GAMING THE IRS'S THIRD-PARTY REPORTING SYSTEM: EVIDENCE FROM PARI-MUTUEL WAGERING

by

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Dedicated to my wife, Katie Ferguson for her love and support, and to my parents, Victor and Elizabeth Ferguson for their guidance throughout my life and educational career.

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ABSTRACT

This study examines whether taxpayers intentionally avoid IRS third-party reports. In 2017 an IRS amendment created an exogenous shock that impacted how third parties report gambling winnings to the IRS. In thoroughbred racing, this shock had a substantial impact on certain types of wagers. This paper considers how gamblers reallocated their money following the shock. Using a difference-in-differences research design that compares U.S. tracks to Canadian tracks, I find that gamblers increased their investment in wager types that had become less likely to trigger third-party reports by 27 percent. In the U.S., over $400 billion in tax revenue goes uncollected annually, largely due to unreported income. Third-party IRS reporting is considered the most effective way to reduce underreporting, but there is limited understanding of how taxpayers interact with third-party reporting rules. This paper provides evidence on this interaction, showing that taxpayers purposefully avoid third-party reports to facilitate tax evasion.

CHAPTER 1. INTRODUCTION

The tax gap is one of the most substantial tax issues in the United States. The Internal Revenue Service (IRS) estimates that during the years 2008–2010 the U.S. government failed to collect an average of $406 billion in tax revenue per year, or over 16 percent of all federal taxes owed (IRS 2016). To put this in perspective, the 2008 U.S. federal budget deficit was $455 billion (Congressional Budget Office 2008). The IRS also estimates that nearly 85 percent of this tax gap is due to underreporting of income, with most underreporting being perpetrated by individual taxpayers (IRS 2016).

In terms of mitigating the tax gap, the IRS suggests that one of the most powerful tools at its disposal is third-party reporting. Third-party reporting is the practice of requiring parties other than the taxpayer to report taxable income to tax authorities.[1] The IRS has found that when income is subject to substantial third-party reporting, the misreporting rate is as low as one percent, but it increases to 63 percent for income that is subject to little or no third-party reporting (IRS 2016). This finding is corroborated by Kleven, Knudsen, Kreiner, and Pedersen (2011) who use tax audit data from Denmark to show that for income subject to third-party reporting the evasion rate is generally below one percent but increases to over 40 percent for self-reported income. Kleven et al. (2011) also find that evasion increases immediately when a taxpayer has self-reported income, and further that the percentage of total income evaded increases with the percentage of income that is self-reported.

While this literature demonstrates the effectiveness of third-party reporting, it has largely overlooked an important part of the third-party reporting process. Before a third-party report is filed, the income in question must meet the criteria to require a report. These criteria vary by income type, but in many cases there is room for taxpayers to adjust their behavior or structure transactions to subvert the third-party reporting system and avoid having a report filed in the first place.[2] This study seeks to provide evidence on this pre-report interaction between taxpayers and the third-party reporting system using the unique setting of thoroughbred racing's pari-mutuel

[1] For example, W-2 reporting of wage income and 1099-D reporting of dividends. Some of these reports will include the withholding of tax as well, but this depends on the circumstances and the type of income.
[2] It is possible for this subversion to be legal or illegal.

wagering pools. Specifically, this paper considers whether taxpayers facilitate tax evasion by adjusting their behavior to avoid third-party tax reports.

In North America, thoroughbred racing employs a pari-mutuel wagering system.[3] Within this system, there are many different types of wagers that a player can make. Some tend to have high win probabilities and low odds (hereafter "low-yield wagers"), while others are much more difficult to win but often return high odds (hereafter "high-yield wagers"). On September 27th, 2017, the IRS implemented an exogenous regulation change that led to a significant decrease in the propensity of high-yield wagers to trigger third-party reports.[4] The horse racing media outlet BloodHorse reported that these changes led to 97 percent fewer third-party reports being filed at the 2017 Breeders' Cup than had been filed at the 2016 Breeders' Cup (Bloodhorse Staff 2017a). While the impact on high-yield wagers was considerable, there was little, if any, change in the tendency of low-yield wagers to trigger third-party reports.[5] I hypothesize that following this IRS change, high-yield wagers increased in popularity relative to other wager types because they became less likely to result in third-party reports.

There are two main reasons why this result cannot be taken for granted. First, to avoid third-party reports following the exogenous IRS change in this setting, taxpayers had to assume additional risk in their wagering strategies. Taxpayers might be unwilling to take on this additional risk to facilitate underreporting. More generally, the behavioral changes that are required to facilitate underreporting might lead to suboptimal decision making that is more costly than potential tax liabilities. Second, individual taxpayers might have moral reservations or legal concerns that keep them from evading taxes; if this is the case there will not be a concerted effort to avoid third-party reports. In other words, the tax gap might be driven by unintentional or opportunistic underreporting rather than tax evasion that is facilitated by the avoidance of third-party reports.

[3] Pari-mutuel gambling is a system that uses separate "pools" (pots of money) for each type of wager and pays winners based on the percentage of money that was wagered on the winning outcome.
[4] This change also adjusted how taxes are withheld from winnings. In the context of this study, this withholding change was much less significant than the third-party reporting change for two major reasons. First, the threshold to have taxes withheld from winnings was more than 8 times higher than the threshold to have winnings reported in both the pre-period and the post-period. Thus, withholding is simply far less common in this setting. Second, an IRS report (2016) shows that subjecting income to withholding has a much smaller marginal impact on misreporting than subjecting income to third-party reporting.
[5] Low-yield wagers were rarely, if ever, subject to third-party reporting before the regulation change, and this has remained the case after the new regulation came into force.

Pari-mutuel wagering is ideal for investigating how taxpayers interact with third-party reporting rules, because the structure of this gambling market allows for direct measurement of the popularity of different wager types. This makes it possible to examine how participants change their investment allocations in reaction to the third-party reporting policy adjustment. This type of direct examination is not possible in other settings, and it allows this study to provide substantial evidence on a topic that has not yet been studied due to data limitations. Additionally, this setting offers a built-in control group for empirical tests that facilitates a difference-in-differences research design. Canadian tracks are extremely similar to those in the U.S. They offer the same wager types and operate in a similar manner. Yet Canadian tracks were not directly impacted by the rule change. Canada does not tax gambling winnings, and this policy remained constant throughout my sample period.

For my primary empirical test, I acquire race-level data for every track in North America from 2009 to 2019. Using a difference-in-differences research design, I find that the U.S. experienced an increase in the popularity of high-yield wagers relative to Canada following the IRS rule change. This finding is consistent with my hypothesis and implies that gamblers found high-yield wagers more appealing once those wagers were less likely to result in a third-party report. More broadly, this finding provides evidence of taxpayers purposefully avoiding third-party tax reports to facilitate tax evasion.

In addition to my primary finding, I perform a cross-sectional analysis to provide additional evidence that the third-party report avoidance observed in this study is purposeful. To do this, I take advantage of discrepancies in thoroughbred racing popularity at a state level. In locations where racing is more prominent, gamblers should be more informed on policy changes such as the one this study focuses on. Third-party report avoidance can only be purposeful if taxpayers are aware of the reporting policy, which means that well informed gamblers should have a stronger reaction to the policy change. I predict, and find, that the results of this study are more pronounced in states where racing is more popular. This implies that there was a stronger reaction to the rule change when awareness of the rule change was higher, which is consistent with purposeful report avoidance.

Because this study employs a difference-in-differences analysis, it is important to consider the parallel trends assumption. To do this, I perform two falsification tests using data from before and after the actual IRS change. Each of these tests use the same specification as my primary analysis, but employ false post-periods. The results of both tests show no significance on my coefficient of interest and reveal substantially smaller magnitudes on this coefficient than my primary analysis. These falsification tests provide confirmation of the parallel trends assumption by showing that the U.S. and Canada were not significantly different during the pre-period or post-period of the study, and they reinforce my primary findings by showing that the results are specific to the study's actual post-period.

To further confirm the robustness of my results, I perform several supplemental analyses. To ensure that my results are not impacted by features of my Canadian data, I run a U.S. only analysis that takes advantage of state-level variation. The results of this test are consistent with my hypothesis, showing that my findings persist when Canada is not used as a control group. Next, I show that the observation count discrepancy between the treatment (U.S.) group and control (Canadian) group does not impact my results. To do this, I re-estimate my primary research design, first by using a U.S. subsample that is matched with my Canadian sample based on racing and track characteristics, and second by using a randomly selected U.S. subsample that is the same size as my Canadian sample. The results obtained using both subsamples are consistent with my main findings. I next perform an analysis with my data aggregated by track-day rather than race to prevent data losses, and I find results consistent with my primary findings. Finally, I perform a supplementary analysis that excludes 2018 and 2019 from my sample to ensure that my results are not driven or impacted by the implementation of the Tax Cuts and Jobs Act (TCJA). The results obtained using this truncated sample are also consistent with my primary results.

The IRS attributes 68 percent of underreported income to individual taxpayers, which is what this setting focuses on (IRS 2016). The findings of this study should generalize to the larger population of U.S. individual taxpayers. There is no reason to believe that the individuals who contribute to this setting are substantially different from the broader individual taxpayer population in terms of willingness to pay taxes or tax sophistication. Additionally, the types of rules that apply to third-party reporting in the setting of horse racing are not unlike those that apply to other types of income. For example, whether a third-party report is filed depends largely on dollar amount and other thresholds that are set by IRS regulations.

This generalizability also extends to awareness of third-party reporting rules. It seems reasonable to expect that business owners and investors understand generally what types of transactions trigger third-party reports. Similarly, the participants in this gambling market are likely aware of the applicable third-party reporting rules, as well as the rule change. Thoroughbred gamblers are generally well informed and tend to stay up to date on the industry. Additionally, the rule change was covered by both industry media outlets such as BloodHorse and popular outlets such as Forbes (BloodHorse Staff 2017b; Genaro 2017). Also, gambling institutions including TVG, Xpressbet, and DRF posted and distributed information about the change (TVG 2017; Xpressbet 2017; DRF 2017). These institutions play an important role in the dissemination of this information. They are some of the most popular outlets through which players place their wagers, and thus these are the institutions that often issue third-party reports. All these organizations issued releases with useful information about the change within 24 hours of its implementation.[6]

This study contributes to the literature on the effectiveness of third-party reporting. It is widely believed that when income is reported to the IRS by a third party, it becomes much more likely that the income will be reported by the taxpayer. This has been confirmed by several academic and government studies (e.g. IRS 2016; Kleven et al. 2011; Slemrod, Collins, Hoopes, Reck, and Sebastiani 2019). However, I am unaware of any evidence on how taxpayers interact with the third-party reporting system prior to the filing of a third-party report. This study seeks to fill this gap by using a unique setting to consider how taxpayers adjusted their behavior following an isolated change in third-party reporting rules.

This question is also of importance to tax enforcement authorities. Given the scale of the underreporting problem in the U.S., and the reliance on third-party reporting to address it, it is important to understand the weaknesses of, and threats to, the third-party reporting system. The finding that taxpayers adjust their behavior to subvert IRS third-party reporting rules suggests that a malicious type of underreporting exists, where income is not underreported opportunistically, but rather taxpayers intentionally avoid third-party reports to enable tax evasion. This implies that taxpayers are not only evading taxes when they file tax returns but also working throughout the year to facilitate this evasion.

This study also contributes to the literature on the strategic game between taxpayers and tax authorities (e.g. Beck and Jung 1989). The analytical literature has considered attempts by the IRS to acquire information and reduce information asymmetry pertaining to individual taxpayers, as well as how taxpayers respond to these attempts (Sansing 1993). However, the empirical literature

[6] These online platforms issue W-2G third-party reports to U.S. taxpayers even if the taxpayer wins money from a Canadian track.

on this topic is very limited, as is literature that considers third-party reporting in this context. This study provides early evidence to fill these gaps.

Finally, this study is relevant to the Scholes, Wolfson, Erickson, Maydew and Shevlin (2014) framework, as well as the broader literature on how much taxes matter (e.g. Shackelford and Shevlin 2001, Hanlon and Heitzman 2010). This literature has not yet considered the impact of third-party reporting, and this study provides early evidence to fill this gap. The finding that third-party reporting alone impacts decision making is novel and interesting because IRS third-party reporting does not change the taxability of income: it only makes the IRS aware of it.

CHAPTER 2. BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Third-Party Reporting and the Tax Gap

The "tax gap" is the amount of money that is legally owed in taxes that the government fails to collect. In the U.S., this number is over $400 billion annually (IRS 2016). The primary driver of this lost tax revenue is individual underreporting of income, which accounts for the majority of the U.S. tax gap (IRS 2016). In the U.S., taxes paid by individuals make up nearly 90 percent of all tax revenue, and in fiscal year 2018 nearly 153 million individual returns were filed (Internal Revenue Service Data Book 2018). This is a tremendous amount of tax return data for the IRS to process, and auditing a significant number of these returns would be quite costly. For calendar year 2017, the IRS audited just 0.6% of individual tax returns filed, and only 25% of those audits were field audits (Internal Revenue Service Data Book 2018). This leaves significant information asymmetries between the IRS and individual taxpayers, and these asymmetries are the reason individuals are able to underreport income and underpay taxes by hundreds of billions of dollars each year.

The IRS believes that third-party reporting is the best method of reducing information asymmetry and making enforcement viable on a large scale. Third-party reporting is the practice of having parties other than the taxpayer report income the taxpayer earns. These reports cover a wide range of income types including wages, dividends, interest, capital gains, and more. Third-party reports allow the IRS to cheaply corroborate information reported by taxpayers, as well as identify income that taxpayers fail to report entirely. The reports are sent to both the taxpayer and the IRS, and the IRS compares the reports to relevant tax filings through its Automated Underreporter (AUR) program. This program matches information on tax returns to information from the 2.7 billion third-party reports the IRS receives annually. If information on a given tax return does not match information on the third-party reports associated with it, the taxpayer is contacted, and the discrepancy is resolved (Internal Revenue Service Data Book 2018).[7]

The IRS's AUR program makes third-party reporting a powerful tax enforcement tool, but for the system to work, third-party reports must be filed. If taxpayers can avoid third-party reports,

[7] The IRS also uses third-party reports for the Automated Substitute for Return Program (ASFR). This program uses information from third-party reports to stand in for returns that did not get filed. The ASFR is smaller in scale than the AUR, and non-filing is a smaller driver of the tax gap than the underreporting of income.

they can avoid this system and maintain their informational advantage over the IRS. This study uses pari-mutuel wagering pools from thoroughbred racing to provide evidence on whether taxpayers do, in fact, adjust their behavior to maintain this informational advantage. If they do, it represents an important weakness in the third-party reporting system—a weakness that helps facilitate the substantial underreporting problem in the U.S.

2.2 Thoroughbred Pari-Mutuel Wagering

In the U.S. and Canada, thoroughbred horse racing employs a pari-mutuel wagering system. This means that rather than betting against the "house" as gamblers generally do when they wager on other sports, horse players bet against each other and the house simply takes a cut of the aggregate amount wagered. To do this, the track establishes a "pool" of money for each type of bet, for each race. For a simple demonstration of how this works, consider a race with a total of $100 in the "win" pool. Now, let's assume that when the race is over, it turns out that $20 of the total amount wagered was bet on the horse that wins the race. The track will take their cut out of the total pool—let's assume the "take out" here is 20 percent—and the remaining $80 ($100×80%) will be paid to winners based on the size of their wagers. So, in this example, a gambler who bet $1 on the winner will receive $4, making his odds for this wager 3/1.[8]

Within this system, there are many different types of wagers that players can make. Some are relatively easy to win but tend to result in low odds (low-yield wagers): an example of this would be picking the winner of a race.[9] These low-yield wagers generally have fewer possible outcomes, and as a result more winners, so therefore the returns tend to be smaller. Other wagers are much more difficult to win but often return substantial odds (high-yield wagers). An example of this type of wager would be picking the winner of six consecutive races.[10] There are many possible outcomes for a wager like this, and as a result there are usually fewer winners for the pool to be split between. Because of the difficult nature of these high-yield wagers, players generally bet on many different possible outcomes. For example, a player picking the winner of five

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[8] The odds are 3/1 because the gambler gets his investment of $1 back and wins $3.
[9] Other examples of low-yield wagers are the following: place bets, show bets, exacta bets, and daily double bets. For a complete list, see Appendix B.
[10] Other examples of high-yield wagers are as follows: pick five bets, pick four bets, and super high five bets. For a complete list, see Appendix B.

consecutive races might pick three horses per race and bet on every possible combination to increase their chances of winning.

2.3 Third-Party Reporting of Gambling Winnings and Hypothesis Development

The criteria for a third-party report to be filed vary by income type and often include key thresholds and other transaction specifics. Many of these criteria leave room for taxpayers to avoid third-party reports by adjusting transactions or altering their behavior and decisions.[11] Winnings from pari-mutuel wagering are no different: they are subject to key reporting thresholds that determine whether a third-party IRS report will be filed. First, the winnings must exceed $600, and second, the payout received must be 300 times greater than the amount wagered (300/1 odds or greater). On September 27th, 2017, the IRS implemented changes to the regulations governing third-party reporting of pari-mutuel winnings.[12] Prior to these changes, the 300/1 odds requirement was calculated based on the individual bet that a gambler won. This means that if a gambler placed fifty $5 bets into a given pool (wagering a total of $250), the odds threshold would have been met if the gambler won $1,500 (i.e. $5×300).

Under this pre-change calculation, low-yield wagers were almost never subject to third-party reporting. Low-yield wagers rarely return odds of 300/1 or greater regardless of how odds are calculated. Conversely, under the pre-change odds calculation, high-yield wagers regularly returned odds to winners that exceeded 300/1. Returning to the example above, under the pre-change policy, a winning gambler placing fifty $5 wagers was not allowed to consider his forty-nine losing wagers when calculating his odds for the purposes of third-party reporting.

The 2017 IRS change altered this odds calculation to allow gamblers to take into consideration all the money they wagered into a given pool when calculating the 300/1 ratio for third-party reporting purposes.[13] This had very little impact on low-yield wagers, which were

[11] Some examples include transacting in cash, timing payments or setting prices to avoid thresholds, and taking advantage of investments that are less likely to generate third-party reports.
[12] Treas. Reg. §31.3402(q)-1 (as amended 2017), Treas. Reg. §31.3406(g)-2 (as amended 2017).
[13] The horse industry advocated for this IRS regulation change for multiple reasons. First, not allowing gamblers to consider losing wagers in their threshold calculations made tax reporting outcomes arbitrary. Winnings from high-yield wagers were often reported even if they returned the same effective odds as low-yield wagers. Gamblers could even have winnings reported on wagers that resulted in a net loss. Second, industry leaders believed that the aggregate amount wagered might increase if reporting and withholding thresholds were raised. In untabulated results, I find no evidence that this increase occurred, meaning that the results found in this paper are driven by changes in high-yield wager popularity, not changes in aggregate wagering levels.

rarely reported before the change. Low-yield wagers pay lower odds in general, meaning they are less likely to exceed the 300/1 ratio, and because these wagers involve fewer possible outcomes, the practice of placing multiple wagers into the same pool is less prominent.[14] Third-party reporting of high-yield wagers, on the other hand, changed significantly. Because gamblers typically make many wagers into the same pool to win these bets, the basis on which a gambler's odds were computed changed substantially. Returning to the previous example, the gambler who placed fifty $5 bets into the same pool now can use the forty-nine losing wagers as part of his calculation, increasing his reporting threshold from $1,500 to $75,000 (i.e. $250×300).

Because of this discrepancy in how the change impacted different wager types, a situation exists where the impact of a third-party reporting change can be observed directly. The change led to a substantial increase in the threshold at which high-yield wagers were subject to third-party reporting, while leaving low-yield wagers relatively unaffected. If taxpayers purposefully avoid third-party reports, they should have found high-yield wagers more appealing following the change. Thus, high-yield wagers should have increased in popularity relative to low-yield wagers following the change. I state my primary hypothesis as follows:

H1: Following the IRS amendment, the percentage of money wagered on high-yield bet types increased.

[14] For the low-yield wager types where a gambler might place multiple wagers into the same pool, they still likely place fewer wagers than they would for a high-yield wager.

CHAPTER 3. DATA AND RESEARCH DESIGN

To test my hypothesis, I use a difference-in-differences research design, where Canada is the control group and the U.S. is the treatment group. Thoroughbred racing is generally uniform in North America; tracks in the U.S. and Canada have similar rules, use the same pari-mutuel wagering structure, and offer the same types of wagers. However, the rule change only directly impacted tracks in the U.S.: Canada does not tax gambling winnings, and there were no changes to this policy during my sample period. This makes Canada an ideal control group for a difference-in-differences design that compares the change in high-yield wager popularity in the U.S. to the change in high-yield wager popularity in Canada following the IRS rule change.

To construct my dataset, I use race-level thoroughbred racing data obtained from the National Thoroughbred Racing Association, Equibase Inc. and the Jockey Club. This dataset includes every thoroughbred race in North America between January 2009 and July 2019. I chose this timeframe due to data availability. The dataset contains descriptive variables for each race as well as the dollar amount bet into each different pari-mutuel wagering pool for each race.[15]

To construct my variable of interest capturing the popularity of high-yield wagers, I categorize wager types based on assigned win probabilities. I classify any wager type with a probability of 0.05 percent or lower as high-yield. I chose this cutoff because it is roughly where bets start to return payouts of 300/1 or greater consistently enough to expect third-party reporting to be a factor.[16] To assign win probabilities to each wager type, I calculate the likelihood of winning a random bet for each wager type in a race with eight identical horses. I use an eight-horse race as a basis because the median (mean) race in my sample has eight (7.96) horses. For example, I assign a 12.5-percent (1/8) chance of winning to the "win" wager type, since you win the bet if the one horse that you have bet on comes in first. Following the same method for a wager that requires a player to pick the winner of three consecutive races, I assign a 0.2-percent (0.1253)

[15] This dataset includes the following for each race: country, date, track, race type, purse, post time, race number, number of horses in the race, surface, distance, age restrictions, sex restrictions, weather, temperature, track condition, and pool sizes for each betting pool (in dollars). For more information on these variables, see Appendix A.

[16] In practice, generic win probabilities must be considerably lower than 1/300 to return odds of 300/1. This is true for a two major reasons. First, the horses with the lowest odds tend to perform the best (because horse racing is predictable), and when horses with low odds perform well, payout odds tend to be lower because the actual outcome of the race will have a disproportionate amount of money wagered on it. Second, the track is profiting by taking a cut out of each pool. This means that in an efficient pool, all wagers will have expected values of less than one.

chance of winning since you need one specific horse out of eight to come in first in three independent races. For a list of commonly available wagers and their assigned win probabilities, see Appendix B. I next construct my variable of interest by taking the sum of all high-yield wager type pools in each race and dividing that sum by the total amount of money wagered on that race.[17]

For my primary analysis, I winsorize continuous variables at 1 percent and 99 percent and cluster standard errors at a track level. I construct a difference-in-differences model for my main test as follows:

$$\begin{aligned} HighYieldRatio = {} & \beta_0 + \beta_1 PostChange + \beta_2 PostChange \times USA + \sum \beta RaceLevelControls \\ & + TrackFixedEffects + YearFixedEffects \end{aligned} \tag{1}$$

Here, *HighYieldRatio* is the percentage of the total money bet that was bet into high-yield wager type pools in each race. *PostChange* is an indicator variable equal to 1 if the date of the race is on or after September 27th, 2017. I include this variable as a control despite having year fixed effects because the amendment went into effect in the third quarter of 2017, so year indicators do not line up perfectly with my post-period.[18] *USA* is an indicator variable equal to 1 if the track is located in the U.S. I do not include the *USA* indicator as a control variable because I include track fixed effects. Tracks do not move, so these fixed effect indicators control for location.[19] Track fixed effects also control for any track-specific idiosyncrasies. Additionally, I include year fixed effects to control for trends over time. I also include race-level controls to ensure my results are not driven by other confounding factors in the horse racing industry. These race-level control variables include number of bets available, number of runners, distance, purse, race number, race type, surface, age restrictions, sex restrictions, weather, and track conditions; additionally, race month and day of the week are included. For more information on these race-level control variables, see Appendix A. My coefficient of interest in this model is β2, this coefficient represents the change in high-yield wager popularity in the U.S. relative to Canada following the IRS rule change.

Table 1 reports the sample statistics for the continuous and simple binary variables used in my primary analysis, where observations are individual races. I drop all observations with no high-

[17] I equally distribute multiple race wagers across all the races to which they pertain. For example, a pick three wager is a bet where gamblers try to pick the winners of three consecutive races. If the pool for a pick three is $30,000, I attribute $10,000 to each of the three races.
[18] Excluding *PostChange* as a control variable does not meaningfully impact my results.
[19] Excluding track fixed effects and including the *USA* indicator does not meaningfully impact my results.

yield wagers available since the numerator of my variable of interest would be 0 for those races.[20] Table 1 does not include all race-level controls, because some can only be included using a set of indicators representing many non-linear possibilities.[21] The mean value of the *USA* indicator is 0.929, this means the majority of my sample is made up of U.S. observations. To ensure that my results are not impacted by this discrepancy I run tests in Table 6 that correct for it. The results of these tests are not meaningfully different than my primary analysis.[22] The mean Purse in this data is $28,804, this is the amount of money available in a race to pay winners. The average race in the data set had 7.962 participating horses (*Runners*), was 6.754 furlongs in distance (a furlong is an eighth of a mile) and offered gamblers 7.551 wager types.[23] Surface is a binary variable that indicates races that were run on dirt or a synthetic dirt surface. The mean value of Surface is 0.849 which implies that about 85% of the races in this sample were run on dirt, while 15% were run on turf.[24]

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[20] The dependent variable in my model, *HighYieldRatio*, is somewhat skewed. I choose not to transform it to maintain interpretability of the economic magnitude. In untabulated tests I perform a natural log transformation. This transformation does not meaningfully change the significance or direction of my coefficient of interest.

[21] For example, there are twenty different race types in the dataset, but there is no linear way to organize them. Hence, they are included in regressions as a set of indicators, but these indicators are not displayed as part of the descriptive statistics. For more information on these variables, see Appendix A.

[22] The mean value of *PostChange* is 0.157 which demonstrates that the pre-period of this study also makes up a disproportionate amount of my sample. To ensure this is not impacting my results, I run an untabulated test estimating my primary regression with a shortened pre-period, using data from January 2015 through July 2019. The results do not meaningfully change.

[23] For the purposes of this *BetsAvailable* variable win, place, and show bets are all considered the same wager type.

[24] An important assumption that this difference-in-differences structure makes is that, in general, Canadians tend to bet on Canadian racetracks and Americans tend to bet on U.S. tracks. This assumption is not necessarily obvious, because when players bet online, they can wager on any track in either country and their money goes into the same pool as individuals from the other country. This assumption is important, however: if it does not hold it would create a bias against finding results, because if every track has the same portion of bettors from both countries, the rule change should have impacted all tracks equally.

Table 1 Summary Statistics

Variables	N	Mean	SD	p25	Median (p50)	p75
HighYieldRatio	382,136	0.056	0.055	0.021	0.038	0.071
PostChange	382,136	0.157	0.364	0	0	0
USA	382,136	0.929	0.257	1	1	1
Purse	382,136	28,804	73,075	10,075	17,600	31,875
Runners	382,136	7.962	1.880	7	8	9
Distance	382,136	6.754	1.257	6.0	6.5	8.0
BetsAvailable	382,136	7.551	1.338	7	7	8
Surface	382,136	0.849	0.358	1	1	1

Table 1: This sample contains all races in North America between January 2009 and July 2019 that offered at least one high-yield wager. *HighYieldRatio* is the variable of interest in this paper: it is the percentage of total money wagered that is wagered on high-yield wager types in each race. This table includes all continuous variables that are used in this paper as well as all indicator variables that are binary. The table excludes some race-level controls because they are not continuous or binary: Race Number, Race Type, Age Restrictions, Sex Restrictions, Weather, and Track Conditions. For the purposes of regression, the variable Purse is transformed using a natural logarithm function. p25 and p75 are 25^{th} and 75^{th} percentile, respectively.

CHAPTER 4. MAIN RESULTS

Table 2 presents the results of my primary difference-in-differences analysis. This analysis uses Canada as a control group and compares the popularity of high-yield wagers in the U.S. following the IRS change to the popularity of high-yield wagers in Canada following the change. The coefficient of interest in these regressions is the interaction between the *PostChange* indicator variable and the *USA* indicator variable.

Column 1 of Table 2 shows a basic difference-in-differences model that includes only the *PostChange* indicator and the interaction of interest, *PostChange×USA*, as well as year and track fixed effects. Column 2 of Table 2 shows the results of the same difference-in-differences design with simple race-level controls added. Column 3 of Table 2 uses the same design but adds both simple race-level controls and race-level indicator controls. All regressions use robust standard errors that are clustered by track. I find that my coefficient of interest is positive and significant in all regressions. This supports my hypothesis by indicating that high-yield wagers increased more in the U.S. following the IRS change than they did in Canada. The coefficient is also consistent, changing very little regardless of what controls are included in the regression.

The dependent variable in these regressions is the percentage of total money wagered that was bet on high-yield wager types. This means that the coefficient on the interaction of interest can be interpreted as the increase in this percentage that the U.S. experienced in the post-period relative to Canada. In all regressions this coefficient is 0.014, which translates to a 1.4 percent increase. To put this in context, the average North American race in the pre-period saw about 5.1 percent of all money bet on high-yield wagers, which means the change led to a 27-percent increase in the popularity of high-yield wagers in the U.S relative to Canada.

Table 2 Difference-in-Differences Main Results

Variables	*HighYieldRatio* (1)	*HighYieldRatio* (2)	*HighYieldRatio* (3)
PostChange	-0.01***	-0.01**	-0.011***
	(-3.02)	(-2.54)	(-3.23)
PostChange×USA	**0.014*** **	**0.014*** **	**0.014*** **
	(4.30)	**(3.56)**	**(3.87)**
LnPurse		-0.000	0.001
		(-0.04)	(0.38)
Runners		-0.003***	-0.003***
		(-10.30)	(-11.31)
Distance		0.001***	0.000***
		(5.89)	(5.26)
BetsAvailable		0.008***	0.005***
		(5.60)	(4.35)
Surface		0.002***	0.002*
		(2.83)	(1.79)
Year Fixed Effects	Yes	Yes	Yes
Track Fixed Effects	Yes	Yes	Yes
Race-Level Indicator Controls	No	No	Yes
Constant	-0.026***	-0.049***	-0.052***
	(-9.41)	(-5.18)	(-2.99)
Observations	382,136	382,136	382,136
R-squared	0.583	0.602	0.628

Table 2: This table shows the results of three difference-in-differences regressions that use Canada as a control group to identify the increase in *HighYieldRatio* following the change in the IRS's third-party reporting rules for pari-mutuel winnings. The coefficient of interest is *PostChange×USA*, and *t*-statistics are included in parentheses. Column 1 is a regression including only difference-in-differences variables with year and track fixed effects. Column 2 includes difference-in-differences variables with simple race-level controls as well as year and track fixed effects. Column 3 includes difference-in-differences variables with simple race-level controls, year and track fixed effects, and race-level indicator controls (these include race number, race type, age restrictions, sex restrictions, weather, track condition, month, and day of the week). All regressions use robust standard errors and cluster standard errors at a track level. *** p<0.01, ** p<0.05, * p<0.1.

4.1 Cross-Sectional State Popularity Test

The main finding of this study provides evidence that taxpayers purposely modify their behavior to avoid third-party reports. However, for avoidance to be purposeful, it is necessary that taxpayers are aware of third-party reporting rules. This leads to a prediction that can further validate my main findings by providing evidence that intentional avoidance of third-party reports is the mechanism being captured in my main test. If gamblers purposely modify behavior to avoid third-party reports, the impact of the IRS change on gamblers' behavior should be proportional to their knowledge of third-party reporting rules. This means that gambling populations that were more aware of the third-party reporting rule change should have had stronger reactions to the change.

To provide evidence on this topic, I take advantage of discrepancies in the popularity of thoroughbred racing across states. In states where racing is more popular, I expect that gamblers will be more sophisticated and thus more cognizant of an important rule change like the one considered in this study. To test this prediction, I use two proxies to measure the popularity of thoroughbred racing in each state and create an indicator variable for races that took place in high popularity states. I then interact that indicator with *PostChange×USA*, creating a triple interaction that measures the additional impact that the rule change had on high popularity states above the impact that it had on low popularity states.

Table 3 presents the results of this test. Column 1 uses statewide average purse to determine the states in which thoroughbred racing is most popular. States with an average purse above the U.S. national average ($28,508) have TopState coded as one, while all other states have TopState coded as zero.[25] Column 2 uses the number of races held during my sample window to determine the states in which thoroughbred racing is most popular. States that make up more than five percent of my U.S. sample (ran more than 17,749 races) have TopState coded as one, while all other states have TopState coded as zero.[26] Column 3 uses the measures from both Column 1 and Column 2, where states that are deemed to have high popularity in terms of both average purse and racing

[25] States coded as 1 using average purse are Arkansas, California, Florida, Kentucky, Maryland, New Jersey, New York, and Virginia. This results in TopState being coded as 1 for 149,879 of the 354,990 U.S. observations in my sample.
[26] States coded as 1 using racing volume are California, Florida, Kentucky, Louisiana, New York, Pennsylvania, and West Virginia. This results in TopState being coded as 1 for 214,510 of the 354,990 U.S. observations in my sample.

volume have TopState coded as one, and all other races have TopState coded as zero.[27] All regressions use a full set of controls and cluster standard errors at a track level.

The coefficient on *PostChange×USA* is positive and significant across all regressions, demonstrating that low popularity states saw an increase in *HighYieldRatio* relative to Canada, but the coefficient on *PostChange×USA×TopState* is much larger in magnitude while also being positive and significant. This result shows that both high and low popularity states saw an increase in *HighYieldRatio* relative to Canada, but as predicted, high popularity states saw a much bigger impact. This additional impact appears to be quite large in a relative sense. To evaluate the impact of the third-party reporting change on high popularity states relative to Canada, the coefficients on *PostChange×USA×TopState* and *PostChange×USA* must be added together. Doing this shows that the impact on high popularity states ranged from 287% to 400% of the impact on low popularity states. The coefficient on *PostChange×USA×TopState* is also 26% larger in Column 3 than in Columns 1 and 2; this is not surprising, because Column 3 combines both proxies for state racing popularity, and thus only the states where racing popularity seems to peak are included in the *TopState* indicator.

[27] States coded as 1 using average purse and racing volume are California, Florida, Kentucky, and New York. This results in TopState being coded as 1 for 124,364 of the 354,990 U.S. observations in my sample.

Table 3 State Popularity Analysis

Variables	*HighYieldRatio* (1: Top Purses)	*HighYieldRatio* (2: Most Races)	*HighYieldRatio* (3: Both)
PostChange	-0.011***	-0.011***	-0.011***
	(-3.35)	(-3.36)	(-3.43)
PostChange×USA	0.008**	0.005*	0.007**
	(2.38)	(1.79)	(2.32)
PostChange×USA×TopState	**0.015*** **	**0.015*** **	**0.019*** **
	(3.09)	**(3.75)**	**(4.12)**
Year Fixed Effects	Yes	Yes	Yes
Track Fixed Effects	Yes	Yes	Yes
Race-Level Indicator Controls	Yes	Yes	Yes
Race-Level Simple Controls	Yes	Yes	Yes
Constant	-0.047***	-0.056***	-0.049***
	(-2.89)	(-3.51)	(-3.10)
Observations	382,136	382,136	382,136
R-squared	0.631	0.631	0.632

Table 3: This table displays the results of three difference-in-differences regressions that use Canada as a control group and demonstrate that the American increase in *HighYieldRatio* was driven by the states in which thoroughbred racing is most popular. The coefficient of interest is *PostChange×USA×TopState*, which represents the amount of *HighYieldRatio* increase that was experienced in states where thoroughbred racing is most popular in excess of that experienced in lower popularity states, relative to Canada. *TopState* is defined differently in each column. Column 1 defines *TopState* by average purse, where races taking place in states with an average purse of over $28,508 (the U.S. national average) are defined as 1 and all other races are defined as 0. Column 2 defines *TopState* by number of races held during the sample period, where races taking place in states that held more than 17,749 races (5% of the total U.S. sample) during my sample period are defined as 1 and all other races are defined as 0. Column 3 defines *TopState* by both purse and number of races, where races taking place in states with an average purse over $28,508 and more than 17,749 races held during my sample period are defined as 1 and all other races are defined as 0. All regressions include year and track fixed effects, as well as race-level indicator controls and race-level simple controls. All regressions use robust standard errors and cluster standard errors at a track level; *t*-statistics are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 5. ADDITIONAL ANALYSIS

5.1 Falsification Tests

This study employs a difference-in-differences research design; as a result, it is important to consider the parallel trends assumption. To investigate this assumption, I perform two falsification tests in which I use subsamples of my data before and after the 2017 IRS regulation change to re-estimate equation 1 using false post-periods.

Table 4 presents the results of these falsification tests. Column 1 uses data from January 2009 to September 2017, which represents the pre-period of my primary analysis. Since I have approximately two years of post-period in my primary analysis, I create a false post-period from September 2015 to September 2017. Column 2 uses data from October 2017 to July 2019, which represents the post-period of my primary analysis. Since this period is considerably shorter than my primary analysis, I use 2019 as my false post-period, and omit year fixed-effects. In both of these specifications my coefficient of interest, *PostChange*×*USA* is statistically insignificant, and the magnitude of this coefficient is 71 (86) percent lower in my pre-period (post-period) falsification test than in my primary analysis.

This test contributes to my analysis in two ways. First, it provides further evidence that the parallel trends assumption is satisfied. My coefficients of interest are insignificant and low in magnitude. This demonstrates that the U.S. and Canada were not significantly different from one another around these false post-dates, implying that they are trending similarly in the pre-period and in the post-period. Additionally, this test confirms that the results shown in Table 2 are sensitive to the actual post-period of the third-party reporting rule change. This demonstrates that the findings in Table 2 are being driven by the rule change and not by underlying trends in the data.

Table 4 Falsification Tests

Variables	*HighYieldRatio* (1: Pre-period)	*HighYieldRatio* (2: Post-period)
PostChange	-0.000	-0.003
	(-0.12)	(-0.98)
PostChange×USA	**0.004**	**0.002**
	(1.01)	**(0.80)**
LnPurse	0.000	0.002
	(0.01)	(1.29)
Runners	-0.003***	-0.006***
	(-11.83)	(-11.71)
Distance	0.000***	0.001***
	(4.90)	(3.30)
BetsAvailable	0.005***	0.009***
	(4.51)	(5.71)
Surface	0.002	0.004
	(1.64)	(1.30)
Year Fixed Effects	Yes	No
Track Fixed Effects	Yes	Yes
Race-Level Indicator Controls	Yes	Yes
Constant	-0.043***	-0.022***
	(-2.78)	(-1.29)
Observations	322,034	60,102
R-squared	0.622	0.628

Table 4: This table shows the results of two difference-in-differences regressions that use Canada as a control group to identify the increase in *HighYieldRatio* during falsified post-periods. Column 1 uses data from January 2009 to September 2017, with the post-period set from September 2015 to my actual post-date in September 2017. Column 2 uses data from October 2017 to July 2019, with the post-period set from January 2019 to the end of my data in July 2019. Year fixed effects are excluded from column 2 because there are only two years in this data subset. The coefficient of interest is *PostChange×USA*; t-statistics are included in parentheses. Both columns include difference-in-differences variables with simple race-level controls, track fixed effects, and race-level indicator controls (these include race number, race type, age restrictions, sex restrictions, weather, track condition, month, and day of the week). Both regressions use robust standard errors and cluster standard errors at a track level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.2 U.S. Sample Analysis

This study utilizes Canada as a control group to measure the impact of a 2017 IRS regulation change on U.S. taxpayer behavior. Canada appears to be a reasonable counterfactual, the parallel trends assumption holds across the U.S. and Canada, and Canada experienced no known shocks to its thoroughbred racing or gambling industry during the period of this study. However, it is possible that some unknown confounding factor exists in Canada that could impact my results. To ensure that this is not the case I conduct an analysis using only my U.S. sample.

To do this, I set up a difference-in-differences test based on the TopState classifications in Table 3, where low popularity states function as a control group, and the high-popularity states that were more strongly impacted act as a treatment group. Like Table 3, this test takes advantage of the cross-state discrepancies in gambler sophistication that are tied to thoroughbred racing popularity. If this IRS change led to an intentional reallocation of gambling funds toward wagers that had become less likely to result in a third-party report, the reallocation should have been strongest among sophisticated gamblers, who are concentrated in high-popularity states. To investigate this, I run a difference-in-differences specification where TopState functions as a treatment indicator.

Table 5 presents the results of this difference-in-differences analysis. The TopState indicators are coded the same as Table 3, where Column 1 is based on statewide average purse, Column 2 is based on the number of races held during my sample window, and Column 3 uses the measures from both Column 1 and Column 2.[28] The results of these specifications consistently show that high popularity states experienced a significant increase in *HighYieldRatio* relative to low popularity states following the 2017 IRS regulation change. This provides evidence on the regulation change's impact that does not rely on a Canadian control group.

[28] As in earlier tests, the treatment indicator here is subsumed by track fixed effects. I also note that the *PostChange* indicator coefficient cannot be interpreted directly because of year fixed effects.

Table 5 U.S. Sample Analysis

Variables	*HighYieldRatio* (1: Top Purses)	*HighYieldRatio* (2: Most Races)	*HighYieldRatio* (3: Both)
PostChange	-0.004	-0.007**	-0.005*
	(-1.50)	(-2.36)	(-1.79)
PostChange×TopState	**0.015*** **	**0.015*** **	**0.019*** **
	(3.07)	**(3.75)**	**(4.13)**
Year Fixed Effects	Yes	Yes	Yes
Track Fixed Effects	Yes	Yes	Yes
Race-Level Indicator Controls	Yes	Yes	Yes
Race-Level Simple Controls	Yes	Yes	Yes
Constant	-0.024	-0.036*	-0.026
	(-1.15)	(-1.77)	(-1.28)
Observations	354,990	354,990	354,990
R-squared	0.658	0.658	0.659

Table 5: This table shows the results of three difference-in-differences regressions that use low popularity states as a control group to identify the increase in *HighYieldRatio* following the change in the IRS's third-party reporting rules for pari-mutuel winnings. The coefficient of interest is *PostChange×USA*, and *t*-statistics are included in parentheses. Column 1 defines *TopState* by average purse, where races taking place in states with an average purse of over $28,508 (the U.S. national average) are defined as 1 and all other races are defined as 0. Column 2 defines *TopState* by number of races held during the sample period, where races taking place in states that held more than 17,749 races (5% of the total U.S. sample) during my sample period are defined as 1 and all other races are defined as 0. Column 3 defines *TopState* by both purse and number of races, where races taking place in states with an average purse over $28,508 and more than 17,749 races held during my sample period are defined as 1 and all other races are defined as 0. All regressions include year and track fixed effects, as well as race-level indicator controls and race-level simple controls. All regressions use robust standard errors and cluster standard errors at a track level; *t*-statistics are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Matched Track and Randomized Analysis

One potential concern in this setting is the fact that there are far more U.S. races in my sample than there are Canadian races. In my main sample, there are 27,146 Canadian races and 354,990 U.S. races. This stems from the fact that there are simply far more tracks located in the U.S. and thus far more races are run. It is not clear that this observation count discrepancy should impact my results, but to ensure that it doesn't, I rerun my primary analysis using two U.S. subsamples in place of my U.S. sample to show that my results persist when the observation count discrepancy is resolved.

Table 6 tabulates the results of these subsample regressions. Column 1 uses a U.S. sample that is matched to my Canadian sample based on two criteria: the number of races run at each track during my sample period and track pre-period average *HighYieldRatio*. My procedure for matching is to first find the five U.S. tracks with the most similar racing volume to each Canadian track. Then, out of those five U.S. tracks, I choose the one with the most similar pre-period *HighYieldRatio* to each Canadian track. Once complete, this matched sample includes 27,146 Canadian races and 26,576 U.S. races. Column 2 uses a random U.S. sample generated by statistical software. This sample includes 27,146 random U.S. races to compare to the 27,146 Canadian races included in my dataset.

The results in both Column 1 and Column 2 are consistent with the results of my primary analysis. The coefficients are both positive and significant, the magnitude in Column 1 is slightly larger than my primary analysis, and the magnitude in Column 2 is the same as in my primary analysis. This finding demonstrates that the observation count discrepancy between the treatment group and control group does not impact my results.

Table 6 Matched/Randomized U.S. Sample

Variables	*HighYieldRatio* (1: Matched)	*HighYieldRatio* (2: Randomized)
PostChange	-0.002	-0.003
	(-0.50)	(-1.35)
PostChange×USA	**0.019*** **	**0.014*** **
	(3.84)	**(3.90)**
LnPurse	0.002	-0.001
	(0.72)	(-0.85)
Runners	-0.004***	-0.004***
	(-6.08)	(-8.43)
Distance	0.001**	0.001***
	(2.28)	(6.72)
BetsAvailable	0.005***	0.005***
	(3.41)	(5.14)
Surface	0.003	0.003*
	(1.46)	(1.68)
Year Fixed Effects	Yes	Yes
Track Fixed Effects	Yes	Yes
Race-Level Indicator Controls	Yes	Yes
Constant	0.044	-0.031**
	(1.72)	(-2.19)
Observations	53,722	54,292
R-squared	0.431	0.490

Table 6: This table shows the results of two difference-in-differences regressions that use Canada as a control group and U.S. subsamples as a treatment group to identify the increase in *HighYieldRatio* following the change in the IRS's third-party reporting rules for pari-mutuel winnings. Column 1 uses a sample constructed by matching each of the seven Canadian racetracks to a U.S. track that is similar in terms of racing volume and pre-period *HighYieldRatio*. Column 2 uses the same specification but compares my entire Canadian sample to a randomly selected U.S. sample of the same size. In both regressions, the coefficient of interest is *PostChange×USA*. The regressions include simple race-level controls, year and track fixed effects, and race-level indicator controls. The regressions use robust standard errors and cluster standard errors at a track level; *t*-statistics are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.4 Daily Totals

Thus far, each test in this study uses individual races as observations. Using race-level observations is preferable relative to other means of aggregating data because it allows for a more detailed analysis and more robust controls. There are, however, also weaknesses to using race-level observations. Several of these can be addressed by aggregating data by track-day.

Table 7 displays the results of my track-day aggregated regressions. Column 1 shows a basic track-day aggregated regression with only difference-in-differences variables as well as year and track fixed effects. Column 2 uses the same difference-in-differences structure with year and track fixed effects, but it also includes all the control variables that it is possible to aggregate at a day-level.[29] The results of these regressions are consistent with my main results, showing a significant and positive coefficient on my variable of interest, *PostChange×USA*. The magnitude of this coefficient is lower than in Table 2, but this is unsurprising because aggregating data by track-day increases the denominator of *HighYieldRatio*.

This test addresses several potential data concerns. First, when creating my primary sample, all races in which no high-yield wagers were offered were dropped. This is necessary because the dependent variable in this study will always be zero, and thus it cannot be interpreted if no high-yield wagers are available. Dropping these observations results in the disposal of 96,244 races, or about 20% of all North American races that were run during my sample period. Using track-day observations allows these data to be included in regressions. Second, because I am observing an increase in the percentage of money wagered on high-yield wager types relative to all money wagered, using race-level observations assumes that gamblers mainly allocate their gambling funds within races rather than across races. Using track-day observations loosens this assumption by capturing daily allocations rather than single race allocations. Finally, many high-yield wagers involve multiple races. The main sample in this study distributes the pools for these multiple race wager types across the races with which they are associated. This is an adequate way of dealing with these wagers, but using track-day observations is more seamless and allows these wager types to be compared to the track-day as a whole.

[29] This includes the natural log of the aggregate daily purse, the total number of runners across all daily races, the number of bets available across all daily races, and the number of races that day, as well as day of the week and month fixed effects.

Table 7 Difference-in-Differences Day Totals

Variables	*Daily_HighYieldRatio* (1)	*Daily_HighYieldRatio* (2)
PostChange	-0.006	-0.007
	(-1.19)	(-1.61)
PostChange×USA	**0.011****	**0.010****
	(2.07)	**(2.22)**
LnPurse_DayTotal		0.002*
		(1.87)
Runners_DayTotal		-0.000***
		(-4.80)
BetsAvailable_DayTotal		0.000**
		(2.10)
NumberofRaces		0.000
		(0.39)
Year Fixed Effects	Yes	Yes
Month Fixed Effects	No	Yes
Day of Week Fixed Effects	No	Yes
Track Fixed Effects	Yes	Yes
Constant	0.033***	-0.062
	(-11.90)	(-5.44)
Observations	51,018	51,018
R-squared	0.764	0.779

Table 7: This table shows the results of two difference-in-differences regressions that use Canada as a control group to identify the increase in *HighYieldRatio* following the change in the IRS's third-party reporting rules for pari-mutuel winnings. These regressions use track-day observations. The coefficient of interest is *PostChange*×*USA*, and *t*-statistics are included in parentheses. Column 1 is a regression including only difference-in-differences variables with year and track fixed effects. Column 2 includes difference-in-differences variables with day-level controls as well as year, month, day of the week, and track fixed effects. All regressions use robust standard errors and cluster standard errors at a track level. *** p<0.01, ** p<0.05, * p<0.1.

5.5 Tax Cut and Jobs Act Analysis

The third-party reporting change on which this paper focuses went into effect on September 27th, 2017, while most components of the Tax Cuts and Jobs Act (TCJA) were effective as of January 1st, 2018. There is no clear intuition on how the TCJA should impact my results; nonetheless, most of the post-period in this study overlaps with the implementation of the TCJA, so it is necessary to address the possibility that it might affect my findings.[30] I take advantage of the period between the implementation of the third-party reporting change and the implementation of the TCJA to show that the TCJA does not drive my results.

Table 8 presents the findings of my TCJA test. This test re-estimates equation 1 using a sample that excludes observations from 2018 and 2019. This leaves the last 96 days of 2017 as the post-period for the study. The results appear very consistent with my main findings. The coefficient of interest is positive and significant, and its magnitude is 0.013. This estimate of my coefficient of interest is only a tenth of a percentage point different from that of my main test, 0.014.

[30] There were a few aspects of the TCJA that could potentially impact gamblers. The reform generally led to lower effective tax rates on individuals, which could give gamblers additional disposable income but also might decrease the incentive to avoid third-party reports. The TCJA also increased the standard deduction for individuals, which makes it more difficult for gamblers to itemize deductions and deduct gambling losses against winnings. These changes do not create a consistent prediction of how the TCJA would impact my results, so I do not expect that there was any meaningful impact on my results.

Table 8 TCJA Aanalysis

Variables	*HighYieldRatio* (1)
PostChange	-0.009*** (-3.86)
PostChange×USA	**0.013*** (3.80)**
Year Fixed Effects	Yes
Track Fixed Effects	Yes
Race-Level Simple Controls	Yes
Race-Level Indicator Controls	Yes
Constant	-0.046*** (-2.97)
Observations	330,182
R-squared	0.624

Table 8: This table shows the results of my TCJA analysis regression. It uses *HighYieldRatio* as the dependent variable and includes the same difference-in-differences specification as Table 2, but with a sample ending on December 31, 2017. The variable of interest is *PostChange×USA*, and the regression includes all race-level controls, as well as year and track fixed effects. This regression uses robust standard errors and clusters standard errors at a track level. T-statistics are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 6. CONCLUSION

This study seeks to provide evidence on how taxpayers interact with third-party reporting rules before third-party reports are filed. Underreporting of taxable income is a major problem in the U.S., and many believe that third-party reports are the best way to prevent it. There is evidence that once third-party reports are filed, underreporting becomes less likely, but the filing of these reports is often subject to thresholds and other criteria that leave room for taxpayers to avoid third-party reports. This paper seeks to provide evidence on whether taxpayers take advantage of this system.

To do this, the study uses the unique setting of thoroughbred racing's pari-mutuel wagering pools. In 2017, the IRS altered how an important threshold was calculated as it pertained to third-party reporting. This exogenous change led to high-yield wagers becoming far less likely to be subject to third-party reporting, while leaving low-yield wagers relatively unaffected. I hypothesize that if taxpayers intentionally avoid third-party reports, the relative popularity of high-yield wagers should have increased following the IRS change.

To test this hypothesis, I take advantage of the consistency of thoroughbred racing in North America, since Canada is very similar to the U.S. in terms of rules and wagering but was not subjected to the third-party reporting rule change. I find evidence supporting my hypothesis using a difference-in-differences research design to show that following the IRS rule change, high-yield wagers did, in fact, increase in popularity in the U.S. relative to Canada.

This study is interesting and important because it explores a question that is both relevant to tax authorities as they consider the best ways to close the tax gap but also difficult to study because of the data limitations surrounding unreported income. This paper brings to light a potential weakness in the third-party reporting system and provides evidence that taxpayers are taking advantage of this weakness.

APPENDIX A. VARIABLE DESCRIPTIONS

Variables	Definitions
Panel A: Independent Variables & Variables of Interest	
HighYieldRatio	Total dollar amount bet into high-yield betting pools for a given race divided by the total dollar amount bet into all pools for a given race.
PostChange	Indicator variable equal to 1 for all races that occurred on September 27^{th}, 2017 or later, and 0 otherwise.
USA	Indicator variable equal to 1 for all races run in the United States and 0 for those that were run in Canada.
Panel B: Race-Level Controls	
BetsAvailable	Number of unique bets available to gamblers in the race.
Runners	Number of runners in the race.
Distance	Distance of race in furlongs (a furlong is one-eighth of a mile).
LnPurse	Natural log of the total money available to be paid out to the race participants.
Race Number	Set of indicator variables for each race number on a given day. The median race day in the sample has 9 races. I use indicators because there is no intuition on why this control should have a linear relationship with my independent variable.
Race Type	Set of indicator variables for each possible type of race. Race type is generally indicative of the caliber of horses in the race. There are twenty different types of races in my sample, but there are a few race types that are much more common than others, for example, around half of my sample is made up of "claiming" races.
Surface	Indicator variable equal to 1 if race was run on dirt or synthetic dirt, and 0 if race was run on turf.
Age Restrictions	Set of indicator variables for each possible race restriction related to horse age. Every race has some type of restriction, and there are fifteen different types of restrictions in my dataset.
Sex Restrictions	Set of indicator variables for each possible race restriction related to horse sex. Most races do not have any restrictions, and there are four different types of restrictions in my dataset.
Weather	Set of indicator variables for the weather during the race. There are seven different weather classifications in my dataset.
Track Conditions	Set of indicator variables for the possible conditions of the track during the race. There are twelve different track condition classifications in my dataset.

APPENDIX B. WAGER TYPES AND ASSIGNED WIN PROBABILITES

High-Yield		
Wager Name	**Win Probability**	**Description**
Pick 9	0.000001%	Gambler must pick the winners of nine independent races.
Pick 7	0.00005%	Gambler must pick the winners of seven independent races.
Tri/Super	0.0002%	Gambler must pick the first three horses to cross the finish line in the correct order in the one race, and the first four horses to cross the finish line in the correct order in the next race.
Pick 6	0.0004%	Gambler must pick the winners of six independent races.
Place Pick All/9	0.0004%	Gambler must pick a horse that finishes either first or second in either nine consecutive races or all the races that are that are run at a particular track that day. (Win probability is based on nine races).
Pick 5	0.003%	Gambler must pick the winners of five independent races.
Super High 5	0.015%	Gambler must pick the first five horses to cross the finish line in a race in the correct order.
Pick 4	0.024%	Gambler must pick the winners of four independent races.
Low-Yield		
Wager Name	**Win Probability**	**Description**
Superfecta	0.06%	Gambler must pick the first four horses to cross the finish line in a race in the correct order.
Pick 3	0.20%	Gambler must pick the winners of three independent races
Trifecta	0.30%	Gambler must pick the first three horses to cross the finish line in a race in the correct order.
Daily Double	1.56%	Gambler must pick the winners of two independent races.
Exacta	1.79%	Gambler must pick the first two horses to cross the finish line in a race in the correct order.
Quintella	3.57%	Gambler must pick the first two horses to cross the finish line in a race in any order.
Win	12.50%	Gambler must pick the horse that wins the race.
Place	25.00%	Gambler must pick a horse that either wins the race or finishes second.
Show	37.50%	Gambler must pick a horse that either wins the race, finishes second, or finishes third.
Roulette	47.37%	Gambler chooses either “red,” “black,” or “green.” Horses are then assigned a color, and gamblers win if a horse with their color wins the race.

Note: I omit from this list any wager type that appears in less than 1,000 races. This is to exclude wager types that are specific to a single track or represent promotional events.

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