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 point decline). 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. We also find that financial institutions respond to the reduced creditworthiness of consumers by restricting access to credit. These results are substantially stronger for states that allow online sports gambling compared to states that restrict access to in-person betting. 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 (LSG) 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

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

data 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. Finally, we study whether the financial system responds by limiting credit access by studying credit card limits and the ratio of secured to unsecured loans on account.

We consider two definitions of treatment. First, we focus on all states that implemented LSG, 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.[2] We use fixed effects to control for state-level time-invariant features and national time trends. Because treatment

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

is staggered and treatment 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 effects for the full population. We find that for all states that implemented LSG, 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 does worsen consumer financial health, especially so when mobile access is allowed. Next, we turn to signs of problematic debt loads. For the full set of states, we find that only one of our measures (auto loan delinquencies) increases by a statistically significant amount. By contrast, when we focus on states with online access to gambling, we also find a roughly 28% increase in bankruptcy likelihood and an 8% increase in debt collection amounts, both statistically significant. These effects generally appear roughly two years after when gambling became legal. Interestingly, we find a decrease in credit card delinquencies, and more generally, we find a restriction in access to credit in the form of lower credit limits and a higher ratio of secured to unsecured loans. Each of these indicates that financial institutions may be reducing their risk exposure in states with legal mobile sports gambling.

Next, we examine the heterogeneous impact of LSG. We use the highly granular consumer credit data to examine effects separately for men and women, old and young male panelists, and 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 strongest for low-income younger men.

[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 are not significantly related to the timing of gambling legalization.

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.

2 Literature: Sports Gambling and Financial Health

There is a large literature studying gambling and its effect on consumers. Past research on gambling has highlighted the potential negative consequences that it can have on individuals' financial health. These studies have shown that excessive gambling is associated with financial difficulties, debt accumulation, rising mortgage delinquencies, and bankruptcy (Clarida, 2020; Griffiths, 2009; Wardle et al., 2011).

Prior research finds that the associated financial harms of gambling vary across consumers. Demographic groups, such as young adults and individuals with lower socioeconomic status, are often more vulnerable to the adverse effects of gambling on financial well-being (Binde, 2009; Hahmann et al., 2021; Hing, Lamont, et al., 2015). In addition to demographics, factors like impulsivity and psychological distress have also been identified as risk factors for financial harm associated with betting (Hing, Cherney, et al., 2015; Wood & Williams, 2007). In our paper, we use these findings to study the heterogeneous impact of sports gambling on groups of consumers who are more likely to be affected.

The legalization of sports gambling led to the rise of online sports betting platforms and mobile gambling apps, which made gambling more accessible. Past research has 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).

Prior economic research on gambling has placed an 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).

To mitigate the negative effects of sports gambling, regulatory interventions, such as mandatory self-exclusion programs, pre-commitment tools, and advertising restrictions, have been implemented (Gainsbury et al., 2015; Russell et al., 2019). Responsible gambling initiatives, including education and awareness campaigns, aim to promote informed decision-making and prevent excessive gambling behavior (Hing et al., 2018; Newall et al., 2019).

A recent working paper (Taylor et al., 2024) attempts to estimate the causal effect of sports gambling legalization on tax revenue, irresponsible gambling behavior, problem gambling hotline calls, and suicides. Using an individual-level credit card panel dataset, they find that legalization increases gambling and irresponsible gambling behavior. The authors also find evidence that online sports betting legalization significantly increases problem gambling hotline calls but find inconclusive evidence that sports betting increases suicide rates.

We add to this recent literature by studying the causal effect of sports betting legalization on consumers' financial health. We do so by using a dataset tracking a wide range of individual-level financial measurements for a representative sample of U.S. consumers. Our data allows us to study changes in consumer financial stress beyond credit card data, therefore complementing the findings discussed in Taylor et al., 2024.

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.

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 continued 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 May 24, 2024, 38 states and the District of Columbia have legalized some form of sports betting.[4]

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 whether to require bets to be placed in person at a qualified location. Currently, 30 states and DC choose to allow some form of online betting accessibility, while the other eight states with LSG only allow retail betting, i.e., betting at a physical location.[5] As shown in Supplementary table 13 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 states make 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 sports betting handles (dark series) have grown over time along with the number of states with LSG (grey series).[6] In Supplementary table 14 in Appendix A, we report handles by state and for both online and retail channels.

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

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

[5]A few states (Tennessee and Wyoming) exclusively offer online access. Several tribal lands in Oregon offer offline sports betting access, but these do not fall directly under the Oregon state government.

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

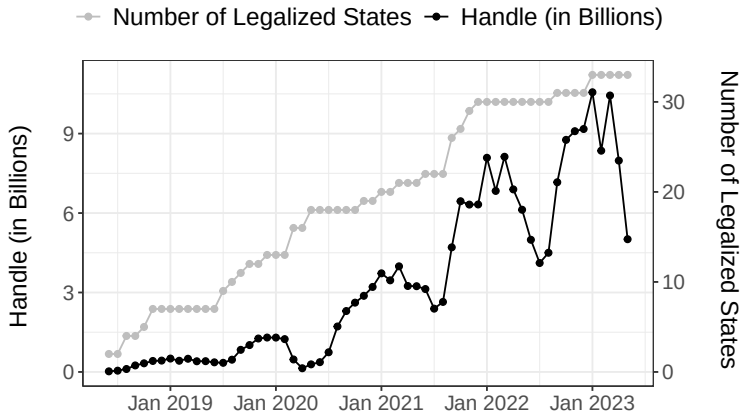


Figure 1: Monthly sports handle in billions and the number of legalized states. The left axis is the sports handle, and the right axis is the number of legalized states. Our data does not contain handles for states where tribal lands run the offline sports gambling market.

U.S. adults with a credit report (i.e., roughly 7 million panelists). Data is tracked from 2004 to the present day. For each year, we observe records from March, June, September, and December.[7] We observe demographic characteristics for nearly all individuals. This includes information such as age, gender, ethnicity, and location. 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.[8]

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

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

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

not deceased. We also remove any individual who moved across states to prevent treatment-control spillovers and any individual whose location or gender information is not present in the data. 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. For this, we consider only states that eventually legalize online gambling. In our analysis, we call this group "Online Access." In our data, 24 states legalized some form of online sports betting as of June 2023.[9] Treatment begins in the first month after the state implements online betting. 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

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

York. No states with both online and offline access implemented online access before offline access. Lastly, three states in our data only offered online access (Tennessee, Wyoming, and Virginia).

A full list of treated states and their legalization timing can be found in Supplementary table 13 in Appendix A. Start dates are calculated based on the first month the state began collecting tax revenue.[10]

3.4 Primary Outcomes of Interest

We focus our analysis on eight outcomes designed to capture overall financial health, the presence of excessive debt, and access to credit.

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. We will estimate percent changes to consumer credit scores using the log of credit scores as a way to measure general changes to consumer credit health.

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 use of debt consolidation loans, a financial strategy for managing and reducing debt by combining multiple debts into a single, more manageable loan. This

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

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.

The third is the total amount of debt on an account that has been sent to collections. This is a measure of how much unpaid debt that 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 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 how much the collection amount is for and whether it is present on the consumer's account.

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.

Access to credit Next, we study the impact on consumer credit through restrictions on access to credit. We focus on two measures of access to credit. The first is credit card limits. These are set and periodically readjusted according to the bank's assessment of a consumer's risk level. Setting credit card limits is a first-order risk management strategy banks use to mitigate defaults (Butaru et al., 2016). A bank generally lowers consumer credit card limits for consumers it finds less trustworthy. We observe the credit limit of each consumer's credit card. We sum up the cumulative level of credit each consumer has and analyze changes to this limit to measure changes in credit accessibility.

The second is the ratio of secured to unsecured loans. Consumers can use secured or unsecured loans to cover debts and make payments. However, the security structure of each type

of loan differs. Secured loans require collateral in case of default, while unsecured loans do not and are based on trust and creditworthiness. Secured loans are generally associated with riskier borrowers (Berger & Udell, 1990; Chen et al., 1998) as it indicates banks are worried about defaults and require collateral. We might expect a relative increase in the number of open secured loans taken out by consumers after the introduction of sports gambling as evidence of increased monetary needs due to problem gambling and as an indication of greater risk from the bank's view. We focus on predominantly personalized-based loans. Specifically, we count the number of loans an individual has open that falls into one of the credit lines: secured loans, partially secured loans, loans secured by cosigner, loans secured by household goods, loans secured by household goods/other collateral, government secured guaranteed loans, or government secured direct loan. Unsecured loans include government unsecured guaranteed loans, personally guaranteed business lines, personally guaranteed business loans, note loans, commercial line of credit, and installment loans. (These categories do not include loans such as auto loans, mortgages, credit cards, or student loans). To measure changes in access to credit within individuals, we calculate the log of the ratio of the number of actively open secured and unsecured loans each consumer has on file.

In Table 1, we present summary statistics from the pre-legalization period for our eight 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
Pr(Consol. Loan)	0	0	0	0.00066	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
Sec./Unsec. Accts	0	0	0	0.047	0	39
Credit Card Limit	0	300	6,100	13,823.900	20,000	1,501,024

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. 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. This is done for computational efficiency purposes using the CS estimator. The estimated Average Treatment on the Treated (ATT) can be interpreted as the average change in treated individuals' financial outcomes.

Since states decide whether to legalize sports gambling, the main concern with our identification strategy is that unrelated trends in consumer financial outcomes correlate with state-level decisions to implement legalization.

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

The second test we perform relates to the timing of gambling legalization. We estimate the relationship between this timing and local economic indicators, namely weekly wages, the quarterly unemployment rate, and the number of COVID cases. We do so using a Cox Hazard model with all states in our data. 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.[11] By doing so, we can validate the parallel 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]

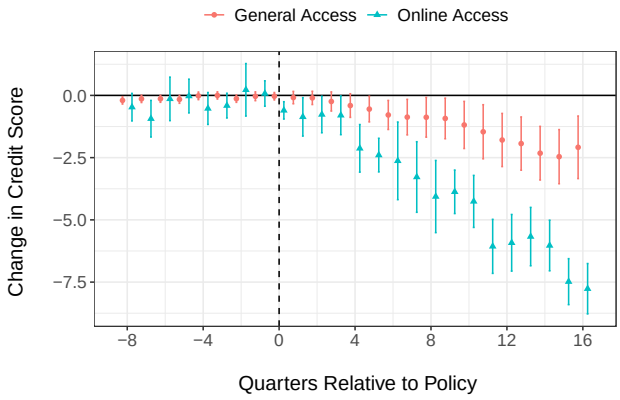


Figure 2: The effect of sports gambling legalization on consumer credit score.

In the post-treatment period, we see that general access to sports betting decreases the average credit score. After about four years, the average credit score declines by about 0.8

[11] In Appendix 5.6, we present estimates by gender, age, and income.
[12] This is the case for all our study outcomes.

points. This negative effect is stronger for Online Access treatment. 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.

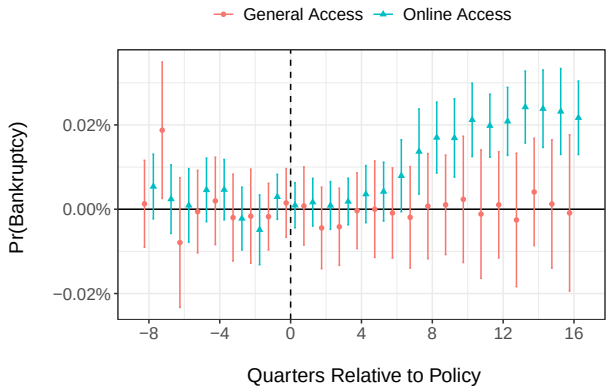
5.2 Indicators of Excessive Debt

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.

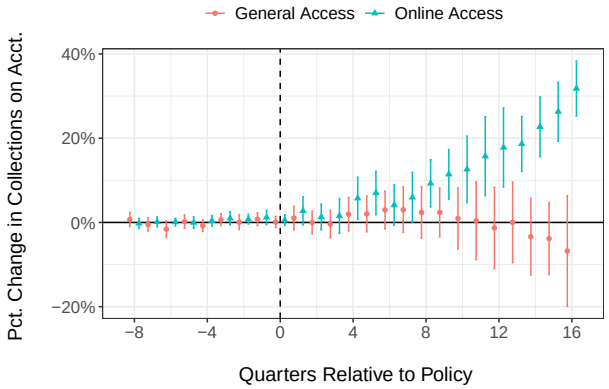
Bankruptcies In Figure 3a, we present the event study estimates for bankruptcies by treatment conditions. We find that while the general accessibility to sports betting leads to insignificant changes to bankruptcy filing, online access significantly increases the likelihood of bankruptcy filing. We also 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. Three to four years after the legalization of online sports gambling, we observe that the likelihood of bankruptcy filing increases by as much as 25-30% when compared to pre-treatment levels.

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.

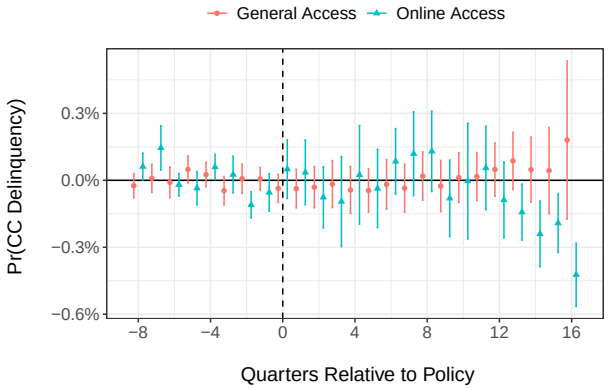
Credit card delinquency In Figure 3c, we present event study estimates for changes in the probability of an individual having a credit card delinquency on file. While initially no effect is present, we find that starting roughly three years after LSG implementation, credit



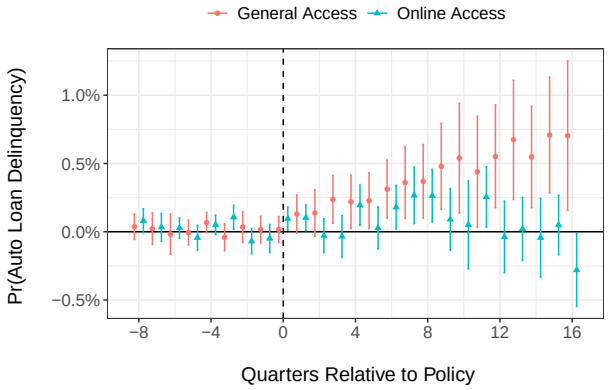
(a) The effect of sports gambling legalization on bankruptcy filing likelihood.



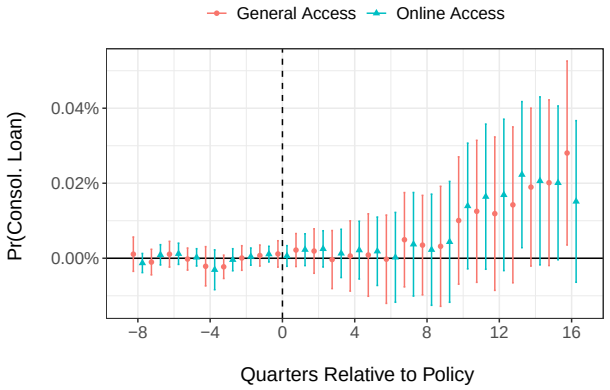
(b) The effect of sports gambling legalization on collections on account.



(c) The effect of sports gambling legalization on the likelihood 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.

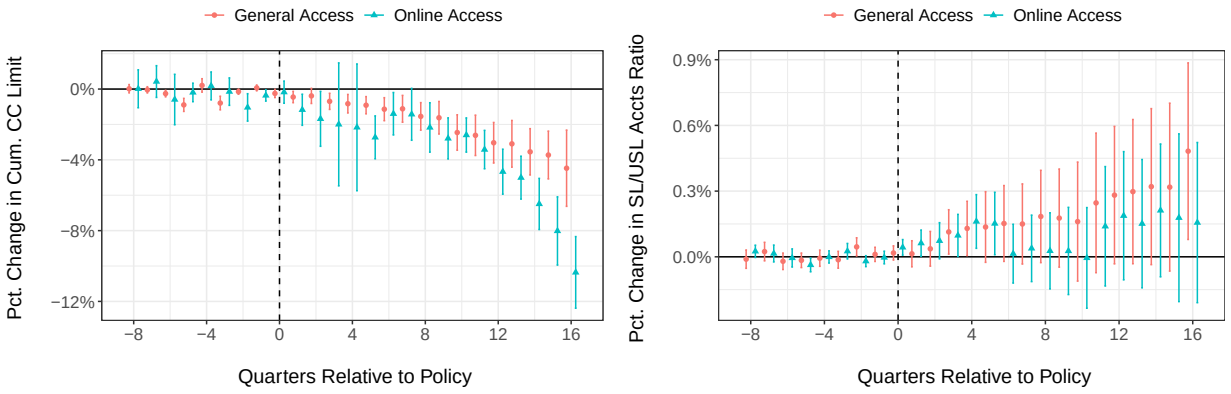
card delinquencies appear to be declining, particularly in states with online access to sports betting. Given we see a decrease in the average credit score, this is somewhat counter-intuitive. However, in Section 5.3, we show that credit agencies appear to be lowering credit card limits to reduce their exposure to consumers with high financial risk. As such, credit card delinquencies may decline due to credit agencies taking proactive measures to mitigate their risk exposure. 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 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.

Debt consolidation Problem gamblers may use debt consolidation loans to consolidate and manage high-interest loans (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), translating to a statistically insignificant average ATT of roughly 0.01%. This translates to about a 7.5% increase in the likelihood of an individual opening a consolidation loan compared to pre-treatment period average rates.

5.3 Restricted Access to Credit

In this section, we study whether financial institutions responded to increased consumers' financial risk by reducing credit card limits and limiting the type of loans they can take.



(a) The effect of sports gambling legalization on cumulative credit card limits.

(b) The effect of sports gambling legalization on the ratio of secured to unsecured loans.

Figure 4: Changes in cumulative credit card limits and the ratio of secured to unsecured loans.

Credit card limits In Figure 4a, we present changes in the cumulative credit card limits for individuals with existing credit cards. We find that credit card limits start to decrease right after gambling legalization and continue to decrease as time passes. For general sports betting access, the overall ATT estimate corresponds to roughly a 1.4% decline in credit card limits, while access to online betting leads to a nearly 2.4% decline. These results suggest that banks are responding to the increased financial risk caused by sports betting and lowering credit card limits to mitigate potential risk exposure.

Secured and unsecured Loans Next, we analyze changes in the ratio of the number of open secured to unsecured loans consumers have on file. In Figure 4b, we present the event study estimates.

We find that, on average, this ratio increases over time. This suggests that individual debts increasingly rely on secured loans compared to unsecured loans. In other words,

consumers are taking riskier loans due to their declining creditworthiness. Compared to pre-treatment period average ratios, our ATT estimates of 0.0015 and 0.0009 translate to roughly 3.2% and 2% increase in secured to unsecured loan usage with any sports betting access and online gambling access, respectively.

5.4 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 pre-treatment and 16 periods post treatment). 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. Furthermore, the effect of sports betting does not appear to be driven by higher credit card delinquencies but by increased exposure and use of hard debts such as consolidation loans, secured loans, and bankruptcies. The fact that credit card delinquencies are unaffected or lower is likely due to financial institutions trying to mitigate their exposure to risk by lowering credit limits. Despite this, we observe consumers missing payments for other loans and products, leading to increased collections and auto loan delinquencies.

5.5 Robustness Checks

iGaming One potential concern could be that our results are driven by the introduction of iGaming, not sports betting. iGaming is other forms of online gambling, including lotteries, slots, and casino games like poker. In our period six states had some form of legalized iGaming accessibility (Pennslyvania, West Virginia, New Jersey, Michigan, Delaware, and Connecticut). The market for iGaming is smaller but still generates substantial revenue. In

November 2024, iGaming company revenue was over $800 million. [13] To test the robustness of our Online Access results, we drop these states and re-estimate the same models used to generate results in Table 4. In Table 5 we present ATT estimates over the time period. We find that our results continue to hold, which suggest these findings are not driven by iGaming accessbility, but by sports gambling.

Coarsened Exact Matching While our hazard model in Table 3 does not show that these 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 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 (**<empty citation>**) 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 6, we present differences in observable characteristics between treated (General Access) and control counties before and after matching. Matching leaves us with 696 eventually treated counties and 696 never treated control counties. (1141

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

treated counties and 571 control counties are dropped).

Similarly, in Table 7, we present differences in observable characteristics between treated (Online Access) and control units. 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. This is done due to the staggered setting varying the underlying post-period for treated and control units, making traditional pre-treatment matching infeasible. One can view our matching as a "light" matching.

This strategy works if county observable characteristics evolve similarly and do not "drift" apart after the 2015-2017 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 (-2), we can look at the differences in observable characteristics between the matched counties. In Table 8 we show that all counties do show observable differences right before treatment. However, once matched, these differences are insignificant, as shown in Table 9. 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 10. We find results that are consistent with our main, unmatched specification.

Border counties We also consider a border cluster identification strategy as an additional robustness check. The identification assumption behind this analysis is that, when focusing on a small geographical area around the border, the only factor affecting one's financial health is whether the person is on the left or the right side of the border, and not a function of changes in external factors (e.g., economic conditions, past personal financial health) that

affect one's financial health.

For this identification strategy, we first identify counties that lie along state borders. Then, for each border county, we find the closest point on the state border from the county's centroid (i.e., project the county onto the state border). For each county, we then find the closest set of other counties that are within a given distance[14] constraint and have the opposite treatment condition. (Control units can only be matched to treated and vice versa). For each county, this gives us a set of "close" counties. This gives us a final dataset of counties and their respective closely neighboring counties as well as the distance between their projected points on the border.

We then set out to create border "clusters", or county pairs where one county is treated and one county is control. To effectively select unique pairs of counties, we rely on Edmond's Blossom algorithm to select the most number of county pairs that minimizes the cumulative distance among counties selected. This allows us to maximize the number of pairs and minimize the cumulative distances between counties that are paired together.

When considering General Access treatment, this procedure translates to 207 unique border pairs. In Figure 3 we present a visual map of these pairs. Similarly, when considering Online Access, we generate 160 unique border cluster pairs. We visualize those county pairs in Figure 3.

Importantly, we want to know that counties in border clusters are similar, except one county is in an eventually treated state and one is not. We can also analyze differences in eventually treated and control counties just before treatment. In Table 11, we show that observable characteristics between counties are not meaningfully different.

To estimate the effect of legalized sports gambling, we estimate Equation 1, where $Y_{i,j,t}$ is the outcome of interest and β_3 is the main parameter of interest. Index t indicates a quarter, index j indicates a border "cluster", and index i indicates a state. We estimate the model with time fixed effects γ_t, state fixed effects α_i, and border "cluster" fixed effects δ_j.

[14] We choose 50m.

β_3 captures the incremental impact of treatment on the treated county within clusters. The identification strategy relies on variation within border clusters to pin down the effect of our different treatment structures.

$$Y_{ijt} = \beta_0 + \beta_1 \text{Post}_{jt} + \beta_2 \text{Treated}_{ij} + \beta_3 \text{Post}_{jt} \times \text{Treated}_{ij} + \alpha_i + \gamma_t + \delta_j + \epsilon_{ijt} \quad (1)$$

To estimate Equation 1, we aggregate individual-level data and estimate with county population weights in the same way we estimate our CS models. In Table 12, we present β_3 coefficient estimates using this identification.

Ultimately, we find results that are consistent with our initial primary findings.

5.6 Heterogeneity Analysis

In this section, we shed some light on the types of consumers who are more affected by the legalization of sports gambling. We do so by estimating the heterogeneous effect for different types of consumers based on demographic characteristics.

The previous literature on sports gambling has found that men, particularly young men, are more susceptible to gambling addiction compared to women and older men (Binde, 2009; Hahmann et al., 2021; Hing, Lamont, et al., 2015). Income also impacts gambling behaviors, with lower-income consumers likely to be more affected by gambling (Binde, 2009; Hing, Lamont, et al., 2015) Following this literature, and to understand which consumers are the most affected by the legalization of sports gambling, we estimate ATTs separately for men and women, young and old men, and young men in high vs. low-income counties.[15] As we have done for the main analysis, we do so for both all sports betting access states and online access states.

[15]While we observe gender and age at consumer level, income is only available at the county level. Because of this, estimates for income groups are less precise.

Sports betting access We first present heterogeneous treatment effect results using any sports gambling access treatment for all the outcomes analyzed in Section 5. Supplementary figure 5 presents ATT estimates by each consumer group and outcome. Confidence intervals are adjusted using the Benjamini-Hochberg procedure.

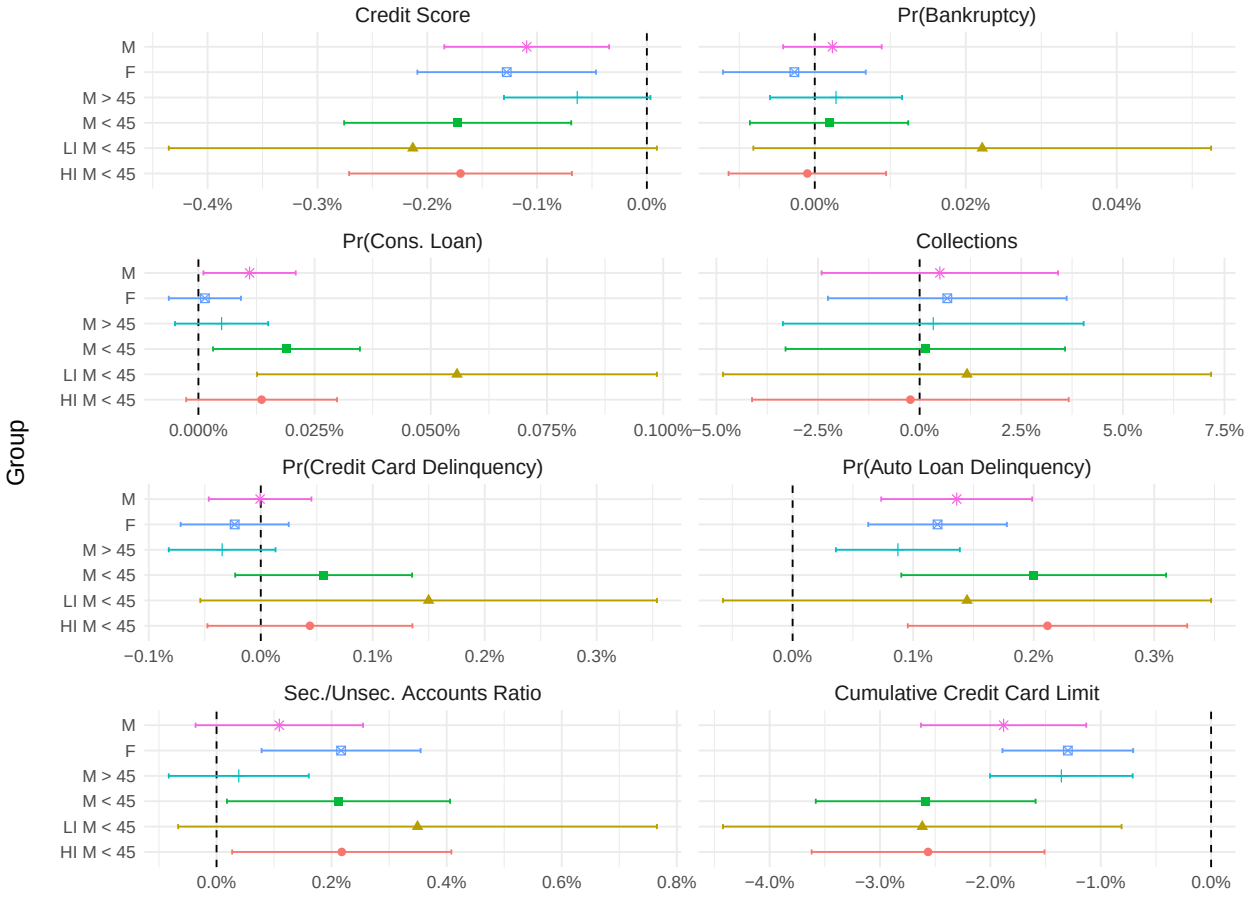


Figure 5: Heterogeneous effect for any sports betting access

In general, we find few statistically different estimates across groups. The credit score is declining for all groups, with slightly larger estimates for young men in low-income counties. Consistent with the results discussed above, we find a largely null effect on bankruptcies; however, young men in low-income counties seem to experience higher bankruptcy rates. We find suggestive evidence that young men in low-income counties use consolidation loans significantly more than other groups, with older men and women having largely null effects.

In line with the main results, collections estimates are largely null, while credit card delinquencies follow a similar pattern to that of consolidated loans. Auto loan delinquencies and the ratio of secured to unsecured loans increase similarly for all consumers. Finally, credit card limits decrease across all groups, with young men experiencing the largest decrease.

Online access Here, we present the results of the heterogeneous treatment effect using online access treatment. Supplementary figure 6 presents ATT estimates by each consumer group and outcome.

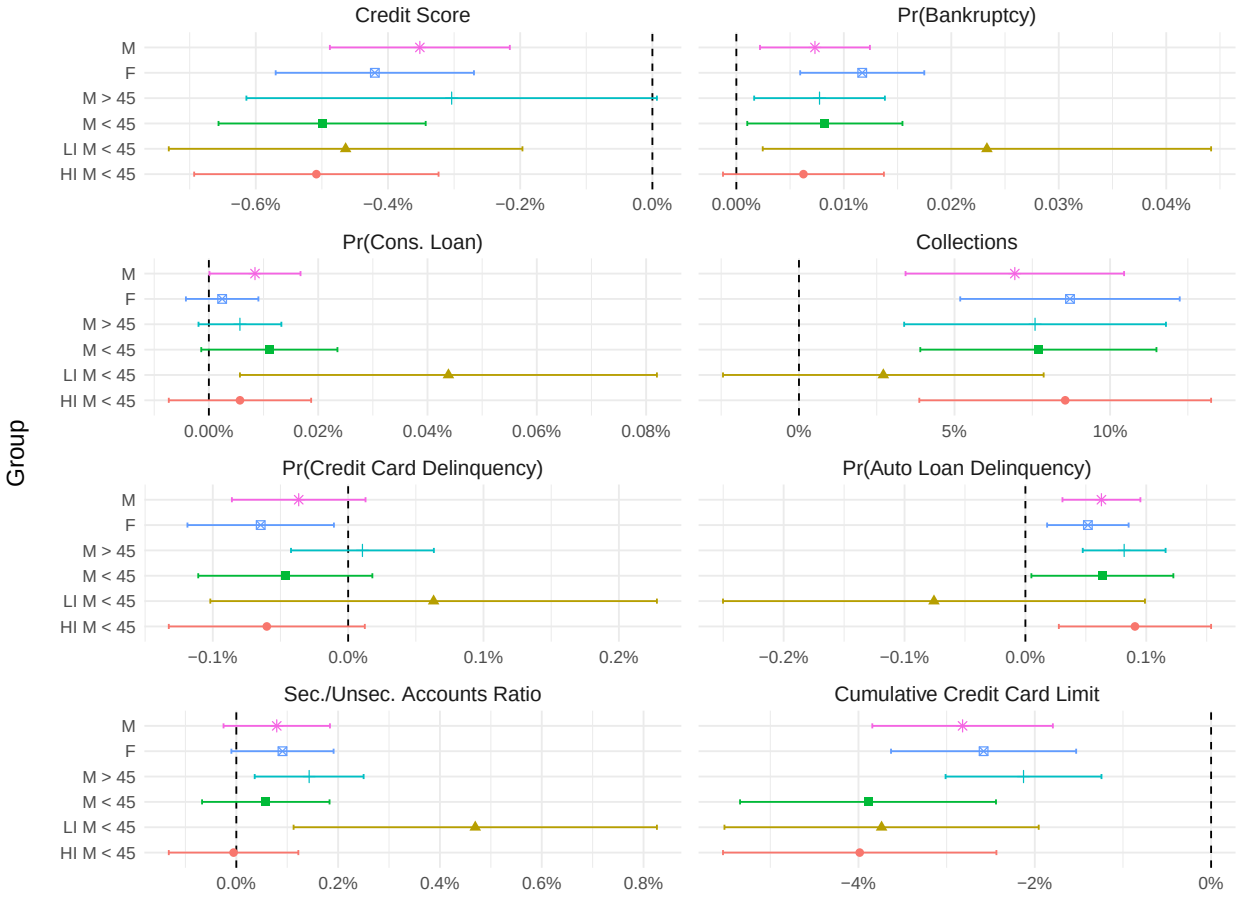


Figure 6: Heterogeneous effect for online access

Similar to the previous analysis, we find a few statistically significant differences across groups. Despite this, we observe a similar trend to that observed when we study heterogene-

ity for any access to sports gambling. That is, there is suggestive evidence that young men in low-income counties experience higher financial distress, with higher rates of bankruptcy, more usage of consolidation and secured loans, and more credit card delinquencies. We also see that it is for your men that credit card limits decrease the most.

Overall, consistent with past literature, the heterogeneity analysis suggests that young men, particularly those in low-income counties, may be the most affected by the legalization of sports gambling.

5.7 Group Effects

With the CS estimator, we can also estimate ATT's by treatment cohort. In Figure 7 we present results for credit scores by treatment status. We see that much of the declines in credit scores are driven by early adopters and the effects are generally much stronger when online gambling is made accessible. These patterns continue to hold when considering shorter post-period windows (e.g., 8 post-treatment periods), though effect estimates are generally smaller. This pattern would be consistent with growing financial strain caused by sports gambling legalization, particularly online legalization.

In Figure 8, we then present group cohort treatment effects for bankruptcies. We find that it is also the early adopters where we see increases in bankruptcies. Given bankruptcies are generally a last

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.

Overall, we find that the legalization of sports gambling decreased consumer financial

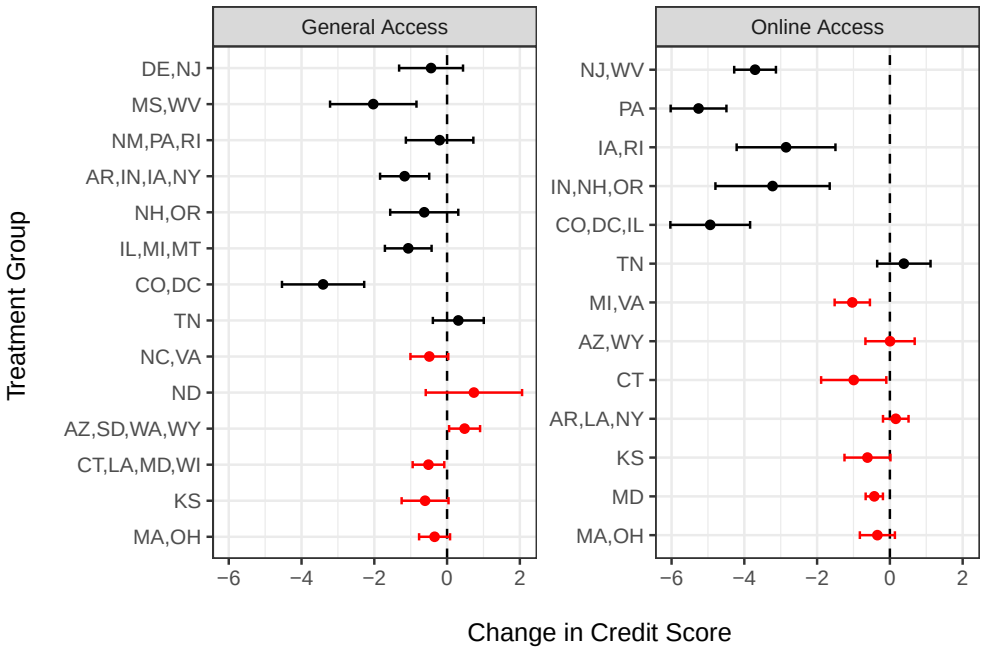


Figure 7: The effect of sports gambling legalization on credit scores by treatment cohort.

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.

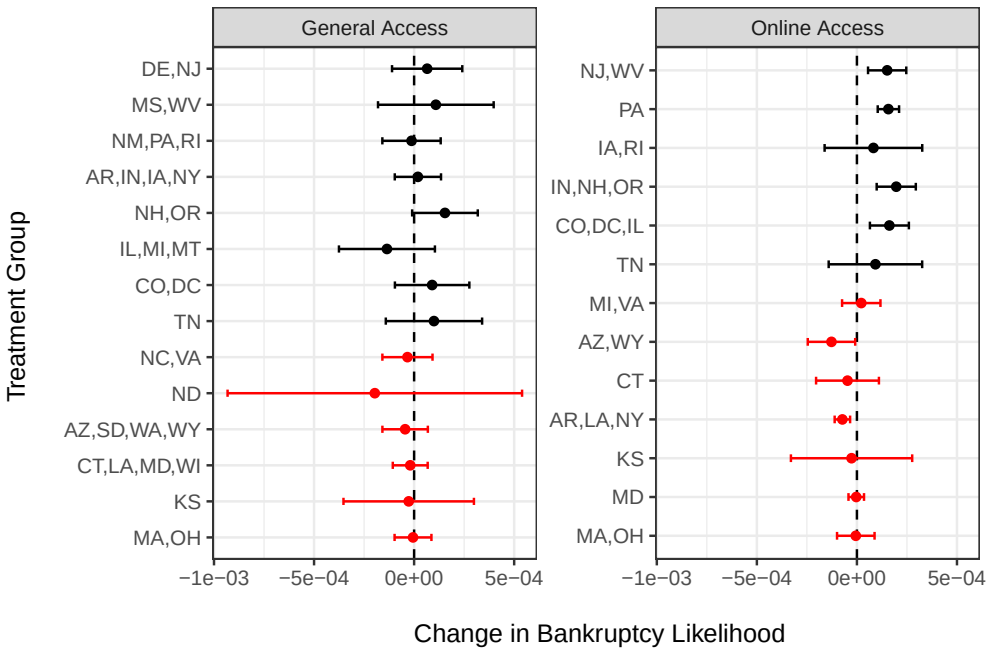


Figure 8: The effect of sports gambling legalization on bankruptcies by treatment cohort.

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

	Dependent variable:
	time = start
Log(COVID Cases)	−0.476
	(1.121)
Percentage Higher Educated	4.668
	(9.896)
Percentage Low Income	5.323
	(24.743)
Percentage Unemployed	63.689
	(67.313)
Log(Median Income)	−0.666
	(4.965)
Log(Total Population)	−0.348
	(0.452)
Men Under 45 (Percent of Population)	−17.293
	(31.159)
Previous Year State Budget, Scaled	0.0002
	(0.006)
Log(Cumulative State Date)	0.113
	(0.563)
3-Year Rolling State Budget Deficit, Scaled	−0.002
	(0.004)
Observations	1,070
R^2	0.005
Max. Possible R^2	0.179
Log Likelihood	−102.493
Wald Test	5.250 (df = 10)
LR Test	5.465 (df = 10)
Score (Logrank) Test	5.414 (df = 10)
Note:	*p<0.1; **p<0.05; ***p<0.01

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)
Access to Credit:		
Cumulative CC Limit	-0.01428***	-0.02389***
	(0.00222)	(0.00362)
Ratio of Sec. to Unsec. Loans	0.00149**	0.00087*
	(0.00053)	(0.00043)

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, and therefore, standard errors are clustered at the county level. All p-values are adjusted using the Benjamini-Hochberg procedure to account for multiple hypothesis testing.

Table 5: 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)
Access to Credit:	
Cumulative CC Limit	-0.01469***
	(0.003)
Ratio of Sec. to Unsec. Loans	0.00135**
	(0.00044)

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, and therefore, standard errors are clustered at the county level. All p-values are adjusted using the Benjamini-Hochberg procedure to account for multiple hypothesis testing.

Table 6: 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.

Table 7: 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.

Table 8: Observable Differences 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.

Table 9: 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.

Table 10: 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)
Access to Credit:		
Cumulative CC Limit	-0.01191***	-0.01779***
	(0.00311)	(0.00314)
Ratio of Sec. to Unsec. Loans	0.00176*	0.0026***
	(0.00079)	(0.00066)

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, and therefore, standard errors are clustered at the county level. All p-values are adjusted using the Benjamini-Hochberg procedure to account for multiple hypothesis testing.

Table 11: 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.

Table 12: Overall ATT estimates with border counties.

	(1) General Access	(2) Online Access
Overall Financial Health:		
Credit Score	-2.40204**	-5.43762***
	(0.87494)	(1.05307)
Excessive Debt Indicators:		
Pr(Bankruptcy)	0.00009	0.00027**
	(0.00006)	(0.00008)
Collections	0.00301	0.13194***
	(0.03806)	(0.03463)
Pr(Auto Loan Delinquency)	0.00351**	0.00368**
	(0.00146)	(0.00155)
Pr(CC Delinquency)	0.00056	-0.00048
	(0.00047)	(0.00054)
Pr(Cons. Loan)	0.000002	0.00017
	(0.00011)	(0.00013)
Access to Credit:		
Cumulative CC Limit	-0.02422	-0.0531**
	(0.01691)	(0.01872)
Ratio of Sec. to Unsec. Loans	0.00142	0.0023
	(0.0028)	(0.0027)

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, and therefore, standard errors are clustered at the county level. All p-values are adjusted using the Benjamini-Hochberg procedure to account for multiple hypothesis testing.

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Appendix

A Treatment Type and Handles

In Table 14, 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 13, we report legalization dates by state.

Supplementary table 13: 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

Supplementary table 14: 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	0	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