneity Analysis

In this section, we estimate heterogeneous effects for different types of consumers based on pre-treatment credit score.

Pre-Treatment Credit Category As a primary form of heterogeneity analysis, we consider how access to online sports gambling affects consumers across credit categories. Credit scores can generally be bucketed into three groups: Sub-prime (credit score < 600), Prime ($601 \leq$ credit score < 780), and Super-prime (credit score > 780). Super-prime captures

[19] https://www.americangaming.org/resources/aga-commercial-gaming-revenue-tracker/

low-risk individuals, Prime captures average risk, and Sub-prime captures high-risk individuals.[20] Sub-prime individuals are financially riskier in the eyes of the lender. Individuals in this category may have missed payments, defaulted, gone bankrupt, taken on significant debt, or have limited historical credit information.

We identify people as being Sub-prime, Prime, or Super-prime in the pre-legalization period by looking at their credit category in the first quarter of 2018 (just before the Supreme Court ruling, and treatment can potentially begin).[21] We then subset our data to only those individuals who fall within each credit score category and re-estimate each CS model for each variable. We present results in Table 13.

We find that where we see the greatest declines in financial security are among the high-risk Sub-prime borrowers.[22] Among these consumers, we find a roughly 11-point drop in average credit scores, a nearly 12% increase in collections on account, increased auto loan delinquencies by roughly 1.3 percentage points, higher credit card delinquencies close to 0.7%, and bankruptcy likelihoods increasing by nearly 12%. These results suggest that in states with legal online sports betting, negative effects on financial health are overwhelmingly concentrated among those with Sub-prime credit prior to legalization.

6 Conclusion

In this paper, we estimate the causal effect of sports gambling accessibility on consumer financial health by exploiting the recent legalization of sports gambling across U.S. states. We focus on changes to consumer credit risk and the composition of loans taken out by consumers across general sports betting accessibility and online accessibility.

[20] Vantage also considers a Near-prime category from 600 to 660. We group these scores with Prime to create three classes.

[21] We choose only the quarter before because the credit score model meaningfully changed in 2017, so we did not want to delegate credit categories using credit scores from different models.

[22] In similar fashion to Baker et al., 2024, we find minor improvements in financial health for those consumers that were Super-prime in the pre-period. Baker et al., 2024 finds that less-financially constrained households see slight increases in available credit, net investments, and lower credit card debt (See Tables A.8, A.11, and A.12.). These improvements would correlate with higher credit scores.

Overall, we find that the legalization of sports gambling decreased consumer financial health. These results seem to be particularly pronounced when states legalize online betting, suggesting that the ease of access to gambling increases the problems associated with it.

Our paper provides a better understanding of how the legalization of sports gambling negatively affects consumer financial health. While many states may have opted for legalization with the hope of increasing tax revenue, the negative effect we document can partially offset tax revenue benefits as more consumers' financial health deteriorates.

While many consumers get real enjoyment from legal gambling, and states benefit in the form of additional tax revenue, there is a corresponding concern that the introduction of sports gambling and the ease at which consumers can now bet online are negatively harming consumer financial health. Our paper provides evidence that this concern is well founded by quantifying the extent to which the recent aggressive expansion of gambling accessibility impacts consumer financial health.

Table 3: Hazard model test of treatment likelihood with all states.

	Dependent variable:
	Time = Start
log(COVID Cases)	−0.476
	(1.121)
College Share	4.668
	(9.896)
Poverty Rate	5.323
	(24.743)
Unemployment Rate	63.689
	(67.313)
log(Median HH Income)	−0.666
	(4.965)
log(Population)	−0.348
	(0.452)
Young Men Rate	−17.293
	(31.159)
Previous Year State Budget, Scaled	0.0002
	(0.006)
log(Cumulative State Debt)	0.113
	(0.563)
3-Year Rolling State Budget Deficit, Scaled	−0.002
	(0.004)
Observations	1,070
R^2	0.005

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Hazard model estimates analyzing the effect of each variable on the timing a state introduces sports gambling ("General Access"). Log(Population) is the log of state population, Young Men Rate is the proportion of men under the age of 45, Unemployment Rate is the proportion of the population unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of state population under the poverty line, log(Median HH Income) is the log of median household income in the state, and College Share is the proportion of the population that has a bachelors degree or higher. These data come from the US Census five-year estimates. Previous Year State Budget is the previous year state Revenues minus Expenditures. 3-Year Rolling is a rolling window. log(Cumulative State Debt) is the sum of cumulative debt starting in 2012.

Table 4: Overall ATT estimates.

	(1) General Access	(2) Online Access
Overall Financial Health:		
Credit Score	-0.804***	-2.74092***
	(0.1793)	(0.28174)
Excessive Debt Indicators:		
Pr(Bankruptcy)	-0.000004	0.00009***
	(0.00003)	(0.00002)
Collections	0.00767	0.0748***
	(0.01315)	(0.01293)
Pr(Auto Loan Delinquency)	0.00323***	0.00089**
	(0.00065)	(0.00038)
Pr(CC Delinquency)	-0.00008	-0.00013
	(0.00021)	(0.0003)
Pr(Cons. Loan)	0.00005	0.00005
	(0.00003)	(0.00003)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Each row shows the coefficients from a separate Callaway and Sant'Anna, 2021 estimation for the dependent variable shown on the left. Column (1) defines treatment based on any form of legal sports gambling and column (2) defines treatment based on access to mobile betting. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. Following the recommendations of de Chaisemartin and D'Haultfœuille, 2023 (see Chapter 2, Page 24), we report clustered standard errors at the county level in parentheses. All p-values are adjusted using the Benjamini-Hochberg procedure to account for multiple hypothesis testing.

Table 5: General Access: 2015-2017 observable differences before/after matching.

	(1) Original Sample	(2) Matched Sample
log(Population)	-0.557***	0.051
	(0.058)	(0.065)
Young Men Rate	-0.007***	-0.0007
	(0.0009)	(0.0012)
Unemployment Rate	-0.0002	0.00017
	(0.0003)	(0.0005)
Poverty Rate	-0.0132***	-0.002
	(0.002)	(0.003)
log(Median HH Income)	0.022**	-0.004
	(0.009)	(0.011)
College Share	0.018***	0.001
	(0.003)	(0.002)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

*Note:*Cross-sectional observable differences between eventually treated (General Access) and never treated units from 2015 to 2017. Column (1) presents differences between variables using the unmatched sample. Column (2) presents the matched differences between variables using the matched sample. All variables come from the US Census. Log(Population) is the log of the population of the county, Young Men Rate is the proportion of men under the age of 45 in the county, Unemployment Rate is the proportion of the population labeled as unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of the county population under the poverty line, log(Median HH Income) is the log of median household income in the county, and College Share is the proportion of the population that has a bachelors degree or higher. A negative (positive) estimate equates to eventually treated counties having a lower (higher) average value compared to never-treated units.

Table 6: Online Access: 2015-2017 observable differences before/after matching.

	(1) Original sample	(2) Matched sample
log(Population)	-0.449***	-0.121
	(0.063)	(0.073)
Young Men Rate	-0.007***	-0.001
	(0.0009)	(0.0012)
Unemployment Rate	0.00009	0.0004
	(0.0003)	(0.0004)
Poverty Rate	-0.015***	-0.002
	(0.002)	(0.002)
log(Median HH Income)	0.037***	0.009
	(0.01)	(0.013)
College Share	0.022***	0.0002
	(0.003)	(0.003)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Cross-sectional observable differences between eventually treated (Online Access) and never treated units from 2015 to 2017. Column (1) presents differences between variables using the unmatched sample. Column (2) presents the matched differences between variables using the matched sample. All variables come from the US Census. Log(Population) is the log of the population of the county, Young Men Rate is the proportion of men under the age of 45 in the county, Unemployment Rate is the proportion of the population labeled as unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of the county population under the poverty line, log(Median HH Income) is the log of median household income in the county, and College Share is the proportion of the population that has a bachelors degree or higher. A negative (positive) estimate equates to eventually treated counties having a lower (higher) average value compared to never-treated units.

Table 7: Observable differences with no matching between all counties just before treatment.

	(1) General Access	(2) Online Access
log(Population)	0.182***	0.387***
	(0.054)	(0.052)
Young Men Rate	-0.0041***	-0.0006
	(0.0012)	(0.0012)
Unemployment Rate	0.00045	0.00054
	(0.000437)	(0.00035)
Poverty Rate	-0.0129***	-0.018***
	(0.0021)	(0.0028)
log(Median HH Income)	0.0455***	0.0661***
	(0.0091)	(0.0089)
College share	0.0189***	0.0153***
	(0.0023)	(0.0024)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Cross-sectional observable differences in variables just before treatment occurs, with no matching between eventually treated (General Access and Online Access) and never treated units. Column (1) presents observable differences in variables just before General Access treatment. Column (2) presents observable differences in variables just before Online Access treatment. All variables come from the US Census. Log(Population) is the log of the population of the county, Young Men Rate is the proportion of men under the age of 45 in the county, Unemployment Rate is the proportion of the population labeled as unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of the county population under the poverty line, log(Median HH Income) is the log of median household income in the county, and College Share is the proportion of the population that has a bachelors degree or higher. A negative (positive) estimate equates to eventually treated counties having a lower (higher) average value compared to never-treated units.

Table 8: Observable differences between matched counties just before treatment.

	(1) General Access	(2) Online Access
log(Population)	0.038	0.033
	(0.067)	(0.073)
Young Men Rate	-0.0009	-0.0006
	(0.0011)	(0.0012)
Unemployment Rate	0.00088*	0.0009
	(0.00046)	(0.0005)
Poverty Rate	-0.0008	-0.0015
	(0.0027)	(0.0028)
log(Median HH Income)	-0.009	-0.018
	(0.011)	(0.012)
College Share	0.0016	-0.0009
	(0.0026)	(0.0028)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Cross-sectional observable differences in variables just before treatment occurs, with matching between eventually treated (General Access and Online Access) and never treated units. Column (1) presents observable differences in variables just before General Access treatment. Column (2) presents observable differences in variables just before Online Access treatment. All variables come from the US Census. Log(Population) is the log of the population of the county, Young Men Rate is the proportion of men under the age of 45 in the county, Unemployment Rate is the proportion of the population labeled as unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of the county population under the poverty line, log(Median HH Income) is the log of median household income in the county, and College Share is the proportion of the population that has a bachelors degree or higher. A negative (positive) estimate equates to eventually treated counties having a lower (higher) average value compared to never-treated units.

Table 9: Overall ATT estimates with matched counties.

	(1) General Access	(2) Online Access
Overall Financial Health:		
Credit Score	-0.81785***	-2.12829***
	(0.22235)	(0.30198)
Excessive Debt Indicators:		
Pr(Bankruptcy)	0.00004	0.0001**
	(0.00005)	(0.00004)
Collections	-0.00009	0.06222***
	(0.03195)	(0.01689)
Pr(Auto Loan Delinquency)	0.00271**	-0.00086
	(0.00082)	(0.00051)
Pr(CC Delinquency)	0.00022	-0.00009
	(0.00036)	(0.00041)
Pr(Cons. Loan)	0.00012*	0.0001**
	(0.00006)	(0.00005)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Each row shows the coefficients from a separate Callaway and Sant'Anna, 2021 estimation for the dependent variable shown on the left. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. We follow the recommendations of de Chaisemartin and D'Haultfœuille, 2023 and cluster standard errors at the county level (See Chapter 2, Page 24).

Table 10: Observable differences between border counties just before treatment.

	(1) General Access	(2) Online Access
log(Population)	0.09	0.04
	(0.101)	(0.11)
Young Men Rate	0.0025	0.0015
	(0.0019)	(0.0021)
Unemployment Rate	0.0005	0.0003
	(0.0006)	(0.0007)
Poverty Rate	-0.0039	-0.0084
	(0.0041)	(0.0045)
log(Median HH Income)	0.0045	-0.018*
	(0.017)	(0.012)
College Share	0.0005	-0.005
	(0.0044)	(0.005)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Cross-sectional observable differences in variables just before treatment occurs among border counties. Column (1) presents observable differences in variables just before General Access treatment. Column (2) presents observable differences in variables just before Online Access treatment. All variables come from the US Census. Log(Population) is the log of the population of the county, Young Men Rate is the proportion of men under the age of 45 in the county, Unemployment Rate is the proportion of the population labeled as unemployed (US Census code: "$B23025\_005$"), Poverty Rate is the proportion of the county population under the poverty line, log(Median HH Income) is the log of median household income in the county, and College Share is the proportion of the population that has a bachelors degree or higher. A negative (positive) estimate equates to eventually treated counties having a lower (higher) average value compared to never-treated units.

Table 11: Overall ATT estimates with border counties.

	(1) General Access	(2) Online Access
Overall Financial Health:		
Credit Score	-0.58266	-2.40478***
	(0.36148)	(0.46668)
Excessive Debt Indicators:		
Pr(Bankruptcy)	0.00004	0.00012***
	(0.00005)	(0.00003)
Collections	0.00533	0.0587***
	(0.02429)	(0.01548)
Pr(Auto Loan Delinquency)	0.00168**	0.00051
	(0.0008)	(0.00059)
Pr(CC Delinquency)	-0.00006	0.00012
	(0.0003)	(0.00041)
Pr(Cons. Loan)	0.00009*	0.00009**
	(0.00005)	(0.00004)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Each row shows the coefficients from a separate Callaway and Sant'Anna, 2021 estimation for the dependent variable shown on the left. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. We follow the recommendations of de Chaisemartin and D'Haultfœuille, 2023 and cluster standard errors at the county level (See Chapter 2, Page 24).

Table 12: Overall ATT estimates excluding iGaming States.

	(1) Online Access
Overall Financial Health:	
Credit Score	-2.23041***
	(0.45237)
Excessive Debt Indicators:	
Pr(Bankruptcy)	0.00008**
	(0.00002)
Collections	0.05729**
	(0.0165)
Pr(Auto Loan Delinquency)	0.00092**
	(0.00039)
Pr(CC Delinquency)	-0.00014
	(0.00037)
Pr(Cons. Loan)	0.00004
	(0.00004)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.
Note: Each row shows the coefficients from a separate Callaway and Sant'Anna, 2021 estimation for the dependent variable shown on the left. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. We follow the recommendations of de Chaisemartin and D'Haultfœuille, 2023 and cluster standard errors at the county level (See Chapter 2, Page 24).

Table 13: Treatment Effects Across Credit Score Categories.

	Online Access		
	Sub-prime	Prime	Super-prime
Overall Financial Health:			
Credit Score	-11.30196***	-5.82868***	0.66841***
	(1.14691)	(0.56126)	(0.14526)
Excessive Debt Indicators:			
Pr(Bankruptcy)	0.00022**	0.0001***	-0.000001
	(0.00009)	(0.00002)	(0.00001)
Collections	0.11963***	0.05871***	-0.0543*
	(0.01588)	(0.0147)	(0.02804)
Pr(Auto Loan Delinquency)	0.01266***	0.00019	-0.00013
	(0.00155)	(0.00028)	(0.00013)
Pr(Credit Card Delinquency)	0.00714***	0.00111**	-0.00027***
	(0.00183)	(0.00043)	(0.00006)
Pr(Cons. Loan)	0.00004	0.00006	0.00003*
	(0.00005)	(0.00005)	(0.00002)

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.

Note: Each row shows the coefficients from a separate Callaway and Sant'Anna, 2021 estimation for the dependent variable shown on the left. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. We follow the recommendations of de Chaisemartin and D'Haultfœuille, 2023 and cluster standard errors at the county level (See Chapter 2, Page 24).

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Appendix

A Treatment Type and Handles

In Table 15, we present cumulative handle amounts (total amount wagered) by state and channel. On average, we observe that roughly 91% of betting is done online in our data.

In Table 14, we report legalization dates by state.

Table 14: Treatment start dates in our dataset.

	State	First Start	Online	Offline
1	Delaware	Jun 2018		Jun 2018
2	New Jersey	Jun 2018	Aug 2018	Jun 2018
3	Mississippi	Aug 2018		Aug 2018
4	West Virginia	Aug 2018	Aug 2018	Aug 2018
5	New Mexico	Oct 2018		Oct 2018
6	Pennsylvania	Nov 2018	May 2019	Nov 2018
7	Rhode Island	Nov 2018	Sep 2019	Nov 2018
8	Arkansas	Jul 2019	Mar 2022	Jul 2019
9	New York	Jul 2019	Jan 2022	Jul 2019
10	Iowa	Aug 2019	Aug 2019	Aug 2019
11	Indiana	Sep 2019	Oct 2019	Sep 2019
12	Oregon	Oct 2019	Oct 2019	
13	New Hampshire	Dec 2019	Dec 2019	Aug 2020
14	Illinois	Mar 2020	Jun 2020	Mar 2020
15	Michigan	Mar 2020	Jan 2021	Mar 2020
16	Montana	Mar 2020		Mar 2020
17	Colorado	May 2020	May 2020	May 2020
18	District of Columbia	May 2020	May 2020	Jul 2020
19	Tennessee	Nov 2020	Nov 2020	
20	Virginia	Jan 2021	Jan 2021	
21	North Carolina	Mar 2021		Mar 2021
22	North Dakota	Jun 2021		Jun 2021
23	Arizona	Sep 2021	Sep 2021	Sep 2021
24	South Dakota	Sep 2021		Sep 2021
25	Washington	Sep 2021		Sep 2021
26	Wyoming	Sep 2021	Sep 2021	
27	Connecticut	Oct 2021	Oct 2021	Oct 2021
28	Louisiana	Nov 2021	Jan 2022	Nov 2021
29	Wisconsin	Nov 2021		Nov 2021
30	Maryland	Dec 2021	Nov 2022	Dec 2021
31	Kansas	Sep 2022	Sep 2022	Sep 2022
32	Massachusetts	Jan 2023	Mar 2023	Jan 2023
33	Ohio	Jan 2023	Jan 2023	Jan 2023

Table 15: Average handle by channel per state. The data does not include handles for states where tribal lands run the offline sports gambling market.

	State	Online	Retail	Pct. Online	Cum. Handle
1	New Jersey	34,569,741,984	3,713,428,792	0.90	38,283,170,776
2	New York	22,913,323,803	494,149,829	0.98	23,407,473,632
3	Illinois	21,675,191,603	897,187,635	0.96	22,572,379,238
4	Pennsylvania	20,038,138,857	2,017,121,329	0.91	22,055,260,187
5	Colorado	11,950,981,364	148,645,515	0.99	12,099,626,879
6	Indiana	10,981,313,615	1,342,513,286	0.89	12,323,826,902
7	Michigan	10,045,093,194	778,801,244	0.93	10,823,894,438
8	Virginia	10,019,131,704	0	1	10,019,131,704
9	Arizona	9,538,088,892	87,268,559	0.99	9,625,357,452
10	Tennessee	8,622,329,752	0	1	8,622,329,752
11	Iowa	5,334,919,136	834,747,402	0.86	6,169,666,538
12	Louisiana	2,974,460,677	531,448,026	0.85	3,505,908,703
13	Ohio	2,932,320,051	81,894,000	0.97	3,014,214,051
14	Maryland	2,400,918,372	410,743,480	0.85	2,811,661,852
15	Connecticut	2,400,899,080	155,720,243	0.94	2,556,619,323
16	New Hampshire	1,848,595,721	444,716,787	0.81	2,293,312,508
17	Massachusetts	1,571,946,198	70,122,644	0.96	1,642,068,843
18	Kansas	1,506,528,875	71,935,725	0.95	1,578,464,600
19	West Virginia	1,412,507,612	593,207,201	0.70	2,005,714,813
20	Oregon	1,254,314,057	NA	1	1,254,314,057
21	Rhode Island	817,111,648	835,880,558	0.49	1,652,992,206
22	Arkansas	247,307,519	198,623,807	0.55	445,931,327
23	Wyoming	238,202,106	0	1	238,202,106
24	DC	159,734,511	419,702,471	0.28	579,436,981
25	Mississippi	0	2,211,473,311	0	2,211,473,311
26	Delaware	0	562,446,621	0	562,446,621
27	Montana	0	143,854,952	0	143,854,952
28	South Dakota	0	12,888,714	0	12,888,714
29	New Mexico	NA	NA	NA	NA
30	North Carolina	NA	NA	NA	NA
31	North Dakota	NA	NA	NA	NA
32	Washington	NA	NA	NA	NA
33	Wisconsin	NA	NA	NA	NA

B Two-Way Fixed Effects with Controls

In Table 16 we present TWFE estimates with controls. Controls include the following variables: (1) log(Population), which is the population of the county, (2) Young Men Rate, which is the proportion of men under the age of 45 in the county, (3) Unemployment Rate, which is the proportion of the county labeled as unemployed by Census Code "$B23025\_005$", (4) Poverty Rate, which is the proportion of the county below the poverty line, (5) log(Median HH Income), which is median household income in the county, (6) College share, which is the proportion of individuals with a bachelors degree or higher, and (7) log(Covid Cases), which is the number of Covid-19 cases in the county. Variables 1-6 come from the US Census, while variable seven comes from USAFacts Covid tracking. Results are consistent with CS estimation results presented in Table 4 without controls.

Table 16: Overall ATT Estimates using TWFE with controls.

	(1) General Access	(2) Online Access
Overall Financial Health:		
Credit Score	-0.87656**	-3.42453***
	(0.33047)	(0.66769)
Excessive Debt Indicators:		
Pr(Bankruptcy)	-0.00004	0.00009*
	(0.00004)	(0.00005)
Collections	0.00049	0.086*
	(0.03343)	(0.04939)
Pr(Auto Loan Delinquency)	0.00343**	0.00186*
	(0.0012)	(0.00095)
Pr(CC Delinquency)	-0.00011	-0.00032
	(0.00028)	(0.00031)
Pr(Cons. Loan)	0.00001	0.00004
	(0.00007)	(0.00007)
Controls	Yes	Yes

Significance Levels: *p<0.1; **p<0.05; ***p<0.01.
Note: Each row shows the coefficients from a separate TWFE estimation for the dependent variable shown on the left. Data is aggregated at the county level. Each county is weighted by the average number of individuals in that county present in our dataset in 2015. Clustered standard errors at the county level are reported in parentheses.