The Effects of Employment Shocks on the Self-Employed: Evidence from Discontinuities in Professional Golf*

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Abstract

Employment shocks can produce persistent earnings losses, yet it is unclear whether these losses result from changes in productivity or labor market frictions. I estimate the long-run effects of a change in job quality on earnings and productivity by exploiting discontinuities in the rules governing membership on professional golf tours. Despite estimating large initial earnings effects, I find that these treatment effects quickly dissipate. Furthermore, I find no productivity effects from treatment. High job transition rates suggest that hiring and firing frictions are weak in golf and, thus, employment shocks have less persistent consequences than in the broader labor market.

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1 Introduction

Temporary employment shocks can have significant and lasting consequences for workers' future earnings prospects. For example, individuals who graduate college during a recession or who are displaced from a job suffer large initial earnings losses than can persist for over a decade.[1] However, it remains unclear whether these losses mainly accrue from productivity losses or from frictions in the hiring and firing process. On the one hand, disruptions to the quality of the work environment have the potential to inhibit productivity growth and produce lasting earnings losses. Workers rarely remain unemployed for long after employment shocks, yet work less hours and are hired by lower paying firms.[2] Thus, the effects of employment shocks are often felt through a deterioration in job quality, and a likely downgrading of peer quality, which may disrupt the skill accumulation process. On the other hand, earnings losses may result from inherent frictions in the hiring or firing process unrelated to productivity. For example, search or informational frictions may delay displaced workers' progress in climbing the job ladder.[3] In addition, regulations or norms that prevent dismissal may reduce the chance of moving down the job ladder for the beneficiaries of employment shocks, such as college graduates in boom times.

These competing explanations have distinct policy implications, yet it is difficult to distinguish between them empirically. One challenge lies in identifying labor-market-level variation in the intensity of hiring and firing frictions. Although frictions can rationalize a wide range of labor

[1]Persistent earnings losses from job displacement are documented in, among others, Jacobson et al. (1993), von Wachter et al. (2009), Couch and Placzek (2010), Davis and von Wachter (2011), Farber (2017), and Lachowska et al. (2019). Individuals who graduate college during recessions have also been found to suffer persistent earnings losses by, among others, Kahn (2010), Oreopoulos et al. (2012), and Genda et al. (2010).

[2]Kahn (2010) and Oreopoulos et al. (2012) find very small effects from graduating college in a recession on initial employment, yet Oreopoulos et al. (2012) find an increased likelihood of initial employment at lower paying and smaller firms. Lachowska et al. (2019) find that displaced workers are only about 10% less likely to have positive earnings one year after displacement, yet work less hours. Schmieder et al. (2018) find that displaced workers are re-employed by low paying firms.

[3]Many wage posting models, starting with Burdett and Mortensen (1998), show that search frictions can create a job ladder such that workers find higher paying jobs over time despite the fact that their productivity remains constant. As an example of informational frictions, firms may infer a negative productivity signal from a worker's past job displacement even if it was only the result of bad luck (Greenwald, 1986; Gibbons and Katz, 1991).

market phenomena, it is difficult to either directly measure them or isolate less affected groups. Typically, studies rely on the structure and assumptions of a model to estimate the impact of labor market frictions as a residual factor. Another challenge is that productivity is often unobservable. Ample evidence suggests that wages are determined by additional factors besides productivity.[4] Yet, since most output is produced in teams, the productivity share of wages is inherently difficult to measure at the individual level. Once again, studies typically estimate productivity through the lens of a model rather than using direct measures. Finally, it is difficult to find natural experiments that produce truly exogenous employment shocks. Studies of job displacement try to isolate displacements that are unrelated to changes in worker productivity. In practice, displacement events are identified based on a threshold of layoffs as a share of total firm employment, which can make it difficult to isolate the different sources of variation driving the estimates. Similarly, studies of graduating in a recession must overcome a complex selection problem involving which types of individuals decide to delay graduation in response to labor market conditions.

I study two natural experiments in professional golf, a setting that lacks hiring and firing frictions, yet includes other relevant features such as changes in job and peer quality that can potentially affect productivity. Since golfers are self-employed, they do not undergo a hiring or firing process. Instead of being hired by firms, golfers are promoted based on their performance according to institutional rules. Thus, we can gain an understanding of the effect of employment shocks in an environment without hiring and firing frictions. Moreover, we can directly observe how productivity responds to employment shocks. Since golf is an individual sport and performance is based on the number of strokes taken to complete a golf course, productivity is observable.

Furthermore, professional golf features some compelling research designs and high-quality data with which to identify the effects of employment shocks. In particular, I exploit the entry rules of the world's top professional golf tour, the PGA TOUR, which reward some successful non-members with membership for the next season. In two separate instances, membership ben-

[4]See Card et al. (2013) and Song et al. (2018) for evidence that some firms provide pay premiums to similar workers. One potential explanation for this result is that firms share rents with workers (Card et al., 2018).

efits change at a discrete threshold such that those who place just below the threshold earn PGA TOUR membership for the next year, while those who place just above the threshold earn membership on the less prestigious Korn Ferry Tour.[5] Small differences in performance across the treatment thresholds coupled with the random variation intrinsic to the game of golf provide excellent conditions to utilize a regression discontinuity design to causally identity the effects of large employment shocks. I am able to measure the short- and long-run consequences of these shocks using high-quality golf data. I assemble administrative earnings records from eight different golf tours from around the world to create a comprehensive picture of each golfer's earnings trajectory covering the period from 1990 to 2014. I construct performance measures using detailed scoring data from the PGA TOUR over the same period. Furthermore, I add Official World Golf Rankings records both to adjust the performance measures by tournament field quality and to understand how peer quality affects performance.

I find very large treatment effects on initial earnings and peer quality for both experiments. Treated golfers enjoy an approximate 100% earnings premium and access to about 20 additional PGA TOUR events in the year after treatment. Furthermore, the average world ranking of treated golfers' playing partners improves substantially. Yet, I find no long-run earnings or performance effects from either treatment. Earnings differences decline significantly in the second year after treatment. By the third year, earnings differences across the treatment groups completely converge and remain statistically insignificant going forward. Moreover, I find no difference in performance between treated and untreated golfers both in the initial years after the employment shock or in subsequent years.

My main contribution is to show that, in contrast to wage-and-salary workers in the broader labor market, self-employed golfers are able to recover quickly from large employment shocks. Thus, hiring and firing frictions appear to play a key role in the persistence of earnings losses for wage-and-salary workers. Indeed, most of the literature emphasizes some form hiring or firing fric-

[5]The two natural experiments are based on the PGA TOUR Qualifying Tournament and the Korn Ferry Tour season-end money listing.

tions to explain the effects of temporary employment shocks. Examples include explanations based on search models, industry- or firm-specific human capital, firm-worker match complementarities, or signaling models.[6] My main results broadly support this emphasis, yet cannot distinguish between these different types of frictions.

To understand more specifically how frictions differ between golf and the broader labor market, I compare the rates of job mobility across markets. Job transition rates for golfers are defined as the rate of moving across golf tours, whereas job transition rates for wage-and-salary workers are defined with respect to movements across firm types. I find that professional golfers compete in a highly fluid labor market with both higher rates of moving up the job ladder (to a higher paying tour) and down the job ladder (to a lower paying tour). In particular, golfers experience a notably high exit rate off the PGA TOUR compared to the rate of moving down the job ladder for wage-and-salary workers. Thus, although we may expect job seekers to benefit from a less frictional labor market, fluidity in the labor market is largely manifested for golfers through a heightened risk of demotion. These findings are consistent with some recent studies which find that nondisplaced workers' job security (i.e. low probability of job loss) is a more important factor than the search frictions faced by displaced workers in accounting for persistent earnings losses from job displacement (Jarosch, 2015; Jung and Kuhn, 2018).

Despite a large initial upgrade in peer quality, I find no improvement in performance for the treatment group. This result also holds for young golfers who are at an important stage of development, further suggesting that, for highly skilled golfers, peers exert little direct influence on future performance. This finding has implications for the literature studying the effect of graduating from an elite law or business school on future earnings. Similar to qualifiers for the PGA TOUR, students at elite professional schools gain exposure to highly talented peers in their formative years. Yet, in contrast to my estimated earnings effects in golf, studies find significant returns to graduating from an elite school relative to a less highly ranked school (Oyer and Schaefer, 2019;

[6]For example, see Davis and von Wachter (2011), Oreopoulos et al. (2012), Jarosch (2015), and Lachowska et al. (2019).

Arcidiacono et al., 2008). The null peer effect result on golf performance supports the view that talented peers may help young professionals to establish job networks rather than to improve skills (Zimmerman, 2019; Oyer and Schaefer, 2019).

More generally, I contribute to the literature studying the self-employed labor market. A common thread throughout these studies is to use the self-employed to approximate a perfectly competitive spot market to shed light on the effects of labor market frictions on the outcomes of wage-and-salary workers.[7] To my knowledge, this is the first study to focus on the effect of employment shocks on population of self-employed workers. The self-employed account for about 10% of the workforce and are over-represented in both the upper and lower tails of the overall income distribution (Parker, 1997; Parker et al., 2005; Krashinsky, 2008). Golfers are located at the upper end of the income distribution, comparable to high-skilled professionals such as journalists, engineers, or architects.

I also contribute to a strand of literature that studies specific labor markets to understand the role of luck in labor market outcomes. For example, Oyer (2006, 2008) studies the impact of initial market conditions on long-term outcomes for economists and MBA students, and Bertrand and Mullainathan (2001) study whether CEOs are rewarded for random fluctuations in stock prices. Contrary to my results, these studies generally find a persistent role for luck in labor market outcomes. The disparity in these results is broadly consistent with a view that, as self-employed individuals, golfers operate in a more competitive environment in which shocks have less persistent effects.

Finally, I contribute to a growing literature that uses sports settings to gain insights into important questions in labor economics.[8] Golf, in particular, has been a fruitful area to apply economic

[7]For example, Krashinsky (2008) studies the role of institutional factors in rising wage inequality, Lazear and Moore (1984) studies how incentive pay can overcome agency problems, Carrington et al. (1996) studies the role of sticky wages in business cycle wage fluctuations, and Moore (1983) studies employer discrimination.

[8]Some examples include a study of the migration response to tax rates in European soccer (Kleven et al., 2013), taste-based racial discrimination in English soccer and Major League Baseball (Szymanski, 2000; Parsons et al., 2011), how soccer players are rewarded for lucky goals (Gauriot and Page, 2019), and the effect of female athletic participation in high school on college enrollment and labor force participation (Stevenson, 2010).

theory due to features such as objective performance, clear prize money structure, and high-quality data.[9] Most relevant to this study, Guryan et al. (2009) test for peer effects in the workplace using variation from the randomization of playing partners in some PGA TOUR tournament rounds. They find no evidence that playing with better golfers improves daily performance. I reach a similar conclusion, yet measure the effect of differences in peer quality over a full season on long-term performance.

In what follows, Section 2 provides an overview of relevant facts about golf and details of the natural experiments as well as describes the data. Section 3 provides some theoretical background for how persistent losses can accrue from temporary employment shocks and how these theories apply in a golf setting. Section 4 reviews the regression discontinuity identification assumptions, describes the estimation methods, and defends the validity of the identification assumptions in this setting. Section 5 presents the main results on earnings and performance as well as assesses the evidence for peer effects. Section 6 presents estimates of job transition rates in professional golf in comparison to transition rates for wage-and-salary workers. Section 7 concludes and discusses the implications of the findings.

2 Background, Data, and Descriptive Stats

2.1 Relevant Facts about Professional Golf

The object of golf is to strike a ball with a club into a hole in as few strokes as possible. Score is tallied over a *round* which consists of a course of eighteen golf holes. A typical golf tournament is a competition among 130 to 170 golfers played over four rounds in four days. Much like other sports, golf is played professionally for high stakes by individuals from around the world. The PGA TOUR is a professional sports league, or *tour*, which hosts some the world's most prestigious and lucrative golf tournaments. In 2012, the PGA TOUR held 45 official tournaments of which the

[9] Examples of golf studies include Ehrenberg and Bognanno (1990) who test for incentive effects of tournament prize structures, Pope and Schweitzer (2011) who test for loss aversion based on putting performance at different reference points relative to par, and Brown (2011) who studies the effect of superstars on competitors' performance.

median golfer competed in 17 and earned $286,089. The PGA TOUR maintains a compensation structure which favors top performers. For instance, first through fifth place earn 18.0, 10.8, 6.8, 4.8 and 4.0 percent of the total tournament prize money, or *purse*, respectively. In contrast, the highest scoring half of the field is disqualified, or *cut*, after the first two rounds of play and do not earn any money. Payoffs taper out such that the last position to make the cut, usually around 70th place, earns just 0.2% of the purse. The result is that 44.4% of the purse goes to the top 5 finishers, 60.05% to the top 10, and 83.35% to the top 25. Annual earnings tend to be heavily skewed towards top performers as well. For instance, in 2012 the leading money winner, Rory McIlroy, earned $8,047,952 while the bottom 25% of golfers on the PGA TOUR earned less than $49,380. Similarly, while some golfers played in upwards of 30 events, the bottom 25% played in three or less.[10] A unique aspect of golf, as opposed to similar sports such as tennis, is that each tour provides a set of golfers with an annual membership, or *tour card*, which provides golfers with the opportunity to participate in most of the season's tournaments.[11]

In addition to the PGA TOUR, there are many other golf tours throughout the world that offer significant prize money. The vast majority of the golfers on these tours are professional and rely on their golf earnings as their primary source of income. Figure 1 shows a hierarchy for golf tours for with I have assembled earnings data with the most prestigious at the top and the least prestigious at the bottom. The dollar figure in each box represents the average tournament purse for each tour over the 2012 season. The PGA TOUR, located in the US, offers the most lucrative prizes, awarding approximately three times the money as the second highest paying tour, the European Tour. Other important second- or third-tier tours are located in Asia, Australia, and South Africa. Some tours explicitly serve as developmental tours for more prestigious tours. For example, the Korn Ferry Tour is a development tour of the PGA TOUR. A dashed line in Figure 1 denotes a relationship between a developmental tour and a major tour. The main purpose of the Korn Ferry

[10] These statistics are computed with the sample of golfers who earn some money on the PGA TOUR in 2012 which includes 368 golfers.

[11] Among tour card holders, golfers can have different status depending on past success. For any given tournament, of those who wish to enter, only those with the highest status are accepted. Regardless, all golfers with a tour card have the opportunity to play in many events.

Tour is to prepare golfers to compete on the PGA TOUR and offer golfers that fail to retain PGA TOUR membership a competitive environment in which to maintain their skills in hopes of making it back to the PGA TOUR. Developmental tours pay substantially less than major tours at about one tenth of the prize money, but can pay enough to make a good living.[12] For instance, in 2012 out of the 287 golfers who earned some money on the Korn Ferry Tour, 106 earned over $50,000 and 57 earned over $100,000. The leading money winner, Casey Wittenberg, earned the substantial sum of $433,453. Given the disparities in pay and prestige, golfers generally strive play on either the PGA TOUR or the European Tour. Success on a lower tour is often awarded with the opportunity to transition to a better tour, likewise poor performance can result in demotion to a lower tour.

2.2 Details of the Natural Experiments

From 1962 to 2012 the PGA TOUR held an annual tournament called the PGA TOUR Qualifying Tournament (Q School) in which the top finishers were awarded a PGA TOUR card. Historically the primary avenue through which golfers earned a tour card, Q School was a four stage tournament with a pre-qualifying stage, first stage, second stage, and final stage. The final stage consisted of six rounds of golf, stages one and two had four rounds, and the pre-qualifying stage had three.[13] In comparison to a regular tournament of four rounds, Q School was a long and challenging event. For example, of the 1205 golfers that competed in 2005, only 32 were awarded a tour card.[14] Although the structure of the stages remained fairly constant over time, the number of tour cards awarded at final stage decreased from 49 in 1990 to 25 in 2012.[15] Of those that fail to qualify for a PGA TOUR card, the top 50 finishers plus ties earn a Korn Ferry Tour tour card. Hence, treatment

[12] See Appendix Figure D.5b for a plot of the ratio of PGA TOUR prize money to Korn Ferry Tour prize money over time. Although fairly stable, this ratio has fluctuated between 7 and 11.5.

[13] Depending on a golfer's status he may directly qualify for either first, second, or final stage without competing in the prior stage.

[14] The source of these numbers is Feinstein (2007), a national bestselling book documenting the challenges of the Q School process.

[15] A significant structural change occurred in 2006 when the pre-qualifying stage was introduced. See Appendix Figure D.2 for a plot of the number of tour cards awarded each year.

is defined as obtaining a PGA TOUR card, whereas untreated golfers receive a Korn Ferry Tour card. Although Q School started in 1962, I only have complete information on the results from 1990 to 2012.

In 1990 the PGA TOUR created a developmental tour, currently named the Korn Ferry Tour.[16] The Korn Ferry Tour hosts about 29 tournaments each year which award prize money with a similar payout structure as PGA TOUR tournaments. The *money list* aggregates this prize money into an annual ranking. Each year the PGA TOUR awards the top finishers on the Korn Ferry Tour money list (Korn Ferry Tour ML) with a PGA TOUR card. While fewer tour cards were awarded through Q School over time, more were awarded through the Korn Ferry Tour ML. These changes reflect the PGA TOUR's perception that the Korn Ferry Tour ML produced higher quality golfers.[17] In 2012 PGA TOUR policy awarded the top 25 golfers on the money list with a PGA TOUR card and those finishing between 26 and 50 with a Korn Ferry Tour tour card. Hence, the award structures at the treatment threshold are very similar for both natural experiments. I analyze the effects of Korn Ferry Tour ML experiments over the same period as Q School, from 1990 to 2012.

The regression discontinuity (RD) designs are built on the assumption that, within a small window around the treatment thresholds, golfers are unable to manipulate their treatment status. This assumption precludes the possibility of a discontinuous jump in ability across the treatment threshold. The key factors that make manipulation difficult for golfers are the high level of competition and the random nature of golf due to factors related to weather, wind, and natural terrain. Section 4.1 presents a more complete case for why the non-manipulation assumption is satisfied in this setting.

[16] At the time of its founding the tour was named the Ben Hogan Tour and at different times has been called the Nike Tour, the Buy.com Tour, the Nationwide Tour, and the Web.com Tour.

[17] Evidence for this claim can be found in a change of PGA TOUR policy in 2013. After this point, PGA TOUR cards have only been awarded through the Korn Ferry Tour ML, whereas Q School provides membership benefits only to the Korn Ferry Tour. To compensate for the loss of Q School qualifiers, the top 50 places on Korn Ferry Tour ML now earn a PGA TOUR card, rather than the top 25. The PGA TOUR website makes the following statement with regard to the reason for the policy change: "The change was made due to a variety of factors, but the overwhelming success of Korn Ferry Tour graduates over 20+ years on the PGA TOUR was the primary motivation for the change." <http://www.pgatour.com/company/pga-tour-faqs.html>

Given the similarity of their treatments, each experiment serves as a replication of the other. It is rare to find two natural experiments that can be used to produce two sets of estimates of a similar treatment. Yet, there are some subtle differences that are important to mention. First, in a given year golfers can tie at the same Q School finish position, whereas there are no ties in the Korn Ferry Tour ML rank. This feature produces a more discrete running variable in the Q School experiment and, as a result, I employ an estimation technique called *local randomization* (Cattaneo et al., 2015). A second difference between the experiments is that Korn Ferry Tour golfers who fail to qualify for a PGA TOUR card can subsequently attempt to earn a tour card through Q School.[18] The opportunity to gain a PGA TOUR card through Q School could potentially weaken the Korn Ferry Tour ML treatment as golfers have a second chance to receive treatment.

A final difference between the experiments is that they affect slightly different populations. Table 1 presents descriptive statistics related to demographics, ability, and experience using only the five closest golfers to each side of the treatment threshold in both experiments.[19] Although the average age and share foreign born is similar across experiments, Q School golfers are slightly younger and more likely to be foreign born. Notably, Korn Ferry Tour ML golfers appear to be of higher average ability than Q School golfers with a lower Official World Golf Ranking (OWGR) and scoring average and higher US earnings. Yet, neither population is obviously more experienced than the other. Q School golfers have more experience on the PGA TOUR, but Korn Ferry Tour ML golfers have more experience on the Korn Ferry Tour. The Q School sample has greater variance in almost all observable characteristics. Indeed Q School rank is likely to be a noisier measure as the Korn Ferry Tour ML rank is tallied over a year's performance, whereas Q School is only one extended tournament. Differences in the dispersion and average levels of ability across the natural experiments open the possibility that heterogeneous treatment effects will create different average treatment effects across the experiments, despite the fact that the actual treatment is similar. Conversely, if we see similar results across both experiments, we may deduce that heterogeneous

[18] See Appendix Figure D.1 for an example timeline of the relevant dates from 2012.

[19] Ties in the running variables are broken alphabetically by first name and then by last name.

treatment effects are insignificant across the range of abilities in the treatment populations.

In addition to qualifying through Q School or the Korn Ferry Tour ML, there are alternative ways to qualify for PGA TOUR events. For instance, the top 125 golfers on the PGA TOUR money list automatically are granted a tour card for the next season. There are also exemptions for exceptional performances such as wining tournaments and accumulating significant career earnings. Golfers that finish between 126 and 150 on the previous year's PGA TOUR money list qualify for *conditional status*. Conditional status provides PGA TOUR membership benefits at lower priority than Q School or Korn Ferry Tour ML graduates.[20] Golfers can also qualify for a medical exemption if they held a tour card in the previous year but missed many events due to a serious injury. Golfers can qualify for single tournaments each week through "Monday qualifiers", which are one round tournaments that accept only a few golfers. Tournaments also offer sponsor's exemptions which grant entry into a single tournament, but these are very limited and generally given to past champions on the PGA TOUR. Golfers that finish in the top 25 of a PGA TOUR tournament are often exempt to play in the next week's event. Also, if a golfer earns prize money greater than or equal to last year's 100th place finisher on the past year's PGA TOUR money list, then he is granted a tour card for the remainder of the season. Although there are multiple paths to playing on the PGA TOUR, it is very difficult for golfers without PGA TOUR status to gain consistent access without entering Q School or the Korn Ferry Tour and, hence, these have historically been the main avenues by which golfers earn a PGA TOUR membership.

2.3 Data

Sample Selection I restrict the sample to golfers between 17 and 55 years of age. I exclude golfers that compete yet hold exemptions, including conditional status on the PGA TOUR, a PGA TOUR card earned through the Korn Ferry Tour ML (which applies only to the Q School sample), medical exemptions, and career money list exemptions. Golfers that hold these exemptions have

[20] On average golfers with conditional status play in 19 PGA TOUR events in the next year, whereas Q School graduates play in 25 events and Korn Ferry Tour ML graduates play in 26.

better outside options should they fail to qualify and, therefore, face a different potential treatment. Mixing both types of golfers may weaken the treatment effect and confuse the interpretation. For my main specification, I drop experiment years 1990 and 1991 from the sample as only five golfers qualified through the Korn Ferry Tour ML in these years.[21]

Earnings Data Given that golf is a global game, it is important to collect worldwide earnings information. To produce such a dataset, I merge the earnings of each golfer going as far back as 1980 from eight golf tours, including: the PGA TOUR, the Korn Ferry Tour, the European Tour, the Challenge Tour, the Japan Tour, the Asian Tour, the PGA Tour of Australasia, and the Sunshine Tour.[22] The most important source of earnings data comes from the PGA TOUR and Korn Ferry Tour. Players on these tours can be linked through a unique identification number, providing a highly reliable merge. Earnings data from tours other than the PGA TOUR and the Korn Ferry Tour are assembled through a merge on golfers' full names. Duplicate names are not common, primarily as a result of the fact that the total number of unique golfers in the sample is modest at 3,696. As earnings can be observed throughout a career across multiple tours, I refer to aggregate earnings from all tours as *world earnings*.

In order to make comparisons of earnings across time, two adjustments are required. First, a standard adjustment for inflation is appropriate. Second, and more unique to the golf setting, earnings should be adjusted for the increase in demand for watching golf over the period. As golf grew in popularity, prize money far outpaced the rate of inflation. For instance, prize money grew at a 12.5% annual rate in the 1990s and 7.8% in the 2000s. Without such an adjustment, the results would implicitly weight recent earnings observations more heavily. My solution is to adjust for the rate of growth in tournament purses in an effort to simultaneously account for inflation and increased viewing demand. Specifically, for each golfer i, I multiply total earnings e in year t by an adjustment factor equal to the average PGA TOUR tournament purse m in year 2012 divided by

[21] See Appendix Section F.4 for the results including exempt golfers and from different time periods.

[22] The Korn Ferry Tour and the Challenge Tour started in 1990. Asian Tour and Sunshine Tour data being in 1995 and 1991, respectively. See Appendix Table E.1 for the full details of earnings data availability by tour.

the average purse in year t. Thus adjusted earnings $\tilde{e}$ can be expressed with the following formula:

$$\tilde{e}_{it} = e_{it}\frac{m_{2012}}{m_t} \qquad \forall i, t \tag{1}$$

which normalizes earnings to 2012 dollars.[23]

Given the strong skewness in the tournament payout distribution, it is not surprising to find that annual earnings distributions are also highly skewed. In fact, the earnings distribution has a skewness of 5.16 and a kurtosis of 43.68. Of course, skewness is common in earnings distributions and, as a result, researchers often use a log transformation. In this setting, such a transformation may be important because the sample sizes are modest and, therefore, more closely approximating a normal distribution can reduce the variance of the estimates. However, another challenge in working with golf earnings data is that "nonemployment" is common, i.e. some golfers register zero earnings in many years of their careers. While the log transformation nicely normalizes earnings, it drops all observations with zero earnings. This presents a problem as the rate of participation (defined as recording any amount of positive world earnings) declines precipitously after treatment.[24] As a result, I employ the inverse hyperbolic sine (IHS) transformation for the main specification.[25] This transformation is a very close approximation to the log transformation while at the same time it is defined for observations with zero earnings.

In addition to tournament prize money, some golfers receive large sponsorship deals from firms which effectively serve as an additional source of income. Lacking data on sponsorship earnings, the results must be interpreted as the effects on tournament prize money only. However, lucrative sponsorship contracts are largely reserved for only a handful of the most recognizable golfers and are likely to be positively correlated with performance. Hence, prize money should be a good proxy for sponsorship earnings.

[23]See Appendix Figure D.5 for a plot of the evolution of average PGA TOUR tournament purses over time.

[24]For example, the rate for participation falls to 85% (70%) four years after treatment and 55%(45%) ten years after treatment for the Korn Ferry Tour ML (Q School) experiment. See Appendix Section B for descriptive statistics on participation and for more information on the golf earnings distribution.

[25]The formula for the IHS is $\sinh^{-1}(x) = \ln\left[x + \left(1 + x^2\right)^{1/2}\right]$.

Performance Data To compute a measure of performance, I use data provided by the PGA TOUR complete with all scores from both PGA TOUR and Korn Ferry Tour events from 1990 to 2014. Although for any given tournament round a golfer's score is a direct measure of performance, to compute an annual measure one must aggregate scores across tournament rounds. However, scores are not easily comparable across tournament rounds as the difficulty of golf courses varies. Even on the same golf course, weather conditions can dramatically affect performance from day to day.

With these challenges in mind, I perform an adjustment in an effort to produce a consistent measure of performance across tournaments and, thus, across golfers. Let score s of golfer i for tournament round r in year t be denoted by s_{irt}. Score can be written implicitly as a function f_1 of the ability of golfer i in round r and year t, the difficulty of the golf course in round r in year t, and residual factors ϵ_{irt}, as:

$$s_{irt} = f_1 \left(\text{golfer ability}_{irt}, \text{golf course difficulty}_{rt}, \epsilon_{irt} \right). \tag{2}$$

A problem with score as a measure of performance is that it depends not only on a golfer's ability but also on the difficulty of the golf courses played which is correlated with ability. One approach would be to try to directly control for the difficulty of golf courses with information such as golf course ratings and weather conditions.[26] However, these measures would not only be challenging to collect, but also can be poor proxies for course difficulty.

I take an alternative approach by comparing each golfer's score to his competitors in the same round. Specifically, I subtract the field leave-out mean score in round r and year t from each score in order to control for any common factors that contribute to course difficulty on a given day. This results in a new implicit function f_2 in which relative score $\tilde{s}_{irt}$ depends both an individual golfer's

[26] Guryan et al. (2009) adjust scores using golf course ratings provided by the United States Golf Association. They do not adjust for weather conditions.

ability, the ability of the field in round r and year t, and residual factors ϵ_{irt}, such that:

$$\tilde{s}_{irt} = s_{irt} - \overline{s}_{rt} = f_2\left(\text{golfer ability}_{irt}, \text{field ability}_{rt}, \epsilon_{irt}\right). \tag{3}$$

In this case a similar problem arises in that relative score $\tilde{s}_{irt}$ is not only a function of the individual golfer's ability but also of field ability which is again correlated with ability. However, in this case, I leverage the system of Official World Golf Rankings (OWGR). The OWGR system is designed to rank golfers who play on different tours throughout the world.[27] I use the OWGR, denoted as x, of each golfer i in round r and year t as a proxy for individual ability and field leave-out mean OWGR $\overline{x}$ in round r and year t as a proxy for field ability. I use third order polynomials in both x_{irt} and $\overline{x}_{rt}$ to flexibility approximate f_2 with the following estimation equation:

$$\tilde{s}_{irt} = \alpha_t + \beta_{1t}x_{irt} + \beta_{2t}x_{irt}^2 + \beta_{3t}x_{irt}^3 + \gamma_{1t}\overline{x}_{rt} + \gamma_{2t}\overline{x}_{rt}^2 + \gamma_{3t}\overline{x}_{rt}^3 + \epsilon_{irt}. \tag{4}$$

I then proceed to estimate equation (4) separately for each year using OLS regressions. To control for field quality, I then adjust the relative score according to the quality of the field. My final measure of adjusted score, $\tilde{\tilde{s}}$, can be expressed as:

$$\tilde{\tilde{s}}_{irt} = \tilde{s}_{irt} - \left[\hat{\gamma}_{1t}\left(\overline{x}_{rt} - \overline{\overline{x}}_t\right) + \hat{\gamma}_{2t}\left(\overline{x}_{rt}^2 - \overline{\overline{x}}_t^2\right) + \hat{\gamma}_{3t}\left(\overline{x}_{rt}^3 - \overline{\overline{x}}_t^3\right)\right] \tag{5}$$

where $\overline{\overline{x}}_t$ represents average golfer OWGR in every PGA TOUR and Korn Ferry Tour tournament in year t. The first component of this formula is the measure of score relative to the field. The second component adjusts for the quality of the field by multiplying the estimated γ regression components from equation (4) by the difference in field quality between round r and an average round. With adjusted scores $\tilde{\tilde{s}}_{irt}$ I then compute an annual adjusted scoring average as:

$$\tilde{\tilde{s}}_{it} = {}^{1}/_{n_{it}} \sum_r \tilde{\tilde{s}}_{irt} \tag{6}$$

[27] See Appendix Section A.1 for an overview of the OWGR data.

where n_{it} is the total number of rounds played by golfer i in year t. Since the treated golfers mostly play in PGA TOUR events while untreated golfers mostly play in Korn Ferry Tour events, average field quality is systematically higher for those in treatment. The key feature of this measure is that it allows one to compare future performance regardless of the tour on which a golfer plays.

2.4 Descriptive Career Profiles

Economists have long observed a life-cycle pattern in which earnings rise quickly in the early career, peak around age 50 to 55, and slowly decline thereafter toward retirement. Figure 2 presents a similar, albeit more dramatic, life-cycle pattern for golfers on the PGA TOUR and Korn Ferry Tour. Specifically, Figure 2a plots the career earnings profile for golfers who played in at least five tournaments on the PGA TOUR or Korn Ferry Tour from 1990 to 2014. The blue circles plot average log earnings by age and the blue solid line plots a fitted curve of an OLS regression of log earnings on a cubic in age. This curve features a steep rise in earnings until about age 37 after which earnings decline. However, this sample construction procedure introduces a potential selection bias as many golfers are not able to record positive prize money every year and are dropped in the log transformation. Whereas top golfers often earn positive earnings in all years, below average golfers are more likely to earn positive money only in their prime years of the mid-30s. To concentrate only on within-golfer earnings growth, the red dashed line plots the age profile of a regression that controls for individual fixed effects.[28] The differences between the regression lines with and without fixed effects lend support to this selection story as the fixed effects curve is steeper than the curve without them, suggesting that systematic negative selection during prime age years flattens the earnings growth curve. Therefore, I focus on the red dashed line when drawing observations about earnings growth. Figure 2a shows that average golfer earnings rise substantially over a short period of time to reach peak earnings at age 33. In just thirteen years, average golfer earnings rise by an incredible 300 log points or by 1908%. For perspective, using US Social

[28] With the addition of individual fixed effects the level of the y-intercept arbitrarily depends on the "leave-out" individual. Therefore, I set the y-intercept equal to the y-intercept in the OLS regression without fixed effects.

Security Administration data Guvenen et al. (2015) find that average earnings increase by 154% from age 20 to 54 in the US labor market. The steep rise in golf earnings is only comparable to the top 1% of lifetime earners who Guvenen et al. (2015) find experience 2600% earnings growth, yet do so over 34 years.

Figure 2b presents evidence that golfers' performance also improve rapidly with experience. Similar to Figure 2a, the figure plots the adjusted annual scoring average by age (blue circles), a fitted OLS regression line of scoring average on a cubic function in age (blue solid line), and a fitted OLS regression line of scoring average on a cubic function in age controlling for individual fixed effects (red dashed line). Given that lower scores are better, a negative slope represents an improvement in performance. Analyzing the fixed effects curve, performance improves sharply during golfers 20s. Peak performance occurs around age 32, slightly earlier that peak earnings. These profiles suggest that productivity and earnings are intimately related and that the 20s are a particularly important period for productivity improvements.

3 Theory

Broadly speaking, theories of persistent losses from employment shocks can be distinguished by whether they attribute earnings losses to productivity losses or to hiring and firing frictions in the labor market. Much of the literature focuses on what I broadly describe as hiring and firing frictions to explain persistent earnings losses from employment shocks. For example, search theory considers the consequences of a frictional job search process in which it takes time to find good job opportunities. In these models, job search can increase earnings without a corresponding increase in productivity.[29] If a worker that has accumulated job search rents suffers an employment shock, she may lose these rents and be left to sample offers at the bottom of the job ladder. Given that job offers come sporadically, it may take time for earnings to recover to the counterfactual level, had she remained employed and entertaining better offers. I include theories of job search, signaling,

[29]For example, Burdett and Mortensen (1998) present a wage posting model in which search frictions create a job ladder such that workers find higher paying jobs over time despite the fact that their productivity remains constant.

long-term contracts, industry- or firm-specific human capital, and firm-worker match complementarities under the umbrella term of *hiring and firing frictions*.[30] All of these theories depend on the characteristics of a joint decision-making process between firms and workers involving features such as job offers, acceptance decisions, contracts of significant duration, quitting decisions, and firing decisions. This joint decision-making process is much more limited for self-employed professionals such as free-lancers. In the case of golfers, this process is non-existant as promotion is based on objective and indiscriminate performance thresholds. Therefore, we should not expect golfers' recovery from employment shocks to be affected by hiring and firing frictions.

On the other hand, employment shocks may produce productivity losses if they significantly disrupt the human capital or skill accumulation process through spells of unemployment or employment in low quality jobs. Evidence from both the job displacement and graduating in recessions literatures suggest that employment in low quality jobs is an important determinant of earnings losses. For instance, both Kahn (2010) and Oreopoulos et al. (2012) find small or insignificant effects of graduating in a recession on unemployment in the first year after graduation. Yet, Oreopoulos et al. (2012) find evidence that recession graduates initially work for smaller and lower paying firms. In terms of job displacement, Lachowska et al. (2019) find that displaced workers are only 10% less likely to earn positive earnings one year after displacement, yet take jobs at lower wages and work less hours. Schmieder et al. (2018) find that displaced workers are re-employed at lower paying firms.[31] If employment shocks cause workers to take jobs at lower quality firms with less talented peers, then they could disrupt the learning process and have lasting consequences on productivity. Importantly, in order to incur lasting productivity effects, workers must be stuck in a poor learning environment for a significant period of time. Thus, either hiring

[30]For examples of signaling models see Greenwald (1986), and Gibbons and Katz (1991). For issues related to long-term contracts see the job displacement survey by Carrington and Fallick (2017). For a discussion of industry-, firm-, or match-specific earnings effects see Neal (1995), Oreopoulos et al. (2012), and Lachowska et al. (2019) among many others.

[31]Using data from Germany, Schmieder et al. (2018) find that displaced workers are 18% less likely to earn positive income one year after displacement. The higher incidence of nonemployment may be due to the more generous unemployment insurance benefits of the German system.

and firing frictions or some other source of persistence must prevent workers from immediately restoring the quality of their work environment.

In the golf context, the employment shocks induced by narrowly missing the treatment thresholds in Q School or the Korn Ferry Tour ML change the quality of the work environment as golfers move from the less prestigious Korn Ferry Tour to the PGA TOUR. This change in work environment may affect performance in multiple ways. First, exposure to the world's best golfers on the PGA TOUR could have important peer effects that improve performance. For example, golfers may learn new swing techniques or course management strategies. Peer effects may be particularly important for young golfers who are at an important state of development.[32] Golfers performance many be affected by other factors as well. For instance, the psychological shock of narrowly missing an opportunity to realize the dream of playing on the PGA TOUR could cause golfers to suffer a loss of confidence that has an effect on future performance.[33] Moreover, the experience of playing on more difficult golf courses, in front of larger audiences, for larger prize money may improve performance as golfers gain experience under pressure. The membership rules of the PGA TOUR assure that these employment shocks last for a full year, which may be a sufficient duration to significantly affect the skill accumulation process. Since this is an indiscriminate institutional rule, I classify this process as an institutional friction, rather than a hiring and firing friction.

4 Identification and Estimation

To discuss identification I adopt the notation of the potential outcomes framework. Let R_i denote a running variable which determines treatment. Depending on the natural experiment under consideration, R_i represents either finish position at PGA TOUR Qualifying School (Q School) or year-end ranking on the Korn Ferry Tour Money List (Korn Ferry Tour ML). For both natural experiments, let D_i be a binary variable which indicates treatment status. The treatment thresholds

[32] See Figure 2b for evidence that the average professional golfer quickly improves from age 20 to 32.

[33] The presence of negative psychological effects from an employment shock could be consistent with evidence of negative health effects from job displacement (e.g. Sullivan and von Wachter, 2009).

define the treatment groups such that all golfers finishing below the threshold are treated while those finishing above the threshold are untreated. In both experiments, treated golfers recieve a PGA TOUR card and untreated golfers receive a Korn Ferry Tour card. Let Y_i denote an observed future outcome of interest for golfer i such as earnings, events played, or scoring average. Let $Y_i(1)$ denote the potential outcome of golfer i with treatment and $Y_i(0)$ capture the potential outcome without treatment. Although each individual has two potential outcomes, only one outcome is observed. Hence, the challenge is to construct an estimate of the unobserved outcome. My research design exploits the sharp qualification cutoffs defined by the PGA TOUR by using the outcomes of golfers who narrowly fail to qualify as a counterfactual outcome for golfers who narrowly succeed in qualifying. This research design structure corresponds to a *sharp* regression discontinuity (RD) design where treatment compliance is either perfect or attention is focused on the intention-to-treat parameter. The sharp RD estimates specifically represent causal effects of gaining PGA TOUR access through Q School or the Korn Ferry Tour ML, rather than estimates of causal effects of playing one season on the PGA TOUR. These two objects may be different as failing to qualify through the experiments does not necessarily preclude golfers from gaining access to PGA TOUR tournaments through other means.[34]

I employ slightly different estimation techniques across the two natural experiments due to some differences in their implementation. Each year in the Q School experiment many golfers tie near the treatment threshold. In contrast, there are no ties in the Korn Ferry Tour ML rank near the treatment threshold. Therefore, the Korn Ferry Tour ML running variable is in practice closer to a continuous variable than in the Q School experiment.[35] For the Korn Ferry Tour ML experiment, I employ the standard RD assumption that the conditional expectation functions of potential outcomes are sufficiently continuous at the treatment threshold, or, in other words, that

[34] As a robustness check, I estimate a fuzzy RD design where PGA TOUR membership is defined as playing in 20 PGA TOUR events. See Appendix Section F.5 for the results and a discussion of the merits of the fuzzy design.

[35] Since I observe multiple occurrences of similar natural experiments over time, I stack these experiments to create one large experiment. The result is that both measures become more discrete, but the Q School running variable is a close enough approximation to a continuous variable that I employ the standard methods for continuous running variables.

the characteristics of golfers do not abruptly change across the treatment threshold (Hahn et al., 2001). For the Q School experiment, I employ *local randomization* methods in which the treatment is assumed to be randomly assigned within a small window around the treatment threshold (Cattaneo et al., 2015). Although technically a different assumption, it also captures the intuition that unobserved characteristics do not abruptly change across the treatment threshold. I discuss both estimation methods and their corresponding identification assumptions in further detail below.

Continuous Running Variable As the Korn Ferry Tour ML experiment features a running variable that is approximately continuous, I employ more standard RD estimation methods in this case. Each golfer with observed running variable R_i above the known threshold $\overline{r}$ is assigned to the non-treated group ($D_i = 0$) and each individual with R_i below $\overline{r}$ is assigned to the treatment group ($D_i = 1$).[36] Thus, $D_i = \mathbb{1}(R_i \leq \overline{r})$ for each individual i in the sample. The main parameter of interest is the average response to treatment at the treatment threshold $\overline{r}$, defined as:

$$\tau_c = \mathbb{E}[Y_i(1) - Y_i(0)|R_i = \overline{r}] \tag{7}$$

where the c subscript is meant to denote the treatment effect in the case of a continuous running variable. Estimation of τ_c is based on taking the difference of the estimates of the right limit of the conditional expectation function $\mathbb{E}[Y_i(1)]$ at $R_i = \overline{r}$ and the left limit of the conditional expectation function $\mathbb{E}[Y_i(0)]$ at $R_i = \overline{r}$.

To estimate τ_c I follow Cattaneo et al. (2016c) in implementing the following steps.[37] First, I choose a polynomial of degree one and a triangular kernel weighting function, $\kappa(\cdot)$, to compute the coverage error optimal RD bandwidths separately on each side of the cutoff, denoted as h_l and h_r. The bandwidth parameters are key to properly identify the limits of the conditional expectation functions at the treatment threshold and are what render the estimates "nonparametric" despite

[36]The treatment threshold is defined as the midpoint between the last golfer that qualified and the first golfer that failed to qualify. For instance, if the 25th placed golfer receives treatment and the 26th placed golfer does not, then $\overline{r} = 25.5$.

[37]I use the Stata software program *rdrobust* described in Calonico et al. (2017).

the use of a linear functional form. Second, I drop all observations outside the neighborhood $W_c = [\overline{r} - h_l, \overline{r} + h_r]$. Hence, these regression are local in the sense that they only use data from within a window around the treatment threshold. Third, I estimate the following equation as a weighted least-squares regression allowing for different slopes on each side of the treatment threshold:

$$Y_i = \alpha + \tau D_i + \beta_1 \overline{R}_i + \beta_2 \overline{R}_i D_i + \epsilon_i \tag{8}$$

with weights $\kappa\left(\overline{R}_i/h\right)$, where $\overline{R}_i = R_i - \overline{r}$ is the re-centered running variable. As Cattaneo et al. (2016c) show, identification of τ_c via the weighted least-squares estimates of τ in the above regression model requires that the conditional expectations functions $\mathbb{E}[Y_i(0)]$ and $\mathbb{E}[Y_i(1)]$ are sufficiently smooth functions around the treatment threshold where $R_i = \overline{r}$.[38] Section 4.1 presents evidence that this assumption is satisfied.

Discrete Running Variable Given the highly discrete nature of the running variable in the Q School experiment, methods designed for continuous running variables may not closely approximate the true average treatment effects. Therefore, I employ the *local randomization* method proposed by Cattaneo et al. (2015) and Cattaneo et al. (2016c). In its most basic form, the idea behind local randomization is simple. This approach assumes that, within a small neighborhood or window around the RD cutoff, the assignment of individuals to treatment or control status is random, as it would be in, say, a randomized controlled trial. Although this seems like a very strong assumption, it may be less so within a very local region.

Define the expected difference between the treated and non-treated groups in the discrete setting as:

$$\tau_d = \mathbb{E}[Y_i(1) - Y_i(0) | i \in W_d]. \tag{9}$$

[38] Specifically, $\mathbb{E}[Y_i(0)|R_i = \overline{r}]$ and $\mathbb{E}[Y_i(1)|R_i = \overline{r}]$ must be three times continuously differentiable.

where $W_d = [\overline{r} - w, \overline{r} + w]$, $w > 0$, is a small window around the treatment threshold $\overline{r}$. Formally, τ_d identifies the average treatment effect under an assumption that the running variable, R_i, is independent of potential outcomes within W_d. Cattaneo et al. (2015) show that a simple difference-in-means statistic across treatment status can be used to obtain an unbiased point estimator of the average treatment effect. Furthermore, under the null hypothesis that the average treatment effect is zero, they show that an exact p-value can be computed for the difference in means statistic using finite sample methods.[39]

The downside of this approach is that the randomization window must be known or estimated. However, in my case I select the most conservative window possible at one stroke in either direction of the treatment threshold. Despite using such as small window, I am still able to estimate average treatment effects relatively precisely in comparison to the local linear regression methods. The identification condition assumes that conditional on finishing within one stroke of the cutoff, luck determines whether a golfer qualifies or not. Section 4.1 presents evidence that this assumption is satisfied.

4.1 Validation of Identification Assumptions

Despite some subtle differences in the nature of the identification assumptions for each experiment, both assume that golfers cannot precisely manipulate their position around the treatment threshold and, hence, their treatment status. In the following section, I provide evidence to suggest that these RD designs satisfy the identification assumptions in four steps. First, I provide evidence of high short-term volatility in golf outcomes, casting doubt on the feasibility of precise manipulation. Second, I present visual evidence of a lack of discontinuities in outcomes at points other than the

[39] A few caveats to these identification and inference arguments should be addressed. First, in order to compute an exact p-value with finite sample inference methods, the treatment assignment mechanism must be known within the window. In this case, the treatment assignment mechanism is assumed to be a Bernoulli distribution with the probability of treatment equal to the total share of treated golfers within one stroke on either side of the treatment threshold. Second, in order to identify the average treatment effect, the treatment effect must be non-negative for all individuals and the Stable Unit Treatment Value Assumption must also be satisfied. See Cattaneo et al. (2015) and Cattaneo et al. (2016c) for the details of the technical issues involved.

treatment threshold throughout the range of the running variable. Third, I provide evidence that the density of golfers on each side of the treatment threshold is balanced. Finally, I supply evidence that pre-treatment observable characteristics are balanced across treated and non-treated groups at the treatment threshold. I conclude that both the Q School and Korn Ferry Tour ML experiments provide compelling conditions in which to employ a RD design and, hence, the results can be given a causal interpretation.

When thinking about potential violations of the identifying assumptions in a golf context, two potential concerns come to mind. The first is an effort story. Lazy, yet talented, golfers may be able to exert low effort until the end of Q School or the Korn Ferry Tour season at which point they exert more effort, improve performance, and narrowly qualify. Furthermore, large PGA TOUR prize money may keep these golfers incentivized to exert full effort once treated which could result in persistent earnings differences. Another possibility is a pressure story. Some golfers may perform better during the final, pressure-packaged stages of a golf tournament or season. Furthermore, golfers that perform under pressure may do better on the PGA TOUR. Although not exhaustive, these examples provide important potential mechanisms which could lead to a violation of the identification assumptions, and, hence, are helpful to bear in mind while assessing the evidence for the validity of the identification assumptions.

Volatility of Short-Term Outcomes Since golf is played outdoors, it is subject to the random disturbances of wind, weather, and the bounce of a ball on natural surfaces. These factors make it difficult to control the outcome in the short-run. In an effort to quantify the short-run volatility in golf, I compute autocorrelations of both short-run and long-run outcomes. I find low autocorrelations in the short-run. The correlation of adjusted score in consecutive rounds is 0.20 and the correlation in finish position at consecutive tournaments of 0.16. In contrast, the correlation over consecutive seasons is 0.72 for year-end rank on the PGA TOUR, 0.65 for annual adjusted scoring average, and 0.87 for year-end OWGR.[40] These findings suggest that performance over the course

[40]The statistics are computed with a sample of golfers who played in at least five PGA TOUR or Korn Ferry Tour events between 1990 and 2014.

of a single round or tournament is a poor indicator of long-run performance. Each time Q School was contested, only one stroke separated the last qualifier from first non-qualifier. For the Korn Ferry Tour ML, the average difference in earnings between the last qualifier and first non-qualifier is about $8,200. This amounts to roughly the difference between 5th and 10th place in a typical Korn Ferry Tour event–positions which are often separated by only one or two strokes. Given such small margins, the short-run volatility inherent to golf would make precise manipulation around a treatment threshold very difficult, if not implausible.

Discontinuities in RD Plots Another way to explore the validity of the identification assumptions is to inspect the data for discontinuities away from the treatment thresholds. Figure 3 presents a plot of the number of PGA TOUR events played in the year after treatment for both experiments. These plots include a global polynomial to provide a sense of the underlying function form of the conditional expectation functions. The plots also include binned mean values to help to check for potential discontinuities away from the treatment threshold and to provide a visual representation of the overall variability of the data.[41]

Both panels of Figure 3 show a strong initial treatment effect on the number of PGA TOUR events played with clear discontinuities at the treatment threshold. The magnitudes of these discontinuities are large relative to the mildly negative slopes of the outcome variables with respect to the running variables. Furthermore, there are no clear discontinuities at any other point in the range of the running variables suggesting that there is no reason to suspect that the discontinuities at the threshold arise spuriously.[42]

Density Balance Another common test of manipulation in a RD design is a test for a discontinuity in the density of the running variable across the treatment threshold. Figure 4 presents

[41] Calonico et al. (2015) develop methods to compute sample means based on bin sizes that are optimal either for detecting discontinuities or representing the underlying variability of the data. I select bins such that the RD plots represent the underlying variability of the data. The local sample means are constructed such that each bin has approximately the same number of observations on each respective side of the cutoff.

[42] Appendix Section D.1 presents RD plots for other relevant outcomes in which similar conclusions can be drawn.

histograms from each experiment according to their respective running variables for both non-exempt and exempt golfers. Panel 4b presents the distribution for the Q School experiment and reveals an approximate normal distribution with perhaps a slight right skew. There are 160 treated and 172 untreated non-exempt golfers within one stroke of the treatment threshold. Visual inspection shows no evidence of a discontinuity in the density at the cutoff. I test for a discontinuity in density at the treatment threshold using methods introduced by Cattaneo et al. (2016b) and fail reject the null hypothesis of no discontinuity at the threshold with a p-value of 0.39.[43]

Panel 4a displays the histogram for the Korn Ferry Tour ML experiment, revealing a very different type of distribution. Since the running variable is an annual aggregation of prize money, there are no ties within a given year. I estimate the effects of the Korn Ferry Tour ML threshold for 23 years from 1990 to 2012, and, as a result, for most values of the running variable there are 23 observations. However, since I drop exempt golfers from my estimation sample, there need not be 23 by definition. Visual inspection shows no evidence of a discontinuity in the density at the treatment threshold and I fail to reject the null hypothesis of no discontinuity with a p-value of 0.95 with the formal test.

Balance in Observable Characteristics I also test for differences in pre-treatment, observable characteristics at the treatment thresholds. Differences in observable characteristics may be an indication that golfers are able to manipulate their treatment status around the threshold. For the balance tests, I apply the same RD estimation methods to pre-treatment characteristics as are used to estimate treatment effects for the outcome variables. Thus I use local linear regression for the Korn Ferry Tour ML experiment and local randomization for the Q School experiment. I test for discontinuities in demographics (age and foreign born), measures of ability (scoring average and OWGR), past experience, and past earnings. Table 2 displays the results of balance test regressions. Panel A presents the results for the Korn Ferry Tour and Panel B shows the results for Q School.

[43] I conduct this test using the software program *rddensity* described in Cattaneo et al. (2016a). This method is an extension of the density test suggested by McCrary (2008) as it does not require pre-binning of density values and it includes bias correction terms for optimal mean squared error bandwidths.

Columns (1) through (4) report the results for observable characteristics in the year of experiment participation while columns (5) through (8) report results for the golfers' total history prior to the year experiment participation. The tables do not report standard errors, but instead report p-values for conciseness.

Most pre-treatment observable characteristics from the Korn Ferry Tour ML in year of experiment participation (year 0) appear to be smooth across at the treatment threshold. The only exception is a negative coefficient on foreign born which is significant at the 10% level. This result suggests that treated golfers are about 16% less likely to be foreign born. There also is some suggestive evidence that treated golfers may be older, but the coefficient is not statistically significant. In terms of OWGR, adjusted scoring average, events played, and earnings, there is no evidence for a discontinuity at the treatment threshold in year 0. Turning to results for the full golfer histories prior to year 0, I find similar results. There is no evidence that treated golfers had a lower past scoring average or played in more events. There is some evidence to suggest that treated golfers accumulated more PGA TOUR earnings with a positive coefficient significant at the 10% level. However, there are no significant differences in world earnings, suggesting that untreated golfers made up for the difference with earnings from outside the US. Overall, I find little evidence that higher ability golfers are able to manipulate their treatment status. There is some evidence that untreated golfers are more likely to be foreign born. However, given that I test for differences in sixteen characteristics, some coefficients are likely to be significant purely by random chance.[44]

The balance test results from Q School present a similar picture. For this experiment, none of the sixteen tests uncover evidence of significant discontinuities at the 10% level. This conclusion remains the same both for the year of experiment participation and across golfers' histories in the preceding years. Thus there is no evidence to suggest that golfers are able to manipulate their treatment status near the threshold.

The weight of the evidence from a variety of sources supports the assumption that golfers

[44] Appendix Section D.1 presents RD plots of the pre-treatment characteristics so the reader can gain a visual understanding of the behavior of these characteristics near the treatment threshold.

cannot manipulation their treatment status near the qualification threshold. The evidence on the volatility of short-run golf earnings, the lack of visual evidence of discontinuities away from the treatment threshold, and the continuity across both the density of golfers and pre-treatment characteristics at the treatments thresholds combine to argue that these experiments offer a compelling setting in which to utilize a RD design and apply a casual interpretation.

5 Results

I present the main results in a series of figures in event study format. I categorize the estimates into pre-treatment, short-run, medium-run, and long-run effects. Time is measured with respect to the year of the experiment so that year 0 represents the year of experiment participation and year t refers to an effect t years after experiment participation. Short-run effects refer to changes in outcomes in the year directly following treatment while medium-run effects refer to two to three years after treatment. Long-run effects (labeled "4+") are estimated by taking a sum of future outcomes from year 4 until either the golfer reaches age 55 or the calendar year reaches 2014. I aggregate long-run outcomes over many years because the variance in the estimates increases substantially with time. As a result the estimates lack the precision to make inference at specific years far into the future. I include pre-treatment effects both to show balance in pre-treatment observable characteristics and to provide a visual understanding of the underlying variance in the estimators. Pre-treatment effects labeled "-1" represent the sum of past outcomes in all eligible years prior to the year of the experiment. Within the figures, the blue circles and red triangles represent the point estimates of the average treatment effect for the Korn Ferry Tour ML and Q School experiments, respectively. The bands represent 95% confidence intervals around these estimates. Appendix Section E provides the exact values of the results in table format along with information regarding the sample size and bandwidths for each estimate.

5.1 Earnings and Events

Figure 5 presents the treatment effect estimates on the number of events played. Panel 5a presents the results for PGA TOUR events. I find a large and statistically significant increase in the number of PGA TOUR events for treated golfers in the first year after treatment. Average treatment effects indicate a 19.6 and 20.7 increase in PGA TOUR events for the Korn Ferry Tour ML and Q School treatments, respectively. These point estimates are close to a full season as the median number of events played by PGA TOUR members is 24.[45] For both treatments these effects quickly dissipate, however. For the Korn Ferry Tour ML treatment, there are no statistically significant differences in PGA TOUR events in years 2 and 3 with point estimates of 2.0 and 3.0 events, respectively. For the Q School treatment, the treatment effect also falls dramatically in year 2 with a point estimate of 2.7 events, yet maintains some statistical significance. The treatment effect becomes statistically insignificant in year 3, however, with a point estimate of 0.3 events. In neither treatment do the estimates suggest a long-run difference in PGA TOUR events played as zero lies comfortably within the sizable confidence interval bands of the year 4+ effect.

Panel 5b shows symmetric, yet inverted, results for Korn Ferry Tour events. Treated goflers are estimated to play in 18.0 and 17.2 less Korn Ferry Tour events in the year after treatment for the Korn Ferry Tour ML and Q School experiments, respectively. These losses are comparable to a full season on the Korn Ferry Tour as the median Korn Ferry Tour member plays in 19 events.[46] Yet, once again these differences quickly dissipate. Neither treatment shows evidence of producing a long-run effect on the number of Korn Ferry Tour events played.

To understand how these differences in participation lead to changes in earnings, I turn to Figure 6 which presents the results on inverse hyperbolic sine (IHS) transformed earnings. Panel 6a shows large and statistically significant earnings effects for both treatments in year 1. This suggests that the earnings gained from increased participation in PGA TOUR events more than make up for the lost earnings from Korn Ferry Tour events. The point estimates are 0.84 and

[45]The sample for this statistic is all golfers who played in at least five PGA TOUR events during one season.

[46]The sample for this statistic is all golfers who played in at least five Korn Ferry Tour events during one season.

0.61 IHS units for the Korn Ferry Tour ML and the Q School treatments, respectively. With a crude approximation, these estimates correspond to a 84% and 131% increase in world earnings, respectively.[47] The treatment effect estimates in terms of log earnings are 0.82 and 0.88 for the Korn Ferry Tour ML and Q School treatments, respectively, which correspond to a 127% and 141% increase in earnings.[48] Both the IHS and log earnings estimates find large short-run earnings increases near or above the 100% range for both treatments. The short-run effects presented in Panels 6b and 6c reveal that these earnings gains are the result of a net gain from increasing PGA TOUR earnings and decreasing Korn Ferry Tour earnings.[49] Despite the large increase in short-run earnings, Panel 6a also shows that the treatment effects are not statistically significant from zero past year 1. Thus there is limited evidence for a long-run earnings effect. Panels 6b and 6c corroborate this story as the long-run earnings estimates are insignificant for both PGA TOUR and Korn Ferry Tour earnings for both treatments.

Theses results tell a consistent story in which both treatments have significant short-run effects on the type of tournaments golfers play and the amount of prize money they earn. These effects are sizable in comparison to similar employment shocks for wage-and-salary workers. For perspective, one survey reports that job displacement studies using administrative data find an initial 30% loss in earnings (von Wachter, 2015), whereas the initial earnings difference is around 100% in the golf context. However, golfers are able to recover quickly as there are no differences between treated and untreated golfers within three years. In contrast, the job displacement literature typically finds earnings losses of 15% four to ten years after displacement.

[47] To produce these numbers I apply the log point to percentage point conversion to IHS units, which is admittedly a crude conversion.

[48] Estimates of changes in log earnings fail to account for differences in non-participation. However, this margin is less important in year 1. In terms of raw earnings, I estimate treatments effects of $183,000 and $279,000 for the Korn Ferry Tour ML and Q School treatments, respectively.

[49] The coefficients for IHS PGA TOUR and Korn Ferry Tour earnings are very large and highly significant. One reason for the size of these coefficients is that there is a substantial non-participation margin as treated golfers mostly play on the PGA TOUR and untreated golfers mostly play on the Korn Ferry Tour.

5.2 Performance

Figure 7 presents the estimated treatment effects on annual adjusted scoring average. These estimates necessarily condition on golfers that play in at least one event, as otherwise scoring average is undefined. As lower scores are better, an improvement in scoring would be reflected in a negative coefficient on scoring average. Although treated golfers substantially increase their earnings, there is no corresponding improvement in performance. Differences in scoring average are statistically indistinguishable from zero in the first year after treatment for both treatments. Furthermore, there are no statistically significant differences in scoring estimated in either the medium-run or long-run effects for either treatment.[50] In terms of magnitudes, the bounds of the 95% confidence interval in the Korn Ferry Tour ML treatment are 0.19 and -0.49 covering a range of 0.68 strokes. The reported standard deviation of scoring average for the Korn Ferry Tour ML experiment is 0.90 (see Table 1). Thus, the estimation could potentially identify changes in performance of less than one standard deviation in magnitude, suggesting that the treatment effects are precisely estimated zeros.

Given the steep learning curve suggested by the age profiles of Figure 2, we may expect the treatments to have a greater effect on younger golfers. In order to test this hypothesis, I split the sample in half at the median age of 30. Yet, I also fail to find statistically significant effects on younger golfers' adjusted scoring average at any point, pre or post treatment.[51] These results suggest that golfers' productivity is resilient to the disruptions of these employment shocks.

Previous research by Guryan et al. (2009) finds no evidence for peer effects in golfers' daily performance based on random variation in the quality of playing partners during PGA TOUR rounds. My findings are consistent with this result, yet perhaps make a stronger case against peer effects in professional golf. Rather than being paired with better golfers for one round, the qualifiers from the Korn Ferry Tour ML or Q School are paired with more skilled golfers for an

[50] Long-run effects are computed with respect to the average scoring average in years 4 to 16. This is a slightly different definition than long-run earnings and events as it is not appropriate to sum scoring averages across years.

[51] See Appendix Sections D.5 and E.3 for the performance results on the younger and older half of the sample.

entire season of play. In fact, I estimate that the average tournament field for treated golfers is over 300 OWGR ranks lower than the average field for untreated golfers in the first year after treatment.[52] Yet, despite competing with top golfers for a year, performance fails to improve. This result further supports the idea that peer effects are less important in environments either with strong financial incentives or with highly skilled professionals (Guryan et al., 2009).

Furthermore, these results can shed light on the mechanisms behind studies of elite law and business schools. Students of elite professional schools also gain exposure to highly talented professionals in their field. Yet, these studies find that elite schools provide significant returns relative to less highly ranked schools (Oyer and Schaefer, 2019; Arcidiacono et al., 2008). The return to law and business school may result either from learning skills from talented peers or from establishing contacts with well-connected peers to improve job networks. The golf environment is unique in that there is little practical use for networks, yet golfers can potentially learn from talented peers. Given that I find no evidence for peer effects in this setting, my results are consistent with the view that job network effects are the primary driver behind peer effects for highly skilled professionals (Zimmerman, 2019; Oyer and Schaefer, 2019).

The performance results also have implications for the existence of economic rents. The PGA TOUR provides about nine times greater prize money than the Korn Ferry Tour. Yet, intense competition may impede the attainment of these rewards. These countervailing forces can create a relationship between skill and expected payoff such that higher ability golfers earn more on the PGA TOUR, while lower ability golfers maximize earnings on the Korn Ferry Tour. In turns out that in these natural experiments treated golfers perform no better than untreated golfers, yet earn a large pay raise while playing on the PGA TOUR. Hence, the balance of competition and prize money across the PGA TOUR and the Korn Ferry Tour effectively creates rents for type of golfer affected by the experiments. Treated golfers only enjoy these rents for a short time, however, suggesting that PGA TOUR entry and exit rules are set efficiently.

[52]This treatment effect is highly statistically significant. See Appendix Section E for the complete results on field quality.

5.3 Participation

As previously described, these natural experiments produce large short-run earnings gains for treated golfers. Yet, within a few years, treated golfers play in similar events and earn similar prize money as untreated golfers. Thus, in addition to producing exogenous employment shocks, these experiments may produce exogenous wealth shocks. Since the opportunity cost of leisure is similar across both groups shortly after treatment, these experiments can be leveraged to estimate the effect of an increase in wealth on the labor supply of golfers. In order to understand the magnitude of these wealth shocks, I calculate the average value of total past prize money accumulated just prior to participation in the experiments. Mean total past earnings are about $2.1 million and $3 million dollars for the Korn Ferry Tour ML and Q School samples, respectively. However, the corresponding median values are significantly lower at $1.2 million and $0.5 million. The point estimates of treatment effects on first year earnings are $183,000 and $279,000 for the Korn Ferry Tour ML and Q School, respectively. Although these calculations do not account for past consumption or other sources of income, they suggest that the increase in earnings as a result of treatment may have substantially increased the wealth of treated golfers, particularly for some golfers in the Q School experiment.

I test for the effect of wealth on labor supply by analyzing retirement behavior. Figure 8 presents estimated treated effects on retirement up to twelve years after treatment. Golfers are defined as retired in year t if for all subsequent eligible years, they record zero world earnings. One hypothesis is that treated golfers, enjoying greater wealth, will retire earlier if golfers value leisure over active competitive. However, the results are inconsistent with this view. For both experiments, there are no statistically significant positive effects for any future year. On the contrary, there is some evidence that treated Q School golfers are less likely to retire six to eight years after treatment. When broken down into PGA TOUR and Korn Ferry Tour retirement, I find that this result is driven by treated golfers participation in Korn Ferry Tour events.[53]

Wealth effects do not appear to reduce the labor supply of golfers. In fact, I find some evidence

[53] See Appendix Section E for retirement results for PGA TOUR and Korn Ferry Tour events.

that golfers increase labor force participation by retiring later. Yet, the career extension for Q School golfers does not appear to be particularly productive as they are not able to accumulate any measurable increase in long-run earnings. A potential explanation for this result is that qualifying for the PGA TOUR provides golfers with name recognition that they can use to secure sponsors exemptions in future Korn Ferry Tour events. These results suggest that professional golfers prefer active competition to retirement, even if they are not performing a high level.

5.4 Robustness

My results are robust to a multitude of sensitivity checks. For the Korn Ferry Tour ML experiment, I explore how the choice of bandwidth affects the results by estimating treatment effects with different bandwidth selection methods and through manual manipulation. I also test how controlling for observable characteristics such as age and OWGR affect the results. For the Q School experiment, I compare the results of the local randomization method to the more standard local linear regression. For both experiments, I assess how changes in the sample affect the results by estimating a specification with balanced sample and by estimating treatment effects across five different time periods. I also explore how restricting the sample to non-exempt golfers affects the estimates by comparing the main specification to estimates based on the full sample of golfers. Finally, I estimate a fuzzy RD design in which treatment is defined as playing in 20 PGA TOUR events. I present the results of all sensitivity analyses for the main outcomes of interest: IHS world earnings and annual adjusted scoring average. Despite the large number of sensitivity checks, all the results support the main qualitative conclusions presented above. Across the board, I find short-run positive effects on earnings, yet no evidence of long-run earnings effects or performance effects. Appendix Section F presents the complete results of the sensitivity analyses.

6 Job Transitions

Employment shocks have been shown to have persistent earnings effects both in instances of job displacement (e.g. Jacobson et al., 1993) and graduating during a recession (e.g. Kahn, 2010). Yet in the golf setting, I find no evidence for persistent earnings effects despite identifying a large employment shock. In an attempt to reconcile these divergent results, I argue that the lack of hiring and firing frictions in golf, and for the self-employed more generally, create a labor market which more closely resembles the perfectly competitive model. Hence, golfers recover quickly from employment shocks. To support this argument and better understand the mechanisms behind my results, I analyze the transitions of golfers on and off the PGA TOUR and compare these rates with job transition rates of wage-and-salary workers in the broader economy.

The convergence in earnings between treated and untreated golfers could result from two forces. Either treated golfers are quickly demoted from the PGA TOUR or untreated golfers are quickly promoted to the PGA TOUR in subsequent seasons. We can explore which of these mechanisms is stronger by comparing the estimated number of PGA TOUR events played for golfers near the treatment thresholds as time passes. For instance, in the Korn Ferry Tour ML experiment, the left-hand side (treatment group) RD limit decreases from 28 to 14 events from year 1 to year 2, whereas the right-hand side (non-treatment group) RD limit increases from 8.4 to 12 events.[54] Although both forces contribute to the convergence, the decline in events played for treated golfers declines more substantially than the gain in events played for untreated golfers at -14 events versus +3.6 events. The same story is also true for the Q School experiment.[55] These results suggest that high exit rates from the PGA TOUR may largely account for the transitory nature of the treatment effects in these experiments.

[54]See Appendix Table E for tables with the complete results. To see a visual representation compare Figure 3 (RD plot of PGA TOUR events played in the year after treatment) with Appendix Figure D.32 which presents an RD plot of the number of PGA TOUR events played in the *second* year after treatment for both Korn Ferry Tour ML and Q School golfers.

[55]The comparable numbers for the Q School experiment are a change in the left-hand side RD limit of -11.1 and a change in the right-hand side limit of 6.8.

In an effort to quantify the degree of mobility in golf, I compute job transition rates for a sample of golfers near the treatment threshold.[56] I define a "job" on the PGA TOUR as a binary variable taking the value of one if a golfer plays at least 20 PGA TOUR events in a single season. Korn Ferry Tour membership is defined as playing in at least 16 Korn Ferry Tour events. I then compute annual job transition rates based on the first instance of either PGA TOUR or Korn Ferry Tour membership after the year of experiment participation. I estimate annual exit rates off the PGA TOUR of 0.58 and 0.57 for the Korn Ferry Tour ML and Q School samples, respectively. On the other hand, I estimate entry rates from the Korn Ferry Tour to the PGA TOUR of 0.31 and 0.23 for the Korn Ferry Tour ML and Q School samples, respectively.[57]

I rely on the literature to compute comparable job transition rates for wage-and-salary workers. von Wachter et al. (2013) use US Social Security Administration data to calculate job transition rates at an annual level. For a males aged 30 to 50, they report a job-to-job transition rate of approximately 0.24 and an employment to nonemployment transition rate of 0.06. To understand the likely direction of job-to-job transitions, I rely on evidence from Haltiwanger et al. (2018) using administrative data from the US Census's Longitudinal Employer-Household Dynamics database. Based on reported transition rates by firm type, I calculate that about 74% of job transitions are movements up the job ladder as opposed to down the job ladder.[58] Putting these numbers together, the probability of transitioning up the job ladder conditional on initial period employment can be

[56] I use the same sample as is used to construct the descriptive statistics for Table 1 by selecting the 5 closest golfers to the treatment threshold in each experiment year.

[57] For complete results along with sample sizes see Appendix Table E.31.

[58] I compute this percentage using the results from Table 4 in Haltiwanger et al. (2018). I count all job transitions which result in wages increase as movements up the job ladder and all job transitions that result in wages decreases as movement down the job ladder. I also assume workers are equally represented in low, medium, and high wage firms in the initial period. Specifically, I compute the share of transitions up the job ladder as: $\frac{1}{3}\left(\frac{22.1+14.1+5}{22.1+14.1+5}\right) + \frac{1}{3}\left(\frac{15.7+8.4}{11.8+15.7+8.4}\right) + \frac{1}{3}\left(\frac{12.8}{3.5+6.5+12.8}\right) = 0.74$.

approximated as:

$$\begin{aligned} P\left(\text{Job to job}\right) * P\left(\text{Up job ladder}|\text{Job to job}\right) &= \\ 0.24 * 0.74 &= 0.18. \end{aligned}$$

While the probability of transitioning to a worse employment state, either down the job ladder or to nonemployment, can be approximated as:

$$\begin{aligned} P\left(\text{Emp to Nonemp}\right) + P\left(\text{Job to job}\right) * P\left(\text{Down job ladder}|\text{Job to job}\right) &= \\ 0.06 + 0.24 * 0.26 &= 0.12. \end{aligned}$$

Based on these transition rates, professional golf appears to have very fluid labor market. Golfers are more likely to transition in either direction with a probability of moving up the job ladder of 0.31 versus 0.18 in the broader labor market and a probability of moving down of 0.58 versus 0.12. Perhaps unsurprisingly, these comparisons suggests that tour-golfer matches are less stable than firm-worker matches. Indeed, while wage-and-salary workers sign contracts, form relationships with management, and are subject to labor market regulations, golfers are promoted and demoted based, almost entirely, on objective performance. We may expect high transition rates in a similarly competitive labor market for wage-and-salary workers in which firms can hire and fire instantaneously.

A second notable finding is the high rate of exit for golfers off the PGA TOUR. In fact, while golfers are 1.7 times more likely to move up the job ladder than wage-and-salary workers, they are 4.8 times more likely to move down the job ladder. Thus golfers are much more likely to be demoted from the PGA TOUR than a wage-and-salary worker is to be laid off. This result draws our attention to an under-emphasized aspect of job displacement and similar employment shocks. Often economists consider the speed with which displaced workers are able to re-enter the labor force or move back up the job ladder. However, equally important is the degree to which non-displaced workers remain employed in future periods. Treated golfers are unable to sustain

an earnings premium, in large part, because they fail to hold on to their high-quality jobs. These results highlight the importance of sticky jobs in explaining the effects of employment shocks, in contrast to more traditional mechanisms related to search frictions faced by job seekers. Indeed, recent research by Jarosch (2015) and Jung and Kuhn (2018) also finds an important role for non-displaced workers' job stability in accounting for displacement losses.

7 Conclusion

I use exogenous variation in employment opportunities induced by discontinuities in the PGA TOUR's membership assignment mechanism to study the long-run earnings and performance effects of temporary employment shocks. Initially, I find large effects on both earnings and events played, with treated golfers earning upwards of a 100% premium and playing in about 20 more PGA TOUR events. Yet, I find no evidence of long-run earnings effects or performance effects. I find no evidence that peer effects improve performance despite a significant improvement the quality of treated golfers' competitors. I also find evidence to suggest that positive wealth shocks do not reduce labor supply, but rather may slightly delay golfers' retirement.

In comparison to employment shocks for wage-and-salary workers, I find less persistent earnings effects. This suggests that hiring and firing frictions are an important determinant of persistent earnings losses for wage-and-salary workers. Furthermore, I find that golfers have higher job transitions rates and, in particular, a greater chance of moving down the job ladder. Thus, golfers compete in a highly fluid labor market with a particularly high risk of demotion. These results provide a new perspective from which to understand the effects of employment shocks. In particular, they highlight the tradeoff between job stability and the cost of job displacement. While stable jobs reduce the incidence of displacement, they may also increase its cost as non-displaced workers are likely to remain employed for a long time. This new perspective may help to explain other findings in the literature. For example, a typical finding is that job displacements are costlier in recessions (Davis and von Wachter, 2011). One explanation for the cyclical nature of losses is

that workers move up the job ladder more slowly during recessions as the job offer rate declines. However, persistent losses may also accrue as displaced workers exit from more stable jobs during recessions and, thus, their non-displaced counterparts are less likely to become displaced in the future.

References

Arcidiacono, Peter, Jane Cooley, and Andrew Hussey, "The Economic Returns to an MBA," *International Economic Review*, 2008, *49* (3), 873–899.

Bertrand, Marianne and Sendhil Mullainathan, "Are CEOs Rewarded for Luck? The Ones Without Principals Are," *Quarterly Journal of Economics*, 2001, pp. 901–932.

Brown, Jennifer, "Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars," *Journal of Political Economy*, 2011, *119* (5), 982–1013.

Burdett, Kenneth and Dale T Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, pp. 257–273.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–2326.

_ , _ , and _ , "Optimal Data-Driven Regression Discontinuity Plots," *Journal of the American Statistical Association*, 2015, *110* (512), 1753–1769.

_ , _ , Max H Farrell, and Rocio Titiunik, "Regression Discontinuity Designs Using Covariates," Technical Report 2016.

_ , _ , _ , and _ , "rdrobust: Software for Regression Discontinuity Designs," *Stata Journal, forthcoming*, 2017.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 2018, *36* (S1), S13–S70.

_ , Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Carrington, William J and Bruce Fallick, "Why Do Earnings Fall with Job Displacement?," *Industrial Relations: A Journal of Economy and Society*, 2017, *56* (4), 688–722.

_ , **Kristin McCue, and Brooks Pierce**, "The Role of Employer/Employee Interactions in Labor Market Cycles: Evidence from the Self-Employed," *Journal of labor Economics*, 1996, *14* (4), 571–602.

Cattaneo, Matias D, Brigham R Frandsen, and Rocio Titiunik, "Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the US Senate," *Journal of Causal Inference*, 2015, *3* (1), 1–24.

_ , **Michael Jansson, and Xinwei Ma**, "rddensity: Manipulation Testing Based on Density Discontinuity," *The Stata Journal*, 2016, pp. 1–18.

_ , _ , **and** _ , "Simple Local Regression Distribution Estimators with an Application to Manipulation Testing," Technical Report, University of Michigan Working Paper, Retrieved from http://www-personal. umich. edu/~ cattaneo/papers/Cattaneo-Jansson-Ma_2016_ LocPolDensity. pdf [Date Accessed: 11/29/2016] 2016.

_ , **Rocio Titiunik, and Gonzalo Vazquez-Bare**, "Comparing Inference Approaches for RD Designs: A Reexamination of the Effect of Head Start on Child Mortality," Technical Report, Working Paper, University of Michigan 2016.

_ , _ , **and** _ , "rdlocrand: Inference in Regression Discontinuity Designs under Local Randomization," *Stata Journal, forthcoming*, 2017.

Couch, Kenneth A and Dana W Placzek, "Earnings Losses of Displaced Workers Revisited," *The American Economic Review*, 2010, *100* (1), 572–589.

Davis, Steven J and Till von Wachter, "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*, 2011, *43* (2 (Fall)), 1–72.

Ehrenberg, Ronald G and Michael L Bognanno, "Do Tournaments Have Incentive Effects?," *Journal of Political Economy*, 1990, *98* (6), 1307–1324.

Farber, Henry S, "Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey," *Journal of Labor Economics*, 2017, *35* (S1), S235–S272.

Feinstein, John, *Tales from Q School: Inside Golf's Fifth Major*, Little, Brown, 2007.

Gauriot, Romain and Lionel Page, "Fooled by Performance Randomness: Over-Rewarding Luck," *Review of Economics and Statistics*, 2019, (0).

Genda, Yuji, Ayako Kondo, and Souichi Ohta, "Long-Term Effects of a Recession at Labor Market Entry in Japan and the United States," *Journal of Human Resources*, 2010, *45* (1), 157–196.

Gibbons, Robert and Lawrence F Katz, "Layoffs and Lemons," *Journal of Labor Economics*, 1991, pp. 351–380.

Greenwald, Bruce C, "Adverse Selection in the Labour Market," *The Review of Economic Studies*, 1986, *53* (3), 325–347.

Guryan, Jonathan, Kory Kroft, and Matthew J Notowidigdo, "Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments," *American Economic Journal: Applied Economics*, 2009, *1* (4), 34–68.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song, "What Do Data on Millions of US Workers Reveal About Life-Cycle Earnings Risk?," Technical Report, National Bureau of Economic Research 2015.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw, "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 2001, *69* (1), 201–209.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer, "Cyclical Job Ladders by Firm Size and Firm Wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan, "Earnings Losses of Displaced Workers," *The American Economic Review*, 1993, pp. 685–709.

Jarosch, Gregor, "Searching for Job Security and the Consequences of Job Loss," *Manuscript, Princeton University*, 2015.

Jung, Philip and Moritz Kuhn, "Earnings Losses and Labor Mobility Over the Life Cycle," *Journal of the European Economic Association*, 2018.

Kahn, Lisa B, "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 2010, *17* (2), 303–316.

Kleven, Henrik Jacobsen, Camille Landais, and Emmanuel Saez, "Taxation and International Migration of Superstars: Evidence from the European Football Market," *American Economic Review*, 2013, *103* (5), 1892–1924.

Krashinsky, Harry, "The Effect of Labor Market Institutions on Salaried and Self-Employed Less-Educated Men in the 1980s," *ILR Review*, 2008, *62* (1), 73–91.

Lachowska, Marta, Alexandre Mas, and Stephen A Woodbury, "Sources of Displaced Workers' Long-Term Earnings Losses," Technical Report, National Bureau of Economic Research 2019.

Lazear, Edward P and Robert L Moore, "Incentives, Productivity, and Labor Contracts," *The Quarterly Journal of Economics*, 1984, *99* (2), 275–296.

Lee, David S and David Card, "Regression Discontinuity Inference with Specification Error," *Journal of Econometrics*, 2008, *142* (2), 655–674.

McCrary, Justin, "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test," *Journal of Econometrics*, 2008, *142* (2), 698–714.

Moore, Robert L, "Employer Discrimination: Evidence from Self-Employed Workers," *The Review of Economics and Statistics*, 1983, pp. 496–501.

Neal, Derek, "Industry-Specific Human Capital: Evidence from Eisplaced Workers," *Journal of Labor Economics*, 1995, pp. 653–677.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, January 2012, *4* (1), 1–29.

Oyer, Paul, "Initial Labor Market Conditions and Long-Term outcomes for Economists," *The Journal of Economic Perspectives*, 2006, *20* (3), 143–160.

_ , "The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income," *The Journal of Finance*, 2008, *63* (6), 2601–2628.

_ **and Scott Schaefer**, "The Returns to Elite Degrees: The Case of American Lawyers," *ILR Review*, 2019, *72* (2), 446–479.

Parker, Simon C, "The Distribution of Self-Employment Income in the United Kingdom, 1976–1991," *The Economic Journal*, 1997, *107* (441), 455–466.

_ **, Yacine Belghitar, and Tim Barmby**, "Wage Uncertainty and the Labour Supply of Self-Employed Workers," *The Economic Journal*, 2005, *115* (502).

Parsons, Christopher A, Johan Sulaeman, Michael C Yates, and Daniel S Hamermesh, "Strike Three: Discrimination, Incentives, and Evaluation," *American Economic Review*, 2011, *101* (4), 1410–35.

Pope, Devin G and Maurice E Schweitzer, "Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition, and High Stakes," *The American Economic Review*, 2011, *101* (1), 129–157.

Schmieder, Johannes, Till von Wachter, and Stefan Bender, "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany," Technical Report 2018.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter, "Firming Up Inequality," *The Quarterly Journal of Economics*, 2018, *134* (1), 1–50.

Stevenson, Betsey, "Beyond the Classroom: Using Title IX to Measure the Return to High School Sports," *The Review of Economics and Statistics*, 2010, *92* (2), 284–301.

Sullivan, Daniel and Till von Wachter, "Job Displacement and Mortality: An Analysis Using Administrative Data*," *The Quarterly Journal of Economics*, 2009, *124* (3), 1265–1306.

Szymanski, Stefan, "A Market Test for Discrimination in the English Professional Soccer Leagues," *Journal of political Economy*, 2000, *108* (3), 590–603.

von Wachter, Till, "Measuring the Short- and Long-Term Cost of Job Displacement in Terms of Worker and Family Outcomes," Technical Report, Working Paper, UCLA 2015.

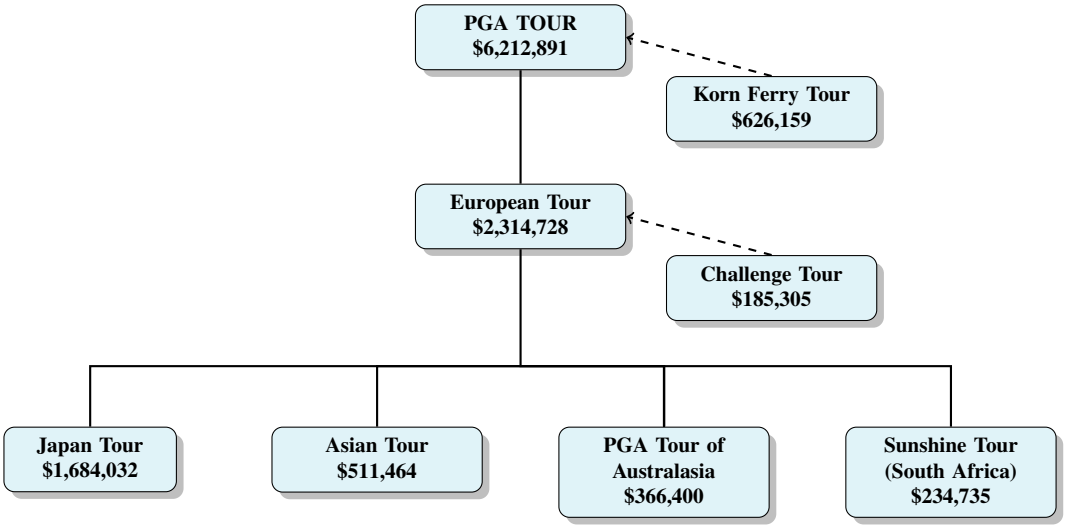
_ , Jae Song, and Joyce Manchester, "Long-Term Earnings Losses Due to Mass Layoffs During the 1982 Recession: An Analysis Using US Administrative Data from 1974 to 2004," Working Paper, Institute for the Study of Labor September 2009.

_ , _ , and _ , "The Effect of Job Displacement on Cumulated Years Worked," *Lifecycle Events and Their Consequences: Job Loss, Family Change, and Declines in Health*, 2013, p. 34.

Zimmerman, Seth D, "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes," *American Economic Review*, 2019, *109* (1), 1–47.

8 Figures

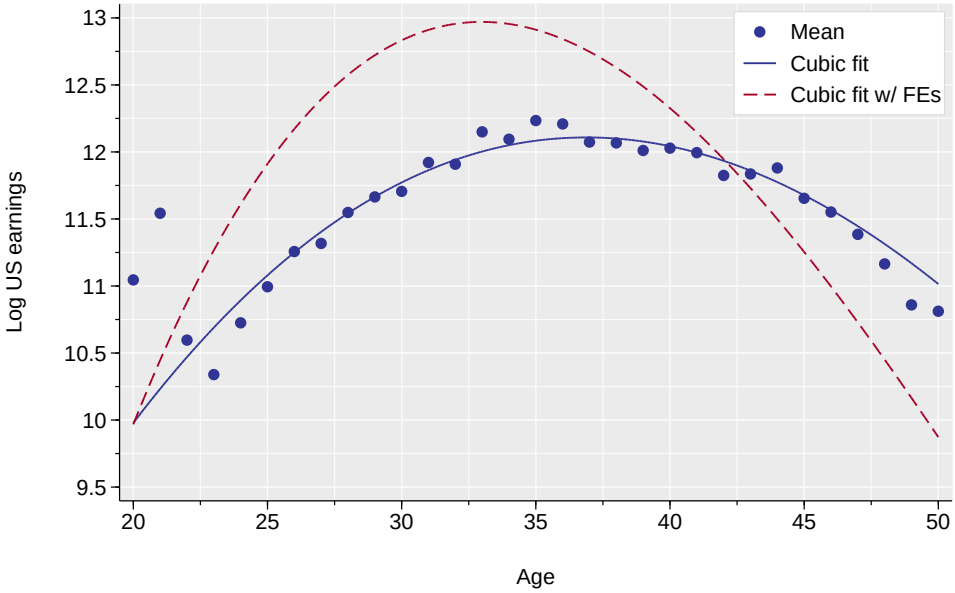
Figure 1: Hierarchy of professional golf tours



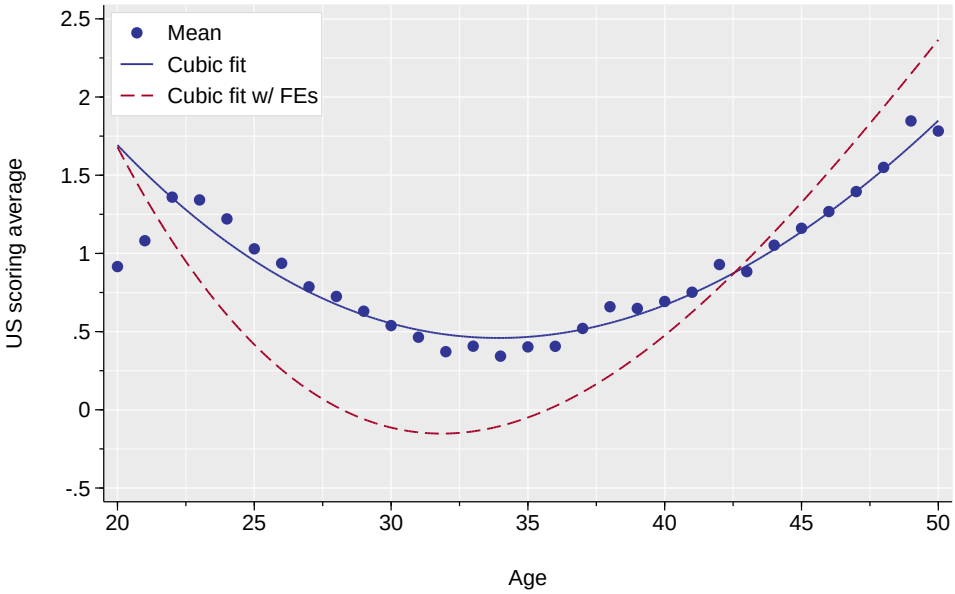
Note: The values indicate the average tournament purse in 2012.

Figure 2: Career profiles of earnings and scoring average

(a) Log US earnings



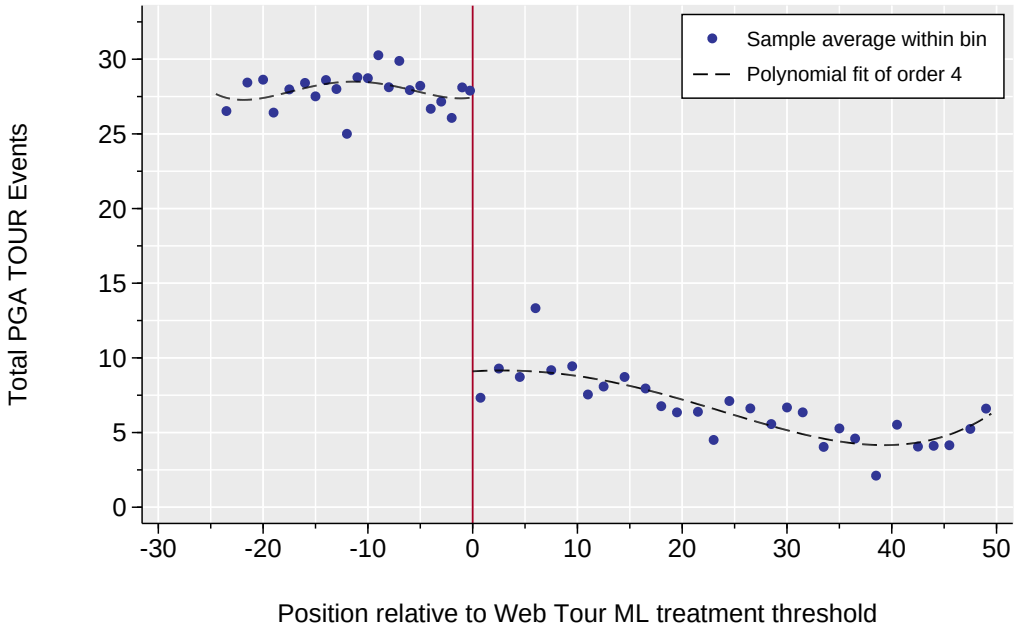
(b) US scoring average



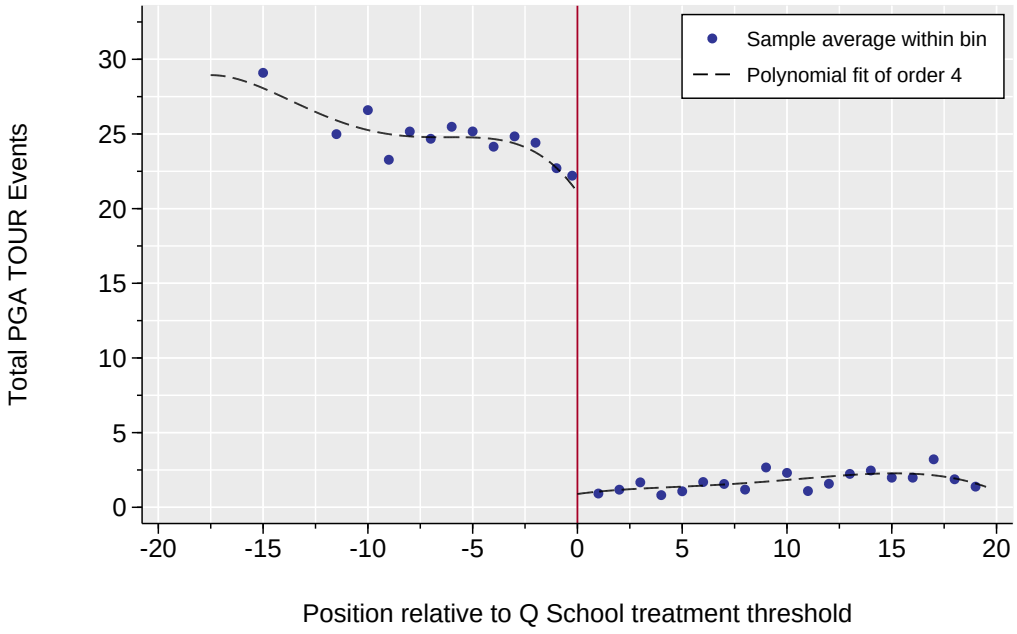
Notes: The sample includes all golfers who played in at least 5 events on the PGA TOUR or Korn Ferry Tour from 1990 to 2014. The blue dots represent the mean values of each outcome at each age. The blue, solid lines represent the prediction line of an OLS regression of each outcome on a cubic in age. The red, dashed lines represent the prediction line of an OLS regression of each outcome on a cubic in age and individual golfer fixed effects. The cubic fit with fixed effects is normalized to begin at the same level as the cubic fit without fixed effects.

Figure 3: RD plots of PGA TOUR events in year after experiment

(a) Korn Ferry Tour ML



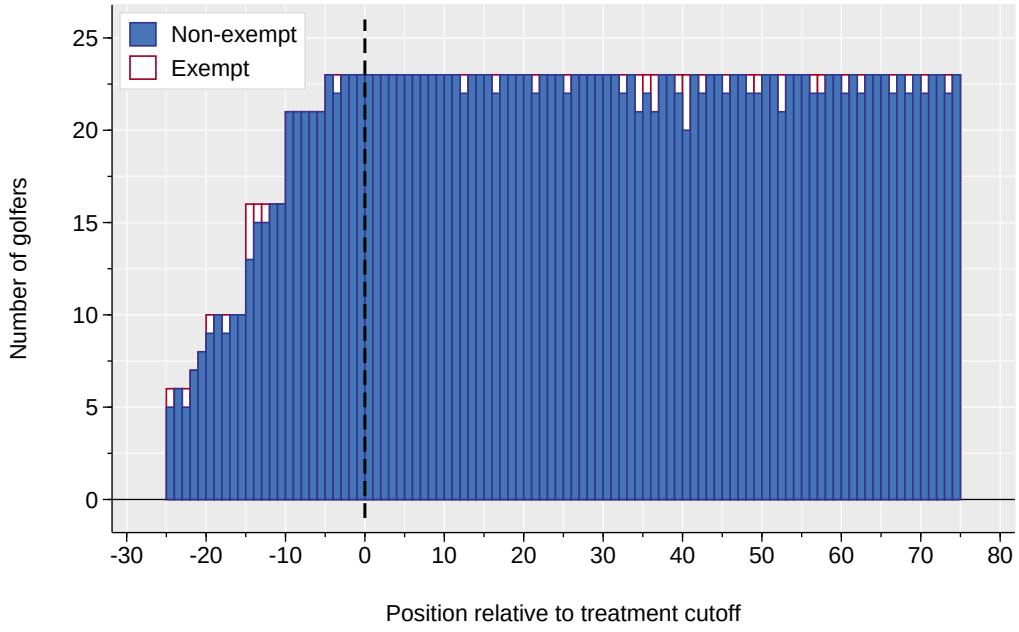
(b) Q School



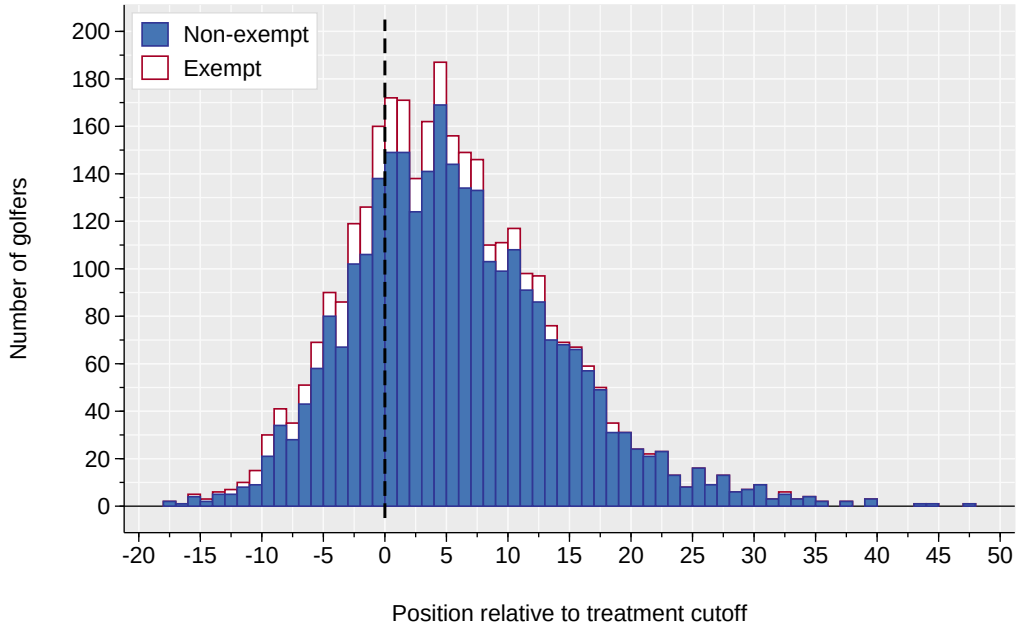
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure 4: Histograms of running variables around treatment threshold

(a) Korn Ferry Tour ML



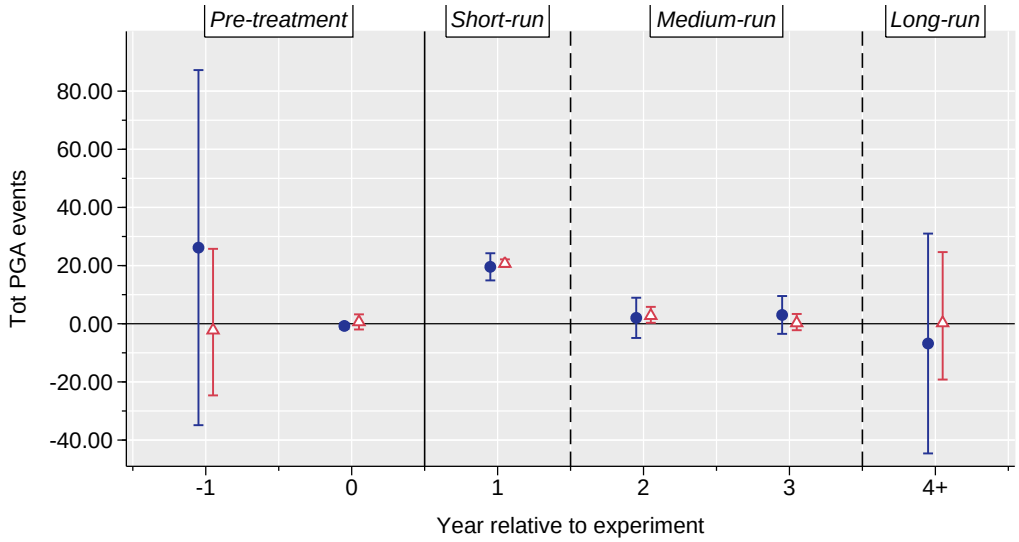
(b) Q School



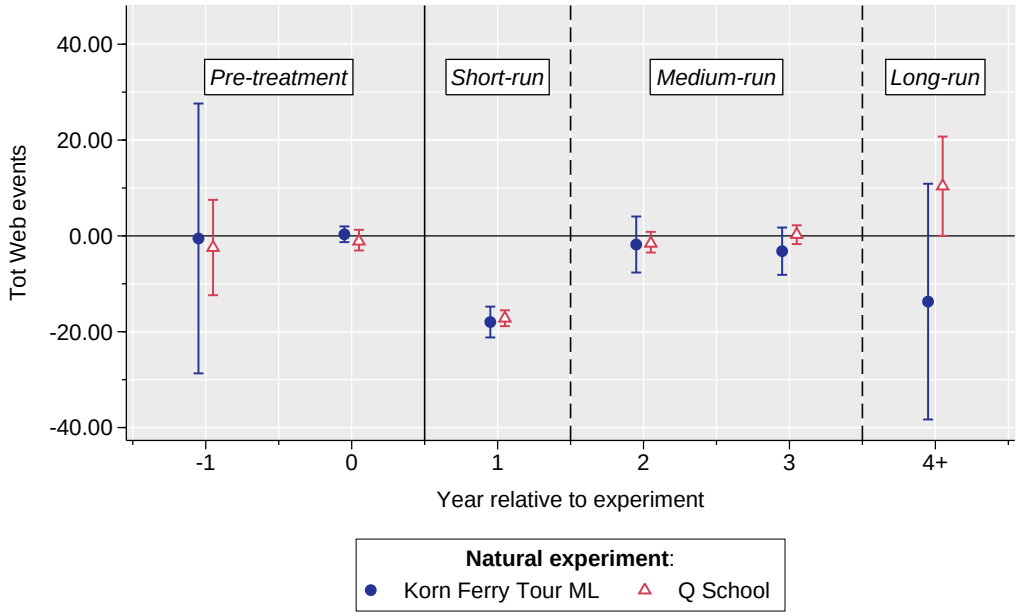
Notes: For the Korn Ferry Tour ML experiment, the running variable is year-end position on the Korn Ferry Tour ML relative to the treathment threshold. For the Q School experiment, the running variable is the final score in the final round of Q School relative to the treatment threshold.

Figure 5: Estimated treatment effects on events

(a) PGA TOUR events



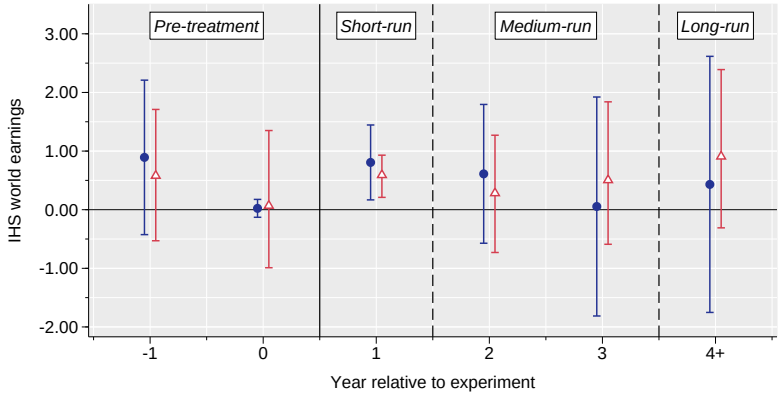
(b) Korn Ferry Tour events



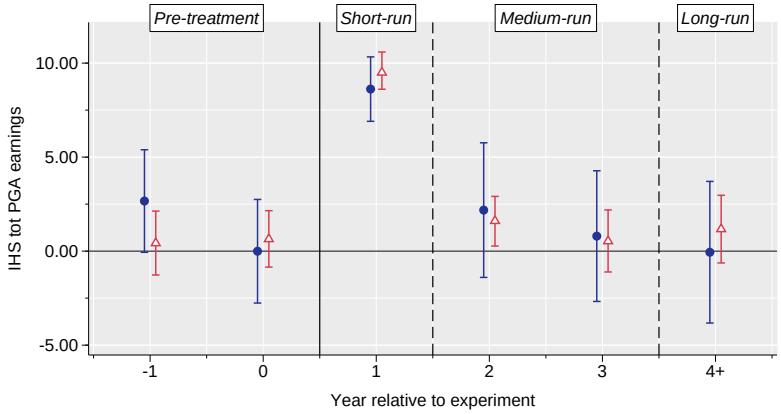
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond.

Figure 6: Estimated treatment effects on earnings

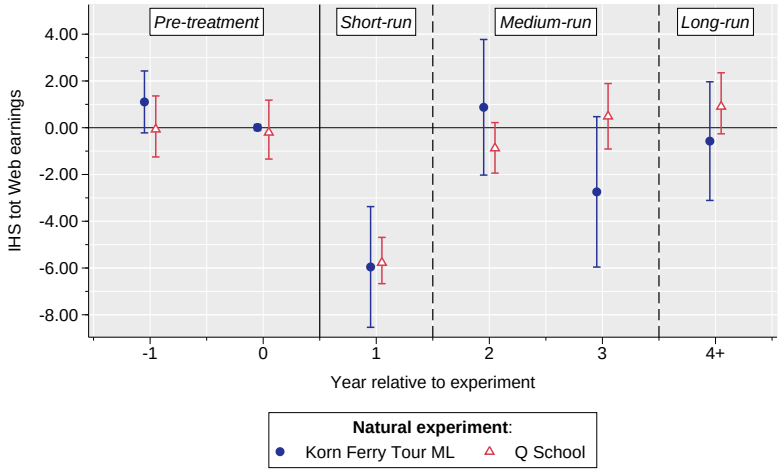
(a) IHS world earnings



(b) IHS PGA TOUR earnings

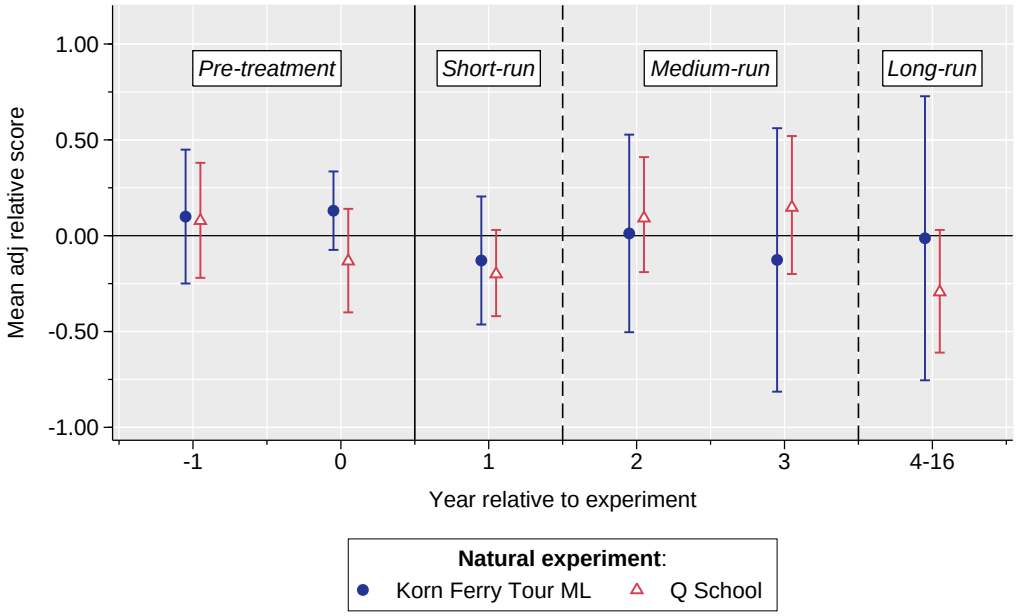


(c) IHS Korn Ferry Tour earnings



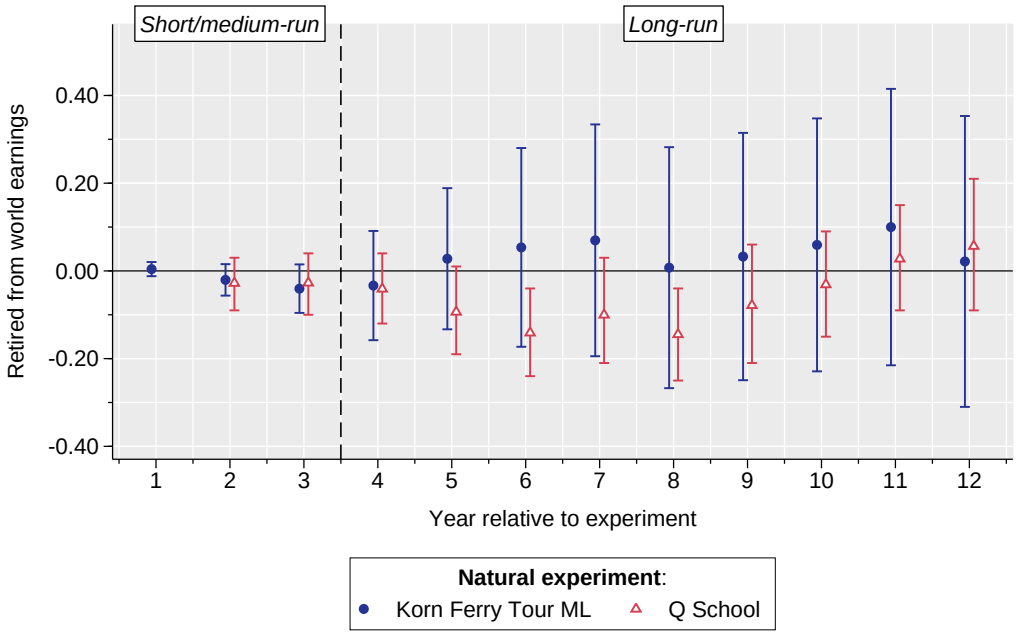
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond.

Figure 7: Estimated treatment effects on scoring average



Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16.

Figure 8: Estimated treatment effects on retirement from world earnings



Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold.

9 Tables

Table 1: Descriptive statistics for each natural experiment

	Demographics:		**Ability:**			**Experience (Events):**	
	Age (1)	Foreign (2)	OWGR (3)	Scoring average (4)	US earnings (5)	PGA TOUR (6)	Korn Ferry Tour (7)
Korn Ferry Tour ML	31.82	0.19	532.82	0.19	9.70	6.09	12.06
	(5.35)	*(0.39)*	*(203.89)*	*(0.95)*	*(5.51)*	*(10.47)*	*(11.69)*
Q School	31.44	0.20	703.55	0.40	7.25	7.30	5.50
	(5.99)	*(0.40)*	*(329.54)*	*(1.32)*	*(6.32)*	*(11.38)*	*(9.30)*

Notes: Reports mean values with standard deviation in parentheses. "OWGR" denotes Offical World Golf Ranking. "US Earnings" denotes average IHS earnings on PGA TOUR and Korn Ferry Tour in past five years. "Events PGA TOUR" denotes average PGA TOUR events over the last five seasons. "Events Korn Ferry Tour" denotes average Korn Ferry Tour events over the last five seasons. Sample is comprised of 5 nearest golfers on both sides of the treatment threshold in each experiment year. For each experiment, calculations are based on the performance records of 230 golfers.

Table 2: Balance tests of pre-treatment observable characteristics

	Year 0				All years prior to year 0			
	τ (1)	Pval (2)	$N_l \mid N_r$ (3)	$h_l \mid h_r$ (4)	τ (5)	Pval (6)	$N_l \mid N_r$ (7)	$h_l \mid h_r$ (8)
Panel A: Korn Ferry Tour ML								
Demographics:								
Age	2.57	0.135	63 | 376	3.34 | 17.54				
Foreign born	-0.16	0.061	125 | 376	6.03 | 17.79				
Ability measures:								
OWGR	-3.83	0.918	125 | 335	6.28 | 16.46	-0.50	0.994	125 | 293	5.53 | 13.71
Scoring average	0.131	0.212	104 | 335	4.90 | 15.79	0.100	0.576	143 | 286	6.56 | 15.23
Events:								
PGA Tour	-0.75	0.153	125 | 355	6.33 | 17.35	26.17	0.401	83 | 376	4.07 | 17.84
Web.com Tour	0.33	0.691	125 | 418	5.74 | 20.12	-0.54	0.970	104 | 335	5.38 | 16.33
IHS earnings:								
World	0.023	0.767	83 | 459	4.29 | 21.53	0.892	0.185	104 | 252	4.69 | 11.66
PGA TOUR	-0.006	0.996	83 | 501	4.31 | 23.65	2.664	0.056	104 | 418	4.61 | 20.38
Web.com Tour	0.011	0.873	83 | 355	4.09 | 16.95	1.104	0.103	104 | 272	4.84 | 13.31
Panel B: Q School								
Demographics:								
Age	-0.36	0.595	129 | 134	0.50 | 0.50				
Foreign born	-0.02	0.683	129 | 134	0.50 | 0.50				
Ability measures:								
OWGR	-62.22	0.159	129 | 134	0.50 | 0.50	-8.66	0.840	129 | 134	0.50 | 0.50
Scoring average	-0.133	0.359	107 | 111	0.50 | 0.50	0.078	0.606	97 | 102	0.50 | 0.50
Events:								
PGA Tour	0.62	0.627	129 | 134	0.50 | 0.50	-2.22	0.870	129 | 134	0.50 | 0.50
Web.com Tour	-1.12	0.355	129 | 134	0.50 | 0.50	-2.44	0.630	129 | 134	0.50 | 0.50
IHS earnings:								
World	0.069	0.913	129 | 134	0.50 | 0.50	0.580	0.444	129 | 134	0.50 | 0.50
PGA TOUR	0.642	0.407	129 | 134	0.50 | 0.50	0.427	0.587	129 | 134	0.50 | 0.50
Web.com Tour	-0.203	0.772	129 | 134	0.50 | 0.50	-0.069	0.918	129 | 134	0.50 | 0.50

Notes: τ denotes the point estimate of the treatment effect. N_l and N_r denote the number of observations used on each size of the treatment threshold to produce the estimates. h_l and h_r denote the bandwidth lengths on each side of the threshold. PWGR denotes end of year Official Wold Golf Ranking. IHS earnings denotes the use of the inverse hyperbolic sine function on earnings. Korn Ferry Tour ML are estimated with a bias-corrected local linear regression. Q School effects are estimated with local randomization methods using the difference-in-means statistic. See Section 4 for details.

Online Appendix

A Construction of Datasets

The PGA TOUR provided to their data portal from which I could request data files. I primarily use two data files the analysis. The first dataset, which I refer to as the *events* dataset, has observations at the level of the golfer and tournament. This dataset records the results of every tournament played from 1983 through 2012 for the PGA TOUR and from 1990 through 2012 for the Korn Ferry Tour. The dataset includes information on final score, finish position, and prize money awarded. I use this dataset primarily to compute earnings, events played, and tournament purses the PGA TOUR and Korn Ferry Tour. The second dataset, which I refer to as the *rounds* dataset, has observations at the level of the round, golfer, and tournament. The dataset includes information detailed information round-by-round scoring and finish position final score.[59] I use this dataset primarily to compute annual scoring averages for each golfer on the PGA TOUR and Korn Ferry Tour. Scoring averages only included official PGA TOUR events and also exclude any match play events.

I assemble earnings data from six golf tours in addition to the PGA TOUR and Korn Ferry Tour. These include tours from Europe (European Tour and Challenge Tour), Japan (Japan Golf Tour), Australia and South Asia (PGA Tour of Australasia), East and South Asia (Asian Tour), and South Africa (Sunshine Tour). Earnings data for these tours is publicly available and posted on each tour's website in the form of a season ending prize money list. Earnings data becomes available at different time for different tours. Appendix Table E.1 provides a full accounting for the time periods of earnings data used from each tour. In order to convert earnings denominated in foreign currencies, I use historic exchange rates downloaded from the Federal Reserve Economic Data (FRED) from the Federal Reserve Bank of St. Louis. In contrast to PGA TOUR data, earnings data from international tours must be merged on the basis of a golfer's name rather than a numeric identification number. After every merge, I check the names that failed to merge and attempt to manually correct for all merging mistakes based on different spellings. Duplicate names

[59] For both the events and rounds datasets, researchers have the option to access many more detailed statistics regarding scoring, but I focus mainly on the final score.

are not common, primarily as a result of the fact that the total number of unique golfers in the sample is modest at 3,696. Another reason for few duplicates is that golfers and golf organizations try to keep names unique. Since golf is an individual sport a golfer's name serves as something analogous to a brand or team name. If a golfer has the same or similar name to another he will often add a middle name to differentiate himself. Therefore, failed merges often result from spelling errors or structural data management differences between tours. For instance, some tours store the full middle name whereas some only include a middle initial. Although, spelling differences can reduce the success of the merge, this measurement error is unlikely unbiased as it results from random variation in the complexity of names. As I do not have access to private data from any of these other tours, I do not compute scoring statistics or have much information on events played for any of the tours besides the PGA TOUR and Korn Ferry Tour.

The results from Q School in 1990, 1991, 1992, and 1994 are incomplete in that the PGA TOUR's records only show the qualifiers and not the golfers that fail to qualify. In order to fill in the missing data, I perform a search through internet newspaper archives. First, I located the sites of each missing Q School tournament and then found a local newspaper from the day after the event finished. In all cases, the full results were listed in the details of the sports section. I then match the names to their unique PGA TOUR identification number.

The PGA TOUR keeps records of the date of birth for most participating golfers. However, for those with a missing data of birth, I perform a web search to find the year of birth. For many cases, I find a direct reference to the year of birth. For those golfers for which I can't find a direct reference to a year of birth, I often approximate year of birth based on the year of college or high school graduation. To classify golfers as foreign-born I primarily rely on the Official World Golf Ranking data. For those without a valid country code, I conduct a manual web search to fill in missing data.

I drop all prize money awarded in Q School. Golfer who qualify earn money while those who fail to qualify do not. This could create a significant treatment effect in earnings in year 0 for the Q School experiment. Q School earnings a minimal compared to regular PGA TOUR or Korn Ferry

Tour events.

For my main sample analysis I record earnings only between ages 17 and 55. Since participation is an important margin, it is important to set some age thresholds. Some golfers qualify at age 17, so I kept that as the youngest age. Golfers are eligible for the Champion's Tour, a golf tour for seniors, at age 50. Most golfers do not compete past after 50 but some do so I capped the age of earnings at 55 to partially allow for this possibility.

To find golfers with partial or full exemption status who nevertheless compete in the Korn Ferry Tour ML or Q School experiments, I rely on the annual lists of All-Exempt TOUR Priority Rankings produced by the PGA TOUR. These list provide a complete tally of exemption status for each golfer prior to the start of a season. Appendix Figure D.3 provides an example of All-Exempt TOUR Priority Rankings for 2011. The main specification excludes any golfer with any type exemption status to the next season's PGA TOUR events except for those earned through the Korn Ferry Tour ML and Q School.[60] I also use the historic PGA TOUR money lists to infer which golfers have conditional status on the PGA TOUR. I count golfers with conditional status as exempt, but both Q School and the Korn Ferry Tour ML qualifiers are offered higher status than golfers with conditional status. The result is that I cannot identify conditional status based purely on the All-Exempt TOUR Priority Rankings as golfer who qualify through say Q School but have conditional status do not show us under the conditional status category.

In general, All-Exempt TOUR Priority Rankings are not a perfect tool for discovering exemption status. Some golfers may choose to use a potential exemption differently depending on whether or not they qualify through the Korn Ferry Tour ML or Q School. For instance, some golfers have exemptions based on lifetime prize money which they can utilize at any point. Some of these golfers may lose status and elect to compete in Q School. If they fail to qualify, they may use their lifetime prize money exemption. Yet if they qualify through Q School, they will save it for another time. Although, this type of manipulation is possible, these type of lifetime prize money exemptions are rare. To test for sensitivity to exemption status, I compare the treatment

[60]Those golfers who play in Q School yet have qualified through the Korn Ferry Tour ML are also counted as exempt for Q School.

effects computed over a sample of non-exempt golfers to all golfers in Appendix Section F.4.

Figure D.2 plots the relationship between qualifiers and exempt qualifiers for both Q School and the Korn Ferry Tour ML. Most exempt qualifiers are from Q School and have conditional status on the PGA TOUR as a result of finishing between 126 and 150 on the previous year's PGA TOUR money list. Conditional status provides an exemption into the final round of Q School and PGA TOUR membership benefits at lower priority than Q School or Korn Ferry Tour ML graduates. On average golfers with conditional status play in 20 PGA TOUR events in the next year, whereas Q School graduates play in 25 events. Hence many golfers with conditional status compete in Q School. Another category of exemption is medical exemption. Medical exemptions are given to golfers who held a tour card in the previous year but missed many events due to a serious injury. These golfers are provided the same status that they had in the past year in which they where unable to play. Another category of exemption for Q School in particular are golfers that earned a tour card already through the Korn Ferry Tour ML. Since the Korn Ferry Tour season ends before Q School, many golfers choose to play in Q School after the Korn Ferry Tour season. In fact, some Korn Ferry Tour golfers are exempt into the final stage of Q School. For example, in 2012 those finishing between 26 and 40 on the Korn Ferry Tour ML were exempt into the final stage. On rare occasions even golfers that earn a tour card by finishing in the top 25 on the Korn Ferry Tour ML compete in Q School in an effort to improve their PGA TOUR status. Within each status group golfers are placed in the following order: 1st place Q School, 2nd place Korn Ferry Tour, 2nd place Q School, 3rd place Korn Ferry Tour, ... , last place to qualify Q School, 25th place Korn Ferry Tour. In practice this ordering makes little difference in the number of tournaments a golfer will have access to in the next year. However, the opportunity to slightly improve one's status is enough for some golfers to compete in Q School. Across the nineteen sample years, 27 golfers enter Q School after qualifying through the Korn Ferry Tour ML. Appendix Figure D.1 presents a timeline of events to clarify the timing issues for an example year of 2012.

A.1 Official World Golf Ranking Data

I compile data on Official World Golf Rankings (OWGR) which are produced by a collaborative organization of professional golf tours and rule making bodies. These rankings are based on a system which allocates points to tournaments around the world based on prestige. Golfers are then allocated a share of the tournament total points based on their performance. Points are tallied over the past two years. The main value of this measure is that it attempts to rank golfers who play on different tours throughout the world. Direct measures of performance are reliable provided that golfers play in the same events. It is more difficult, however, to rank golfers when they play in different events. Since OWGRs are produced through a collaboration of global tours and rule making bodies, they can credibly judge the relative prestige of tournaments from around the world.

While the main advantage of OWGRs are that they are able to plausibly compare golfer performance from around the world, there are two main drawbacks that prevent the use of OWGR as the primary measure of performance. First, OWGRs use performance over the past two years so they are more of a long-term measure of performance. Second, OWGRs depend on tour access. Golfers who aren't members of the PGA TOUR have fewer chances to earn points. Given that the primary treatment of the natural experiments is access to the PGA TOUR, OWGR would not provide an accurate picture of short-term performance in the years following treatment.

I link OWGR data to earnings data by matching golfers' full names. For those observations that fail to merge, I manually check for any spelling discrepancies. For those that still fail to merge, I impute the highest possible OWGR for that month. In many cases this is the correct ranking since the golfer has in fact not accumulated any points. In other cases, I expect measurement error to be unbiased since it will be biased on differences in spellings of names.

B Properties of Golf Earnings Distributions

Golf earnings distribution are heavily skewed to the right (high earnings) with very fat tails. Appendix Table E.2 reports the sample moments of the world earnings distribution for all golfers who

played in at least five events on either the PGA TOUR or Korn Ferry Tour from 1990 to 2014 from age 20 to 40. Column (1) shows the descriptive statistics for raw earnings for which the reported skewness and kurtosis are 5.16 and 43.68, respectively. Given the heavy skewness and fat tails of the earnings distribution, it is a poor approximation for the normal distribution. With a moderate sample size, these features may increase the variance in the estimates of treatment effects. As a result, I transform earnings with either the natural log or inverse hyperbolic sine functions. Column (2) shows that skewness is closer to zero and kurtosis is closer to 3 with the log transformation. However, the log transformation ends up dropping a significant portion of the sample with zero recorded earnings. To both transform earnings and keep golfers with zero earnings, I use the inverse hypberbolic sine (IHS) function. Similar to the log transformation, skewness and kurtosis are much closer to a normal distribution with the IHS transformed earnings than with raw earnings. The tails of the IHS distribution are thinner than a normal distribution, but this likely results from the large incidence of zero earnings.

To better understand the participation margin, Appendix Figure D.4 plots the career profile of the probability of positive US earnings for the same sample, but without the age restriction. Average participation rise quickly from age 20 to 32 and the falls quickly until age 50. To understand the participation margin in terms of the treatment effect estimates, Appendix Table E.3 reports average labor force participation rate (LFPR) relative to the year that a golfer participated in an experiment. The LFPR is defined as the ratio of golfers with positive world earnings. These statistics are computed for the five nearest golfers to each side of the treatment threshold in both experiments. Five years after treatment, the LFPR is 0.81 and 0.69 for the Korn Ferry Tour ML and Q School samples, respectively. At ten years after treatment these rates dwindle to 0.55 and 0.45, respectively. The low LFPRs in the later years likely drive the large increase in variance for long-run treatment effects estimated at the annual level. As a result, I aggregate all outcomes from four year after the experiment onward to understand the long-run effects of treatment, yet with reduced variance in the estimates.

The size of the estimated treatment effects at different points in time may depend on the relative

size of the prize money awarded on the PGA TOUR versus the Korn Ferry Tour. Appendix Figure D.5 plots the average purses over time. Panel D.5a shows the growth in the average nominal purse on both the PGA TOUR and Korn Ferry Tour. The growth in PGA TOUR purses amounts to about a 10% annual rate with higher growth prior to 2004. As purses grow faster than inflation, I deflate earnings by the growth in purses rather than the inflation rate. Panel D.5b shows the ratio of PGA TOUR to Korn Ferry Tour purses. Prize money on the PGA TOUR is about nine times greater than the prize money on the Korn Ferry Tour over this period. This ratio is relatively stable, yet with some yearly fluctuations. Appendix Section F.4 assesses the changes in treatment effects over time.

C Details of Estimation Methods

For both natural experiments, I pool multiple experiment episode across many years to obtain the main estimates. This pooling could have various ramifications. First, the treatment effect may change over time and, thus, pooling across experiments may mask these differences. Second, the treatment threshold for both experiments changes over time. If there are heterogeneous treatment effects at different thresholds, pooling will average across these differences. The treatment threshold becomes more stringent over time for Q School and more relaxed over time for the Korn Ferry Tour ML. I explore the scope for changing treatment effects over time in a sensitivity analysis in Appendix Section F.4.

Pooling experiments across time produces a different sample depending on how far in the future treatment effects are estimated. Appendix Table E.4 outlines the implications of this pooling in terms of the different samples that are used to compute treatment effects at different years after the experiments. The main takeaways are long-run treatment effects rely on fewer and older experiments and a younger sample of golfers. To explore whether these different sample systematically affect the results, I re-estimate the treatment effects using a balanced sample of golfers covering only experiment years 1992 to 2004 and golfers aged 17 to 47 at the time of experiment

participation. The results are presented in Appendix Section F.4.

In all specifications I net out experiment year fixed effects from all outcomes prior to running the estimation. Given that the treatment thresholds are changing over time, this goes some way to ensure that experiments are comparable over time. For the main specification, I also drop experiment years 1990 and 1991 from the sample. During these years, only five golfers qualified through the Korn Ferry Tour ML. I decided that this is too few a number of golfers to produce a valid limit estimate for the treatment side during these years. However, Appendix Section F.4 presents results from different eras including 1990 and 1991. I also can present results that include 1990 and 1991 upon request. These results are very similar to the main specification.

Local Linear Regressions I use the Stata software program *rdrobust* described in Calonico et al. (2017) to implement the local linear regressions. I implement the regressions with a triangular kernel and a linear function form with different slopes on each side of the treatment threshold. I also compute separate bandwidths on each side of the treatment threshold since there are less golfers on the treated side of the threshold. I use coverage error rate (CER) optimal bandwidths. Calonico et al. (2014) note that methods for computing optimal bandwidths include a first order bias term resulting from bandwidths that are too "large". My main specification incorporates a bias correction to treatment effects and a standard error correction to compute robust confidence intervals. However, I compute the estimates with both methods and do not find large differences in the results. See Appendix Section F.1 for the results. Additionally, Calonico et al. (2016) develop formal local polynomial methods allowing for pre-intervention covariate adjustments which can reduce standard errors. I adjust for age, age squared, and OWGR in a sensitivity analysis with results in See Appendix Section F.2. I do not incorporate all pre-treatment characteristics in order to maximize sample size.

I cluster at running variable position and experiment year level as this is the level of the treatment assignment (Lee and Card, 2008). For the Korn Ferry Tour ML this clustering does not have an effect in most cases at there are no ties in running variable in any given experiment year. However, when this clustering takes effects for outcomes that pool across multiple years such as when

I estimate the effect on adjusting scoring average four to sixteen years after treatment.

Local Randomization I use the Stata software program *rdlocrand* described in Cattaneo et al. (2017) to implement the local randomization method. I assume that the treatment assignment mechanism follows a Bernoulli distribution in which the probability of treatment estimated as the share of treated golfers within one stroke of the treatment threshold. I set the number of repetitions at a level slightly lower than the default value as this yields a big improvement on processing time. The default value is 1,000 and I set the value to 800. The program is not compatible with clustering and, therefore, I cannot cluster at the experiment year level.

D Additional Figures

Figure D.1: Time Line of Events (Example: 2012-2013)

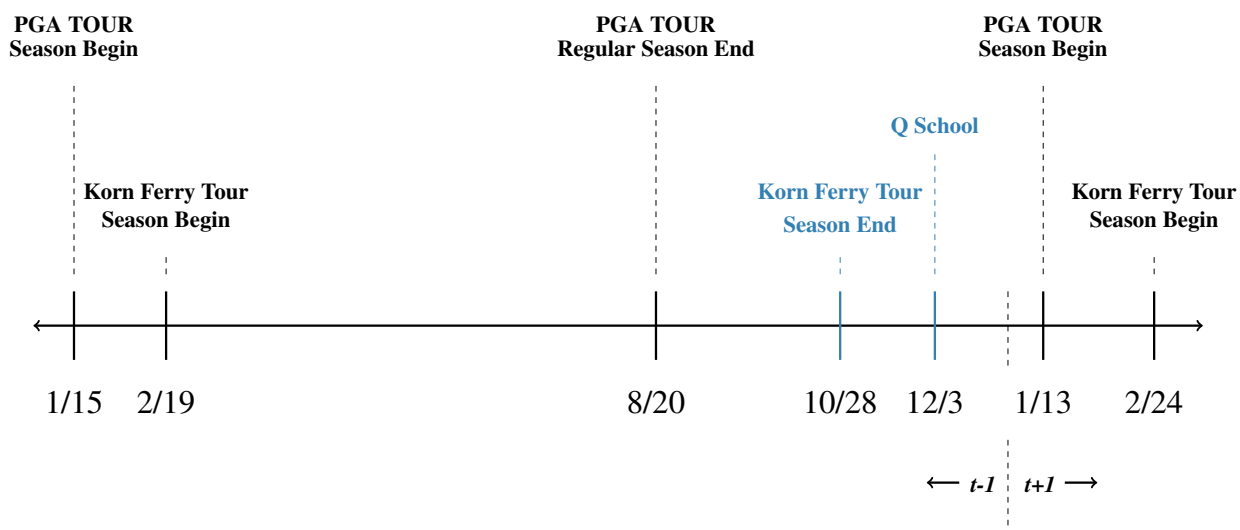


Figure D.2: PGA TOUR Cards Awarded by Experiment

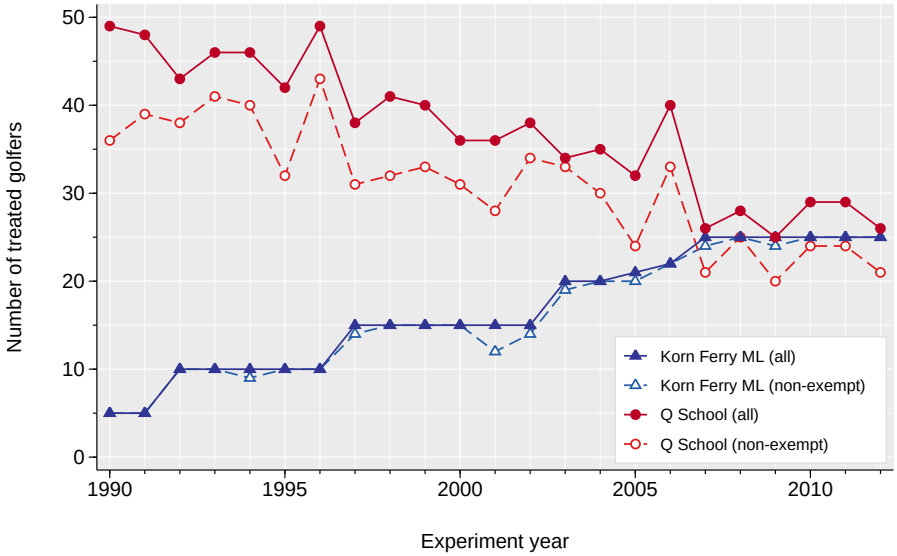


Figure D.3: Example of the All-Exempt TOUR Priority Rankings from 2011

All-Exempt TOUR Priority Rankings

Each PGA TOUR player has earned a position on the priority ranking system that will be used to select tournament fields. The complete ranking system, in order of priority, is as follows:

1. Winner of PGA Championship or U.S. Open prior to 1970 or in the last 10 calendar years:
(Beginning in 1998, this is a five-year exemption.)
Jack Burke Jr. **Lucas Glover** **Arnold Palmer**
Angel Cabrera **Padraig Harrington** **Gary Player**
Billy Casper **Don January** **Lee Trevino**
Dow Finsterwald **Gene Littler** **Ken Venturi**
Jack Fleck **Graeme McDowell** **Tiger Woods**
Raymond Floyd **Bobby Nichols** **Y.E. Yang**
Doug Ford **Jack Nicklaus**
Al Geiberger **Geoff Ogilvy**

2. Winner of THE PLAYERS Championship in the last 10 calendar years:
(Beginning in 1998, this is a five-year exemption.)
Stephen Ames **Tim Clark** **Sergio Garcia**
Phil Mickelson **Henrik Stenson**

3. Winners of the Masters Tournament in the last 10 calendar years:
(Beginning in 1998, this is a five-year exemption.)
Trevor Immelman **Zach Johnson**

4. Winners of the British Open in the last 10 calendar years:
(Beginning in 1998, this is a five-year exemption.)
Stewart Cink **Louis Oosthuizen**

5. Winners of THE TOUR Championship, beginning in 2005 (a three-year exemption):
Jim Furyk **Camilo Villegas**

6. Winners of World Golf Championships events, beginning in 2005 (a three-year exemption):
Ernie Els **Hunter Mahan** **Ian Poulter**
Vijay Singh

7. The winner of the FedExCup:

8. The leader in PGA TOUR official earnings in each of the last five calendar years:
Matt Kuchar

9. Winners of PGA TOUR co-sponsored or approved events (except team events) within the last two calendar years, or during the current year; winners receive an additional year of exemption for each additional win, up to five years:
Stuart Appleby **Nathan Green** **Pat Perez**
Arjun Atwal **Bill Haas** **Kenny Perry**
Cameron Beckman **Charley Hoffman** **Carl Pettersson**
Matt Bettencourt **Dustin Johnson** **John Rollins**
Jason Bohn **Jerry Kelly** **Justin Rose**
Michael Bradley **Anthony Kim** **Rory Sabbatini**
Jonathan Byrd **Martin Laird** **Adam Scott**
Paul Casey **Derek Lamely** **Heath Slocum**
K.J. Choi **Justin Leonard** **Steve Stricker**
Ben Crane **Bill Lunde** **David Toms**
Jason Day **Troy Matteson** **Bo Van Pelt**
Fred Funk **Rocco Mediate** **Nick Watney**
Robert Garrigus **Ryan Moore** **Bubba Watson**
Brian Gay **Sean O'Hair** **Mark Wilson**
Retief Goosen **Ryan Palmer**

10. Leaders in official PGA TOUR career earnings, as follows:
   A. Players among the top 50 in career earnings as of the end of the preceding calendar year may elect to use a one-time, one-year exemption for the next year:
   Chris DiMarco **Nick Price** **Steve Flesch**
   Fred Couples **Tim Herron** **Jesper Parnevik**
   B. Players among the Top 25 in career earnings as of the end of the preceding calendar year may elect to use this special exemption for a second year, provided that the player remains among the Top 25 on the career money list.
   Mark Calcavecchia

11. Sponsor exemptions (a maximum of eight, which may include amateurs with handicaps of 0 or less), on the following basis:
   A. Not less than two sponsor invitees shall be PGA TOUR members not otherwise exempt.
   B. Not less than two of the top 25 finishers and ties from the last Qualifying Tournament, as well as 2-25 from the 2009 Nationwide Tour money list, if not all of them can otherwise be accommodated. (Note: PGA TOUR members may receive an unlimited number of sponsor invitations. Non-TOUR members may receive a maximum of seven per year.)

12. Two international players designated by the Commissioner.

13. The current PGA Club Professional Champion for a maximum of three open events, in addition to any sponsor selections.
Mike Small

14. PGA Section Champion or Player of the Year of the Section in which the tournament is played.

15. Four low scorers at Open Qualifying which shall normally be held on Monday of tournament week.

16. Past champions of the particular event being contested that week, if co-sponsored by the PGA TOUR and the same tournament sponsor (except for Team events), as follows:
   A. Winners prior to July 28, 1970: unlimited exemptions for such events.
   B. Winners after July 28, 1970 and prior to Jan. 1, 2000: 10 years of exemptions for such events.
   C. Winners after Jan. 1, 2000: five years of exemptions for such events.

17. Life Members (who have been active members of the PGA TOUR for 15 years and have won at least 20 co-sponsored events).
Davis Love III **Tom Watson**

18. Top 30 on the previous year's FedExCup points list.
Luke Donald
Kevin Streelman
Kevin Na
Robert Allenby
Jeff Overton

All-Exempt TOUR Priority Rankings (cont.)

19. Top 125 on previous year's Official Money List: If not exempt under "Special Exemptions," the top 125 PGA TOUR members on the previous year's Official Money List, in order of their position:

Rickie Fowler
J.B. Holmes
Brendon de Jonge
Vaughn Taylor
Ricky Barnes
Fredrik Jacobson
Scott Verplank
Brian Davis
D.J. Trahan
Brandt Snedeker
Charlie Wi
Marc Leishman
Charles Howell III
Steve Marino
Bryce Molder
Michael Sim
John Senden
Alex Prugh
Matt Jones
Spencer Levin
Tom Gillis
Jason Dufner
Paul Goydos
Kris Blanks
J.J. Henry
Tim Petrovic
Ryuji Imada
Shaun Micheel
Josh Teater
Chris Riley
Greg Chalmers
Andres Romero
D.A. Points
Webb Simpson
Chad Campbell
Blake Adams
Steve Elkington
Graham DeLaet
Chris Stroud
Jimmy Walker
Kevin Stadler
David Duval
Alex Cejka
Chris Couch
Aaron Baddeley
Boo Weekley
Garrett Willis
J.P. Hayes
Michael Connell
Corey Pavin
Dean Wilson
Kevin Sutherland
Chad Collins
Ben Curtis
Jeff Maggert
Roland Thatcher
Joe Durant
Troy Merritt

20. Players who finished in the Top 125 on the 2009 PGA TOUR Money List as non-members:
Robert Karlsson **Charl Schwartzel**

21. Major Medical Extension: If granted by the Commissioner, if not otherwise eligible, and if needed to fill the field, Special Medical Extension.

Mike Weir
Brett Wetterich
Bart Bryant
Arron Oberholser
Jeff Klauk
Joey Snyder
Dudley Hart
Nick O'Hern
Jose Maria Olazabal
Hank Kuehne
Chez Reavie
Harrison Frazar
Rich Beem
Jose Coceres
Marc Turnesa
Wes Short
Patrick Moore

22. Leading Money Winner from 2010 Nationwide Tour.
Jamie Lovemark

23. Top-10 and Ties among professionals from the previous open tournament whose victory has official status are exempt into the next open tournament whose victory has official status.

24. Top 25 and Ties from the previous year's PGA TOUR Qualifying Tournament, in order of their finish, and players 2-25 on the 2010 Nationwide Tour money list.

Billy Mayfair
Chris Kirk
William McGirt
Hunter Haas
Ben Martin
Tommy Gainey
Cameron Tringale
Daniel Summerhays
Jarrod Lyle
Brendan Steele
Michael Putnam
Jhonattan Vegas
Brandt Jobe
Martin Piller
Zack Miller
Kevin Chappell
Kyle Stanley
Tag Ridings
Paul Stankowski
Kevin Kisner
Gary Woodland
Fabian Gomez
Chris Baryla
David Mathis
Nate Smith
Keegan Bradley
Scott Stallings
Colt Knost
Bio Kim
Bobby Gates
Matt McQuillan
Steven Bowditch
Michael Thompson
D.J. Brigman
Joseph Bramlett
Jim Herman
Sunghoon Kang
Scott Gutschewski
Kent Jones
David Hearn
James Driscoll
Joe Affrunti
Alexandre Rocha
Peter Tomasulo
Jim Renner
Richard S. Johnson
Justin Hicks
Andres Gonzales
Scott Gordon
Billy Horschel
Will Strickler
Duffy Waldorf
(medical)
Shane Bertsch
(medical)
Neal Lancaster
(medical)
Carl Paulson
(medical)
David Berganio, Jr.
(medical)
Fran Quinn
(medical)

25. Nationwide Tour three-win promotion to any player winning three times during the current season, in priority determined by the date in which they win their third event:

26. Minor Medical Extension.
Craig Bowden
Garth Mulroy
Matt Every
Jerod Turner
Jeev Milkha Singh

27. Next 25 members after the Top 125 members from previous year's Official Money List. If needed to fill the field, the next 25 PGA TOUR members after the top 125 PGA TOUR members from the previous year's Official Money List, in order of their position on the list.

Johnson Wagner
Briny Baird
Woody Austin
Michael Allen
Aron Price
Bob Estes
John Mallinger
Scott Piercy
George McNeill
Tom Pernice, Jr.
John Merrick
Scott McCarron
Joe Ogilvie
Cameron Percy
Jeff Quinney
Lee Janzen
Chris Tidland
Charles Warren
Michael Letzig

28. Non-Exempt, Major Medical Extension
Matt Weibring

29. Past Champions, Team Tournament Winners and Veteran Members Beyond 150 on Money List: If not otherwise eligible and as needed to fill the field, Past Champion members, Team Tournament Winners and Veteran members beyond 150th place on the previous year's Money List, in order of their combined official PGA TOUR and Nationwide Tour earnings in the previous year.

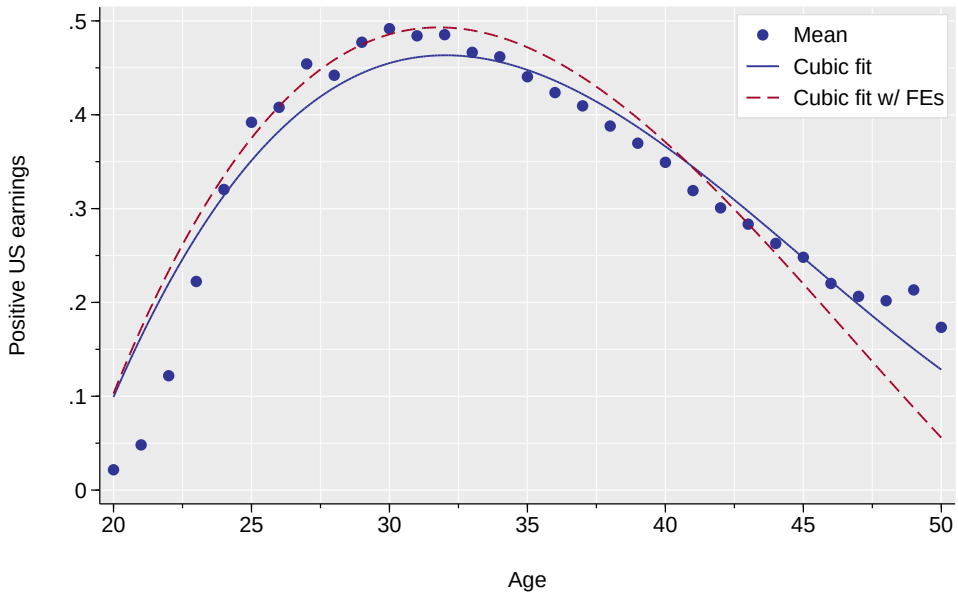
30. Past Champion Members: If not otherwise eligible and if needed to fill the field, Past Champion members, in order of the total number of co-sponsored or approved events won, excluding Team events. If two or more players are tied, the player who is higher on the PGA TOUR Career Money List shall be eligible.

31. Special Temporary: If during the course of a PGA TOUR season, a non-member of the PGA TOUR wins an amount of official money (e.g., by playing in PGA TOUR events through sponsor exemptions, Open Qualifying, etc.) equal to the amount won in the preceding year by the 150th finisher on the official money list, he will be eligible for the remainder of the year.

32. Team Tournament Winners: If not otherwise eligible and if needed to fill the field, winners of co-sponsored team championships, in order of the total number of team championship tournaments won. If two or more players are tied based on the number of such tournaments won, the player who is higher on the official PGA TOUR Career Money List shall be eligible.

33. Veteran Members: If not otherwise eligible and if needed to fill the field, Veteran members (players who have made a minimum of 150 cuts during their career), in order of their standing on the PGA TOUR Career Money List.

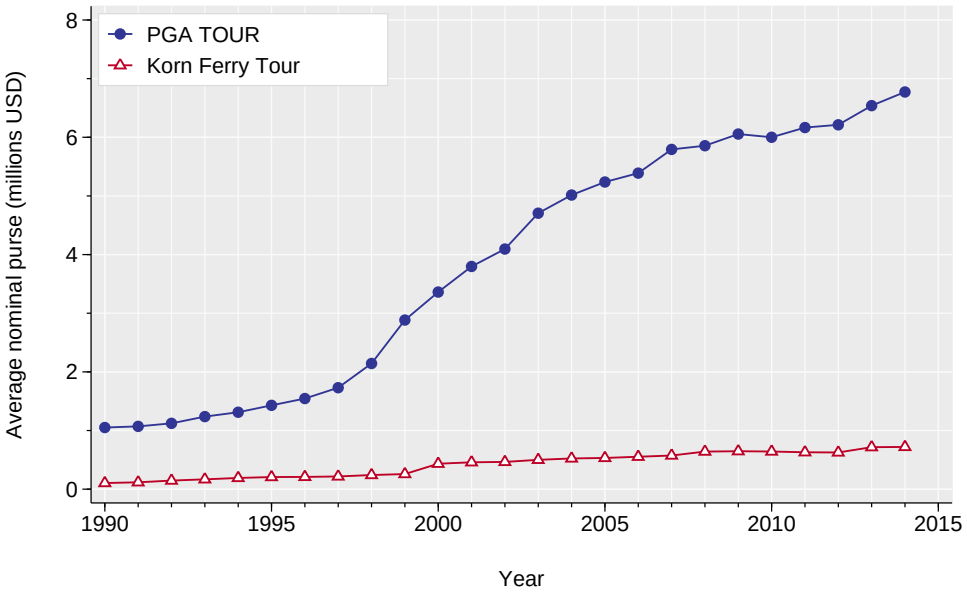
Figure D.4: Career profile of participation: probability of positive US earnings



Notes: The sample includes all golfers who played in at least 5 events on the PGA TOUR or Korn Ferry Tour from 1990 to 2014. The blue dots represent the mean values of each outcome at each age. The blue, solid lines represent the prediction line of an OLS regression of each outcome on a cubic in age. The red, dashed lines represent the prediction line of an OLS regression of each outcome on a cubic in age and individual golfer fixed effects. The cubic fit with fixed effects is normalized to begin at the same level as the cubic fit without fixed effects.

Figure D.5: Growth in golf earnings over time

(a) Average nominal PGA TOUR and Korn Ferry Tour purses



(b) Ratio of PGA TOUR to Korn Ferry Tour average purse

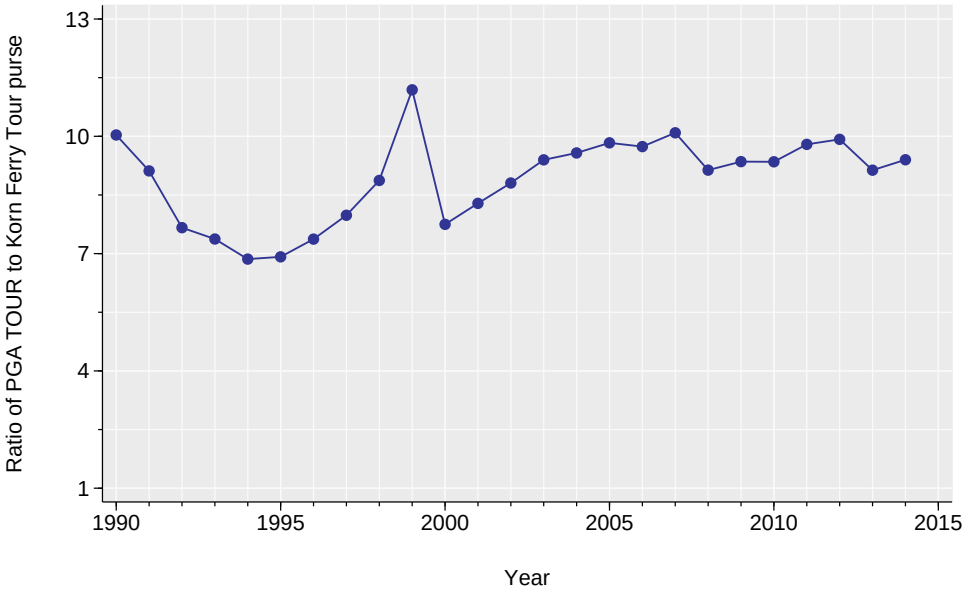
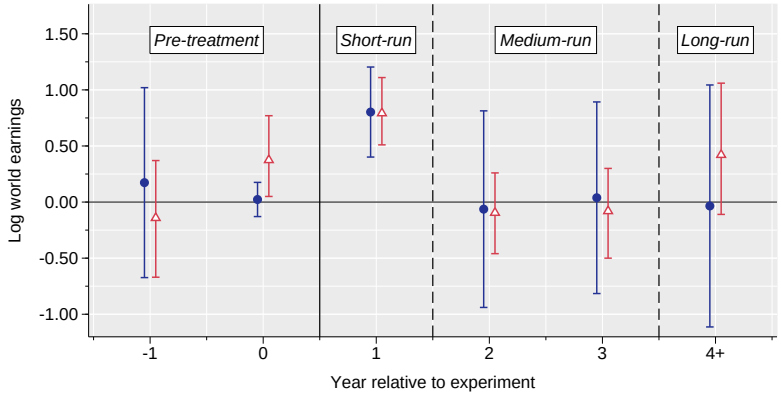
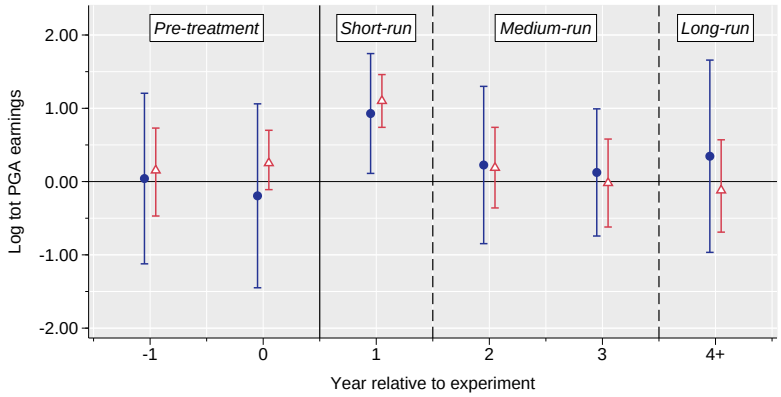


Figure D.6: Estimated treatment effects on log earnings

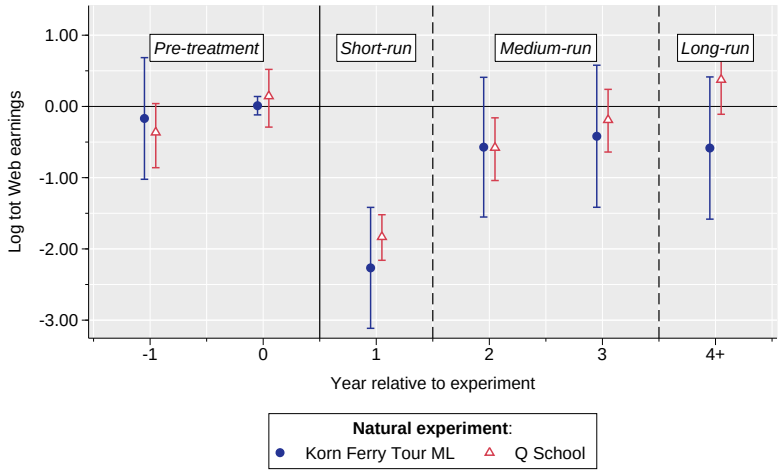
(a) Log world earnings



(b) Log PGA TOUR earnings



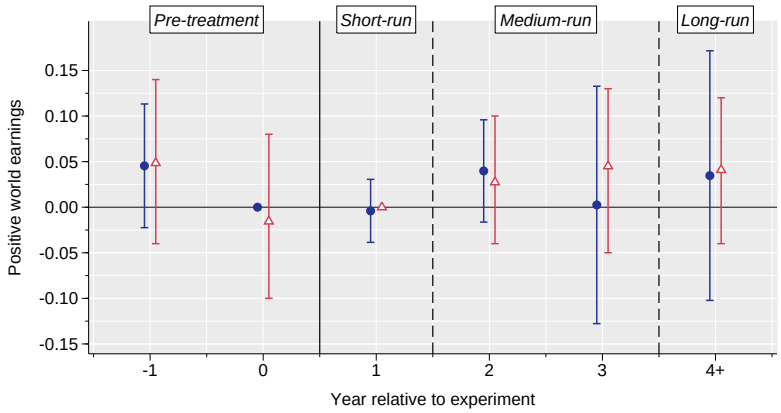
(c) Log Korn Ferry Tour earnings



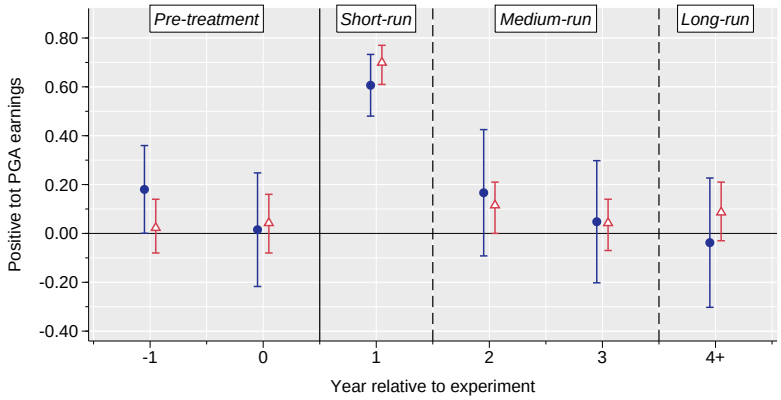
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, respectively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

Figure D.7: Estimated treatment effects on probability of positive earnings

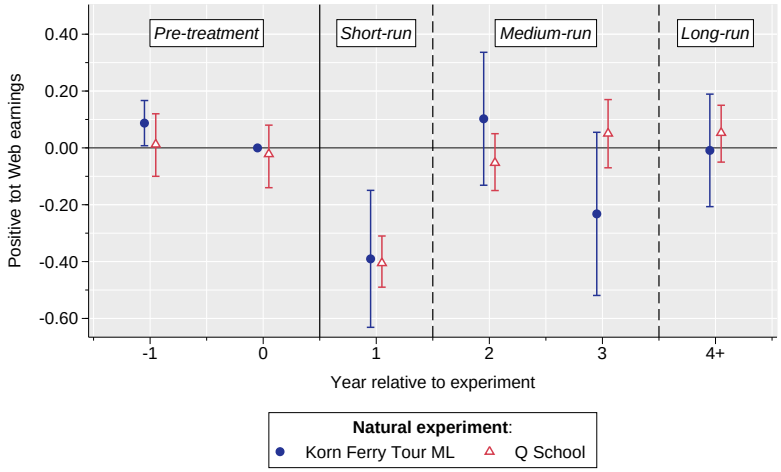
(a) Positive world earnings



(b) Positive PGA TOUR earnings



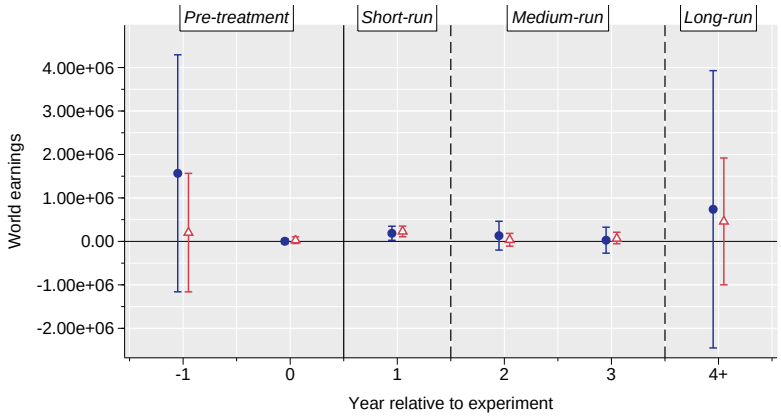
(c) Positive Korn Ferry Tour earnings



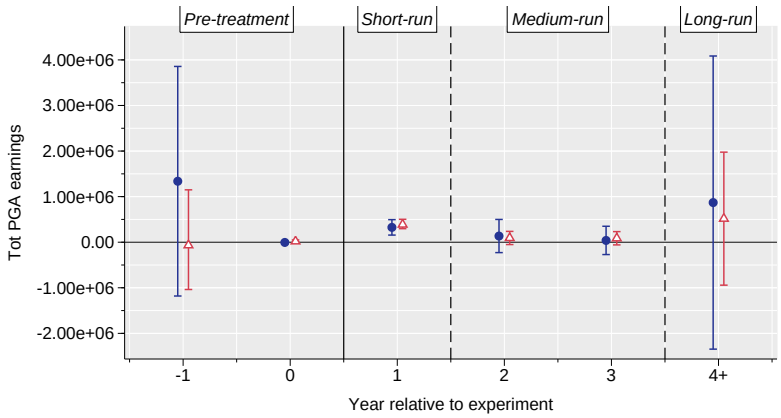
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, respectively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

Figure D.8: Estimated treatment effects on earnings

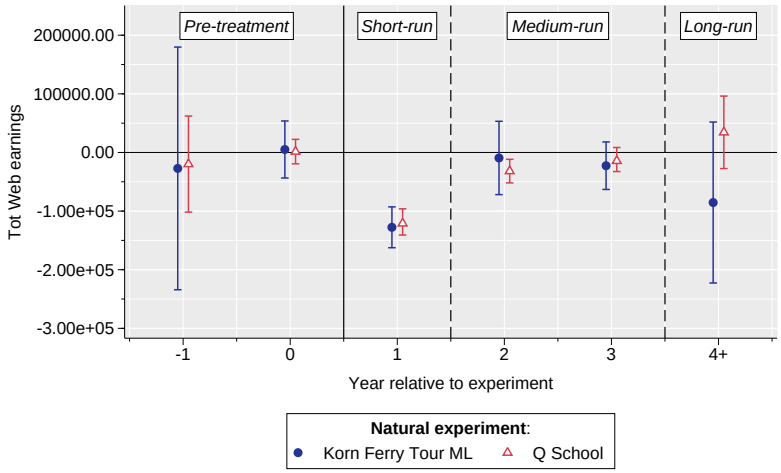
(a) World earnings



(b) PGA TOUR earnings



(c) Korn Ferry Tour earnings



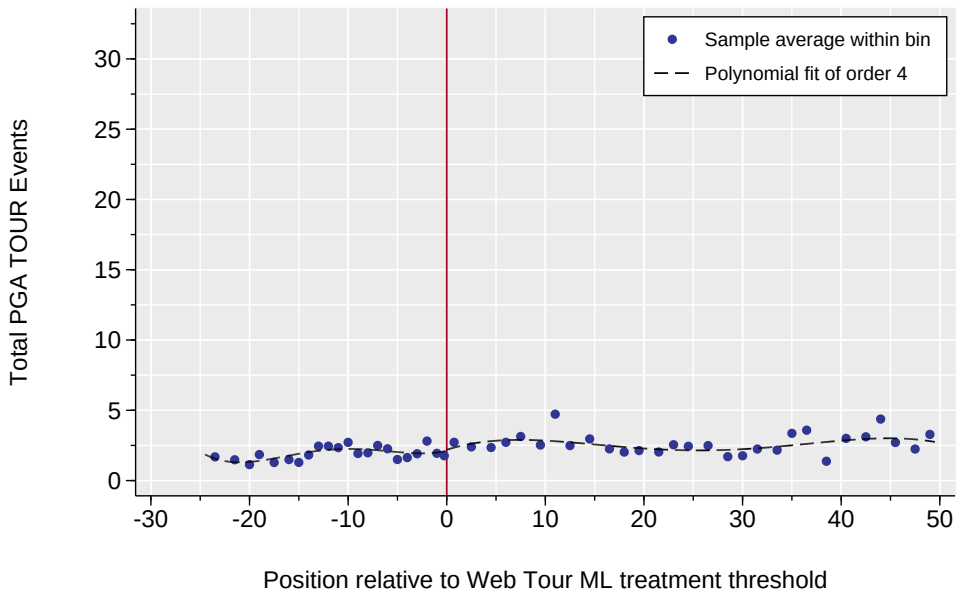
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, respectively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

D.1 Additional Regression Discontinuity Plots

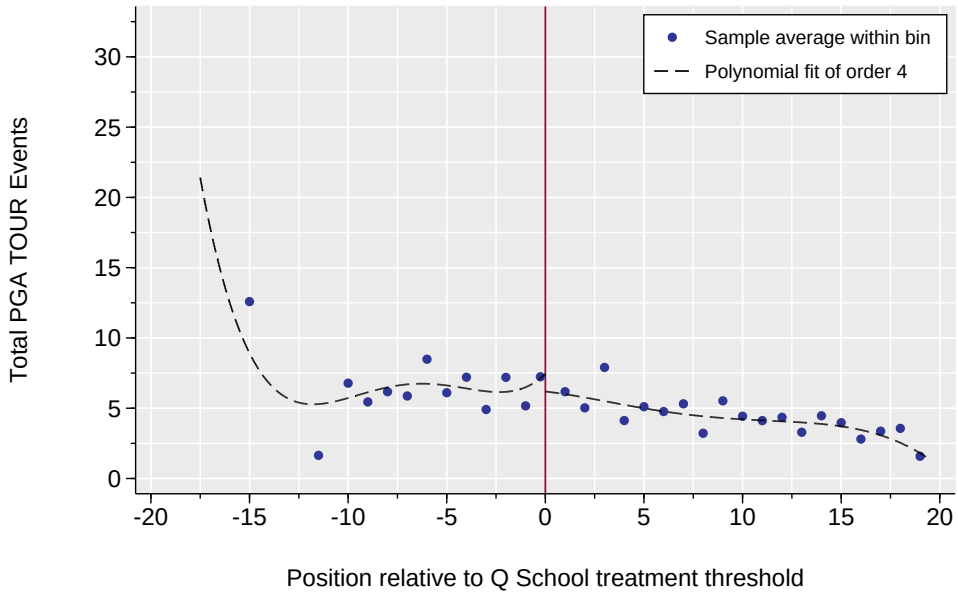
D.2 Pre-Treatment Outcomes

Figure D.9: RD plots of PGA TOUR events in **year 0**

(a) Korn Ferry Tour ML



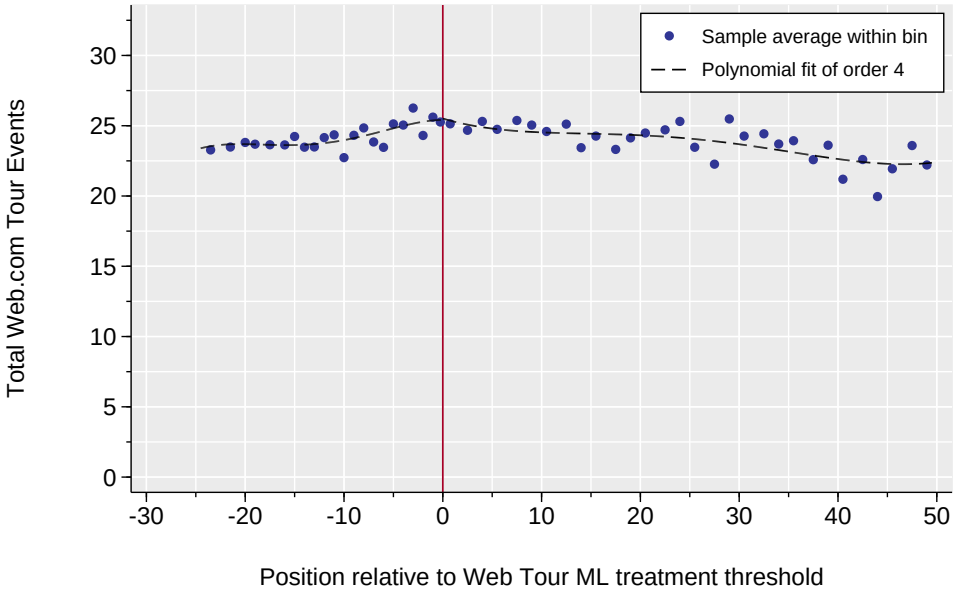
(b) Q School



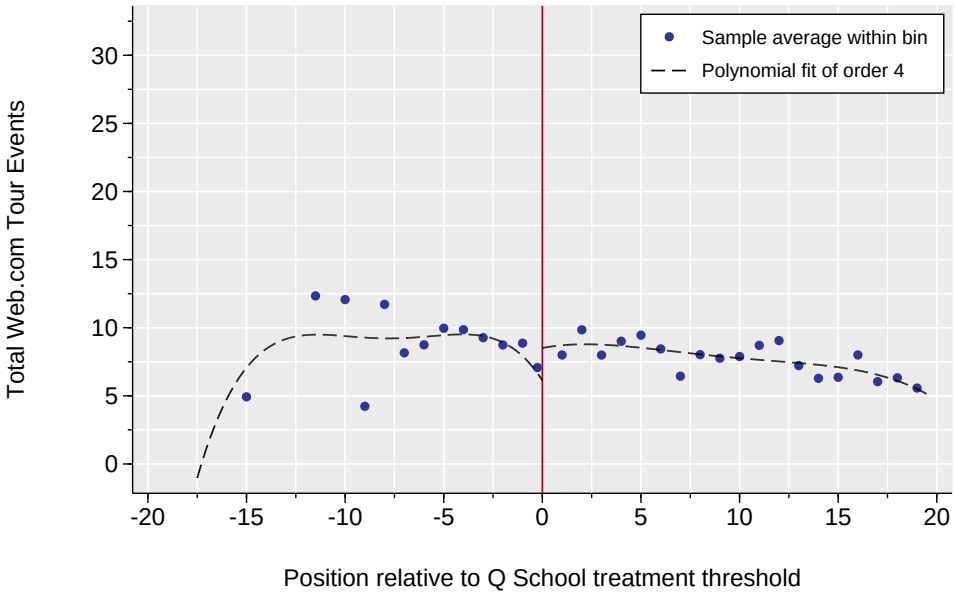
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.10: RD plots of Korn Ferry Tour events in **year 0**

(a) Korn Ferry Tour ML



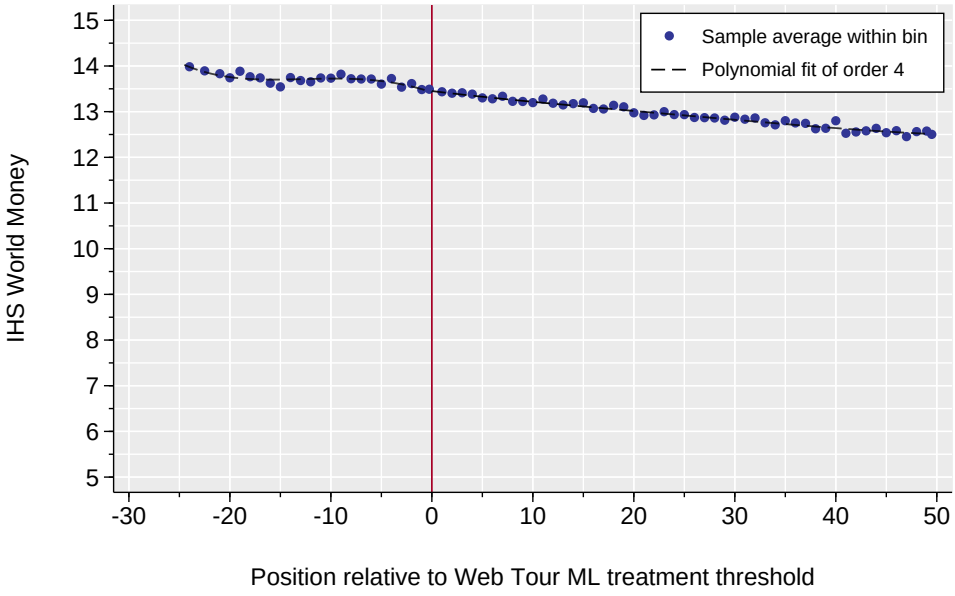
(b) Q School



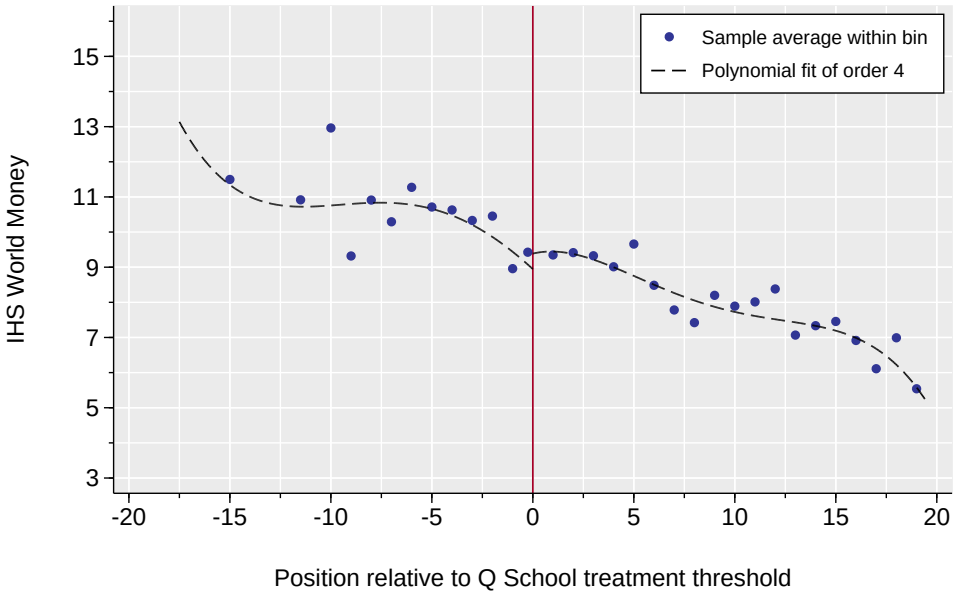
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.11: RD plots of IHS World earnings in **year 0**

(a) Korn Ferry Tour ML



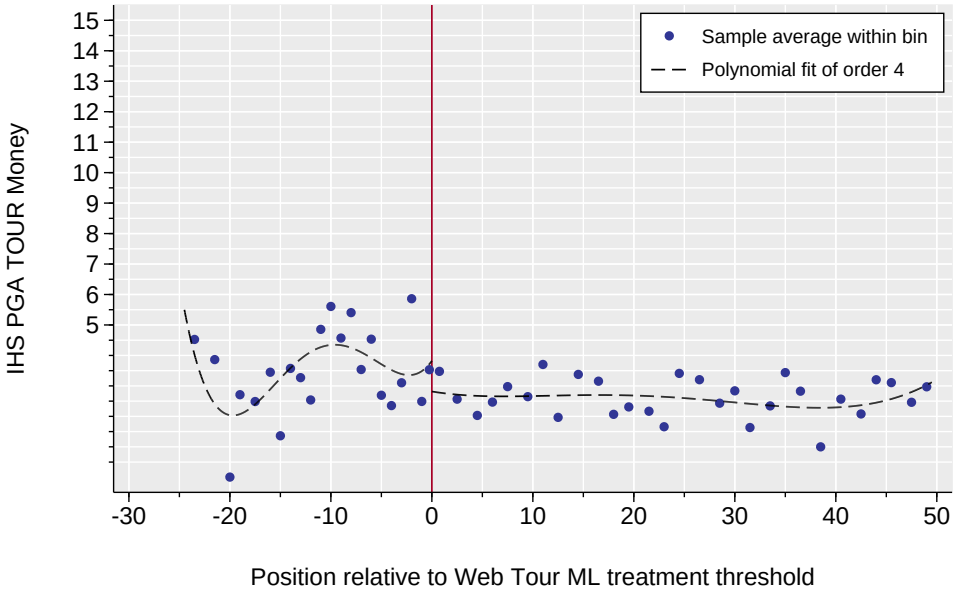
(b) Q School



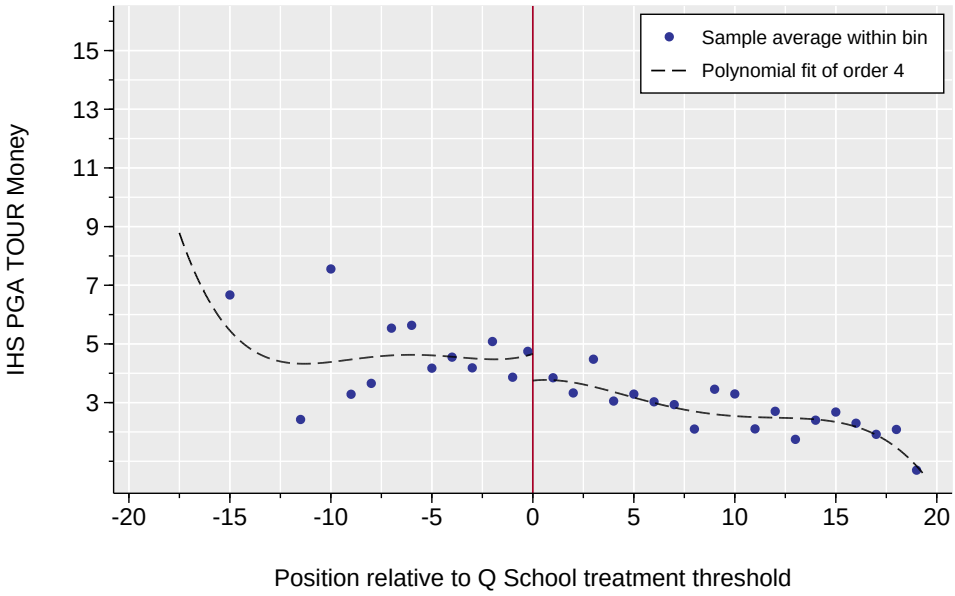
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.12: RD plots of IHS PGA TOUR earnings in **year 0**

(a) Korn Ferry Tour ML



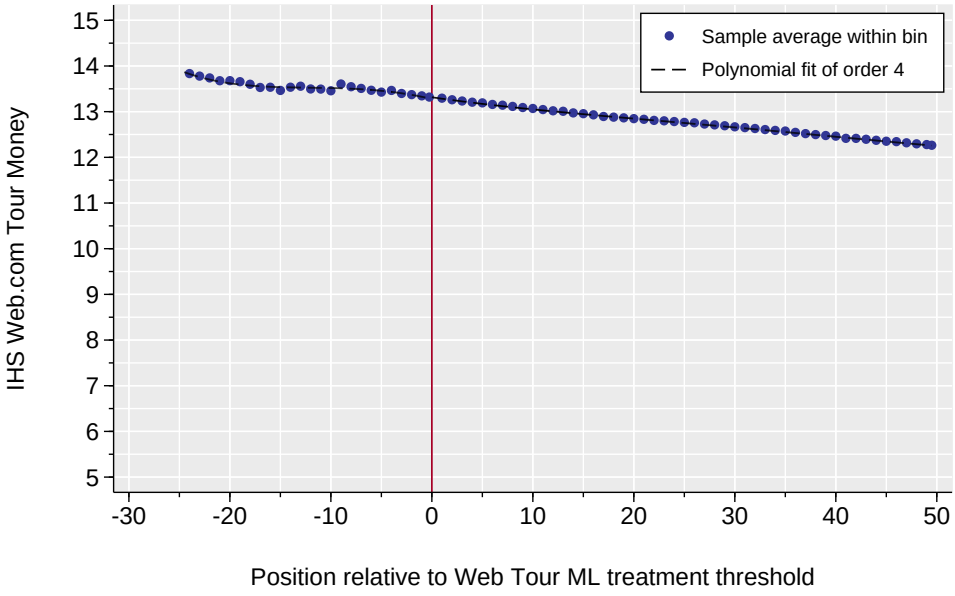
(b) Q School



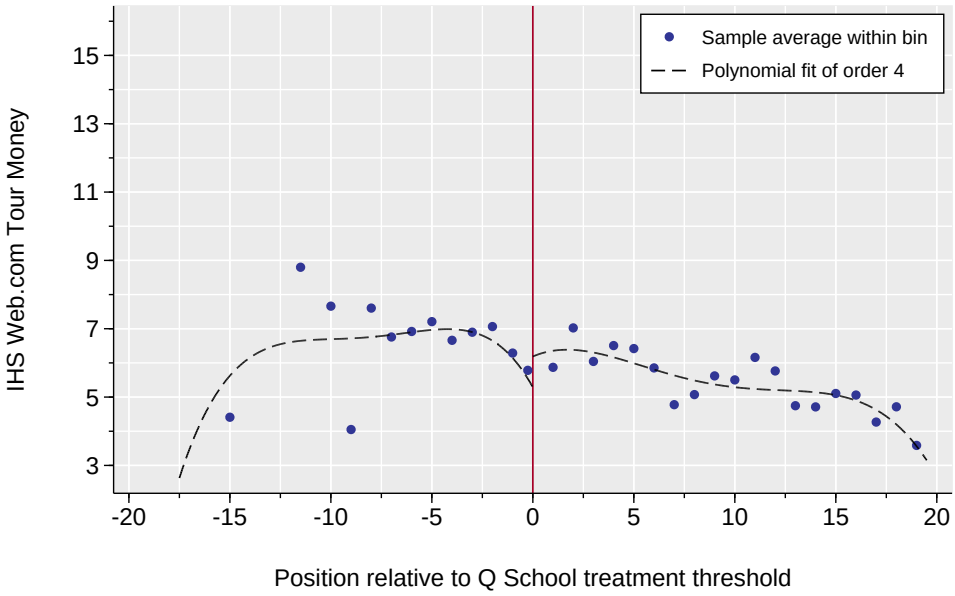
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.13: RD plots of IHS Korn Ferry Tour earnings in **year 0**

(a) Korn Ferry Tour ML



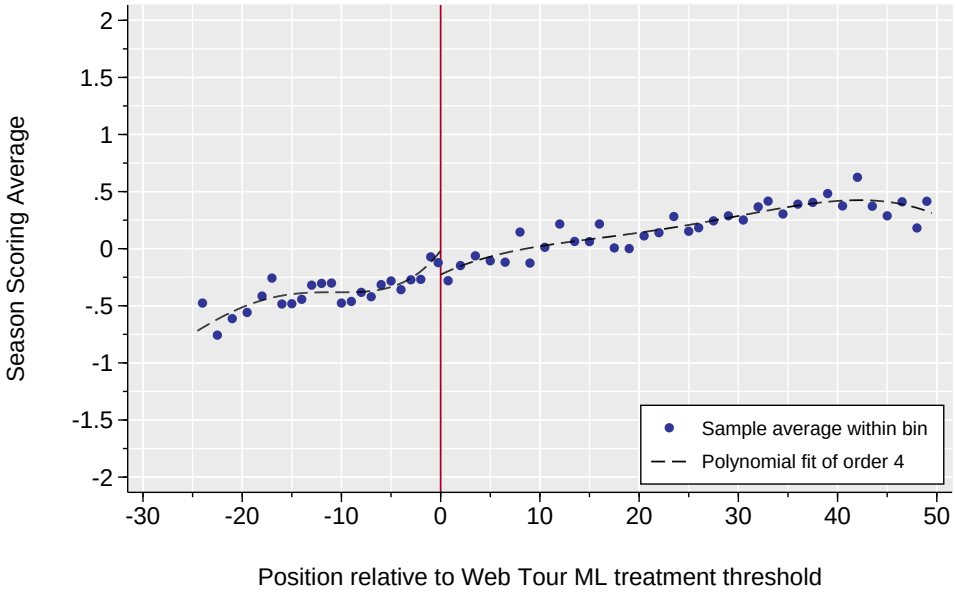
(b) Q School



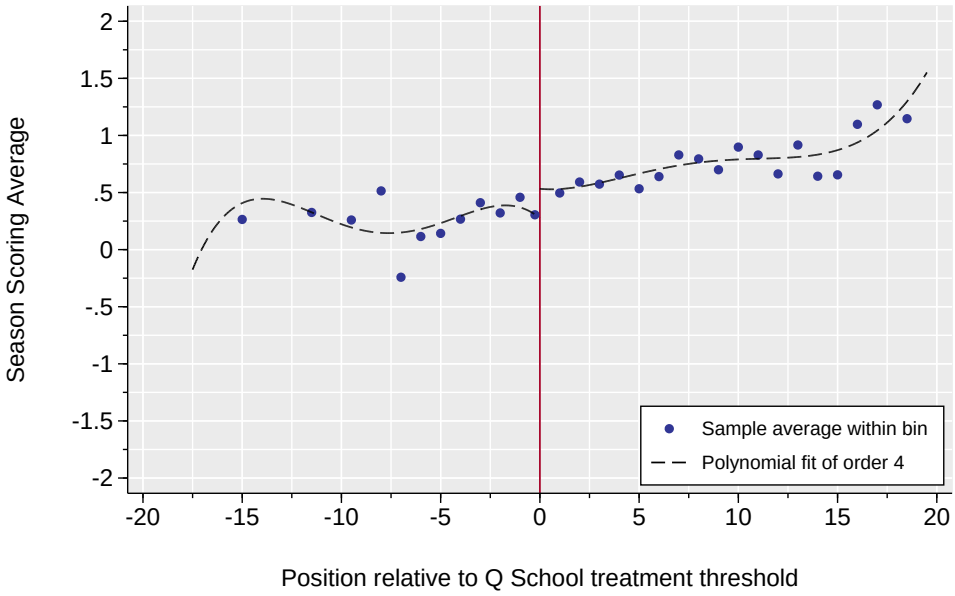
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.14: RD plots of adjusted scoring average in **year 0**

(a) Korn Ferry Tour ML



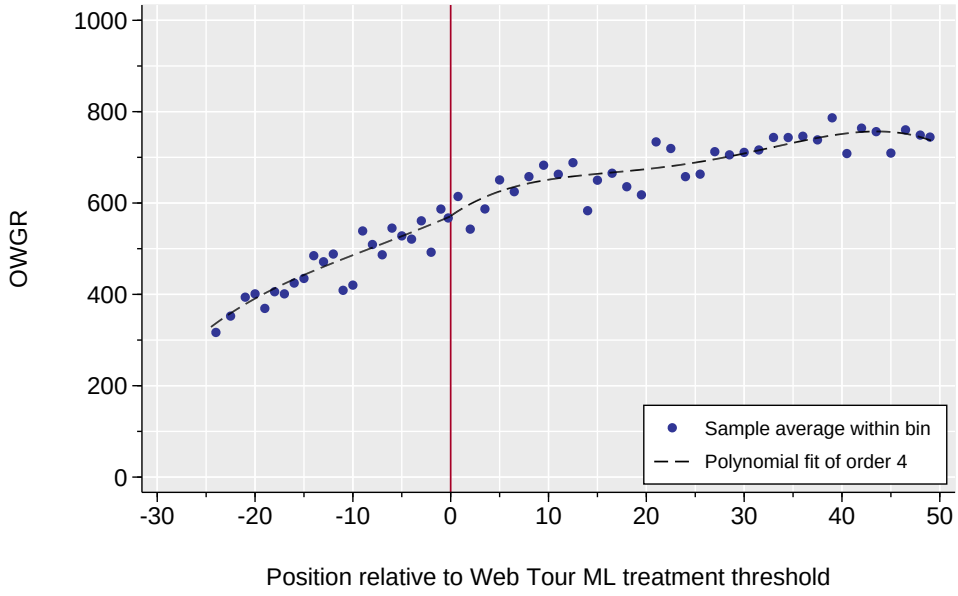
(b) Q School



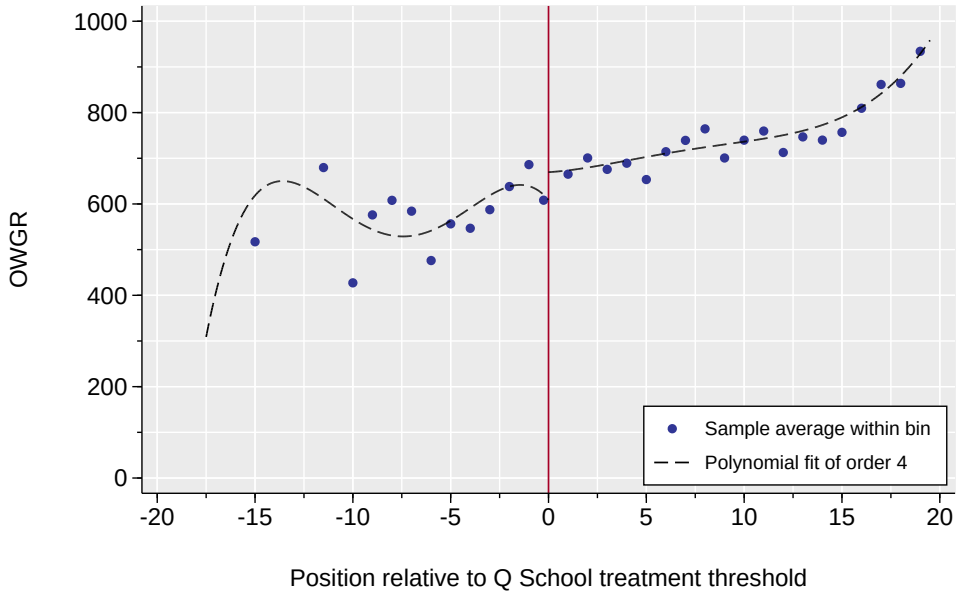
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.15: RD plots of OWGR in **year 0**

(a) Korn Ferry Tour ML



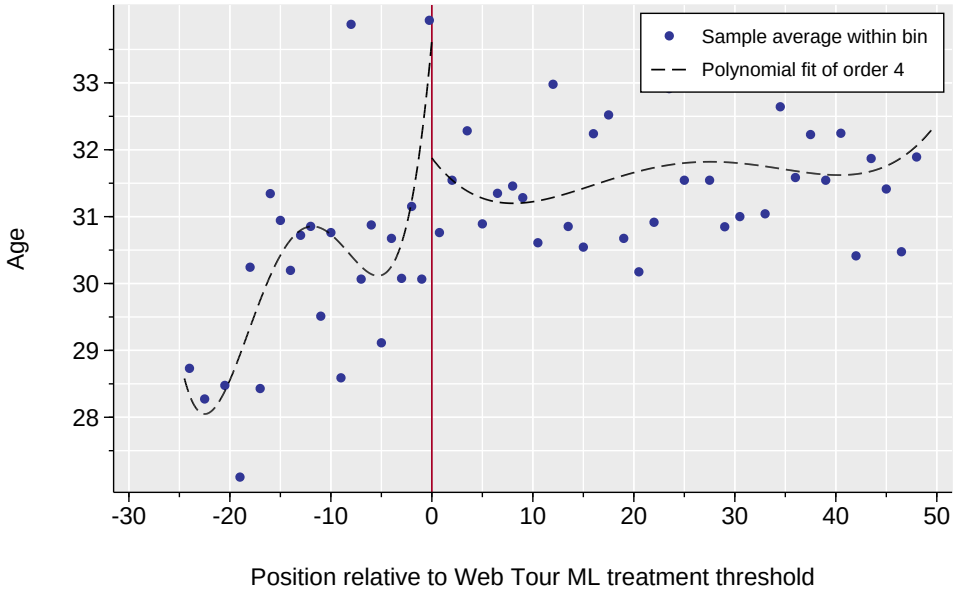
(b) Q School



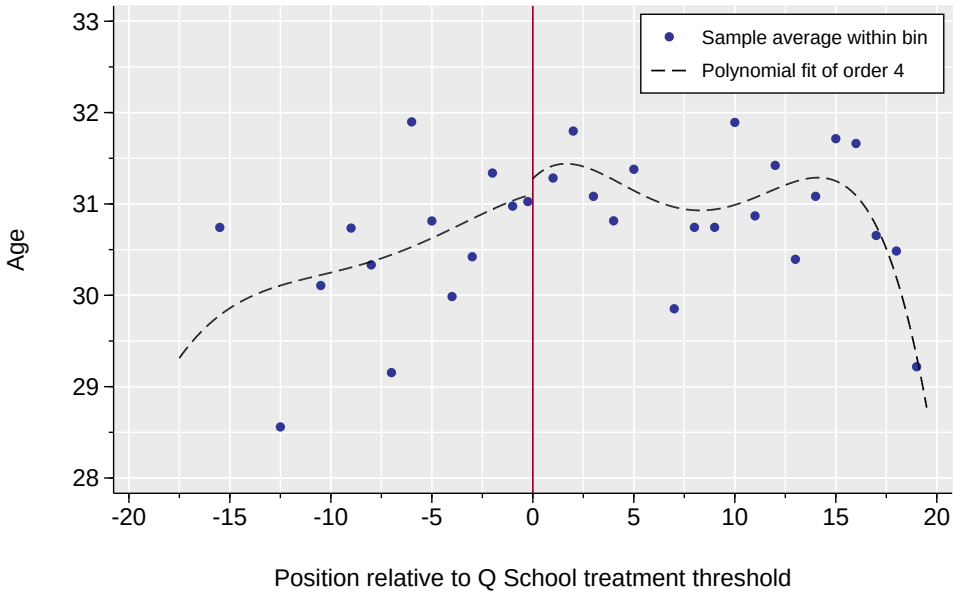
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.16: RD plots of age in **year 0**

(a) Korn Ferry Tour ML



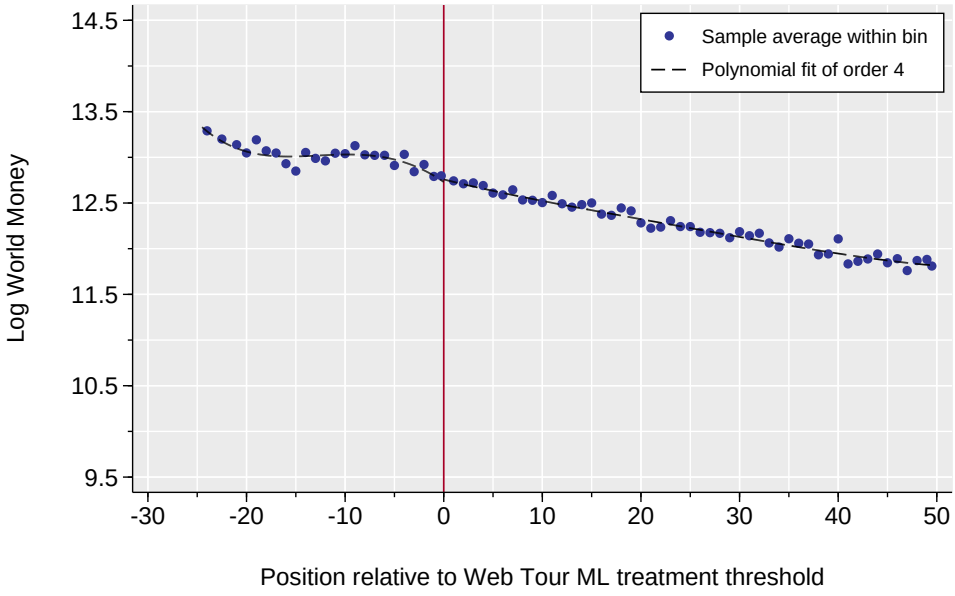
(b) Q School



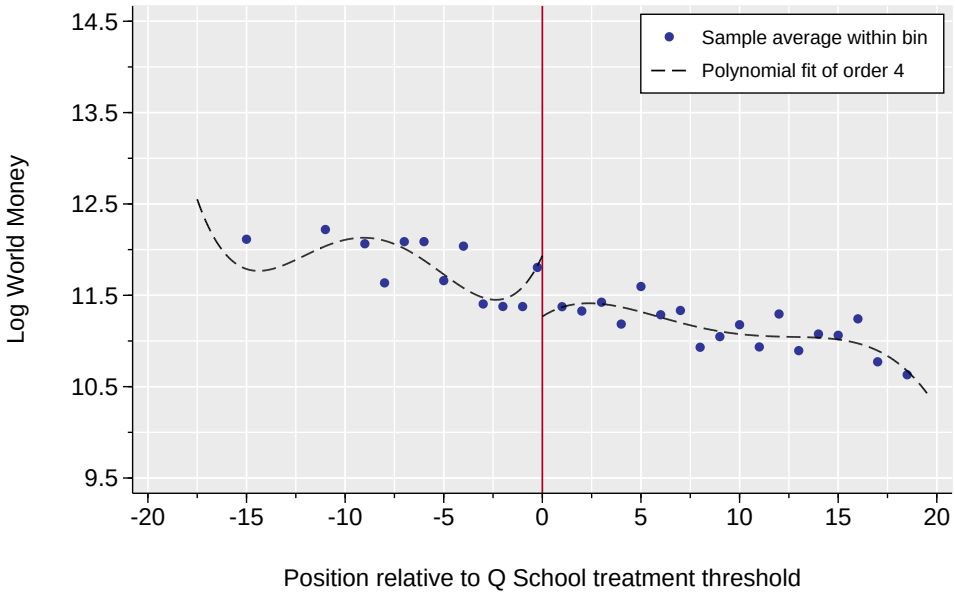
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.17: RD plots of log world earnings in **year 0**

(a) Korn Ferry Tour ML



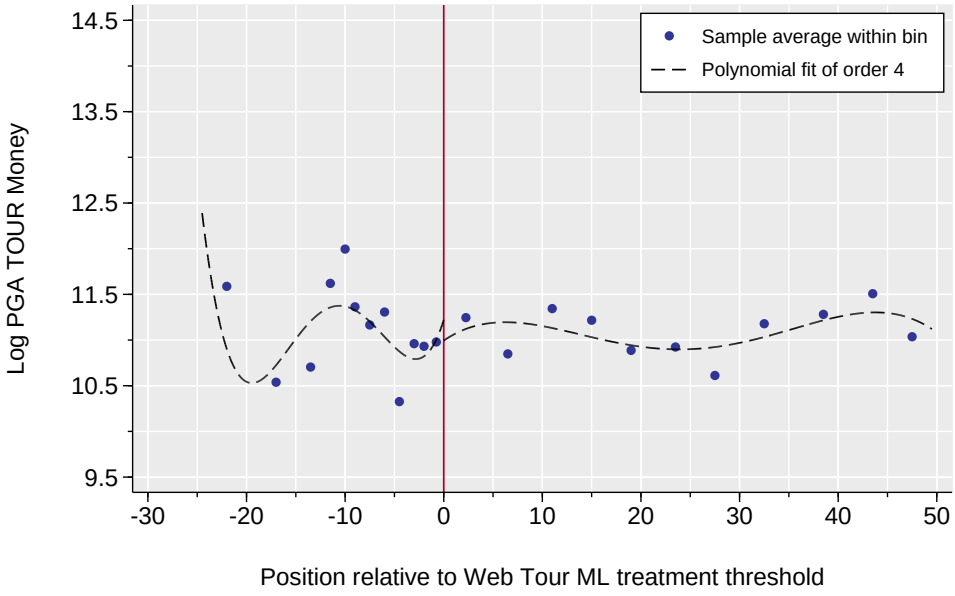
(b) Q School



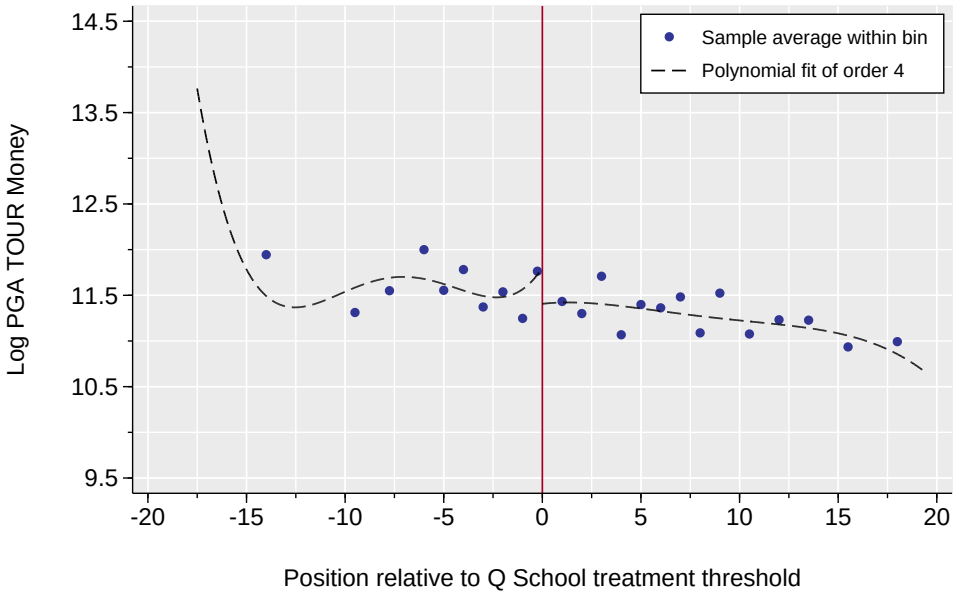
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.18: RD plots of log PGA TOUR earnings in **year 0**

(a) Korn Ferry Tour ML



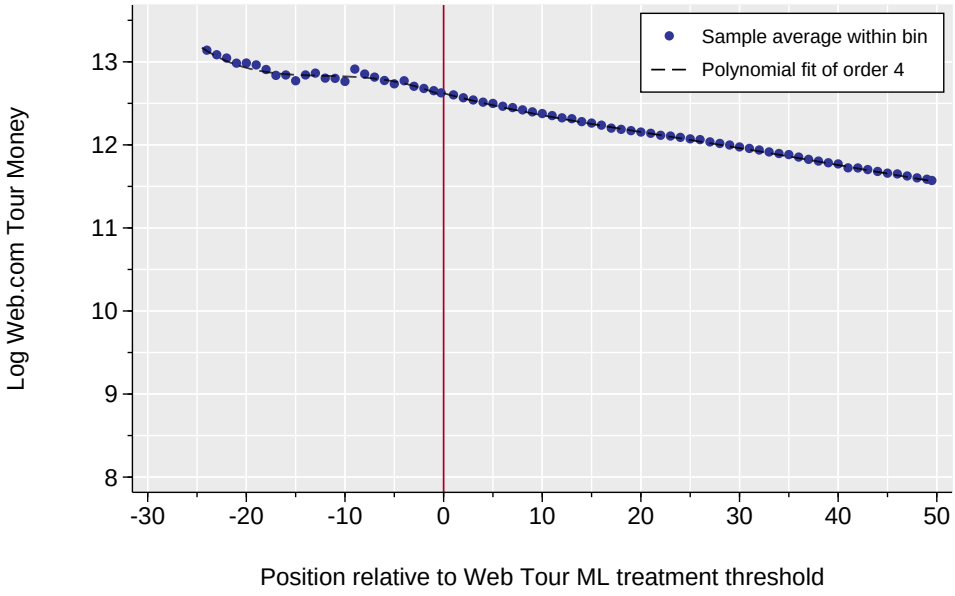
(b) Q School



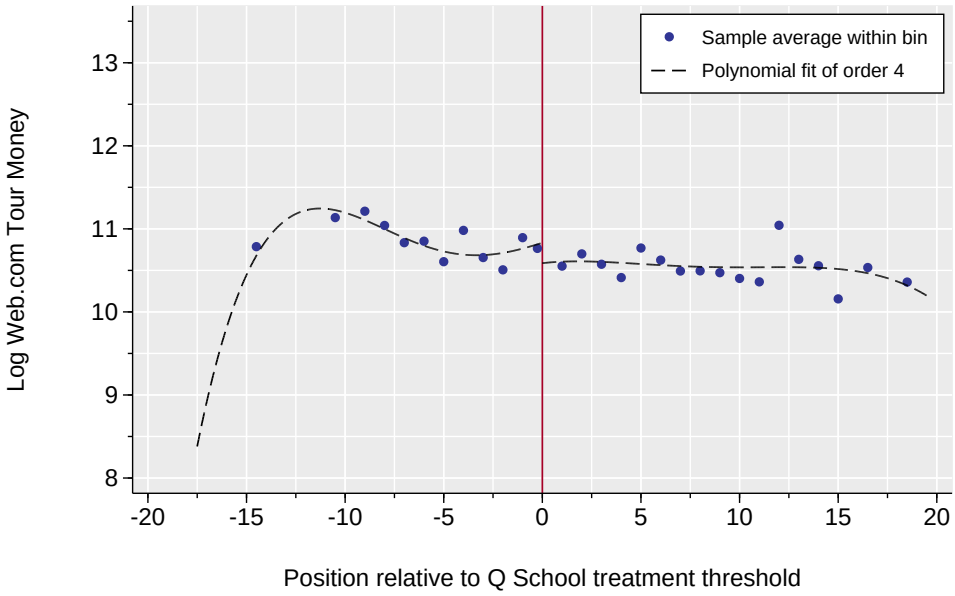
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.19: RD plots of log Korn Ferry Tour earnings in **year 0**

(a) Korn Ferry Tour ML



(b) Q School

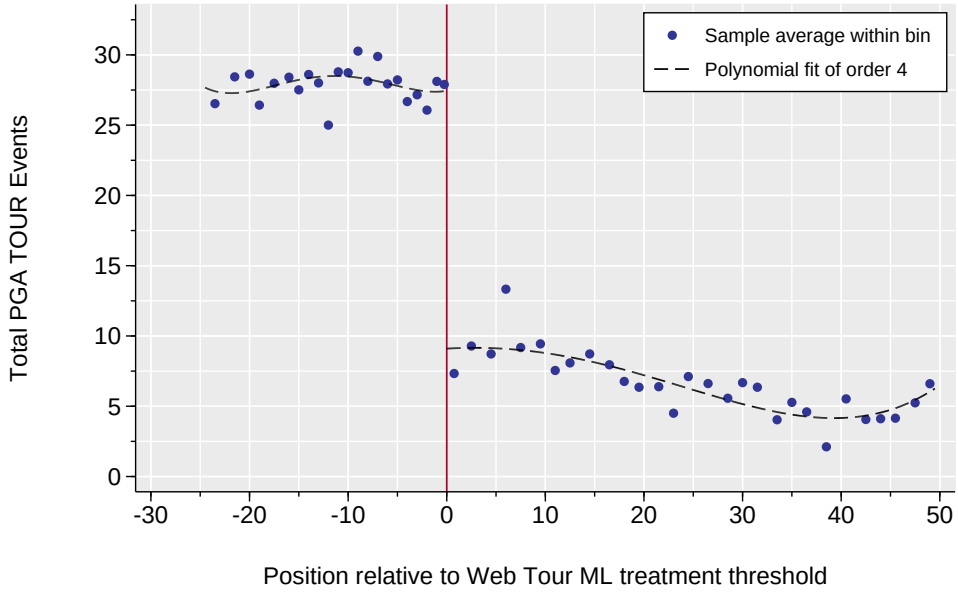


Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

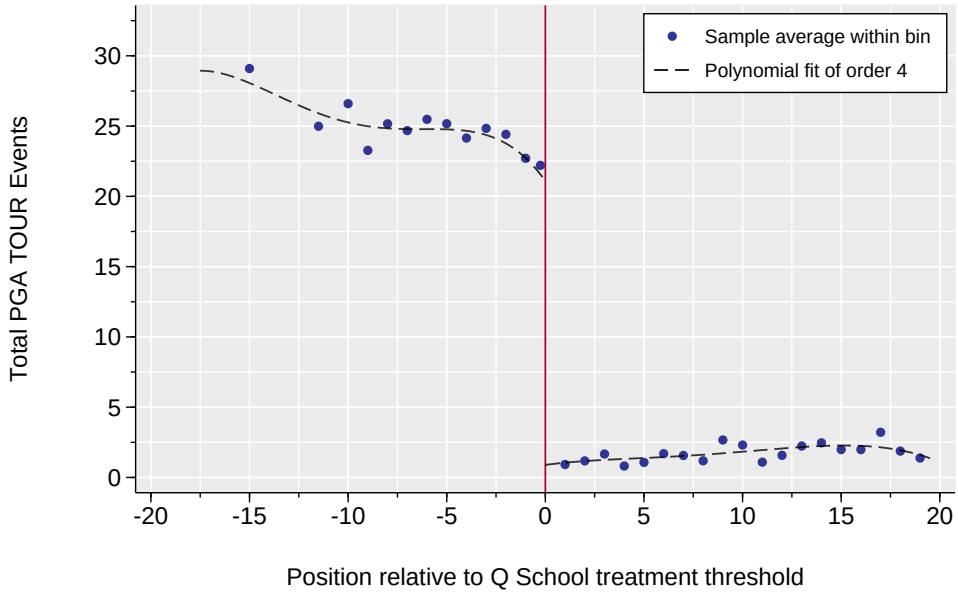
D.3 Post-Treatment Outcomes

Figure D.20: RD plots of PGA TOUR events in **year 1**

(a) Korn Ferry Tour ML



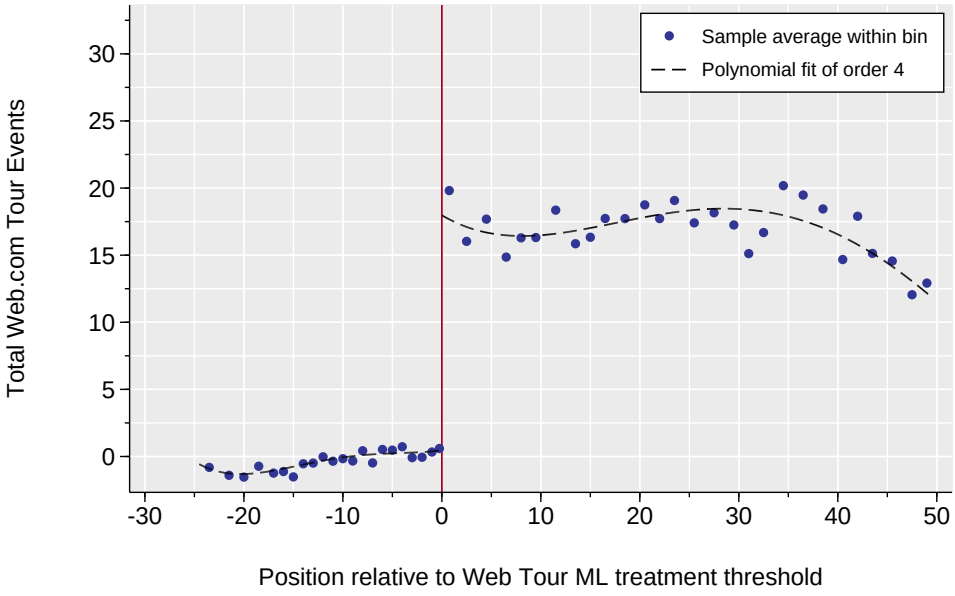
(b) Q School



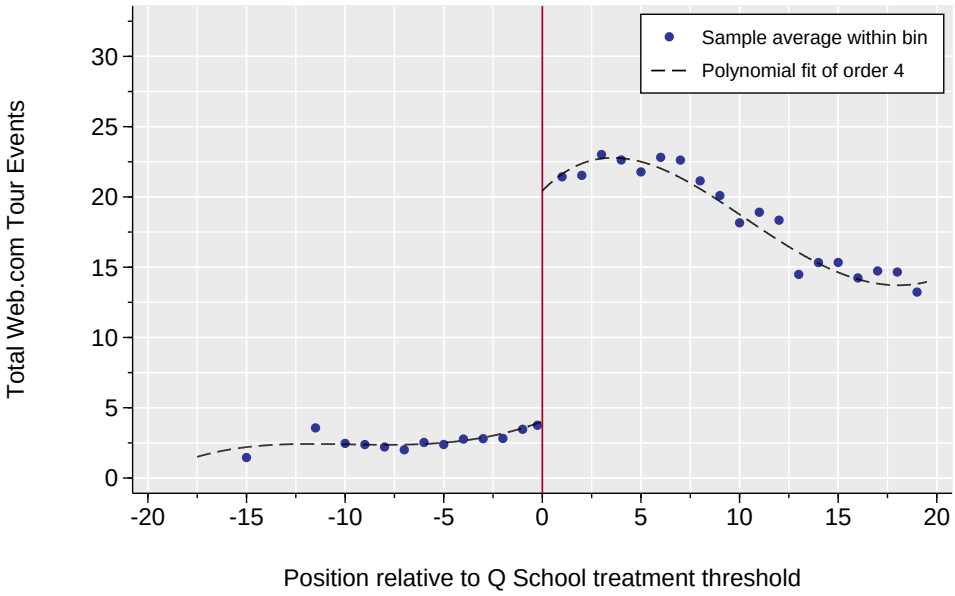
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.21: RD plots of Korn Ferry Tour events in **year 1**

(a) Korn Ferry Tour ML



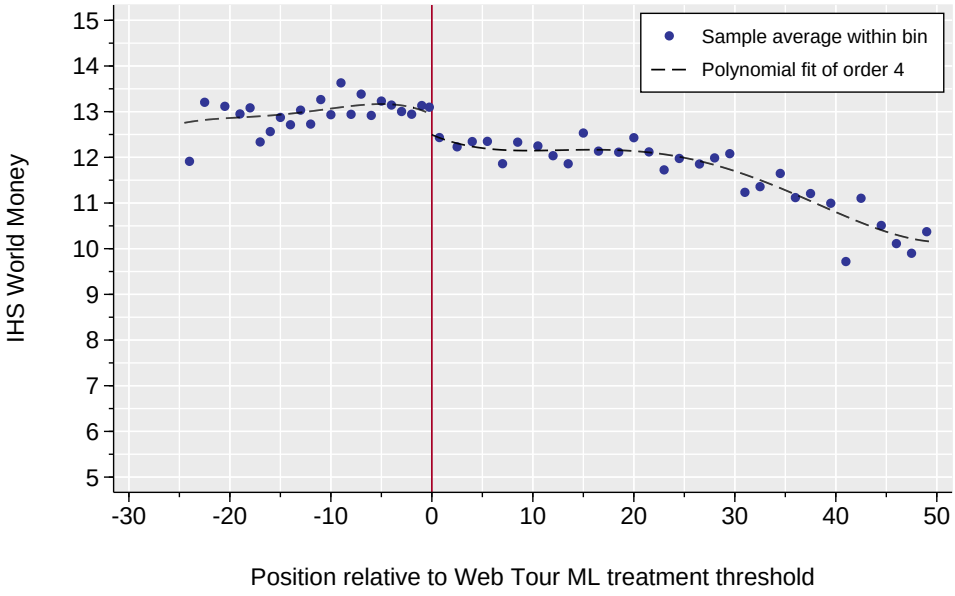
(b) Q School



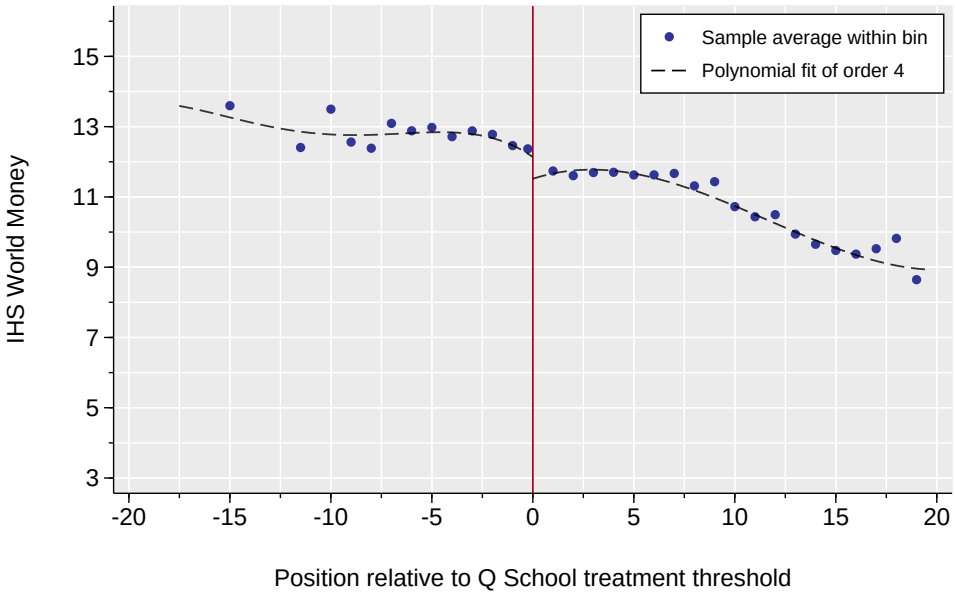
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.22: RD plots of IHS World earnings in **year 1**

(a) Korn Ferry Tour ML



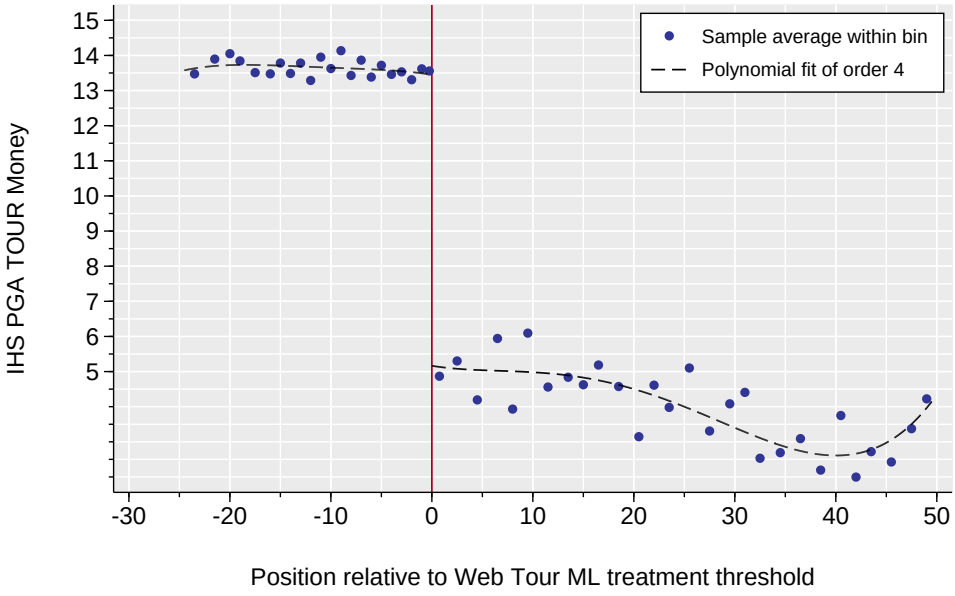
(b) Q School



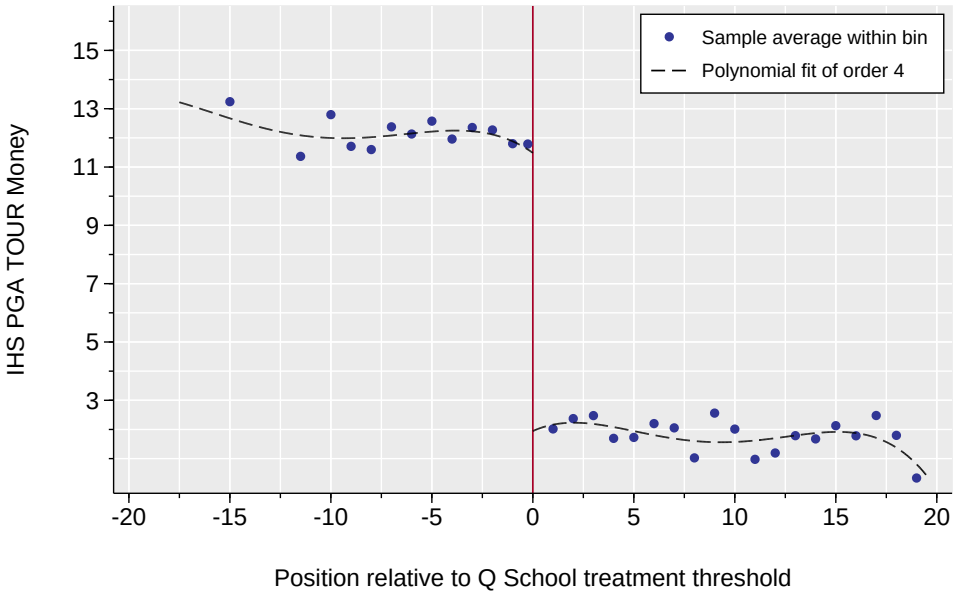
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.23: RD plots of IHS PGA TOUR earnings in **year 1**

(a) Korn Ferry Tour ML



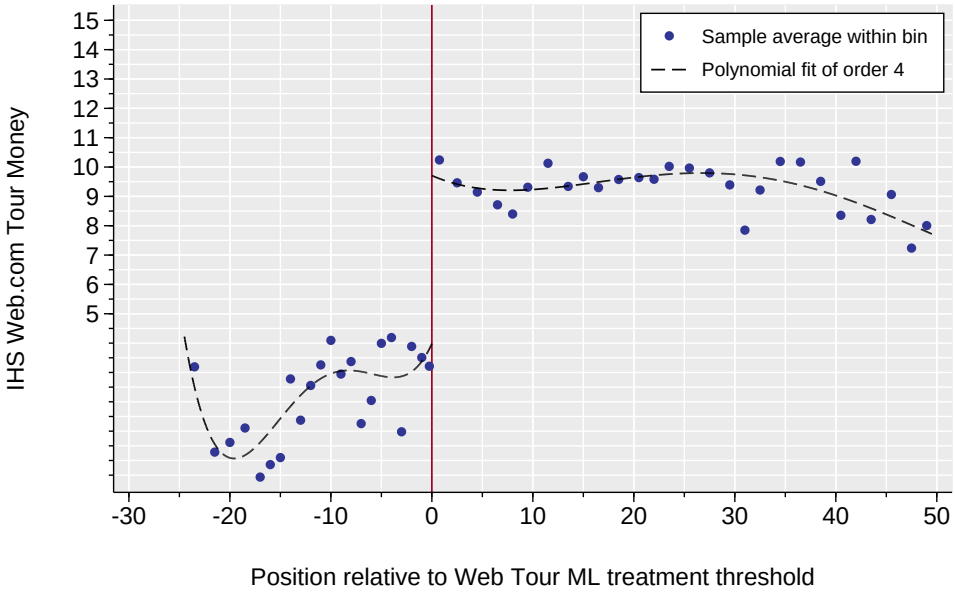
(b) Q School



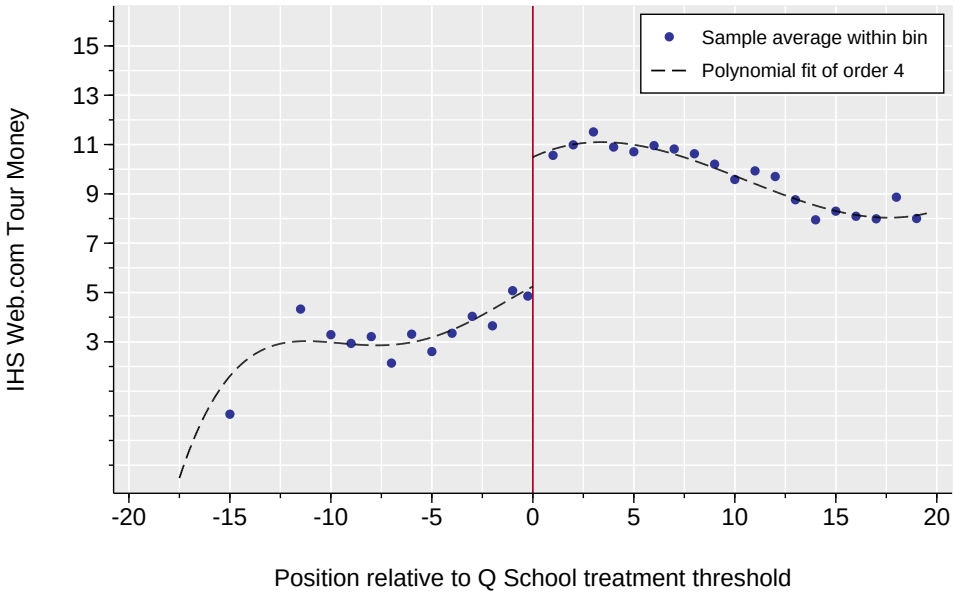
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.24: RD plots of IHS Korn Ferry Tour earnings in **year 1**

(a) Korn Ferry Tour ML



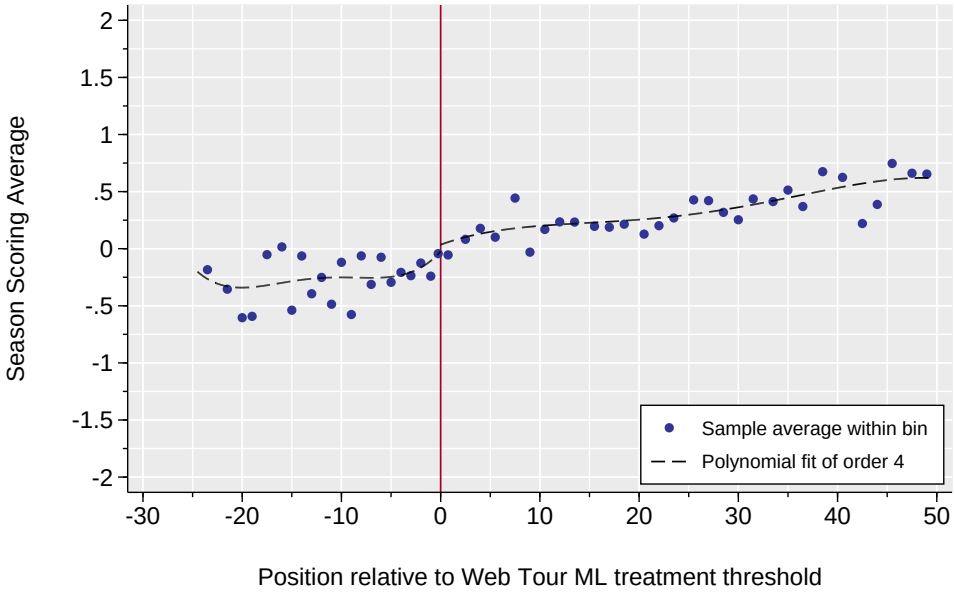
(b) Q School



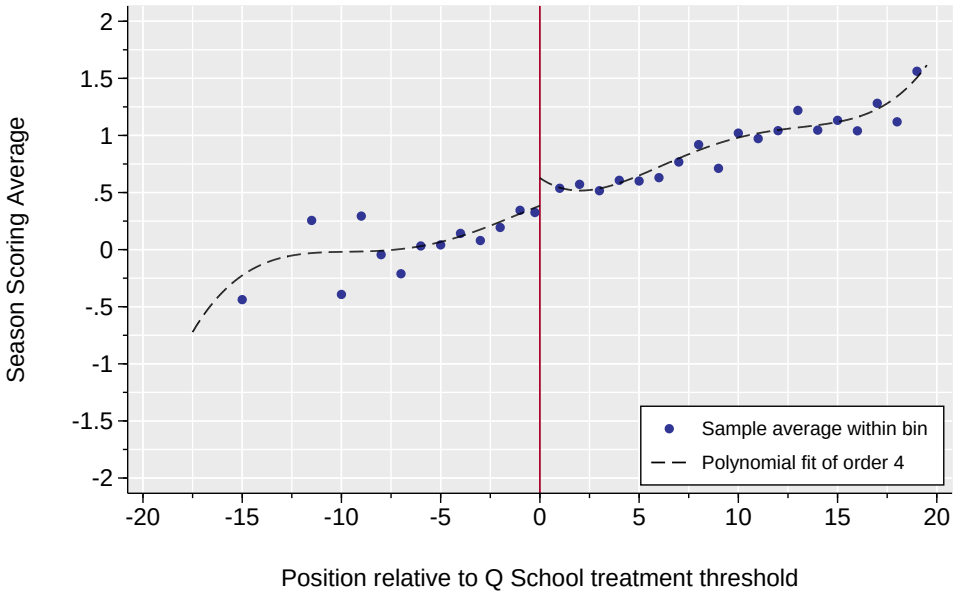
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.25: RD plots of adjusted scoring average in **year 1**

(a) Korn Ferry Tour ML



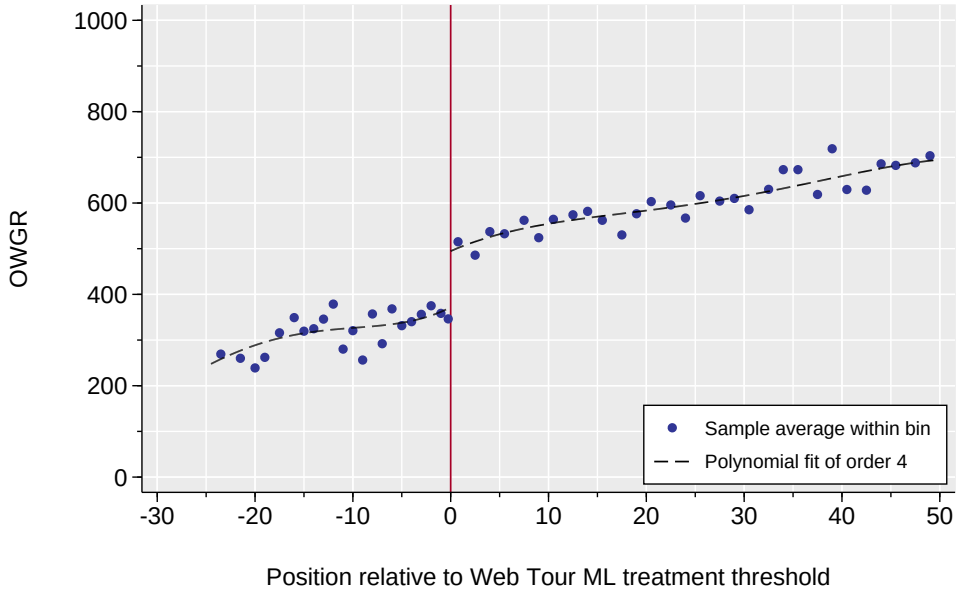
(b) Q School



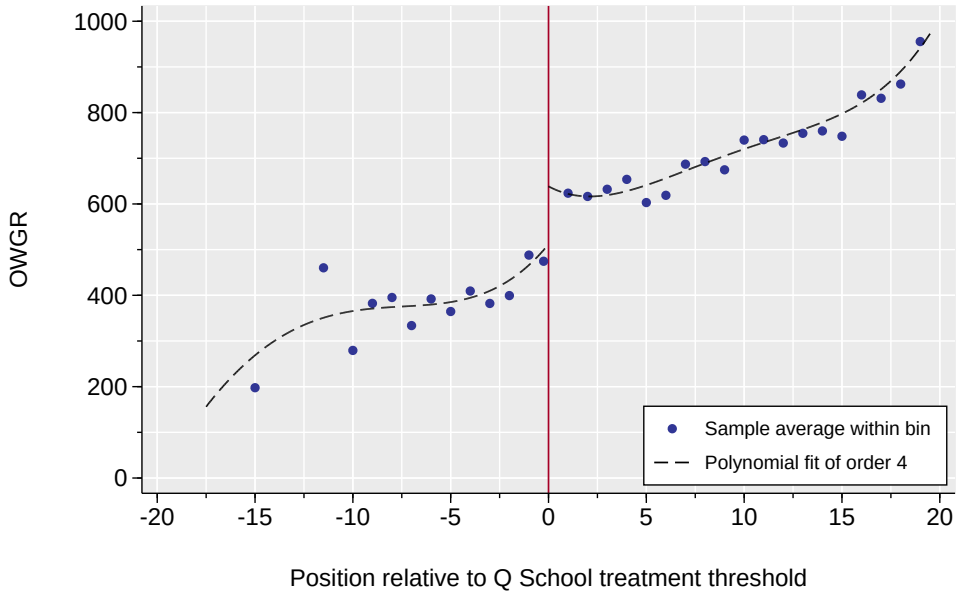
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.26: RD plots of OWGR in **year 1**

(a) Korn Ferry Tour ML



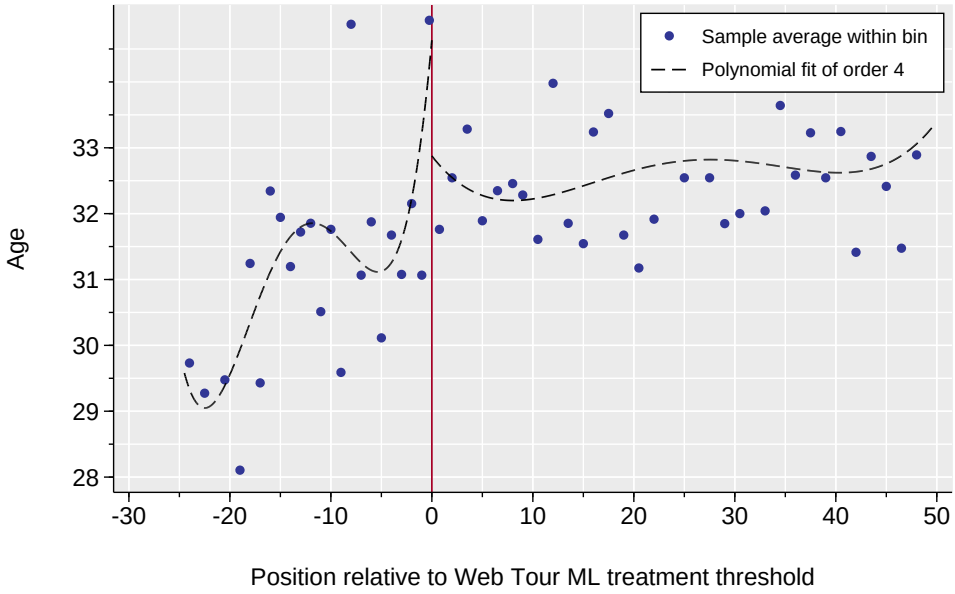
(b) Q School



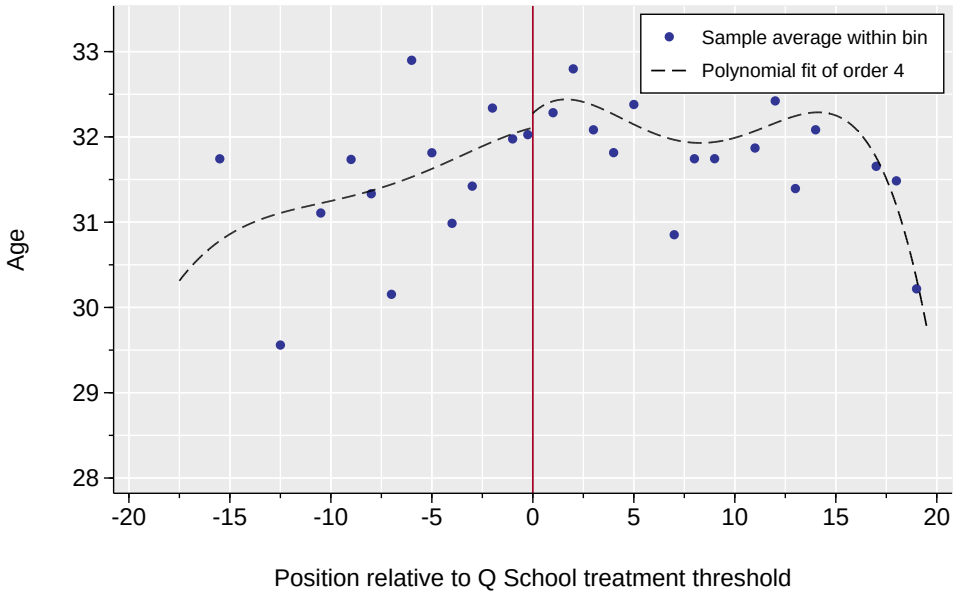
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.27: RD plots of age in **year 1**

(a) Korn Ferry Tour ML



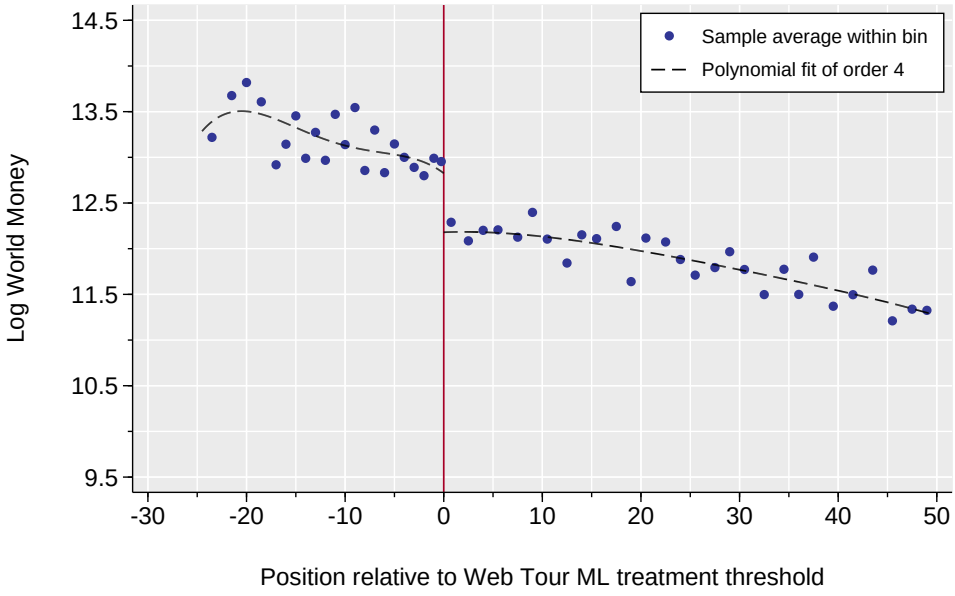
(b) Q School



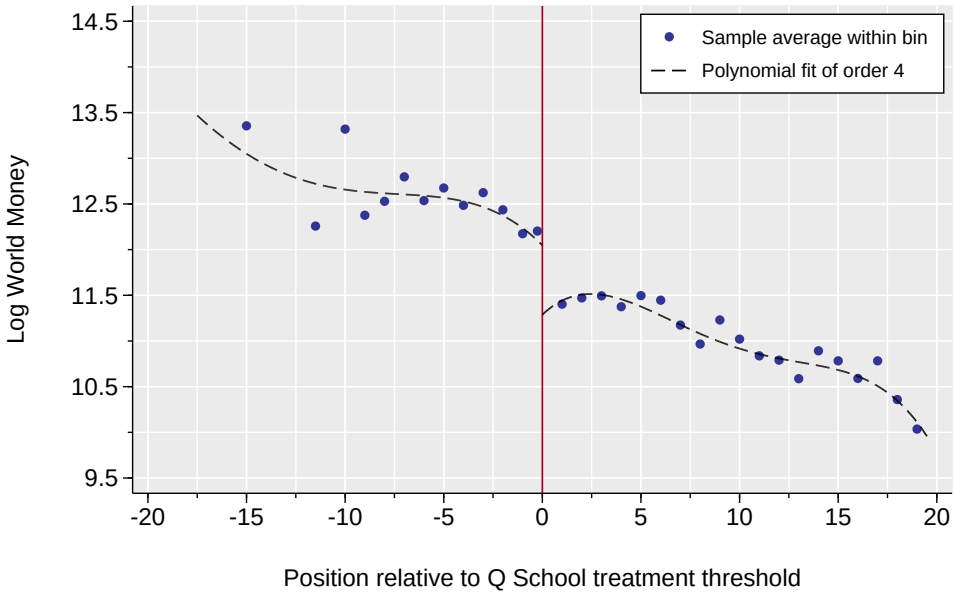
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.28: RD plots of log world earnings in **year 1**

(a) Korn Ferry Tour ML



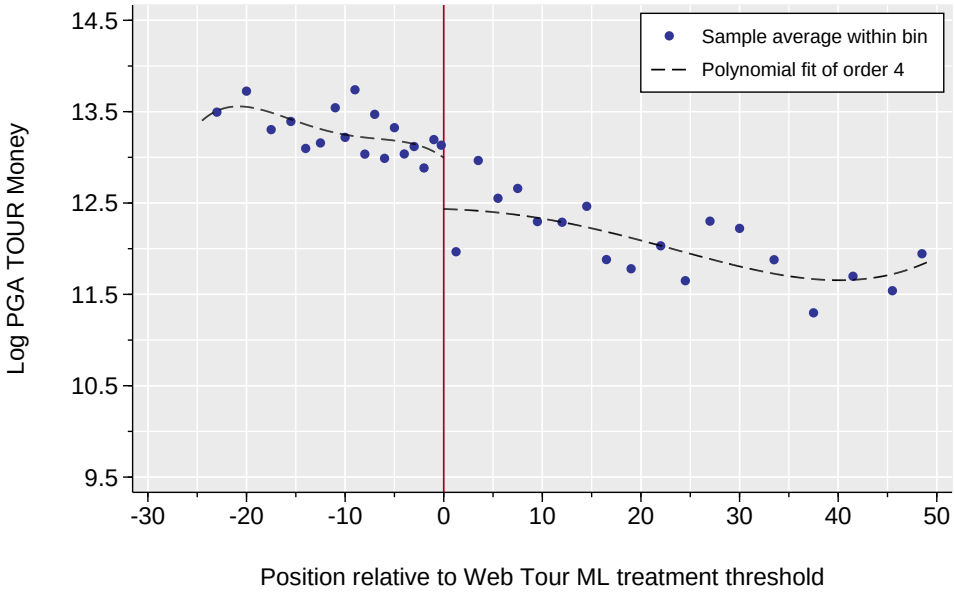
(b) Q School



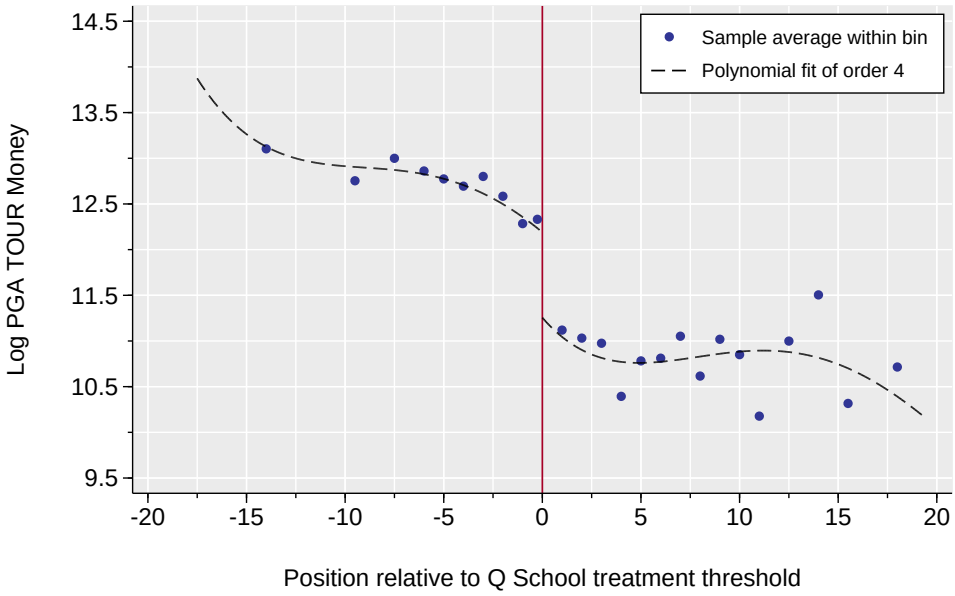
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.29: RD plots of log PGA TOUR earnings in **year 1**

(a) Korn Ferry Tour ML



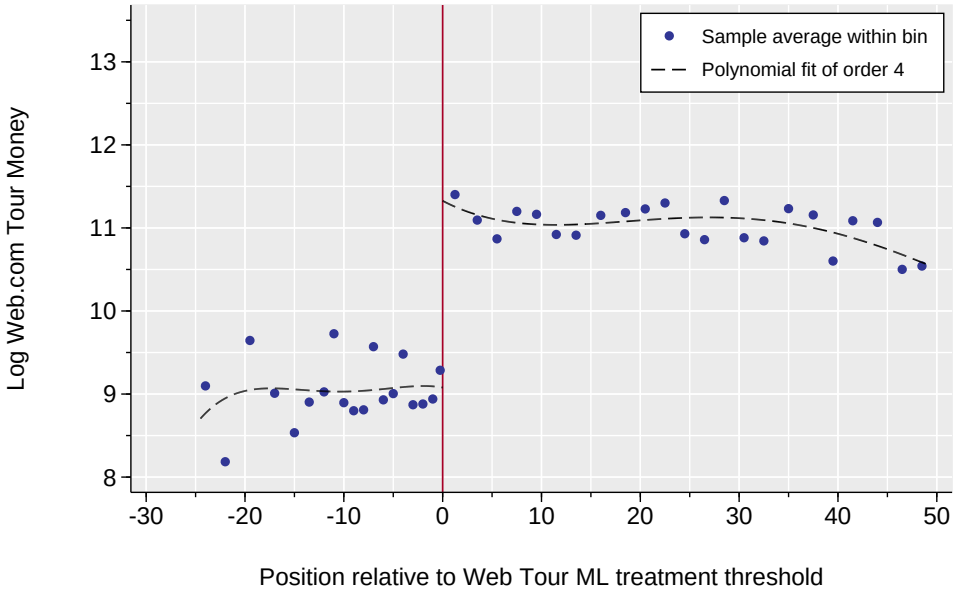
(b) Q School



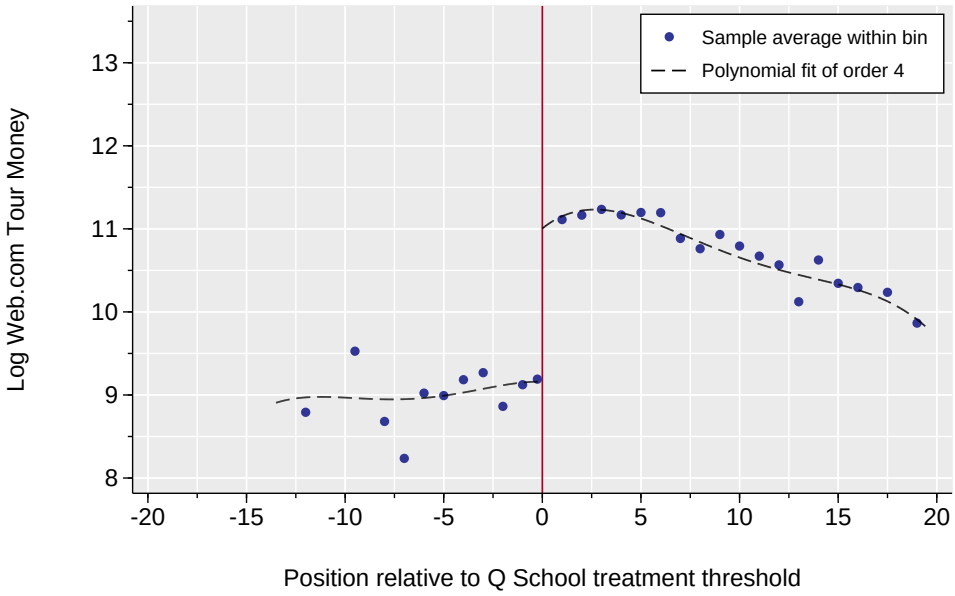
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.30: RD plots of log Korn Ferry Tour earnings in **year 1**

(a) Korn Ferry Tour ML



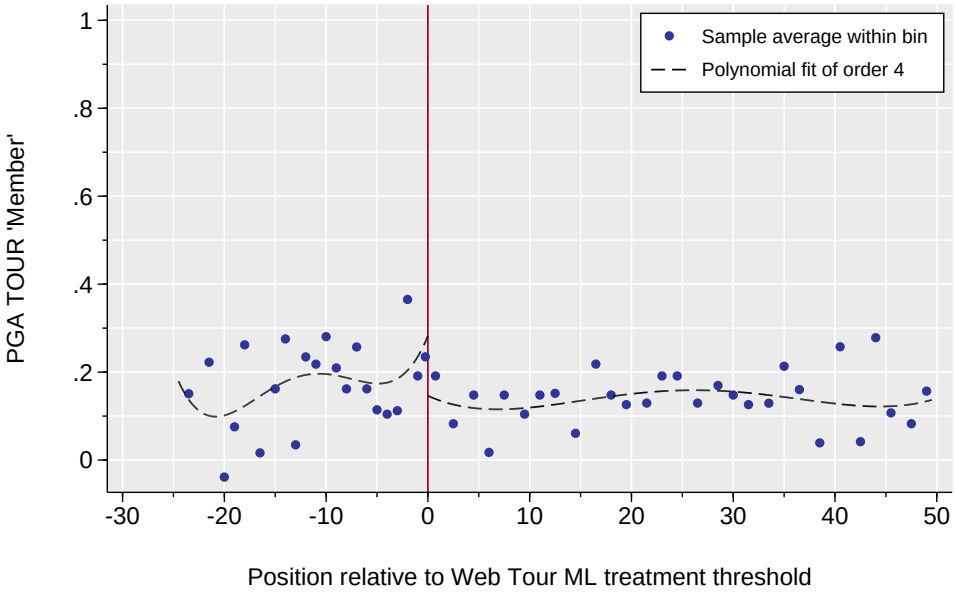
(b) Q School



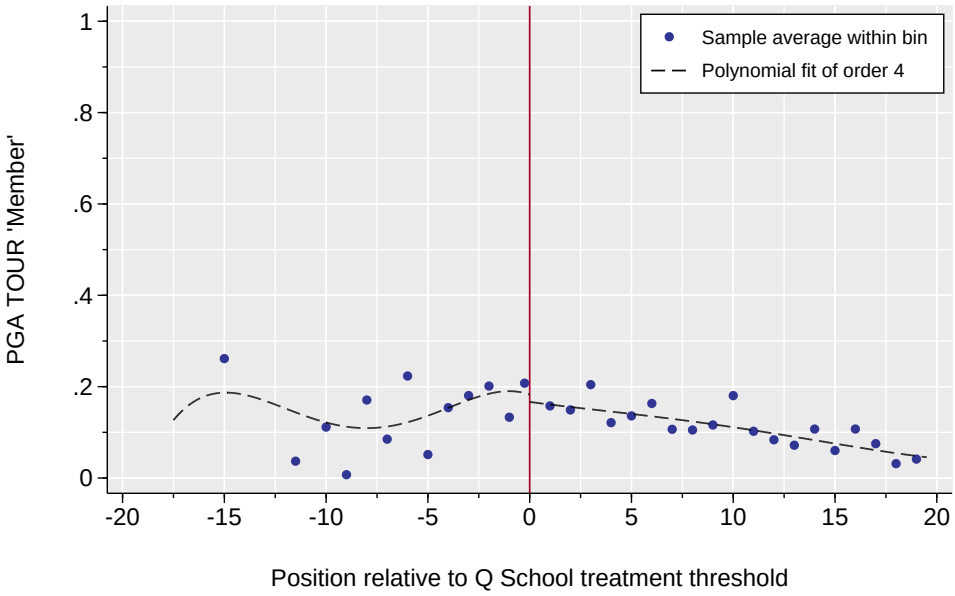
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.31: RD plots of probability of PGA TOUR membership in **year 1**

(a) Korn Ferry Tour ML



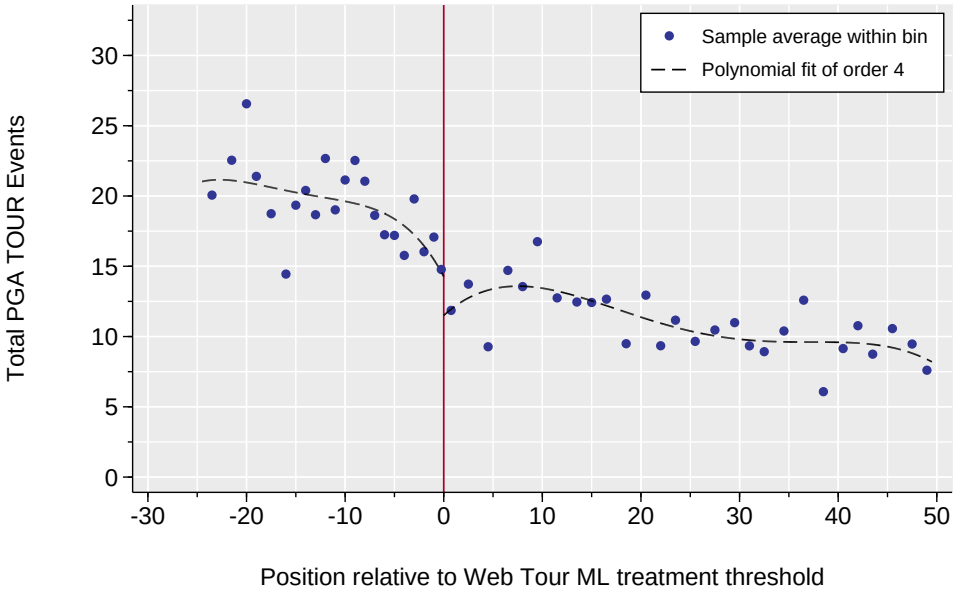
(b) Q School



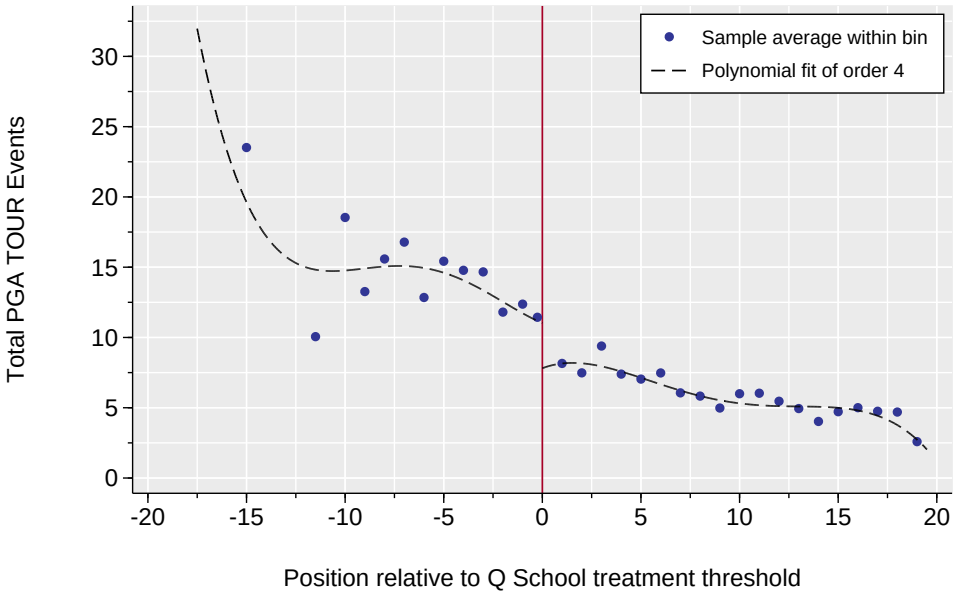
Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

Figure D.32: RD plots of PGA TOUR events in **year 2**

(a) Korn Ferry Tour ML



(b) Q School

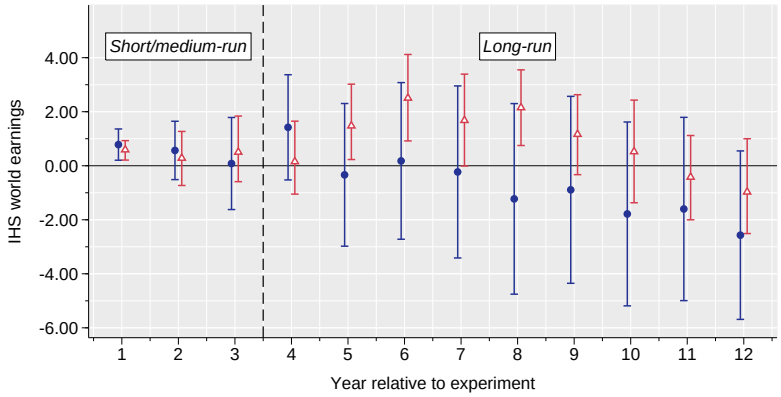


Notes: Curves represent a fourth degree polynomial fitted on each side of the cutoff. Dots represent averages within bins. Bins are selected optimally to represent the underlying variability of the data. Each bin is selected to have approximately the same number observations as other bins on the same side of the treatment threshold. The running variable for Q School is strokes from the treatment threshold, whereas the running variable for the Korn Ferry Tour ML is money list positions from the treatment threshold.

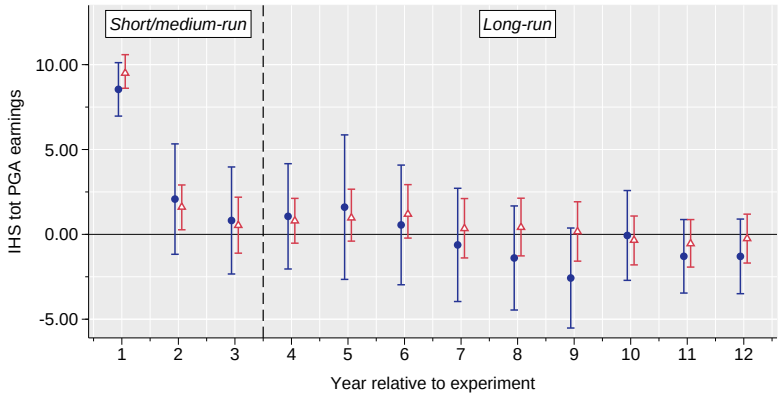
D.4 Regression Discontinuity Results by Year

Figure D.33: Estimated treatment effects on earnings

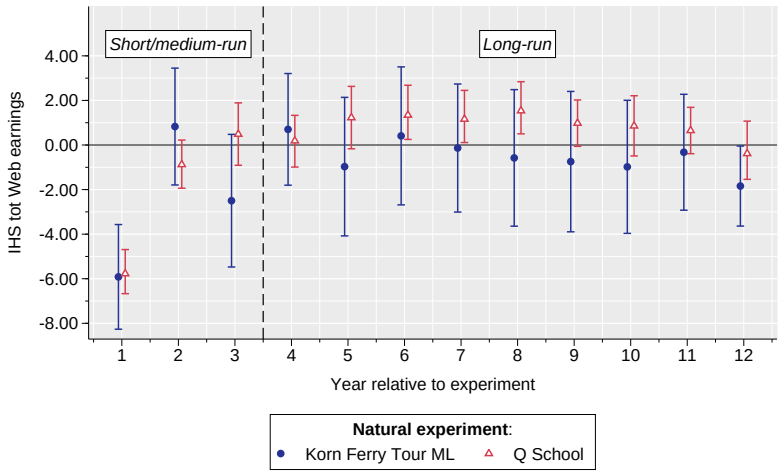
(a) IHS world earnings



(b) IHS PGA TOUR earnings

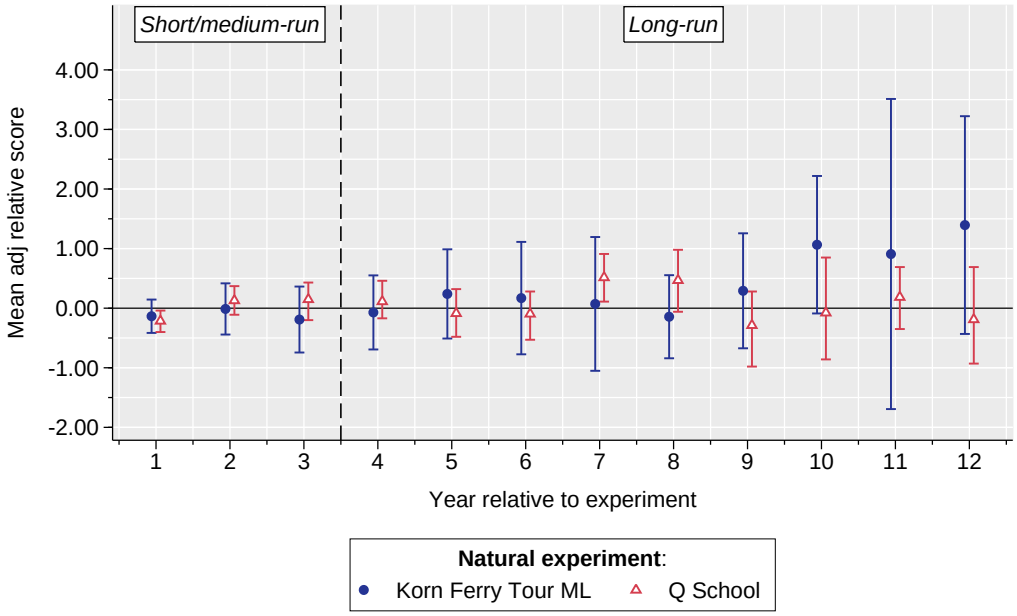


(c) IHS Korn Ferry Tour earnings



Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

Figure D.34: Estimated treatment effects on scoring average

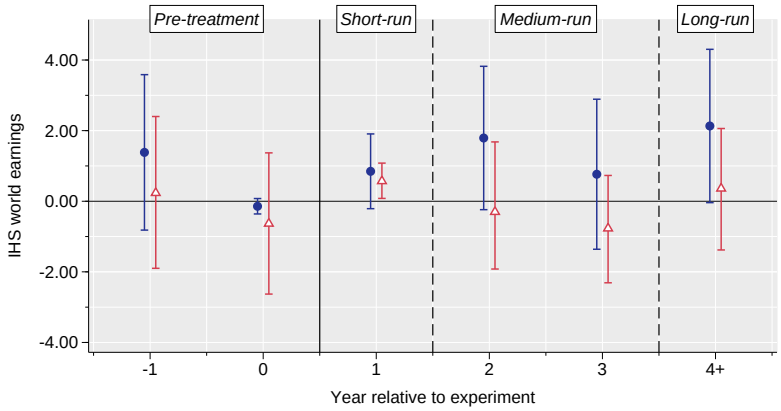


Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

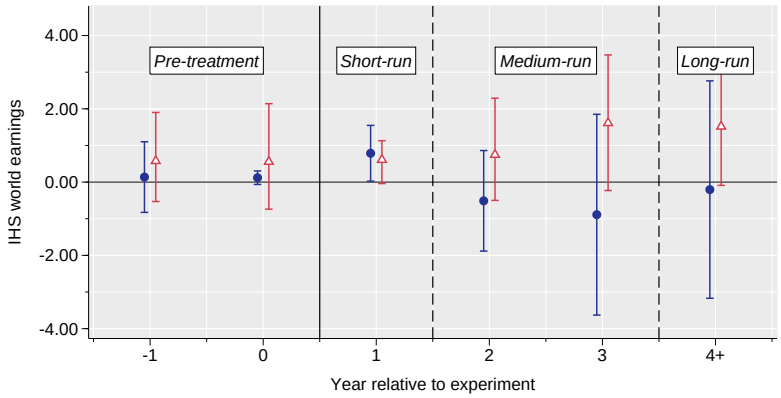
D.5 Regression Discontinuity Results by Age

Figure D.35: Estimated treatment effects on IHS world earnings by age

(a) Young golfers (17-30)



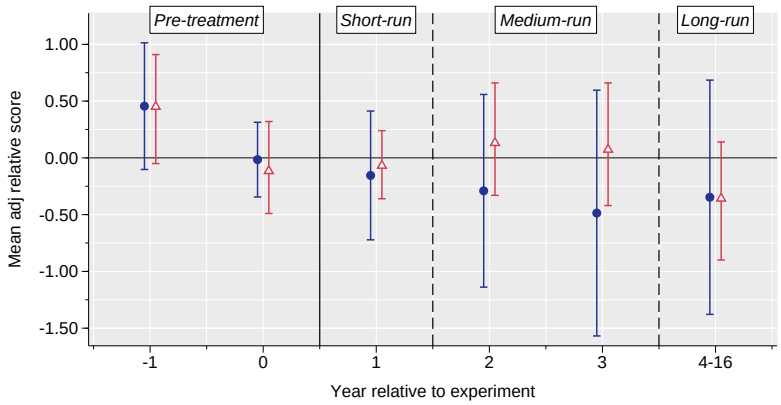
(b) Old golfers (31-55)



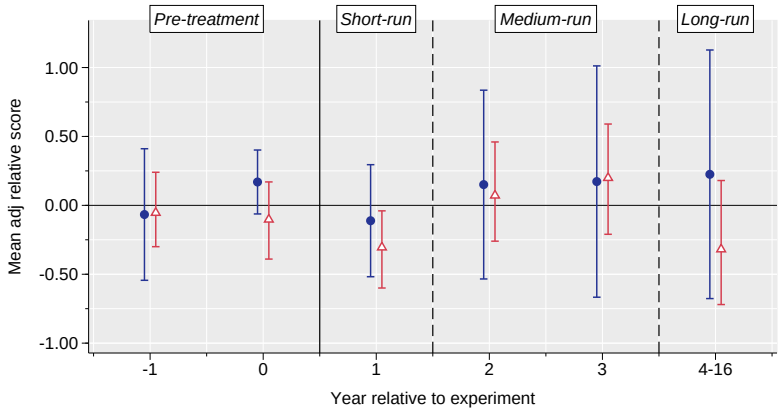
Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

Figure D.36: Estimated treatment effects on scoring average by age

(a) Young golfers (17-30)



(b) Old golfers (31-55)



Notes: The blue circles and red diamonds represent point estimates of the average treatment effects for the Korn Ferry Tour ML and Q School treatments, resepctively. Bands represent 95% confidence intervals. Korn Ferry Tour ML is estimated with a bias corrected local linear regression. Q School is estimated with local randomization methods using the difference-in-means statistic with a window of one stroke around the treatment threshold. See Section 4 for estimation details.

E Additional Tables

Table E.1: Worldwide Earnings Data Coverage

Tour	Earnings data coverage
PGA TOUR	1980-2014
European Tour	1980-2014
Korn Ferry Tour	1990-2014
Challenge Tour	1990-2014
Japan Golf Tour	1985-2014
PGA Tour of Australasia	1980-2014
Asian Tour	1995-2014
Sunshine Tour	1991-2014

Table E.2: Moments of world earnings distribution

	Earnings (1)	Log earnings (2)	IHS earnings (3)
Mean	319,987.22	11.99	5.79
Standard deviation	878,666.13	2.08	6.47
Skewness	5.16	-0.44	0.31
Kurtosis	43.68	2.39	1.24
N	29,194	13,333	29,194

Notes: "Earnings" denotes world earnings. The sample includes all golfers who played in at least 5 events on the PGA TOUR or Korn Ferry Tour from 1990 to 2014. Sample moments are computed over earnings in the prime age years of 20 to 40 years old.

Table E.3: Participation after treatment for treatment populations

Year relative to treatment	Korn Ferry Tour ML LFPR (1)	Korn Ferry Tour ML N (2)	Q School LFPR (3)	Q School N (4)
-5	0.54	230	0.46	228
-4	0.61	230	0.50	229
-3	0.68	230	0.58	229
-2	0.78	230	0.66	229
-1	0.92	230	0.71	229
0	1.00	230	0.78	230
1	1.00	230	1.00	230
2	0.97	230	0.83	230
3	0.91	220	0.78	220
4	0.85	210	0.70	210
5	0.81	200	0.69	200
6	0.77	190	0.63	190
7	0.70	180	0.62	180
8	0.63	169	0.51	170
9	0.63	159	0.48	159
10	0.55	148	0.45	150

Notes: The sample is comprised of 5 nearest golfers on both sides of the treatment threshold in each experiment year.

Table E.4: Time and Age Composition of Sample by Years After Treatment

Years after treatment (1)	Experiment years (2)	Potential age at treatment (3)
1	1990-2012	17-54
2	1990-2012	17-53
3	1990-2011	17-52
4	1990-2010	17-51
5	1990-2009	17-50
⋮	⋮	⋮
15	1990-1999	17-40
⋮	⋮	⋮
24	1990	17-31

E.1 Korn Ferry Tour ML Regression Discontinuity Results

Table E.5: Korn Ferry ML Results: Events

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: PGA TOUR Events						
-1	26.17	31.15	0.401	74.75 | 48.57	83 | 376	4.07 | 17.84
0	-0.75	0.52	0.153	1.85 | 2.59	125 | 355	6.33 | 17.35
1	19.57	2.38	0.000	27.99 | 8.41	63 | 314	3.43 | 14.89
2	2.02	3.53	0.567	14.04 | 12.01	104 | 376	4.73 | 18.15
3	3.03	3.32	0.362	15.94 | 12.91	99 | 518	5.39 | 25.88
4+	-6.79	19.29	0.725	60.78 | 67.58	113 | 247	6.13 | 13.12
Panel B: Korn Ferry Tour Events						
-1	-0.54	14.37	0.970	48.00 | 48.54	104 | 335	5.38 | 16.33
0	0.33	0.83	0.691	25.13 | 24.79	125 | 418	5.74 | 20.12
1	-17.98	1.64	0.000	0.38 | 18.36	125 | 231	5.57 | 10.66
2	-1.80	2.98	0.547	12.45 | 14.25	104 | 335	4.81 | 15.81
3	-3.19	2.52	0.205	6.53 | 9.72	139 | 359	6.65 | 17.59
4+	-13.72	12.55	0.275	47.63 | 61.34	75 | 322	4.04 | 17.14

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.6: Korn Ferry ML Results: IHS Earnings

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	0.892	0.672	0.185	14.21 | 13.32	104 | 252	4.69 | 11.66
0	0.023	0.078	0.767	13.42 | 13.40	83 | 459	4.29 | 21.53
1	0.806	0.326	0.014	13.07 | 12.26	83 | 293	4.13 | 13.79
2	0.611	0.604	0.312	13.41 | 12.80	104 | 397	4.78 | 18.97
3	0.055	0.953	0.954	12.52 | 12.47	99 | 339	5.50 | 16.56
4+	0.431	1.114	0.699	14.21 | 13.78	94 | 285	4.85 | 15.33
Panel B: IHS PGA TOUR Earnings						
-1	2.664	1.391	0.056	12.40 | 9.74	104 | 418	4.61 | 20.38
0	-0.006	1.406	0.996	2.81 | 2.81	83 | 501	4.31 | 23.65
1	8.618	0.874	0.000	13.54 | 4.92	83 | 335	3.80 | 15.79
2	2.182	1.826	0.233	8.21 | 6.03	104 | 335	5.13 | 16.18
3	0.798	1.773	0.653	8.31 | 7.51	99 | 399	5.21 | 19.95
4+	-0.059	1.922	0.976	11.25 | 11.31	94 | 247	4.85 | 13.12
Panel C: IHS Korn Ferry Tour Earnings						
-1	1.104	0.676	0.103	13.14 | 12.04	104 | 272	4.84 | 13.31
0	0.011	0.066	0.873	13.27 | 13.26	83 | 355	4.09 | 16.95
1	-5.955	1.317	0.000	3.54 | 9.49	104 | 293	5.28 | 14.38
2	0.875	1.480	0.555	8.45 | 7.58	104 | 418	4.87 | 20.08
3	-2.743	1.641	0.095	3.80 | 6.54	79 | 300	4.50 | 15.48
4+	-0.573	1.295	0.659	10.23 | 10.80	113 | 435	6.37 | 23.18

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.7: Korn Ferry ML Results: Scoring

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adjusted Scoring Average						
-1	0.100	0.178	0.576	0.40 | 0.30	143 | 286	6.56 | 15.23
0	0.131	0.104	0.212	-0.06 | -0.19	104 | 335	4.90 | 15.79
1	-0.129	0.170	0.448	-0.08 | 0.05	104 | 375	5.13 | 18.12
2	0.012	0.263	0.964	0.45 | 0.44	124 | 343	6.10 | 16.64
3	-0.126	0.351	0.719	0.36 | 0.48	116 | 369	6.10 | 21.15
4-16	-0.013	0.378	0.972	0.91 | 0.93	542 | 1,344	4.78 | 13.23
Panel B: Unadjusted Scoring Average						
-1	0.179	0.209	0.392	-0.14 | -0.32	103 | 268	5.18 | 14.06
0	0.111	0.100	0.270	-0.93 | -1.04	104 | 335	5.12 | 15.80
1	0.825	0.157	0.000	0.34 | -0.48	125 | 231	5.81 | 11.44
2	0.114	0.208	0.584	0.15 | 0.03	103 | 422	4.74 | 20.85
3	0.028	0.284	0.922	0.36 | 0.33	135 | 337	7.31 | 19.30
4-16	-0.105	0.288	0.716	0.61 | 0.71	434 | 1,655	4.36 | 16.37

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.8: Korn Ferry ML Results: Official World Golf Rankings

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Year-End OWGR						
-1	-0.50	67.78	0.994	613.85 | 614.35	125 | 293	5.53 | 13.71
0	-3.83	36.94	0.918	575.35 | 579.17	125 | 335	6.28 | 16.46
1	-161.33	46.05	0.001	345.02 | 506.36	83 | 418	4.09 | 20.21
2	-132.31	65.80	0.045	405.94 | 538.25	104 | 480	5.18 | 23.09
3	11.23	98.32	0.909	547.73 | 536.50	119 | 260	5.86 | 13.09
4-16	12.76	97.72	0.896	980.47 | 967.71	992 | 2,516	5.74 | 15.07
Panel B: Field Average OWGR						
-1	-9.18	49.50	0.853	654.21 | 663.39	103 | 406	4.79 | 21.30
0	4.17	9.10	0.647	705.63 | 701.45	125 | 459	5.74 | 21.76
1	-305.45	29.55	0.000	264.91 | 570.36	104 | 292	5.20 | 14.20
2	-50.17	60.81	0.410	529.25 | 579.43	103 | 305	4.86 | 15.07
3	-58.91	60.49	0.331	486.68 | 545.60	116 | 421	5.58 | 24.43
4-16	15.46	56.17	0.783	602.17 | 586.70	682 | 1,344	6.45 | 13.37

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.9: Korn Ferry ML Results: Log Earnings

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Log World Earnings						
-1	0.173	0.432	0.689	13.81 | 13.64	123 | 327	5.56 | 16.60
0	0.023	0.078	0.767	12.73 | 12.71	83 | 459	4.29 | 21.53
1	0.803	0.205	0.000	12.97 | 12.17	83 | 333	4.01 | 15.85
2	-0.063	0.447	0.888	12.30 | 12.37	102 | 408	5.42 | 20.90
3	0.038	0.436	0.930	12.32 | 12.28	92 | 263	5.22 | 15.21
4+	-0.035	0.550	0.950	13.19 | 13.23	141 | 384	7.55 | 23.74
Panel B: Log PGA TOUR Earnings						
-1	0.041	0.594	0.945	12.79 | 12.75	97 | 300	5.76 | 22.09
0	-0.194	0.640	0.762	10.96 | 11.15	30 | 98	5.36 | 22.18
1	0.929	0.417	0.027	13.14 | 12.22	83 | 122	4.02 | 15.25
2	0.226	0.548	0.680	13.09 | 12.87	66 | 202	4.72 | 21.07
3	0.125	0.443	0.779	13.00 | 12.87	85 | 141	7.48 | 15.28
4+	0.346	0.669	0.606	13.56 | 13.21	109 | 142	7.63 | 12.21
Panel C: Log Korn Ferry Tour Earnings						
-1	-0.169	0.436	0.699	12.38 | 12.55	101 | 247	5.17 | 12.91
0	0.011	0.066	0.873	12.57 | 12.56	83 | 355	4.09 | 16.95
1	-2.266	0.433	0.000	9.14 | 11.41	66 | 219	6.74 | 11.60
2	-0.572	0.500	0.254	10.92 | 11.49	66 | 186	4.88 | 13.79
3	-0.418	0.509	0.411	10.52 | 10.94	53 | 247	5.47 | 20.79
4+	-0.584	0.509	0.252	11.46 | 12.05	74 | 297	5.46 | 20.59

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.10: Korn Ferry ML Results: Probability of Positive Earnings

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Positive World Earnings						
-1	0.045	0.035	0.190	0.97 | 0.93	104 | 252	4.79 | 12.47
0	0.000	0.000	0.000	0.00 | 0.00	0 | 0	0.00 | 0.00
1	-0.004	0.018	0.820	0.95 | 0.96	104 | 189	5.15 | 9.48
2	0.040	0.029	0.165	1.02 | 0.98	83 | 355	3.57 | 17.10
3	0.002	0.066	0.970	0.96 | 0.96	119 | 359	6.29 | 18.49
4+	0.035	0.070	0.620	1.02 | 0.99	94 | 266	4.70 | 14.05
Panel B: Positive PGA TOUR Earnings						
-1	0.180	0.092	0.050	0.90 | 0.72	104 | 439	5.00 | 20.99
0	0.015	0.119	0.898	0.25 | 0.24	104 | 501	4.69 | 24.37
1	0.606	0.064	0.000	0.99 | 0.38	125 | 355	5.56 | 16.52
2	0.167	0.132	0.207	0.60 | 0.44	104 | 335	5.43 | 15.67
3	0.048	0.128	0.707	0.61 | 0.56	99 | 419	5.25 | 21.22
4+	-0.038	0.135	0.780	0.80 | 0.84	94 | 209	4.75 | 10.87
Panel C: Positive Korn Ferry Tour Earnings						
-1	0.087	0.041	0.032	1.01 | 0.93	83 | 355	4.20 | 17.06
0	0.000	0.000	0.000	0.00 | 0.00	0 | 0	0.00 | 0.00
1	-0.390	0.123	0.002	0.38 | 0.77	104 | 335	5.28 | 16.40
2	0.103	0.119	0.391	0.72 | 0.62	104 | 439	5.13 | 20.87
3	-0.232	0.146	0.114	0.34 | 0.57	79 | 300	4.37 | 15.47
4+	-0.009	0.101	0.931	0.84 | 0.85	132 | 435	6.79 | 22.88

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.11: Korn Ferry ML Results: Earnings

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: IHS World Earnings						
-1	1,566,251.50	1,391,159.38	0.261	3,046,071.00 | 1,479,819.50	83 | 335	3.66 | 16.41
0	2,828.20	28,377.99	0.921	361,504.06 | 358,675.88	83 | 376	4.14 | 17.62
1	186,534.42	82,841.66	0.025	476,391.28 | 289,856.84	104 | 293	4.99 | 13.59
2	131,449.42	169,282.81	0.438	617,073.63 | 485,624.19	104 | 522	5.20 | 24.59
3	27,833.66	152,343.27	0.855	437,561.66 | 409,727.97	99 | 438	5.17 | 22.06
4+	738,527.81	1,627,587.75	0.650	2,913,023.00 | 2,174,495.25	113 | 285	5.50 | 15.30
Panel B: IHS PGA TOUR Earnings						
-1	1,337,899.13	1,284,905.13	0.298	2,321,075.00 | 983,175.88	83 | 376	3.64 | 18.00
0	-4,509.88	13,507.00	0.739	44,400.11 | 48,909.99	83 | 418	4.29 | 20.30
1	325,775.78	86,418.11	0.000	486,037.41 | 160,261.64	104 | 272	4.91 | 13.41
2	135,625.06	185,604.58	0.465	538,017.69 | 402,392.59	104 | 563	4.87 | 26.61
3	39,424.25	158,275.84	0.803	399,148.22 | 359,723.97	99 | 458	4.99 | 22.67
4+	869,648.56	1,640,631.50	0.596	2,731,458.50 | 1,861,810.00	94 | 285	5.34 | 15.22
Panel C: IHS Korn Ferry Tour Earnings						
-1	-27,181.14	105,599.27	0.797	370,582.56 | 397,763.72	104 | 335	4.63 | 16.44
0	5,061.34	24,811.59	0.838	308,215.41 | 303,154.06	83 | 335	3.61 | 15.64
1	-127,686.90	17,774.08	0.000	-12,171.21 | 115,515.69	146 | 335	6.92 | 15.74
2	-9,371.77	31,897.81	0.769	82,009.28 | 91,381.05	83 | 459	3.79 | 22.16
3	-22,595.21	20,668.34	0.275	21,066.46 | 43,661.67	99 | 339	5.10 | 17.48
4+	-85,406.34	70,028.72	0.223	188,948.89 | 274,355.22	75 | 398	4.01 | 21.28

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

E.2 Q School Regression Discontinuity Results

Table E.12: Q School Results: Events

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: PGA TOUR Events						
-1	-2.22	0.870	25.76 | -24.64	63.34 | 65.55	129 | 134	0.50 | 0.50
0	0.62	0.627	3.23 | -1.97	7.41 | 6.79	129 | 134	0.50 | 0.50
1	20.70	0.000	22.15 | 19.54	22.46 | 1.76	129 | 134	0.50 | 0.50
2	2.77	0.060	5.81 | 0.32	11.35 | 8.58	129 | 134	0.50 | 0.50
3	0.27	0.853	3.36 | -2.22	9.36 | 9.08	126 | 129	0.50 | 0.50
4+	0.27	0.986	24.64 | -19.19	80.00 | 79.73	123 | 121	0.50 | 0.50
Panel B: Korn Ferry Tour Events						
-1	-2.44	0.630	7.52 | -12.38	26.06 | 28.51	129 | 134	0.50 | 0.50
0	-1.12	0.355	1.27 | -3.05	6.73 | 7.84	129 | 134	0.50 | 0.50
1	-17.20	0.000	-15.54 | -18.84	3.58 | 20.77	129 | 134	0.50 | 0.50
2	-1.57	0.196	0.84 | -3.48	8.61 | 10.18	129 | 134	0.50 | 0.50
3	0.27	0.832	2.21 | -1.71	7.35 | 7.08	126 | 129	0.50 | 0.50
4+	10.38	0.111	20.73 | 0.01	51.34 | 40.95	123 | 121	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.13: Q School Results: IHS Earnings

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	0.580	0.444	1.71 | -0.53	11.77 | 11.19	129 | 134	0.50 | 0.50
0	0.069	0.913	1.35 | -0.99	9.50 | 9.43	129 | 134	0.50 | 0.50
1	0.592	0.004	0.93 | 0.21	12.40 | 11.81	129 | 134	0.50 | 0.50
2	0.282	0.658	1.27 | -0.73	11.08 | 10.80	129 | 134	0.50 | 0.50
3	0.505	0.468	1.84 | -0.59	10.46 | 9.95	126 | 129	0.50 | 0.50
4+	0.908	0.235	2.39 | -0.31	12.08 | 11.18	123 | 121	0.50 | 0.50
Panel B: IHS PGA TOUR Earnings						
-1	0.427	0.587	2.13 | -1.27	8.46 | 8.04	129 | 134	0.50 | 0.50
0	0.642	0.407	2.15 | -0.85	4.79 | 4.14	129 | 134	0.50 | 0.50
1	9.500	0.000	10.59 | 8.61	11.95 | 2.45	129 | 134	0.50 | 0.50
2	1.608	0.040	2.91 | 0.27	6.70 | 5.09	129 | 134	0.50 | 0.50
3	0.530	0.531	2.19 | -1.11	5.73 | 5.20	126 | 129	0.50 | 0.50
4+	1.173	0.237	2.97 | -0.63	9.67 | 8.50	123 | 121	0.50 | 0.50
Panel C: IHS Korn Ferry Tour Earnings						
-1	-0.069	0.918	1.36 | -1.25	8.39 | 8.46	129 | 134	0.50 | 0.50
0	-0.203	0.772	1.18 | -1.34	5.75 | 5.95	129 | 134	0.50 | 0.50
1	-5.772	0.000	-4.69 | -6.67	4.57 | 10.35	129 | 134	0.50 | 0.50
2	-0.877	0.209	0.22 | -1.94	6.00 | 6.88	129 | 134	0.50 | 0.50
3	0.487	0.501	1.89 | -0.91	5.64 | 5.15	126 | 129	0.50 | 0.50
4+	0.905	0.211	2.35 | -0.26	9.28 | 8.37	123 | 121	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.14: Q School Results: Scoring

Year	τ	Pval	95% CI	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adjusted Scoring Average						
-1	0.078	0.606	0.38 | -0.22	0.46 | 0.38	97 | 102	0.50 | 0.50
0	-0.133	0.359	0.14 | -0.40	0.30 | 0.44	107 | 111	0.50 | 0.50
1	-0.200	0.084	0.03 | -0.42	0.32 | 0.52	129 | 132	0.50 | 0.50
2	0.091	0.584	0.41 | -0.19	0.32 | 0.23	112 | 113	0.50 | 0.50
3	0.147	0.451	0.52 | -0.20	0.43 | 0.28	108 | 102	0.50 | 0.50
4-16	-0.294	0.147	0.03 | -0.61	0.83 | 1.12	110 | 107	0.50 | 0.50
Panel B: Unadjusted Scoring Average						
-1	0.101	0.511	0.33 | -0.15	0.18 | 0.08	97 | 102	0.50 | 0.50
0	-0.047	0.712	0.22 | -0.28	0.03 | 0.08	107 | 111	0.50 | 0.50
1	0.772	0.000	0.93 | 0.61	0.56 | -0.21	129 | 132	0.50 | 0.50
2	0.278	0.045	0.55 | 0.05	0.07 | -0.21	112 | 113	0.50 | 0.50
3	0.141	0.456	0.48 | -0.15	0.19 | 0.05	108 | 102	0.50 | 0.50
4-16	-0.288	0.099	-0.01 | -0.57	0.64 | 0.93	110 | 107	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. See Appendix Section C for details.

Table E.15: Q School Results: Official World Golf Rankings

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Year-End OWGR						
-1	-8.66	0.84	80.66 | -80.17	623.98 | 632.64	129 | 134	0.50 | 0.50
0	-62.22	0.16	18.21 | -126.60	598.71 | 660.93	129 | 134	0.50 | 0.50
1	-139.33	0.00	-66.58 | -212.08	470.60 | 609.93	129 | 134	0.50 | 0.50
2	-47.11	0.29	23.62 | -135.50	591.31 | 638.42	129 | 134	0.50 | 0.50
3	-35.66	0.49	63.08 | -114.67	676.66 | 712.31	126 | 129	0.50 | 0.50
4-16	-46.61	0.41	58.91 | -152.09	892.68 | 939.29	123 | 121	0.50 | 0.50
Panel B: Field Average OWGR						
-1	-6.33	0.87	58.29 | -70.91	564.39 | 570.72	97 | 102	0.50 | 0.50
0	-31.15	0.31	14.04 | -76.36	532.68 | 563.82	107 | 111	0.50 | 0.50
1	-331.89	0.00	-299.96 | -357.47	327.19 | 659.08	129 | 132	0.50 | 0.50
2	-65.41	0.03	-7.67 | -111.62	506.05 | 571.46	112 | 113	0.50 | 0.50
3	-2.95	0.91	61.55 | -67.45	575.98 | 578.93	108 | 102	0.50 | 0.50
4-16	-3.19	0.91	36.08 | -42.48	572.77 | 575.96	110 | 107	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. See Appendix Section C for details.

Table E.16: Q School Results: Log Earnings

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Log World Earnings						
-1	-0.141	0.674	0.37 | -0.67	13.12 | 13.26	110 | 107	0.50 | 0.50
0	0.375	0.064	0.77 | 0.05	11.80 | 11.42	101 | 106	0.50 | 0.50
1	0.792	0.000	1.11 | 0.51	12.22 | 11.43	128 | 134	0.50 | 0.50
2	-0.095	0.665	0.26 | -0.46	12.22 | 12.32	110 | 109	0.50 | 0.50
3	-0.080	0.771	0.30 | -0.50	11.84 | 11.93	104 | 99	0.50 | 0.50
4+	0.421	0.196	1.06 | -0.11	13.64 | 13.21	103 | 95	0.50 | 0.50
Panel B: Log PGA TOUR Earnings						
-1	0.153	0.681	0.73 | -0.47	13.04 | 12.88	80 | 80	0.50 | 0.50
0	0.252	0.304	0.70 | -0.11	11.82 | 11.57	56 | 52	0.50 | 0.50
1	1.101	0.000	1.46 | 0.74	12.31 | 11.21	127 | 37	0.50 | 0.50
2	0.189	0.488	0.74 | -0.36	12.75 | 12.56	69 | 55	0.50 | 0.50
3	-0.019	0.960	0.58 | -0.62	12.42 | 12.44	61 | 56	0.50 | 0.50
4+	-0.119	0.745	0.57 | -0.69	13.80 | 13.92	81 | 68	0.50 | 0.50
Panel C: Log Korn Ferry Tour Earnings						
-1	-0.364	0.171	0.04 | -0.86	11.31 | 11.68	90 | 91	0.50 | 0.50
0	0.145	0.536	0.52 | -0.29	10.67 | 10.52	69 | 74	0.50 | 0.50
1	-1.831	0.000	-1.52 | -2.16	9.21 | 11.04	65 | 121	0.50 | 0.50
2	-0.579	0.035	-0.16 | -1.04	10.66 | 11.24	66 | 75	0.50 | 0.50
3	-0.189	0.509	0.24 | -0.64	10.57 | 10.76	62 | 56	0.50 | 0.50
4+	0.375	0.165	0.89 | -0.11	11.76 | 11.38	88 | 79	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.17: Q School Results: Probability of Positive Earnings

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Positive World Earnings						
-1	0.049	0.326	0.14 | -0.04	0.85 | 0.80	129 | 134	0.50 | 0.50
0	-0.016	0.757	0.08 | -0.10	0.76 | 0.78	129 | 134	0.50 | 0.50
1	0.000	0.000	0.00 | 0.00	0.96 | 0.97	0 | 0	0.00 | 0.00
2	0.027	0.530	0.10 | -0.04	0.86 | 0.83	129 | 134	0.50 | 0.50
3	0.045	0.379	0.13 | -0.05	0.83 | 0.79	126 | 129	0.50 | 0.50
4+	0.041	0.415	0.12 | -0.04	0.85 | 0.81	123 | 121	0.50 | 0.50
Panel B: Positive PGA TOUR Earnings						
-1	0.023	0.691	0.14 | -0.08	0.61 | 0.59	129 | 134	0.50 | 0.50
0	0.043	0.482	0.16 | -0.08	0.38 | 0.34	129 | 134	0.50 | 0.50
1	0.699	0.000	0.77 | 0.61	0.91 | 0.21	129 | 134	0.50 | 0.50
2	0.115	0.049	0.21 | 0.00	0.50 | 0.38	129 | 134	0.50 | 0.50
3	0.043	0.501	0.14 | -0.07	0.44 | 0.40	126 | 129	0.50 | 0.50
4+	0.086	0.194	0.21 | -0.03	0.67 | 0.59	123 | 121	0.50 | 0.50
Panel C: Positive Korn Ferry Tour Earnings						
-1	0.012	0.834	0.12 | -0.10	0.70 | 0.69	129 | 134	0.50 | 0.50
0	-0.022	0.716	0.08 | -0.14	0.51 | 0.53	129 | 134	0.50 | 0.50
1	-0.405	0.000	-0.31 | -0.49	0.47 | 0.88	129 | 134	0.50 | 0.50
2	-0.053	0.379	0.05 | -0.15	0.53 | 0.58	129 | 134	0.50 | 0.50
3	0.051	0.415	0.17 | -0.07	0.50 | 0.45	126 | 129	0.50 | 0.50
4+	0.053	0.351	0.15 | -0.05	0.75 | 0.70	123 | 121	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.18: Q School Results: Earnings

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	202,087.41	0.774	1,564,908.25 | -1,160,733.38	2,778,310.25 | 2,576,223.00	129 | 134	0.50 | 0.50
0	27,439.44	0.496	103,660.59 | -48,781.71	219,612.80 | 192,173.36	129 | 134	0.50 | 0.50
1	229,556.52	0.000	352,451.09 | 106,661.98	406,275.88 | 176,719.36	129 | 134	0.50 | 0.50
2	36,798.04	0.631	184,057.16 | -110,461.04	426,367.00 | 389,568.94	129 | 134	0.50 | 0.50
3	63,503.62	0.436	210,487.91 | -54,083.84	380,826.38 | 317,322.78	126 | 129	0.50 | 0.50
4+	459,610.34	0.644	1,919,435.38 | -1,000,214.81	3,612,433.75 | 3,152,823.50	123 | 121	0.50 | 0.50
Panel B: IHS PGA TOUR Earnings						
-1	-65,715.23	0.920	1,149,283.88 | -1,037,714.56	1,895,420.50 | 1,961,135.75	129 | 134	0.50 | 0.50
0	19,683.52	0.305	49,993.27 | -10,626.25	83,167.05 | 63,483.53	129 | 134	0.50 | 0.50
1	388,516.69	0.000	502,998.06 | 296,931.53	406,550.84 | 18,034.17	129 | 134	0.50 | 0.50
2	92,899.87	0.195	237,762.72 | -51,962.98	356,859.19 | 263,959.31	129 | 134	0.50 | 0.50
3	86,715.45	0.252	232,267.16 | -58,836.24	320,293.38 | 233,577.92	126 | 129	0.50 | 0.50
4+	516,781.44	0.605	1,976,149.25 | -942,586.44	3,284,483.50 | 2,767,702.00	123 | 121	0.50 | 0.50
Panel C: IHS Korn Ferry Tour Earnings						
-1	-19,793.73	0.634	62,134.13 | -101,721.57	186,666.56 | 206,460.30	129 | 134	0.50 | 0.50
0	1,474.65	0.879	22,330.85 | -19,381.55	49,535.34 | 48,060.69	129 | 134	0.50 | 0.50
1	-120,980.23	0.000	-96,160.09 | -140,836.36	-2,125.69 | 118,854.53	129 | 134	0.50 | 0.50
2	-31,790.81	0.005	-11,683.95 | -51,897.71	50,815.00 | 82,605.81	129 | 134	0.50 | 0.50
3	-14,342.79	0.216	8,443.23 | -32,571.66	42,023.71 | 56,366.51	126 | 129	0.50 | 0.50
4+	34,327.65	0.387	96,196.80 | -27,541.52	220,336.64 | 186,009.00	123 | 121	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

E.3 Results by Age

E.3.1 Korn Ferry Tour Regression Discontinuity Results

Table E.19: Korn Ferry ML Results: Events for Young Golfers (17-30)

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: PGA TOUR Events						
-1	16.18	12.43	0.194	24.53 | 8.35	49 | 240	5.18 | 25.18
0	-1.28	0.72	0.078	1.63 | 2.91	49 | 195	5.13 | 20.22
1	18.43	3.43	0.000	27.70 | 9.27	40 | 158	4.26 | 15.84
2	7.48	6.10	0.222	18.94 | 11.46	49 | 149	4.73 | 14.62
3	5.90	4.45	0.186	22.50 | 16.60	57 | 227	6.06 | 24.84
4+	4.07	36.04	0.910	107.82 | 103.75	71 | 125	7.90 | 13.65
Panel B: Korn Ferry Tour Events						
-1	21.47	12.94	0.098	39.77 | 18.30	49 | 218	5.39 | 21.74
0	0.31	1.26	0.808	25.16 | 24.85	71 | 207	7.31 | 21.48
1	-16.55	2.59	0.000	0.26 | 16.81	49 | 149	5.00 | 14.81
2	-4.22	4.53	0.351	7.97 | 12.19	59 | 229	6.01 | 23.64
3	-5.71	3.59	0.113	2.27 | 7.99	57 | 196	6.49 | 21.18
4+	-22.51	19.38	0.247	38.77 | 61.28	44 | 196	4.81 | 22.10

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.20: Korn Ferry ML Results: Events for Old Golfers (31-55)

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: PGA TOUR Events						
-1	20.76	41.99	0.621	100.56 | 79.80	66 | 177	5.58 | 15.77
0	-0.70	0.74	0.349	1.98 | 2.68	102 | 232	8.57 | 21.14
1	19.68	2.71	0.000	28.16 | 8.48	55 | 223	4.63 | 20.49
2	-0.82	4.20	0.846	11.34 | 12.16	55 | 282	5.20 | 24.64
3	1.65	4.40	0.707	11.69 | 10.04	51 | 214	5.37 | 19.69
4+	-15.20	14.85	0.307	31.40 | 46.60	50 | 257	4.51 | 24.79
Panel B: Korn Ferry Tour Events						
-1	-25.90	22.63	0.254	47.70 | 73.59	43 | 241	4.39 | 21.87
0	0.45	1.09	0.678	25.23 | 24.78	66 | 232	6.25 | 21.47
1	-18.40	1.78	0.000	0.44 | 18.84	66 | 138	5.97 | 12.39
2	-0.94	3.68	0.799	14.24 | 15.18	55 | 165	4.98 | 15.25
3	-3.13	3.33	0.348	9.04 | 12.17	83 | 149	7.69 | 13.64
4+	-17.49	16.83	0.300	47.20 | 64.68	40 | 149	4.43 | 15.06

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.21: Korn Ferry ML Results: IHS Earnings for Young Golfers (17-30)

Year (1)	τ (2)	SE (3)	Pval (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	1.384	1.123	0.219	13.40 | 12.02	49 | 149	4.90 | 15.25
0	-0.142	0.111	0.204	13.28 | 13.42	49 | 174	5.31 | 18.44
1	0.848	0.540	0.118	13.17 | 12.33	40 | 168	4.17 | 16.65
2	1.791	1.036	0.086	14.30 | 12.51	40 | 114	4.39 | 12.19
3	0.765	1.084	0.481	14.07 | 13.30	57 | 142	6.34 | 14.62
4+	2.131	1.108	0.056	16.61 | 14.48	44 | 167	4.98 | 18.87
Panel B: IHS PGA TOUR Earnings						
-1	2.256	2.223	0.311	8.99 | 6.73	71 | 218	6.99 | 21.69
0	-0.096	2.383	0.968	2.61 | 2.71	40 | 240	3.68 | 25.32
1	8.116	1.308	0.000	13.83 | 5.71	40 | 174	3.99 | 17.77
2	4.747	3.020	0.118	10.20 | 5.46	59 | 127	6.36 | 13.07
3	2.469	2.296	0.283	11.79 | 9.32	48 | 217	5.47 | 23.53
4+	2.246	1.792	0.211	14.71 | 12.46	53 | 177	6.36 | 19.73
Panel C: IHS Korn Ferry Tour Earnings						
-1	2.979	1.251	0.018	13.32 | 10.34	40 | 218	4.31 | 21.95
0	-0.007	0.113	0.948	13.24 | 13.25	49 | 223	4.75 | 23.49
1	-3.181	2.146	0.140	5.46 | 8.64	49 | 183	4.75 | 19.25
2	-1.244	2.690	0.644	5.54 | 6.79	49 | 223	5.27 | 22.69
3	-3.195	2.137	0.136	2.27 | 5.47	68 | 165	6.57 | 17.90
4+	-1.814	2.928	0.536	8.12 | 9.93	44 | 187	4.80 | 21.08

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.22: Korn Ferry ML Results: IHS Earnings for Old Golfers (31-55)

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: IHS World Earnings						
-1	0.137	0.492	0.781	14.57 | 14.43	55 | 272	5.37 | 23.54
0	0.120	0.094	0.205	13.50 | 13.38	55 | 223	4.84 | 20.10
1	0.786	0.388	0.044	12.97 | 12.18	55 | 138	5.31 | 11.92
2	-0.511	0.700	0.466	12.71 | 13.22	66 | 112	5.70 | 10.12
3	-0.890	1.398	0.525	11.53 | 12.42	62 | 118	5.53 | 11.20
4+	-0.204	1.514	0.893	12.95 | 13.16	50 | 131	5.20 | 13.46
Panel B: IHS PGA TOUR Earnings						
-1	1.856	1.212	0.127	13.80 | 11.95	66 | 272	6.03 | 24.27
0	1.582	1.553	0.309	4.15 | 2.57	88 | 214	7.81 | 19.07
1	9.046	1.043	0.000	13.38 | 4.34	55 | 202	4.84 | 18.08
2	0.676	2.173	0.756	7.47 | 6.79	55 | 307	5.02 | 26.52
3	-0.122	2.342	0.958	6.16 | 6.28	51 | 179	5.36 | 16.87
4+	-0.992	2.710	0.715	9.51 | 10.50	50 | 111	4.52 | 11.04
Panel C: IHS Korn Ferry Tour Earnings						
-1	-0.618	0.504	0.222	12.92 | 13.53	55 | 124	4.74 | 10.82
0	0.017	0.075	0.823	13.28 | 13.26	55 | 202	5.04 | 18.46
1	-7.978	1.522	0.000	2.09 | 10.06	66 | 156	6.27 | 13.69
2	1.880	1.655	0.257	9.89 | 8.01	55 | 232	5.09 | 20.61
3	-2.697	2.164	0.214	5.06 | 7.76	51 | 131	4.68 | 11.69
4+	-0.067	1.501	0.964	11.23 | 11.30	68 | 202	6.58 | 19.91

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.23: Korn Ferry ML Results: Scoring for Young Golfers (17-30)

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adjusted Scoring Average						
-1	0.455	0.285	0.112	0.73 | 0.27	40 | 128	3.66 | 14.82
0	-0.016	0.168	0.926	-0.23 | -0.21	40 | 174	4.15 | 17.73
1	-0.155	0.289	0.593	-0.16 | -0.01	59 | 173	6.10 | 18.32
2	-0.290	0.433	0.503	-0.05 | 0.24	58 | 147	6.45 | 14.65
3	-0.486	0.552	0.379	-0.06 | 0.43	73 | 201	7.52 | 23.70
4-16	-0.347	0.526	0.510	0.21 | 0.56	450 | 874	6.63 | 15.28
Panel B: Unadjusted Scoring Average						
-1	0.345	0.345	0.319	-0.05 | -0.40	30 | 118	3.48 | 13.98
0	-0.030	0.160	0.850	-1.09 | -1.06	49 | 158	4.62 | 16.22
1	0.632	0.255	0.014	0.21 | -0.42	59 | 167	5.62 | 17.42
2	0.214	0.329	0.516	0.06 | -0.15	48 | 155	4.66 | 16.18
3	-0.243	0.513	0.636	0.27 | 0.51	66 | 182	6.92 | 21.19
4-16	-0.429	0.349	0.219	0.17 | 0.60	280 | 1,074	5.14 | 18.66

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. All estimates are based on local linear regressions. See Appendix Section C for details.

Table E.24: Korn Ferry ML Results: Scoring for Old Golfers (31-55)

Year	τ	SE	Pval	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adjusted Scoring Average						
-1	-0.067	0.244	0.785	0.23 | 0.30	54 | 224	5.13 | 21.35
0	0.170	0.118	0.153	0.00 | -0.17	75 | 214	7.16 | 18.72
1	-0.112	0.207	0.591	-0.06 | 0.05	55 | 145	5.49 | 13.42
2	0.151	0.350	0.667	0.68 | 0.53	55 | 169	5.33 | 16.41
3	0.173	0.428	0.687	0.62 | 0.45	60 | 147	5.51 | 16.29
4-16	0.225	0.460	0.624	1.42 | 1.19	215 | 888	3.66 | 20.52
Panel B: Unadjusted Scoring Average						
-1	0.013	0.280	0.962	-0.26 | -0.27	64 | 180	6.18 | 16.77
0	0.155	0.116	0.180	-0.85 | -1.01	75 | 223	7.30 | 19.51
1	0.908	0.191	0.000	0.44 | -0.47	75 | 124	6.74 | 11.39
2	0.192	0.258	0.456	0.27 | 0.08	66 | 158	6.30 | 15.02
3	0.336	0.331	0.312	0.45 | 0.12	60 | 119	6.24 | 13.01
4-16	0.098	0.396	0.804	0.88 | 0.78	215 | 847	4.30 | 18.51

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to the estimated regression discontinuity limits on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. All estimates are based on local linear regressions. See Appendix Section C for details.

E.3.2 Q School Regression Discontinuity Results

Table E.25: Q School Results: Events for Young Golfers (17-30)

Year	τ	Pval	95% CI	$\beta_l \mid \beta_r$	$N_l \mid N_r$	$h_l \mid h_r$
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: PGA TOUR Events						
-1	-4.87	0.220	1.15 | -10.85	1.83 | 6.71	58 | 64	0.50 | 0.50
0	-1.90	0.185	0.33 | -4.15	2.62 | 4.53	58 | 64	0.50 | 0.50
1	21.78	0.000	23.39 | 20.19	21.76 | -0.02	58 | 64	0.50 | 0.50
2	0.00	0.999	4.73 | -3.82	9.84 | 9.84	58 | 64	0.50 | 0.50
3	-1.11	0.634	2.64 | -4.80	7.72 | 8.83	55 | 60	0.50 | 0.50
4+	-12.33	0.580	23.37 | -47.99	103.35 | 115.68	53 | 57	0.50 | 0.50
Panel B: Korn Ferry Tour Events						
-1	-3.42	0.406	4.52 | -9.79	6.97 | 10.39	58 | 64	0.50 | 0.50
0	-1.46	0.459	2.22 | -4.44	6.86 | 8.33	58 | 64	0.50 | 0.50
1	-18.82	0.000	-16.70 | -20.90	4.59 | 23.40	58 | 64	0.50 | 0.50
2	-0.99	0.611	2.74 | -4.01	8.98 | 9.96	58 | 64	0.50 | 0.50
3	-0.38	0.861	2.82 | -3.58	9.21 | 9.59	55 | 60	0.50 | 0.50
4+	12.50	0.270	30.20 | -5.24	62.30 | 49.80	53 | 57	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.26: Q School Results: Events for Old Golfers (31-55)

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: PGA TOUR Events						
-1	-5.78	0.789	39.53 | -51.07	113.58 | 119.36	71 | 70	0.50 | 0.50
0	2.47	0.224	6.43 | -0.68	11.31 | 8.85	71 | 70	0.50 | 0.50
1	19.65	0.000	21.44 | 17.84	23.03 | 3.39	71 | 70	0.50 | 0.50
2	5.16	0.010	9.06 | 1.26	12.59 | 7.43	71 | 70	0.50 | 0.50
3	1.32	0.538	5.44 | -2.76	10.62 | 9.30	71 | 69	0.50 | 0.50
4+	14.61	0.195	36.59 | -3.01	62.32 | 47.71	70 | 64	0.50 | 0.50
Panel B: Korn Ferry Tour Events						
-1	-3.41	0.658	12.04 | -18.86	41.66 | 45.07	71 | 70	0.50 | 0.50
0	-0.79	0.621	2.36 | -3.94	6.61 | 7.40	71 | 70	0.50 | 0.50
1	-15.62	0.000	-13.26 | -17.96	2.75 | 18.37	71 | 70	0.50 | 0.50
2	-2.07	0.222	1.10 | -5.20	8.32 | 10.38	71 | 70	0.50 | 0.50
3	1.01	0.489	3.30 | -1.26	5.90 | 4.90	71 | 69	0.50 | 0.50
4+	9.96	0.198	21.65 | -1.71	43.04 | 33.07	70 | 64	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.27: Q School Results: IHS Earnings for Young Golfers (17-30)

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	0.235	0.856	2.40 | -1.90	8.50 | 8.26	58 | 64	0.50 | 0.50
0	-0.633	0.543	1.37 | -2.63	7.92 | 8.56	58 | 64	0.50 | 0.50
1	0.571	0.029	1.08 | 0.08	12.38 | 11.81	58 | 64	0.50 | 0.50
2	-0.301	0.748	1.68 | -1.92	10.38 | 10.68	58 | 64	0.50 | 0.50
3	-0.768	0.426	0.73 | -2.31	10.46 | 11.23	55 | 60	0.50 | 0.50
4+	0.361	0.740	2.06 | -1.38	12.99 | 12.63	53 | 57	0.50 | 0.50
Panel B: IHS PGA TOUR Earnings						
-1	-0.507	0.620	1.61 | -2.59	3.80 | 4.31	58 | 64	0.50 | 0.50
0	-0.520	0.582	1.37 | -2.05	2.10 | 2.62	58 | 64	0.50 | 0.50
1	10.796	0.000	11.83 | 9.75	11.66 | 0.86	58 | 64	0.50 | 0.50
2	0.046	0.964	2.48 | -1.93	4.84 | 4.79	58 | 64	0.50 | 0.50
3	0.020	0.986	2.03 | -1.97	4.56 | 4.54	55 | 60	0.50 | 0.50
4+	-0.177	0.886	1.97 | -2.35	10.51 | 10.69	53 | 57	0.50 | 0.50
Panel C: IHS Korn Ferry Tour Earnings						
-1	-0.183	0.859	1.93 | -2.27	6.04 | 6.22	58 | 64	0.50 | 0.50
0	-0.122	0.911	1.92 | -1.77	5.67 | 5.79	58 | 64	0.50 | 0.50
1	-4.854	0.000	-3.40 | -6.30	6.18 | 11.04	58 | 64	0.50 | 0.50
2	-0.978	0.319	0.68 | -2.60	5.53 | 6.50	58 | 64	0.50 | 0.50
3	-0.552	0.629	1.19 | -2.68	6.00 | 6.55	55 | 60	0.50 | 0.50
4+	0.651	0.551	2.47 | -1.13	9.39 | 8.74	53 | 57	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.28: Q School Results: IHS Earnings for Old Golfers (31-55)

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: IHS World Earnings						
-1	0.577	0.395	1.90 | -0.53	14.43 | 13.86	71 | 70	0.50 | 0.50
0	0.556	0.479	2.14 | -0.74	10.79 | 10.23	71 | 70	0.50 | 0.50
1	0.609	0.080	1.13 | -0.04	12.41 | 11.81	71 | 70	0.50 | 0.50
2	0.747	0.325	2.29 | -0.50	11.66 | 10.91	71 | 70	0.50 | 0.50
3	1.612	0.104	3.47 | -0.23	10.45 | 8.84	71 | 69	0.50 | 0.50
4+	1.517	0.146	3.51 | -0.09	11.39 | 9.88	70 | 64	0.50 | 0.50
Panel B: IHS PGA TOUR Earnings						
-1	0.827	0.393	2.74 | -0.68	12.27 | 11.45	71 | 70	0.50 | 0.50
0	1.443	0.194	3.57 | -0.30	6.98 | 5.53	71 | 70	0.50 | 0.50
1	8.288	0.000	9.93 | 6.96	12.18 | 3.89	71 | 70	0.50 | 0.50
2	2.856	0.010	5.01 | 0.71	8.22 | 5.36	71 | 70	0.50 | 0.50
3	0.863	0.419	3.06 | -0.90	6.64 | 5.78	71 | 69	0.50 | 0.50
4+	2.488	0.035	4.83 | 0.60	9.04 | 6.55	70 | 64	0.50 | 0.50
Panel C: IHS Korn Ferry Tour Earnings						
-1	-0.195	0.836	1.51 | -1.89	10.32 | 10.51	71 | 70	0.50 | 0.50
0	-0.285	0.776	1.24 | -1.80	5.81 | 6.09	71 | 70	0.50 | 0.50
1	-6.454	0.000	-5.24 | -7.64	3.26 | 9.71	71 | 70	0.50 | 0.50
2	-0.831	0.375	1.00 | -2.33	6.39 | 7.22	71 | 70	0.50 | 0.50
3	1.424	0.127	3.23 | -0.37	5.36 | 3.94	71 | 69	0.50 | 0.50
4+	1.146	0.251	3.03 | -0.39	9.19 | 8.04	70 | 64	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the sum off the respective outcome in year -1 and prior. "4" refers to the sum the respective outcome in year 4 and beyond. See Appendix Section C for details.

Table E.29: Q School Results: Scoring for Young Golfers (17-30)

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Adjusted Scoring Average						
-1	0.450	0.116	0.91 | -0.05	1.14 | 0.69	34 | 44	0.50 | 0.50
0	-0.116	0.636	0.32 | -0.49	0.50 | 0.61	41 | 51	0.50 | 0.50
1	-0.069	0.669	0.24 | -0.36	0.48 | 0.54	58 | 63	0.50 | 0.50
2	0.132	0.647	0.66 | -0.33	0.39 | 0.26	46 | 55	0.50 | 0.50
3	0.073	0.796	0.66 | -0.42	0.34 | 0.27	46 | 52	0.50 | 0.50
4-16	-0.358	0.268	0.14 | -0.90	0.46 | 0.82	48 | 54	0.50 | 0.50
Panel B: Unadjusted Scoring Average						
-1	0.248	0.430	0.85 | -0.35	0.62 | 0.37	34 | 44	0.50 | 0.50
0	-0.160	0.441	0.26 | -0.54	-0.01 | 0.15	41 | 51	0.50 | 0.50
1	0.915	0.000	1.20 | 0.66	0.63 | -0.29	58 | 63	0.50 | 0.50
2	0.213	0.384	0.67 | -0.23	0.08 | -0.13	46 | 55	0.50 | 0.50
3	0.129	0.688	0.68 | -0.31	0.04 | -0.09	46 | 52	0.50 | 0.50
4-16	-0.358	0.195	0.17 | -0.82	0.36 | 0.72	48 | 54	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. See Appendix Section C for details.

Table E.30: Q School Results: Scoring for Old Golfers (31-55)

Year (1)	τ (2)	Pval (3)	95% CI (4)	$\beta_l \mid \beta_r$ (5)	$N_l \mid N_r$ (6)	$h_l \mid h_r$ (7)
Panel A: Adjusted Scoring Average						
-1	-0.054	0.728	0.24 | -0.30	0.09 | 0.14	63 | 58	0.50 | 0.50
0	-0.103	0.530	0.17 | -0.39	0.18 | 0.29	66 | 60	0.50 | 0.50
1	-0.305	0.069	-0.04 | -0.60	0.19 | 0.50	71 | 69	0.50 | 0.50
2	0.072	0.721	0.46 | -0.26	0.27 | 0.20	66 | 58	0.50 | 0.50
3	0.199	0.438	0.59 | -0.21	0.49 | 0.29	62 | 50	0.50 | 0.50
4-16	-0.319	0.218	0.18 | -0.72	1.11 | 1.43	62 | 53	0.50 | 0.50
Panel B: Unadjusted Scoring Average						
-1	0.085	0.520	0.35 | -0.15	-0.06 | -0.14	63 | 58	0.50 | 0.50
0	0.040	0.825	0.32 | -0.24	0.05 | 0.01	66 | 60	0.50 | 0.50
1	0.647	0.000	0.92 | 0.38	0.50 | -0.14	71 | 69	0.50 | 0.50
2	0.341	0.023	0.60 | 0.06	0.07 | -0.27	66 | 58	0.50 | 0.50
3	0.109	0.621	0.45 | -0.27	0.31 | 0.20	62 | 50	0.50 | 0.50
4-16	-0.287	0.192	0.16 | -0.65	0.87 | 1.15	62 | 53	0.50 | 0.50

Notes: τ refers to the estimated treatment effect. β_l and β_r refer to mean values of the dependent variable on the left and right sides of the treatment threshold. N_l and N_r refer to the number of observations with the bandwidths on the left and right sides of the treatment threshold. h_l and h_r refer to the coverage error rate optimal bandwidths estimated on the left and right sides of the treatment threshold. "-1" refers to the outcome in year -1 only. "4-16" refers to the average of the respective outcome from year 4 to 16. See Appendix Section C for details.

E.4 Job Transitions

Table E.31: Annual tour transition rates for each experiment sample

	PGA TOUR$_t$ to PGA TOUR$_{t+1}$ (1)	PGA TOUR$_t$ to Korn Ferry Tour$_{t+1}$ (2)	Korn Ferry Tour$_t$ to PGA TOUR$_{t+1}$ (3)	Korn Ferry Tour$_t$ to Korn Ferry Tour$_{t+1}$ (4)
Korn Ferry Tour ML	0.42	0.41	0.31	0.47
	153	*153*	*132*	*132*
Q School	0.43	0.31	0.23	0.45
	111	*111*	*114*	*114*

Notes: Annual transition rates and sample sizes are reported for each tour transition. Base sample is comprised of the nearest 5 golfers to each treatment threshold from 1990 to 2014, a total of 230 golfers for each experiment. PGA TOUR membership defined as having played in at least 20 PGA TOUR events. Korn Ferry Tour memerbship defined as having played in at least 16 Korn Ferry Tour events. Transition rates are computed based on a golfer's first season on either the PGA TOUR or Korn Ferry Tour after the potential experiment treatment year.

F Sensitivity Analysis

Throughout this section I present the results of a variety of sensitivity analyses regarding the main outcomes of interest: IHS world earnings and adjusted scoring average. Despite the large number of sensitivity checks, all the results support the main qualitative conclusions presented above. Across the board, I find short-run positive effects on earnings, yet no evidence of long-run earnings effects or performance effects.

F.1 Korn Ferry Tour ML: Bandwidth Sensitivity

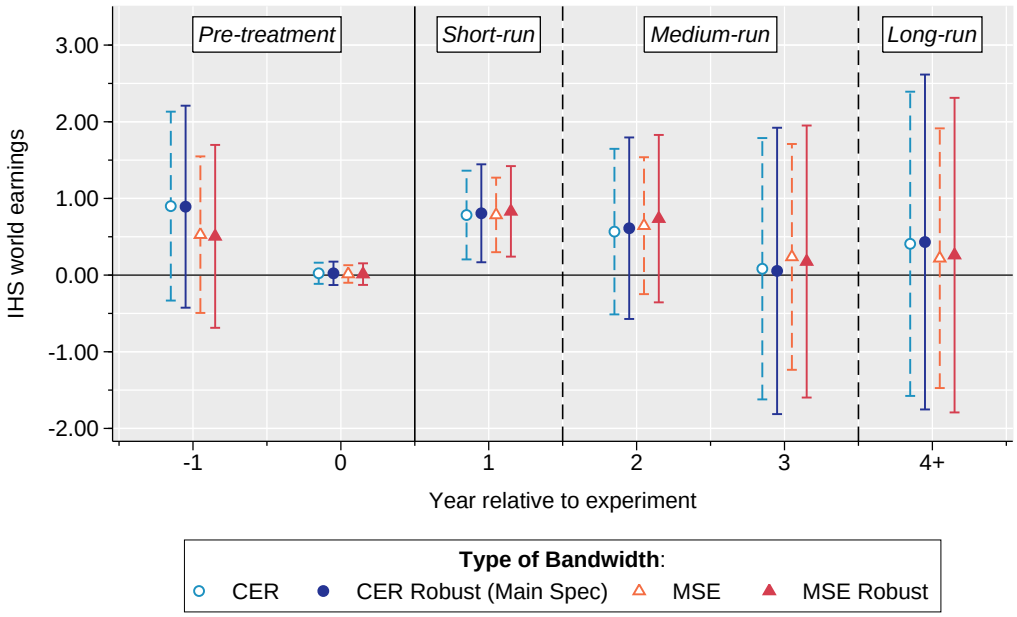
This section presents the results of an analysis of the sensitivity of the estimated treatment effects in the Korn Ferry Tour ML experiment to the selection of the length of the bandwidths on either side of the treatment threshold. The program *rdrobust* allows for the use of coverage error rate (CER) optimal or mean square error (MSE) optimal bandwidths. The programs also computes bias-corrected treated effect and a standard error correction to compute robust confidence inter-

vals. Appendix Figure F.1 compares the results with both CER and MSE optimal bandwidths and robust and standard treatment effects and confidence intervals. These choices end up making little difference in the final estimates for either earnings or scoring average. In most all cases the main specification of CER robust has the largest confidence intervals and thus may be considered the most conservative choice out of these estimators.

I allow experiment with the bandwidth lengths by manually selecting a 'small", "medium", and "large" bandwidth length that is the same regardless of the year relative to the experiment. The small bandwidth has a left bandwidth of 5 and a right bandwidth of 10. The medium bandwidth has a left bandwidth of 8 and a right bandwidth of 20. The large bandwidth has a left bandwidth of 15 and a right bandwidth of 30. Appendix Figure F.2 presents the results of this analysis. The treatment effects are similar across all bandwidth types. The small bandwidth appears "too small" with the largest variance and some deviations its point estimates relative to the others.

Figure F.1: Sensitivity of treatment effects to bandwidth selection method

(a) Korn Ferry Tour ML: IHS world earnings



(b) Korn Ferry Tour ML: Adjusted scoring average

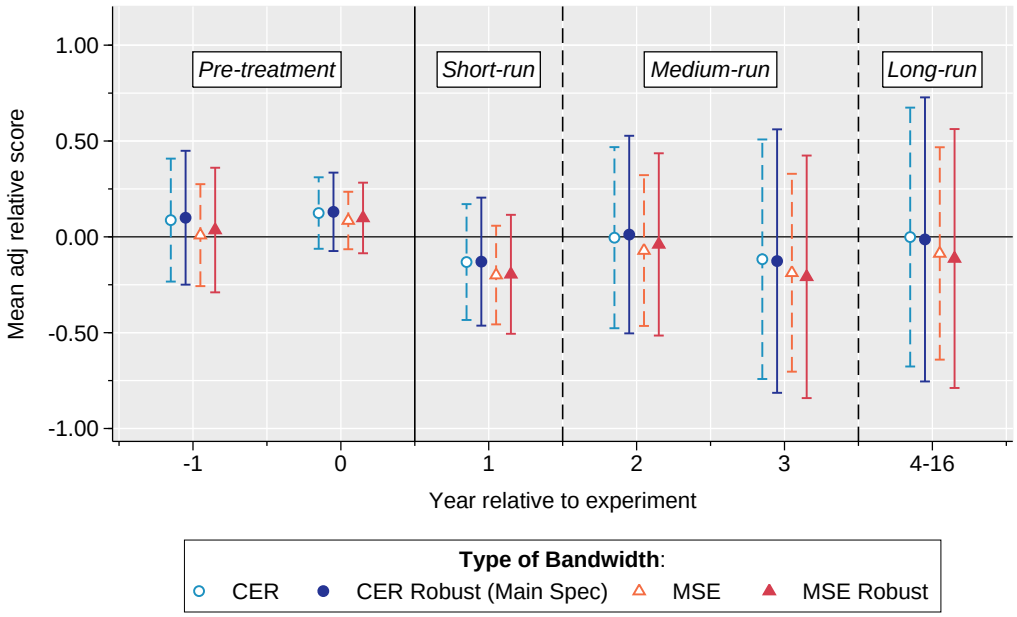
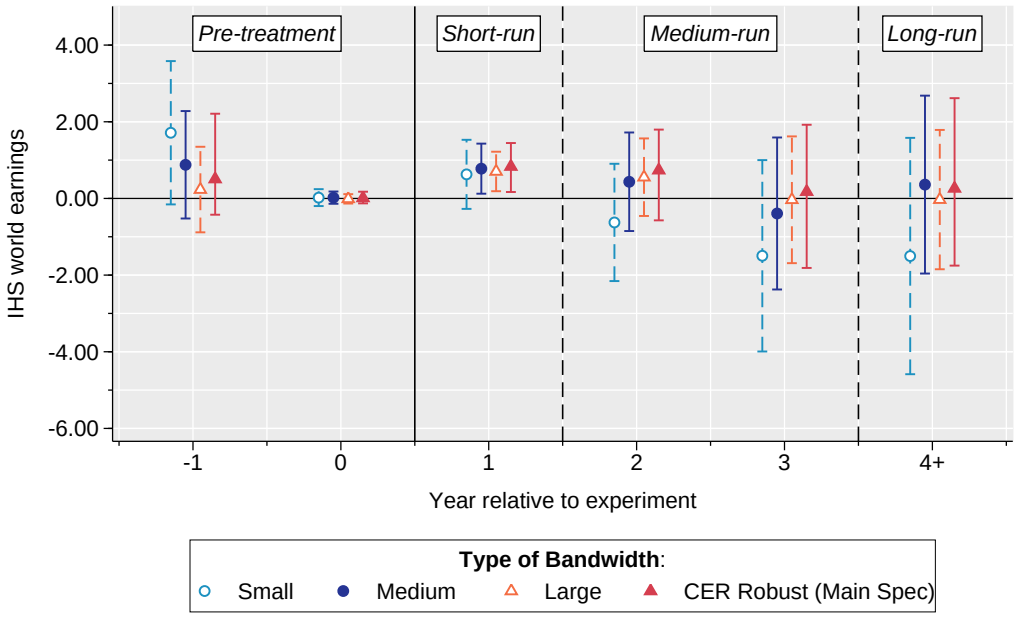
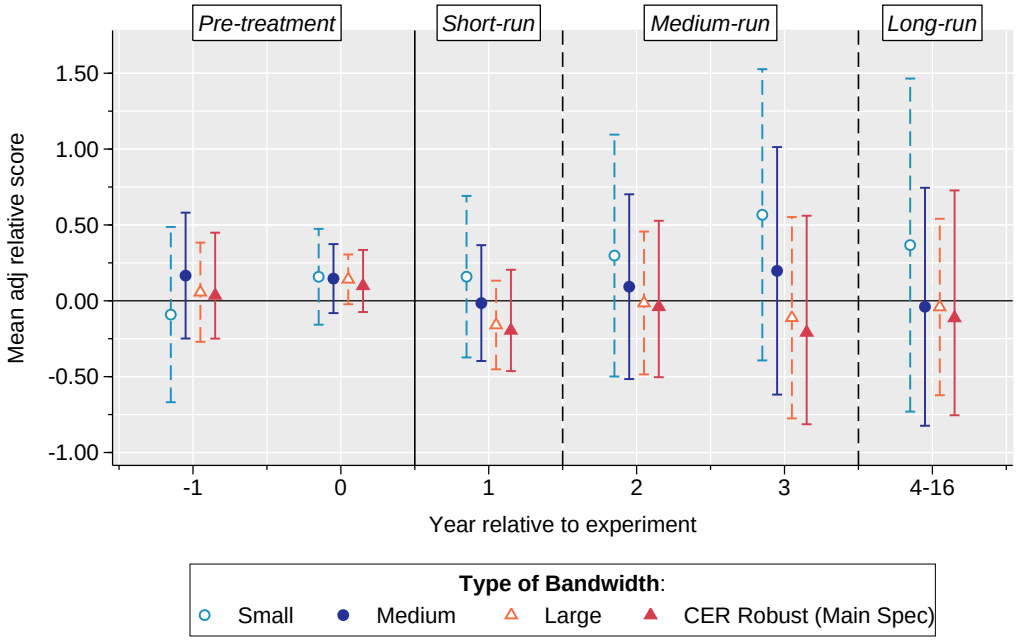


Figure F.2: Sensitivity of treatment effects to bandwidth length

(a) Korn Ferry Tour ML: IHS world earnings



(b) Korn Ferry Tour ML: Adjusted scoring average

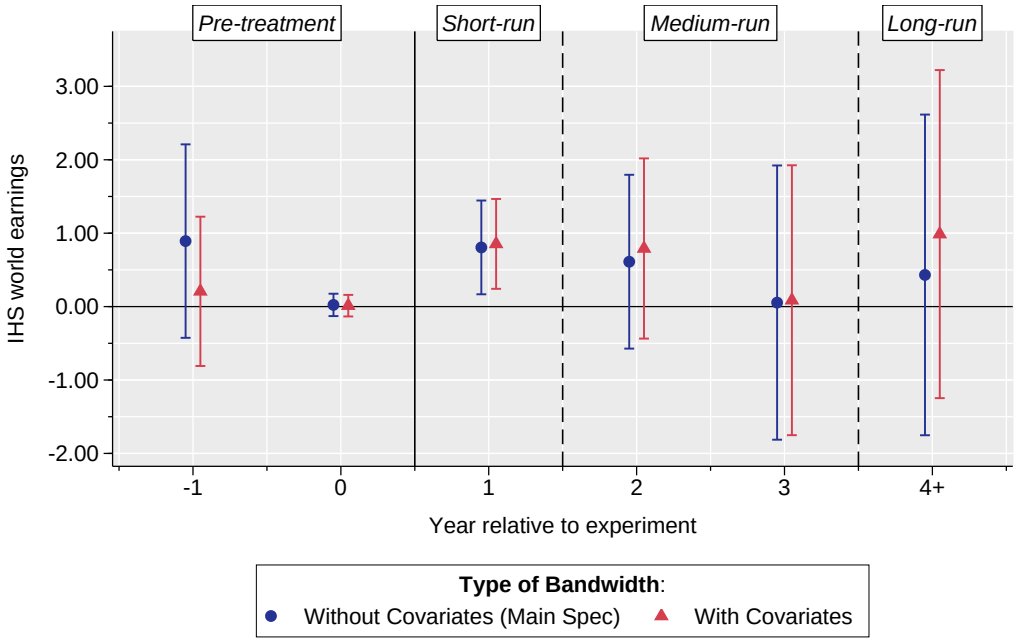


F.2 Korn Ferry Tour ML: Controlling for Pre-Treatment Characteristics

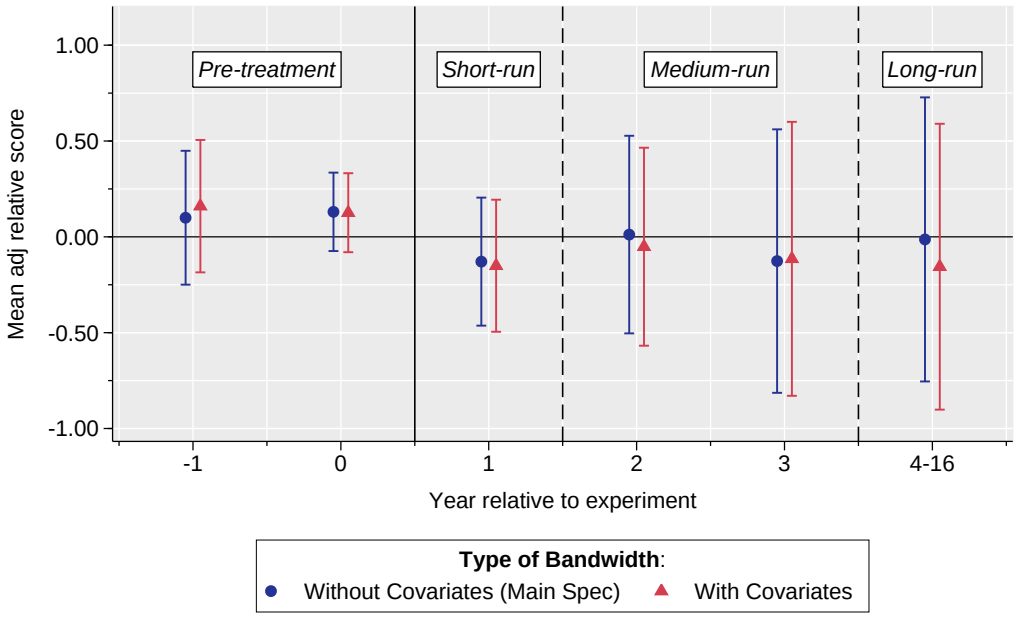
Section 4.1 presented some results which show some potential discontinuities in the age and ability of Korn Ferry Tour ML at the treatment threshold. If these differences are not spurious but represent true differences in underlying ability at the threshold, then we may expect to arrive at difference results when controlling for observable factors such as age and OWGR. Another reason to control for covariates is to potentially reduced the variance in the estimated treatment effects. Appendix Figure F.3 compares the results of the main specification with a specification that controls for age, age squared, and OWGR. The results are very similar for both specifications and there does not appear to be any significant gain in precise when controlling for covariates. This evidence supports the view of a spurious discontinuity in age at the treatment threshold rather than one that reflects a true underlying difference in ability.

Figure F.3: Sensitivity of treatment effects to covariates

(a) Korn Ferry Tour ML: IHS world earnings



(b) Korn Ferry Tour ML: Adjusted scoring average

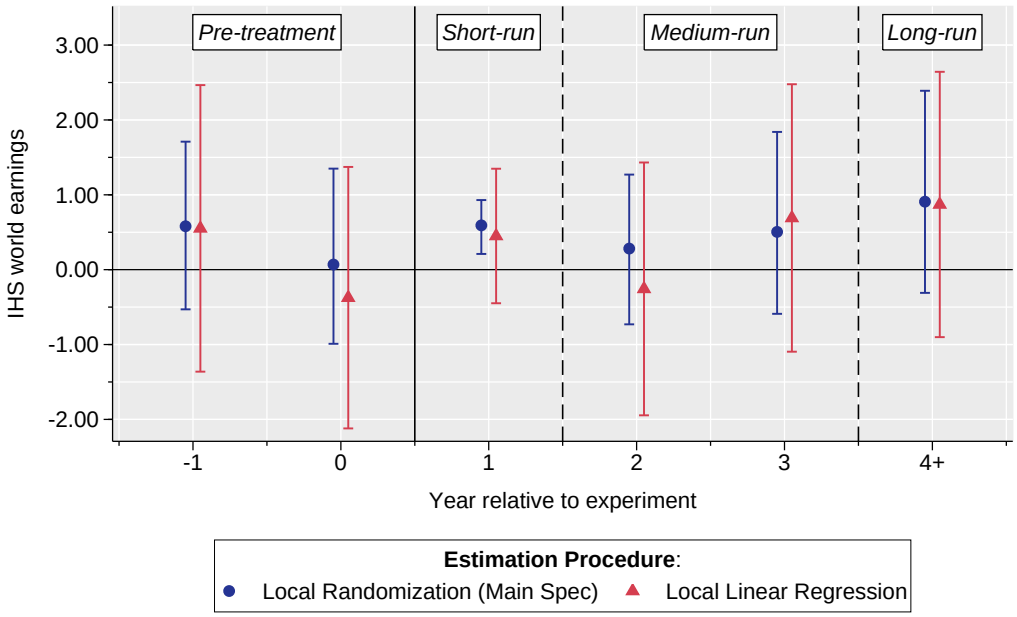


F.3 Q School: Local Randomization versus Local Linear Regression

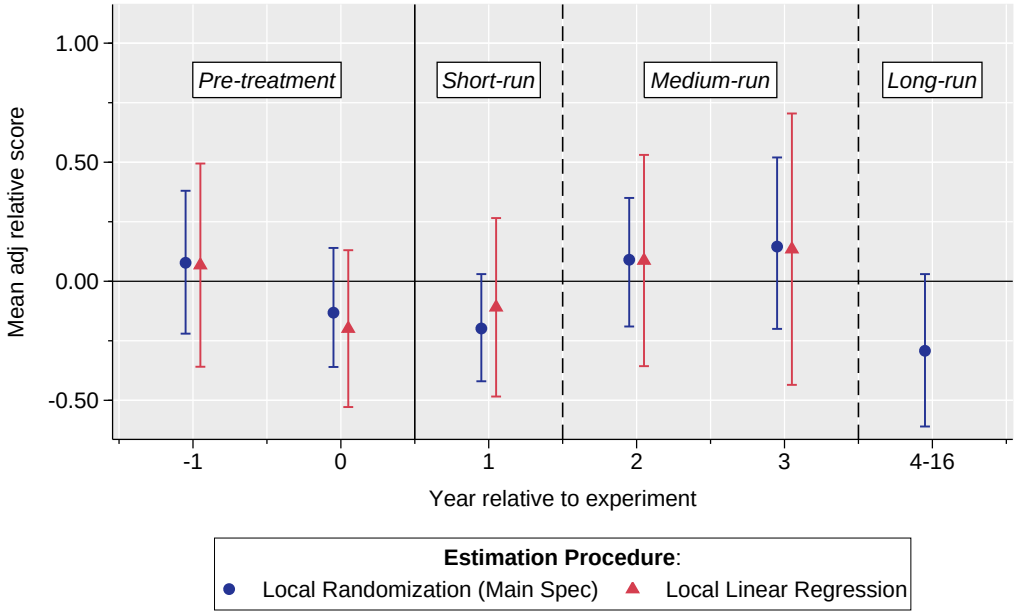
Appendix Figure F.4 presents estimates of the treatment effects of the Q School experiment using both local randomization and local linear regression methods. The treatment effects are similar in both methods for both earnings and scoring average. Yet, treatment effects with the local randomization method tend to have smaller standard errors. It is theoretically ambiguous whether the local randomization method will increase the power of inference relative to the local linear regression method. On one hand, assuming that the randomization process is known increases power. On the other hand, using finite sample inference methods tends to reduce power. These results suggest that first force dominates in this case.

Figure F.4: Sensitivity of treatment effects to estimation method

(a) Q School: IHS world earnings



(b) Q School: Adjusted scoring average



F.4 Sensitivity of treatment results to sample selection

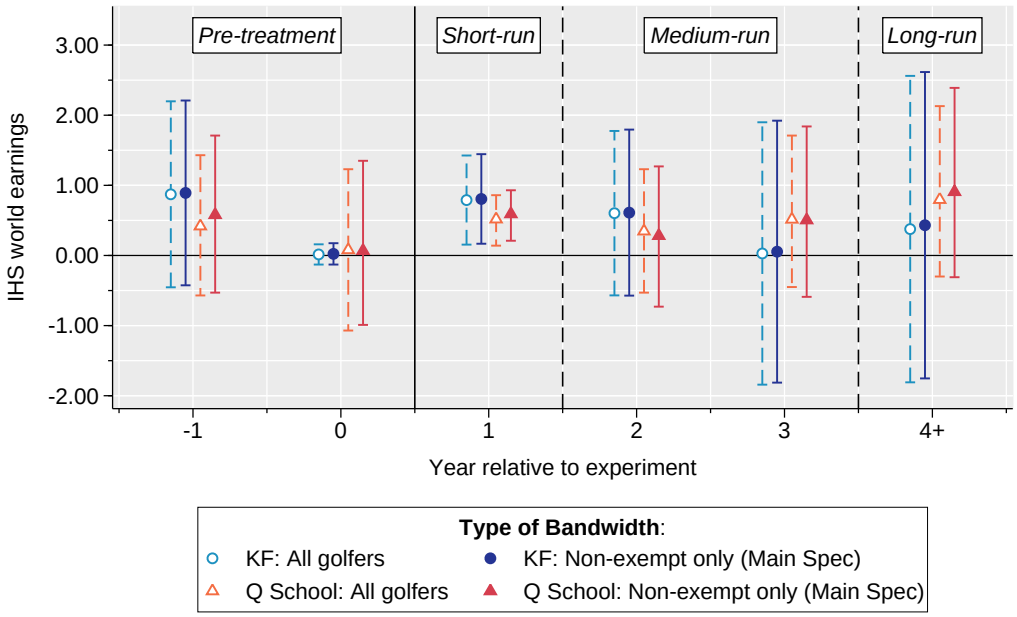
I drop golfer with partial exemption from the main specification. Appendix Figure F.5 shows the results if the exempt golfers are left in the sample. The results are quite similar for earnings and scoring average for both experiments. I drop partially exempt golfers as they have different outside options and may weaken the treatment effect. However, these results suggest that there are not enough exempt golfers near the treatment thresholds to make much of a different in the estimates.

The main specification pools across many different experiments to estimate a common treatment effect. One implication of this pooling is that the sample becomes younger in age and older in experiment year as I estimate longer-run effects. To understand the potential effects of the unbalanced sample, Appendix Figure F.6 compares the results of the main specification to those with a balance sample. These estimates are displayed at an annual level from year 0 to year 8. For both experiments, the balanced sample treatment effects lie comfortably within the confidence intervals of the treatment effects from the main specification. The balanced sample necessarily throws out some observations and has a smaller sample size. This smaller sample size appears to be reflected in the wider confidence intervals of the balanced sample estimates. The point estimates show a similar pattern to the main specification. The primary result of using the balanced sample is that the first year earnings effect loses some statistical significance as the estimates have larger variance.

Another consequence of pooling experiments across time is that I may potentially mask different treatment effects from different eras. Appendix Figures F.7 and F.8 present estimates of treatment effects from five different eras for the Korn Ferry Tour ML and Q School experiments, respectively. I chose these eras based on the number of tour cards that were awarded in each experiment at different points in time. Appendix Figure D.2 shows the evolution of tour cards awarded by experiment. The results do not show any strong trends in the short-run or long-run fixed effects. These estimates rely are less observations and, as a result, appear to noisier. In fact, the first year earnings effects loses statistical significance in many specifications, but the point estimate are quite similar. There are some statistically significant long-run earnings effects, but these appear to be the result the increased noise rather than an indication of a consistent pattern.

Figure F.5: Sensitivity of treatment effects to exemption status

(a) IHS world earnings



(b) Adjusted scoring average

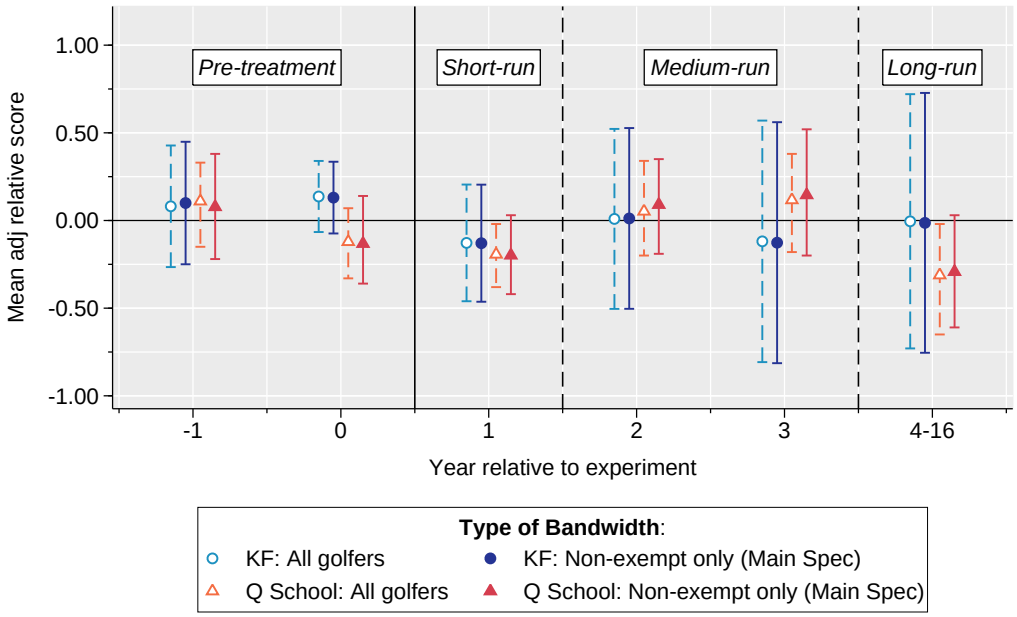
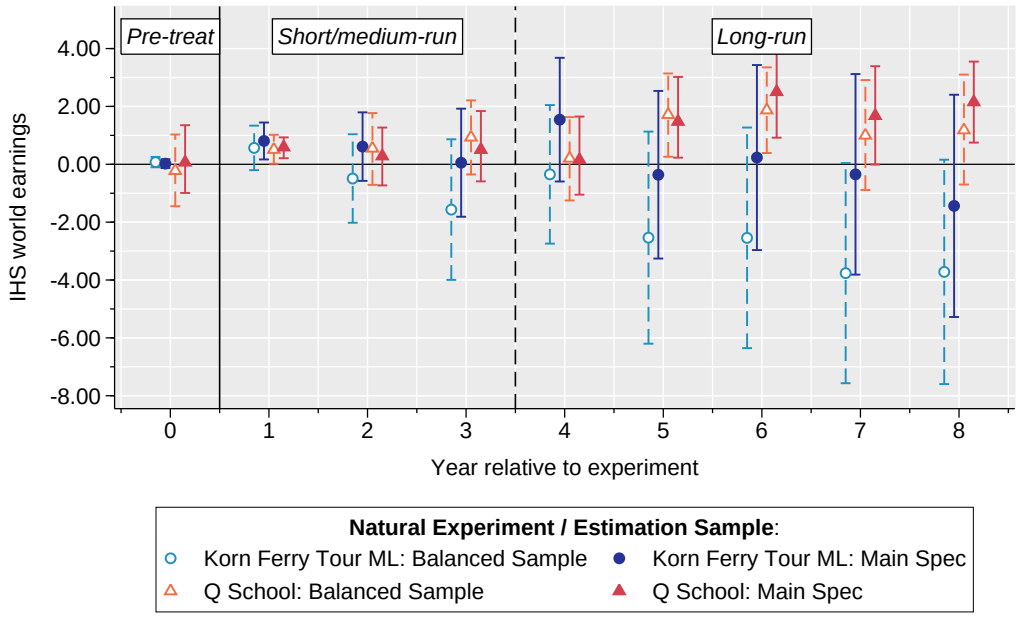


Figure F.6: Treatment effects with a balanced sample (age: 17-47, exp year: 1992-2004)

(a) IHS world earnings



(b) Adjusted scoring average

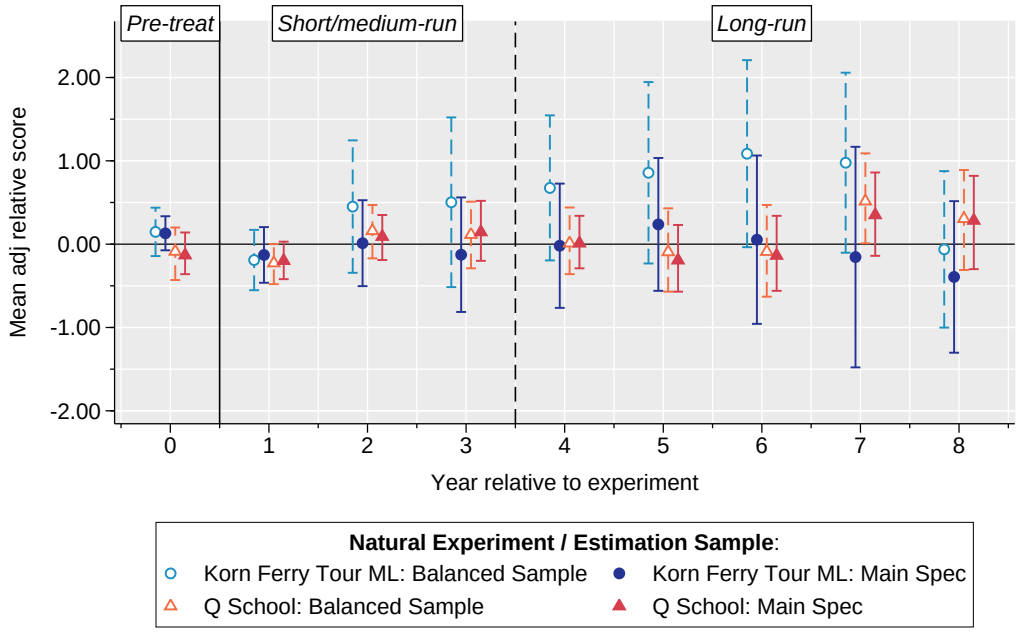
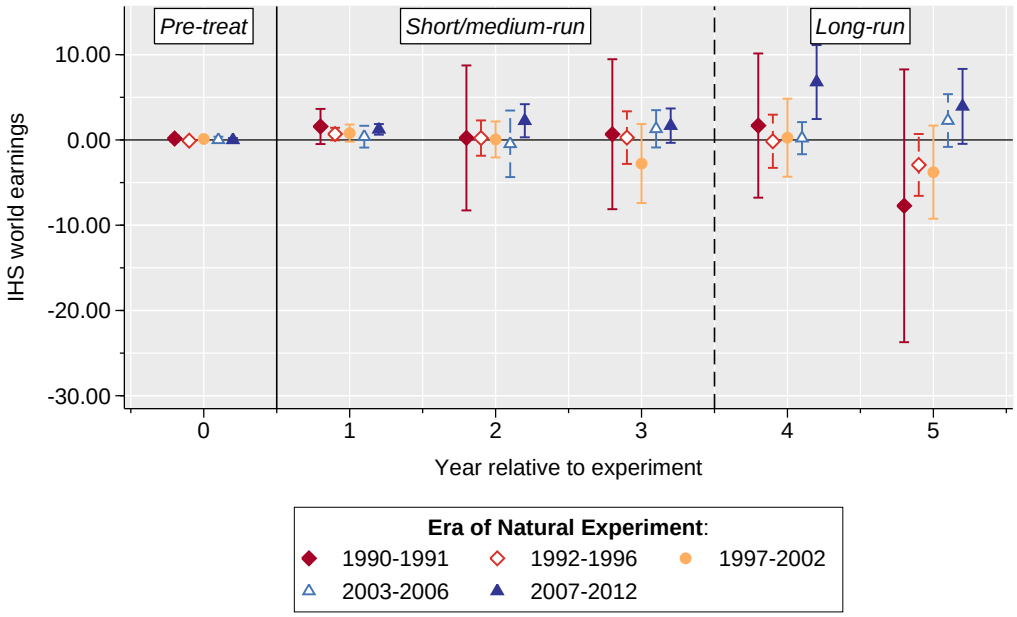


Figure F.7: Korn Ferry Tour ML: Treatment effects over time

(a) Korn Ferry Tour ML: IHS world earnings



(b) Korn Ferry Tour ML: Adjusted scoring average

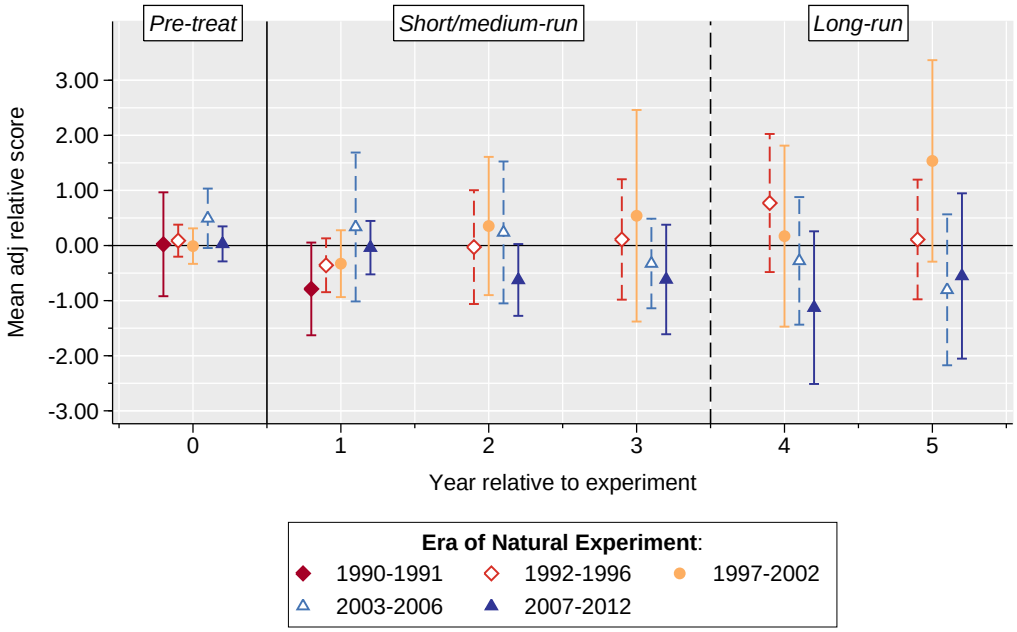
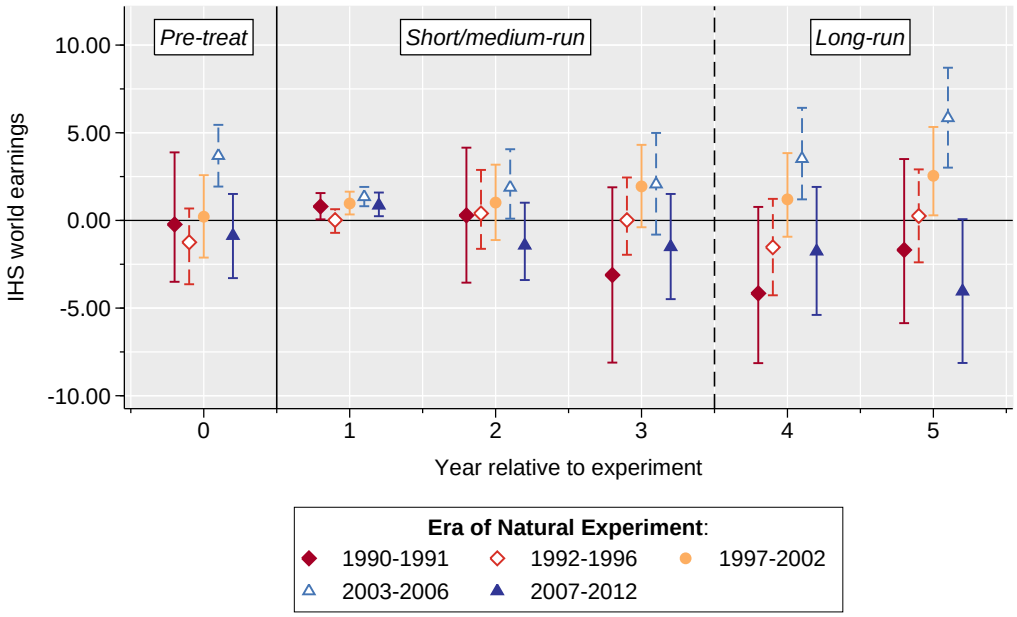
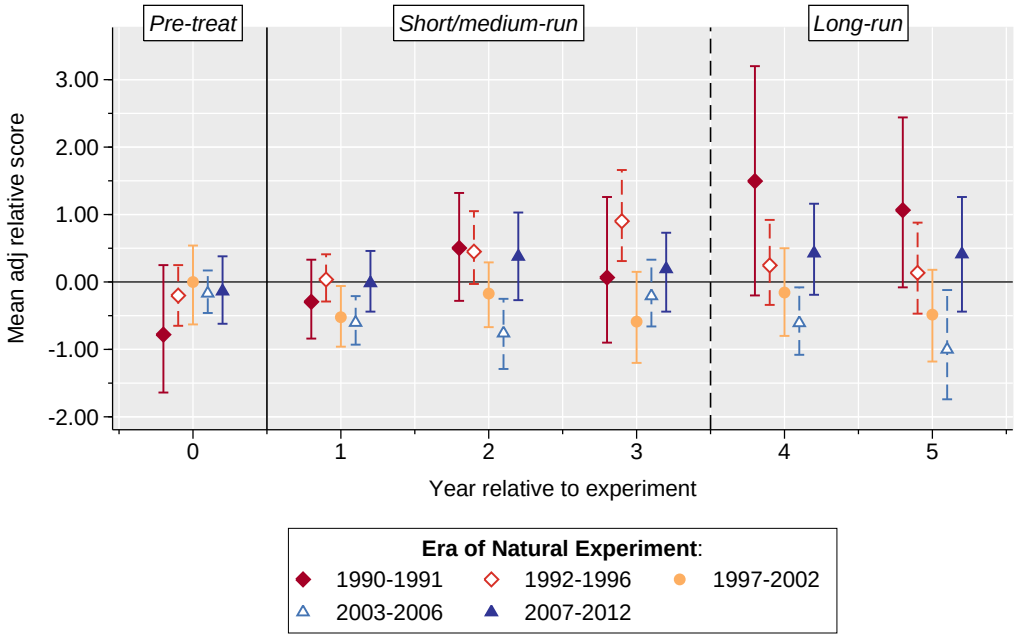


Figure F.8: Q School: Treatment effects over time

(a) Q School: IHS world earnings



(b) Q School: Adjusted scoring average



F.5 Fuzzy Regression Discontinuity Design

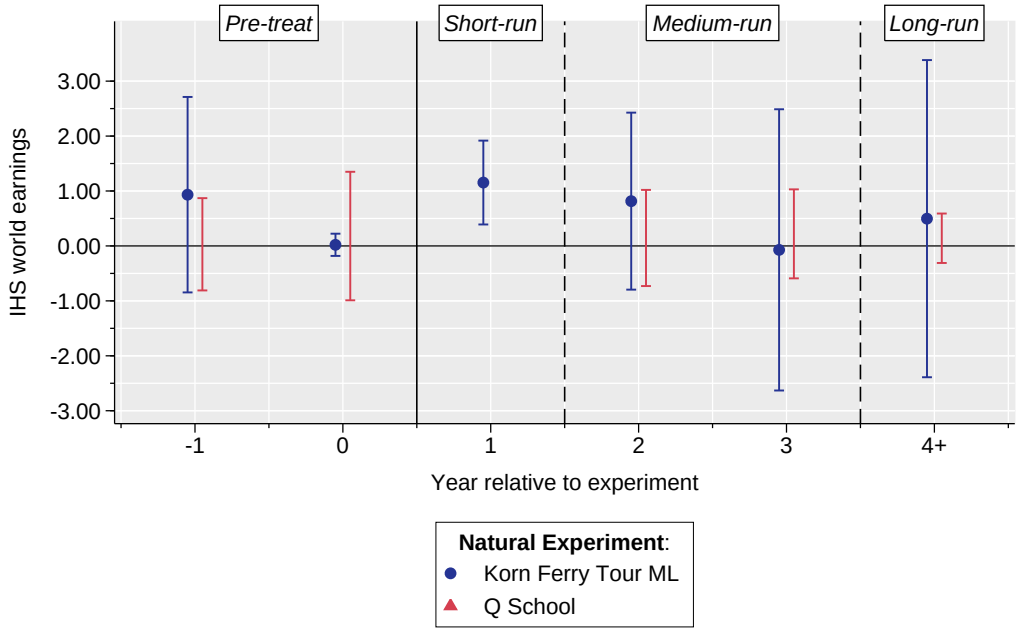
An alternative approach to the sharp regression discontinuity (RD) design is to define treatment as an annual membership on the PGA TOUR and employ a *fuzzy* RD design. This approach involves scaling the estimated coefficients by the differential probability of treatment at the treatment threshold. This design is relevant to the case in which we are interested in identifying the effect of playing an additional year on the PGA TOUR. On the one hand, this design speaks directly to the question of how a year of PGA TOUR membership affects career outcomes. On the other hand, a PGA TOUR membership is not a well defined object. In any given year, each golfer receives slightly different playing privileges. The fuzzy design requires an arbitrary definition of PGA TOUR membership such as, for example, a threshold number of PGA TOUR events played. Furthermore, identification of the treatment effect relies on an exclusion restriction that the experiments only affect future outcomes through membership on the PGA TOUR. The weaknesses of this approach are that the results are sensitive to the definition of a "PGA TOUR membership" and that it is difficult to define a measure that simultaneously takes into account both the quantity and quality of events played. Both quality and quantity of tournaments matter as some top golfers do not play in many events despite enjoying full access, rather they mostly just play in the most prestigious events.

Appendix Figure F.9 presents the results of the fuzzy RD design. Despite my reservations, the results appear very similar to the results from the sharp RD design and support the main qualitative conclusions. Appendix Figure D.31 provides a depiction of the strong first stage, i.e. the effect of the experiments on the probability of playing 20 PGA TOUR events in year 1. Note the the local randomization method are not able to compute point estimates, yet the confidence intervals are still about to provide set identification.[61]

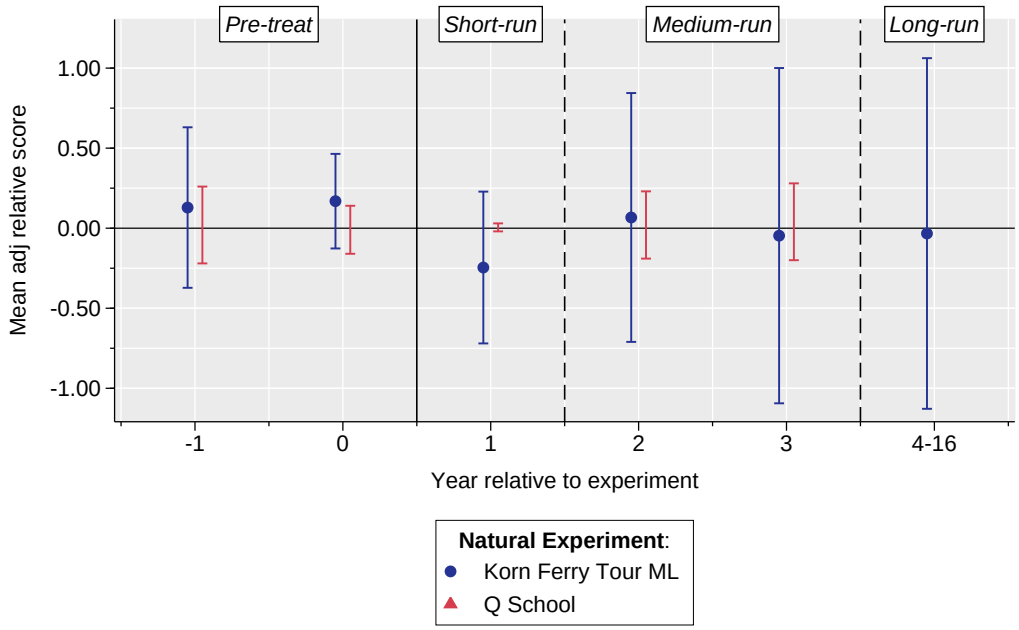
[61] I am unable to compute the fuzzy RD estimation in year 1 for IHS earnings in the Q School experiment as the program produces an error for unknown reasons.

Figure F.9: Treatment effects from fuzzy RD design

(a) IHS world earnings



(b) Adjusted scoring average



F.6 Results Across Age Groups

Appendix Sections D.5 and E.3 presents the estimated treatment effects on IHS earnings and adjusted scoring average separately for a sample of young and old golfers. I split the sample in half according to the median age so that young golfers are defined to between ages 17 and 30 during the year of experiment participation. Old golfers are defined to be between ages 31 and 55 during the year of experiment participation.

Appendix Figure D.35 presents the estimated treatment effects on earnings. The results are similar across age groups. Both groups appear to experience a short-run increase in earnings. The short-run effects lose some statistical significance, but this is likely due to the loss of observations. The long-run treatment effects are more erratic. The results hint that young golfers have a positive long-run treatment effect in the Korn Ferry ML experiment, but not in the Q School treatment. However, none of the treatment effects are significant at the 5% level. In the Q School treatment, the results suggest that older golfer may benefit more from treatment in the long-run. Yet, once again, the results are not statistically significant at the 5% level.

Appendix FigureD.36 presents the estimated treatment effects on adjusted scoring average. All the results fail to reject the null hypothesis of zero treatment effect except for the year 1 treatment effect for older golfers in the Q School treatment. Given the steep growth in performance and earnings for golfers in their 20s, I am particularly interested to see if young golfers improve their performance as a result of treatment. However, I find no evidence for this hypothesis as all coefficients on future performance suggest no improvement in adjusted scoring average.

The coefficient for old golfers is slightly negative and statistically significant. However, there is no evidence that treated golfers continue their improved play into the next season. If golfers learned from their the season in year 1, the most likely place to find a treatment effect would be year 2. Since, I do not find an improvement in performance in year 2 or any other future year, I am reluctant to conclude that older golfers improve their performance due to treatment. Overall, since the estimates do not tell a consistent story, I interpret the suggested long-run effects as more likely to emerge from statistical noise, rather than reflecting true long-run differences in outcomes.