Reference Dependent Preference towards Risk – Evidence from the U.S. Professional Golf Tour

Master Thesis
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Spring 2019
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Abstract

The standing debate regarding how preferences should be defined is still evident in research today. Are they invariant to current endowment as a neoclassical practitioner would proclaim, or reference dependent as a behavioural economist would state? This theoretical discrepancy, regarding how preferences should be defined, when agents are experienced at what they do is found by List (2003) to be non-existing. In recollection of this notation, this thesis investigates how professional agents adopt risk in reference to a point that a neoclassical practitioner would deem irrational. With data on professional golf players on the U.S professional golf tour during 2013-2018, I find evidence that players respond in terms of what risk they adapt to a normatively irrelevant reference point in accordance to what Prospect Theory would predict. Indicating that even experienced agents have reference dependent preference towards risk. To give what the data proclaim a causal interpretation I adopt a quasi-experimental regression kink design. My estimates indicate a causal kink at my artificial threshold but are proven fragile to bandwidth alterations. Even though a causal claim is questionable, a sensitivity analysis finds evidence that my artificial threshold drives the relationship. Supporting the viewpoint that preference towards risk are reference dependent and that experience does not eradicate the difference between what we do and what we should do.
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Introduction

A feature that still divides economists of today is how individual preferences should be defined. A neoclassical economist would argue that preferences are independent in regards to current endowment, especially if individuals are experience at what they do (List, 2003). A behavioural economist, with acknowledgement of Prospect Theory (Kahneman & Tversky 1979), would argue that they are reference dependent. (Angner et al, 2012). The discrepancy between these theoretical approaches is that the neoclassical states how we should behave, while the behavioural how we actually behave. The interest in setting these against each other is found in a paper by List (2003) where market experience is found to erode this described difference, between how be behave and how we should behave. Thereby, this thesis evaluate the question:

*Are preferences towards risk reference dependent even amongst professional golfers on the U.S. Professional Golf Tour?*

The professional golf tour creates a natural setting to investigate this thesis question. Each standard tournament starts with roughly 150 players that play a specific course for four days. The goal for each player is to complete this course with the use of as few hits on a golf ball as possible. The player with the least amount of hits, after the four days, ends up as the winner. One feature of a golf tournament is that after the second day only the players within the top 70 positions (with the least amount of hits) are qualified for the final two days. Hence it is only these that could actually win the tournament and earn any money, the others are so called cut.

Being within this cut already after the first day (as I define as the artificial cut) is arguable salient for a golfer, but normatively inapt. This is because she should, normatively, only care about making the actual two-day cut. Thereby, this artificial cut should not alter a player’s preference towards risk in a neoclassical perspective. Prospect Theory on the other hand, defines individuals to evaluate decisions in terms of gains and losses in relation to some salient reference point. Where my artificial cut constitutes such a potential reference point. Additionally, Prospect Theory predicts that
individuals have a higher preference towards risk when facing a loss. Hence, a player outside my artificial cut should assert more risk than when within it.

To investigate which of these theoretical methodologies’ is more applicable, in terms of preference towards risk amongst experienced agents, I have collected data on player statistics from the professional golf tour during the years 2013 – 2018. A first graphical analysis of my data depicts a kink at the artificial cut in terms of what risk players use the second day of a tournament. Indicating that preferences towards risk are reference dependent and that my artificial cut is a salient reference point. To get a causal measure of the evident kink in the data, I utilize the fact that players just around my artificial cut are as if randomly distributed and employ a regression kink design approach. I estimate that the relative difference in risk across positions is about 37 times larger outside my artificial cut compared to within. A figure that is arguably economically significant.

As players use more risk outside my artificial cut, this indicates what Prospect Theory predicts, that individuals facing a loss have higher preference towards risk. Additionally, as I investigate professional golfers, these results also indicate that even experience agents have reference dependent preferences towards risk.

By investigating the robustness of my estimates I find them fragile to bandwidth alternations, hence any causal claim of my results should be taken with precaution. Nevertheless, my sensitivity analysis gives an implicit indication that the shift in preference towards risk is driven by the artificial cut.

The finding in my thesis adds to a growing literature of real world evidence of behavioural anomalies such as reference dependent preference. By constructing my analysis to capture risk in a direct way, I give according to my knowledge new empirical evidence of features in Prospect Theory.

The following parts of this thesis will be structured as follows. Chapter 2 gives an overview of Prospect Theory and empirical findings of reference dependent preferences. Chapter 3 presents a benchmark neoclassical model of how we should behave. Chapter 4 presents the data, my main findings and relevant robustness checks. Finally, Chapter 5 concludes.
Prospect Theory and Previous Findings

This paper falls in to the field of behavioural economics. A field that builds on incorporating ideas from psychology to economic theory (e.g. see Thaler, 1985, Kahneman, Knetsch & Thaler, 1991, Benartzi, & Thaler, 1995, Fama, 1998, Barberis & Thaler, 2003, DellaVigna, 2009, and Barberis, 2013). In general, I investigate how individual decision-making should be modelled under uncertainty. This corresponds to this field’s idea of theorizing behaviour that is systematically irrational from a neoclassical perspective. One of the most famous examples of such is Kahneman & Tversky’s Prospect Theory (1979).

One feature of this behavioural model is that when individuals make decisions involving uncertainty, they evaluate these in terms of gains and losses in relation to some reference point. With an S-shaped utility function (convex for losses and concave for gains) this model predicts a kink in preference towards risk at a defined reference point. When in the loss domain, individuals’ are portrayed as risk seeking and in the gain domain as risk averse. Hence, preferences towards risk are according to this theoretical approach reference dependent.

A general disclaimer for ideas within behavioural economics in is presented by Levitt & List (2008). They argue that even though individuals are not the canonical Homo economicus, behavioural economics lack real world application. Concluding that this field is in desperate need of empirical proof in a natural occurring setting. Thereby, this thesis has the intent to give such further evidence by looking into if preferences are reference dependent.

Previous evidence of such is found by Cramerer et al (1997). Where New York cabdrivers are found reference dependent in terms of the labour hours the supply. Also, Engström et al (2015) find that Swedish taxpayers are reference dependent and loss averse when claiming deductions from preliminary tax statements. Allen et al (2016) finds that marathon runners’ evaluate their performance in terms of gains and losses. Dellavigna et al (2017) use a reference dependent preference model on unemployed individuals in Hungary. They find that current income work as a reference point in terms of work search.

Similarly to this thesis Pope & Schweitzer (2011) use data from the professional golf tour, but evaluate Prospect Theory’s idea loss aversion. By tracking individual golfers they find a significant increase in probability of making a put if it is for par (the
hole average). They contribute this to the fact that a missed put (if it is for par) would induce a loss, as it indicates an outcome worse than what is expected of them. Differently, this thesis looks at the how the second day cut is used as a reference point already after the first day. And evaluate what risk players choose to adopt in relation to this. Hence I evaluate how risk preferences are effect by a normatively irrelevant reference point. Additionally, by creating a neoclassical model of what this perspective would deem optimal I also get a comparative picture if market experience makes actual behaviour, optimal behaviour.

Before turning to the data that constitute this thesis empirical backbone, I present my simple neoclassical model. This model will serve as a benchmark for what is at least in a neoclassical perspective the optimal response in risk. Then, I simulate this model and construct a neoclassical prediction of what we should do. In forthcoming Chapter 2 (Graph 2) I can conclude that my neoclassical model would not predict any drastic shift or jump in the relationship between risk day two and position day one, at the artificial cut. Hence, if market experience make what we do and what we should do the same, the data should return a similar pattern.

The Neoclassical Prediction

The first step in evaluating the neoclassical approach is to produce what this theoretical branch actually predicts. To do so, I construct a simple model based on the theoretical assumptions of such given theory.

A Stylized Model

Consider a model of a single player the first two days of a tournament. Players are assumed risk averse and utility maximizing. Let’s say that \( x_1 \) and \( x_2 \) are the outcome (read position) of day one and two respectively. Total performance (or position) is simply the sum of the outcome of the days, namely, \( X = x_1 + x_2 \). Utility is assumed increasing in \( X \) and strictly concave, such that:

\[
U'(X) > 0 \\
U''(X) < 0
\]
and assumed to take the following form

\[ U(X) = \ln(X) + \gamma I(X \geq c) \]  

(1)

Where \( \gamma > 0 \) and \( I \) an indicator function (i.e. making the cut, \( c \)). The individual then partly gains utility from better performance (higher \( X \)) and partly from making the cut.

The model describes the behavior during day 2, outcome of day 1 is therefore exogenous (sunk) and given by

\[ x_1 = s + \varepsilon_1 \]

where \( s \) is the deterministic skill level and \( \varepsilon_1 \) is an error term, assumed uniformly distributed between \(-\sigma\) and \( \sigma \). Differently, outcome of day two is depicted as

\[ x_2 = s + \varepsilon_2 \]

The error term day two, \( \varepsilon_2 \) is for simplicity assumed to take only two equally likely values. The value it takes depends on the level of uncertainty (or risk) a player chooses to assert, defined as \( d \). So after the first day, with knowledge of the outcome of day one, the player can choose this \( d \) during day two in accordance with her preferences for risk. This choice variable, \( d \) is chosen to maximize a risk averse individual’s utility. To clarify how a player choose to add risk the second day, see to the following cases that depict a player’s optimal choice of \( d \) during the second day.

First, if

\[ x_1 + s > c \]

a risk averse, rational player sets \( d = 0 \) as this would induce her to make the cut with certainty. The reason for this is because with this decision a player gains utility from both the continuous performance of \( X \) and from the additional utility of making the cut.

Secondly, and the more interesting case, is when
as the player now faces a trade-off. First option is to choose no risk, i.e. set $d = 0$. This entails no cost of adding risk but at the loss of not enjoying the extra utility from making the cut. The alternative to this is to introduce uncertainty to her game by increasing $d$. The level needed, call this level of risk, $d_c$ is what would satisfy

$$x_1 + s + d_c = c$$

for a player to have a chance to make the cut. This expression describes the minimum amount of risk a player needs to potentially make the cut and is by this the optimal level.

Rearranging yields

$$d_c = c - x_1 - s$$

(3) depicts an expression for the minimum, and optimal, risk needed for a player to have a chance of making the cut and gaining the additional utility from the cut, ($\gamma$). Knowing this, the player now has two choices. Set $d = d_c \equiv c - x_1 - s$ to yield a 50/50 chance of making the cut, as the error term day two only takes two values by construction. Or alternatively, choose $d = 0$ which induce full utility gain from the expected outcome $x_1 + s$, but at the same time leave no chance of making the cut.

By this, the player finds it optimal to set $d = d_c \equiv c - x_1 - s$ if and only if

$$\ln(x_1 + s) \leq \frac{1}{2}\ln(x_1 + s - d_c) + \frac{1}{2}[\ln(x_1 + s + d_c) + \gamma]$$

(4)

where the left hand side is the utility from “playing it safe” and choosing $d = 0$ and the right hand side is the utility from taking the risk and making the cut with a 50% probability. This expression captures the realistic assumption that not all players after day 1, as in (2), would find it optimal to set $d = d_c \equiv c - x_1 - s$ as the gain from $\gamma$ does not compensate the cost of introducing risk for all individuals.

To find the lower bound for when a player choose $d = d_c \equiv c - x_1 - s$ I treat (4) as an equality. The reason that I can treat (4) as an equality is because $\varepsilon_2$ can only
take two values and players are assumed risk averse. In other words any higher level of \( d \) only increase the cost of higher risk and any lower, she does not make the cut.

(4) then postulates a condition for when a player has the incentive to introduce risk during the second day. Solving it for the expected value \( E(X) = (x_1 + s) \) returns the lower bound for when it is optimal for \( d = d_c \equiv c - x_1 - s \). With some simple algebra we get that

\[
\ln(x_1 + s) - \frac{1}{2} \ln(2x_1 + 2s - c) - \frac{1}{2} \ln c = \frac{1}{2} \gamma
\]

\[
\frac{e^{(x_1+s)}}{e^{\frac{1}{2} \ln(2x_1 + 2s - c) + \frac{1}{2} \ln c}} = e^{1/2\gamma}
\]

\[
(x_1 + s)^2 = e^{\gamma} c(2x_1 + 2s - c)
\]

For simplicity define the lower bound when a player finds it optimal to introduce risk as

\[
E(X) = x_1 + s \equiv \rho
\]

Then one can then solve the second degree equation

\[
\rho^2 - 2e^{\gamma} c \rho + c^2 e^{\gamma} \equiv 0
\]

which yields the closed form solution

\[
\rho = e^{\gamma} c - ce^{\gamma \sqrt{e^{\gamma} - 1}}
\]

(5)

The model returns an explicit lower bound of the expected value (\( \rho \)). I.e. when it is optimal to assert \( d_c = c - x_1 - s > 0 \), as \( x_1 + s < c \). This lower bound depends
on the value assumed for \( c \) and \( \gamma \) and also dictates which subset of players finds it optimal to play risky by choosing \( d = d_c \equiv c - x_1 - s \) instead of \( d = 0 \).

Graph 1 below tracks alternations of \( \gamma, c \), the value assigned to the cut, is kept constant to keep the following model simulation tractable. The obvious observational fact is that the lower bound for when \( d_c = c - x_1 - s \) is optimal, is decreasing in \( \gamma \). Or in a different perspective, an increase in \( \gamma \) increase the range where \( d_c = c - x_1 - s \) is optimal when \( x_1 + s < c \).

**Graph 1. Lower Bound**

![Lower Bound](image)

The next step is to simulate this model to give a neoclassical prediction of the relationship between past performance and optimal risk.

**Model Simulation**

I now simulate the model to get a neoclassical prediction of how the predetermined outcome day one affects risk day two. To make it comparable with my sample, the simulation is based on 20 000 observations. Each observation (read player) can take any predetermined constant skill level between (30, 70). To account for that the outcome of day one is also dependent of \( \sigma \), I allow \( x_1 \) to deviate from initial skill level by a randomly assigned value between (-20, 20). This procedure allows \( x_1 \) to take any value between (10, 90). Even though skills are heterogeneous, this procedure entails
a random player to have an expected outcome of day one of 50. A feature in making my model predictions comparable with the data, I aggregate the individual risk variable by averaging over first day outcome. This procedure is comparable with averaging over a given position in a given tournament.

Under the assumption that a tournament contains observations in the range of $x_1$ between (40, 60) I get a prediction of the average risk within position. Assuming this range of $x_1$ corresponds to a ten-position deviation from the mean value of the outcome in $x_1$. Yet again, assumed to get the model as comparable with the data as possible.

As previously discussed, the array of players that will find $d = d_c \equiv c - x_1 - s$ optimal will depend on values of $c$ and $\gamma$. Graph 2 below presents the relationship between optimal risk day 2 and outcome day 1 where $\gamma$ is allowed to vary. As the model simulation is constructed to be as comparable as possible with the data, I let $c$ be constant. I.e. $c = 100$, as it creates a situation where an outcome of 50 in the model compares to the artificial cut in the data. Altering $c$ would alter the outcome in the model that corresponds to the artificial cut in the data. Hence, $c$ is assumed to be 100 in all simulations. In Graph 2 the extra utility of making the cut, $\gamma$, is set to 0.04 in blue and 0.1 in orange. The red line at 50 corresponds to what would be the artificial cut.

Altering the value assigned to $\gamma$ clearly affects which players and in extension what risk is optimal to use for each outcome day 1. Additionally, one can see that optimal risk is increasing in $\gamma$. Graph 2 also shows that this neoclassical model does not predict any drastic shift or kink in optimal risk around what is comparable to the artificial cut. To make this theoretical argument more intuitive, recall that even if a random player has the expected value that corresponds to the cut (50), players’ are modelled with heterogeneous skill levels. This rather logical assumption implies that even players with a position (outcome) after day one above the artificial cut could find it optimal to play risky. To clarify this, consider two players that end up at the artificial cut after day one (at 50 in the model). Assume that one have a skill level of 30, and the other a skill level of 70. As a player knows this skill level and also knows that $c = 100$, the relatively high-skilled player would not find it optimal to play risky and choose the safe play and set $d = 0$. On the other hand the relatively low-skilled player does not have enough skill to make the cut as $50 + 30 < 100$. If the utility of setting $d = d_c \equiv c - x_1 - s > d = 0$ he would find it optimal of add risk to his game. This argument holds for all positions that contain players with different skill levels.
In summary, the model give a normative prediction that a player should not take the artificial cut into account when determining what level of risk to use the second day of a tournament. With such predictions I now turn to look at what professional golf players actually do.

**Empirics**

I now have a neoclassical view point of how player choose to assert risk the second day based on what position they have after the first day. To investigate if this prediction is comparable with what players actually do, I turn to my empirical data.

**Data and Descriptive Statistics**

The data that constitutes the empirical and real world application of this thesis has been collected from the United States Professional Golf Tour. This cross-sectional dataset tracks season 2014 until the end of 2018. Due to the scheduling of a golf season, the first tournament starts during the fall previous year. Hence, the first observations begin in October 2013 and the last in September 2018. The dataset contains information regarding who played each tournament, scoring each day, date and month for each tournament, course, course par, country, area, player age and yearly scoring average previous season.
During a season on the PGA-tour some tournaments differ from the example tournament previously depicted. These tournaments differ in the manner of what rule defines which players are cut or if any players are cut at all. “Major tournaments” that occur four times a year and the last four tournaments, playoff tournament, are not under the same cut-rule system. Given this, they are excluded from the working sample. Tournaments that do not have a cut are kept despite their incomparable cut-rule, i.e. non-existing cut-rule. I do so as they facilitate an alternative placebo case approach to identify the behavioural effect the artificial cut has on players risk adoption.

To investigate how the artificial cut affects risk adoption day 2, I utilize the fact that more than one player usually end up with the same amount of hits after day one. Hence, also have the same position. With this I can create a conventional measure for risk, namely a variance for each position after day one. The equation for this variable is structured as

$$\bar{Y}_{its} = \frac{1}{N} \sum_{j=1}^{N} (S_{jits} - \bar{S}_{its})^2$$  \hspace{1cm} (1)$$

Where the outcome is the average variance in hits by position day one, during day 2 by player j at given position i, in tournament t, and season s. The idea is that the variance measure captures differences in what risk is asserted for different players at the same position, and hence comparable to \( d \) (measure for optimal risk in my model). But instead of measuring what risk is optimal, it measure the risk actually used.

The central part of this thesis is to investigate if and how risk during day two is affected by an artificial cut after day one. Thereby, the construction of this artificial cut is based on what position would be the actual cut after the second day. Additionally, which position that entails the artificial cut differ across tournaments, as players with the same amount of hits that share a position is not always the same. To get a single position that entails the artificial cut, I normalize the data so that zero indicates the artificial cut. To clarify, it is this position that contains players with the least amount of hits after day one but still would be cut, ceteris paribus.

To give a first look at the data, Table 1 below portrays some descriptive statistics. The statistics are presented in total and in relationship to my artificial cut after the first day. On average players inside my artificial cut are about half a year younger, 32.96 compared to 33.44. They also have a slightly better scoring average the year
before, 70.81 compared to 70.94. I present statistics on these factors as they are
commonly used as predictors for risk preferences and performance (e.g. Rosenqvist &
Nordström Skans, 2015 and Jianakoplos, & Bernasek, 2006). If these parameters are
presumably comparable, it strengthens the assumption that the measured effect is a
result of the artificial cut, and not due to any other underlying covariate. The
relationship regarding comparability will be further investigated both graphically and
statistically in forthcoming section.

From Table 1 one can also conclude that players outside the artificial cut does
play more varied than those within. This crude negative relationship is also confirmed
in Graph 3 below, where the average variance outside the artificial cut is 9.31 compared
to within at 7.95.

Table 1. Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean (s.d)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>Age</td>
<td>33.23</td>
</tr>
<tr>
<td>Avg. Scoring T-1</td>
<td>70.88</td>
</tr>
<tr>
<td>Variance (Risk Measure)</td>
<td>8.73</td>
</tr>
<tr>
<td>Outcome Day 1</td>
<td>-0.11</td>
</tr>
<tr>
<td>Actual Position</td>
<td>63.96</td>
</tr>
</tbody>
</table>

Comment: Outcome Day 1 represent a normalization of positions for player after the first day of a
tournament where zero corresponds to the artificial cut.

One notational feature that gets evident from Table 1 is the average position
after day one. If the reader directs the attention to the column that describes Outcome
Day 1, the total average outcome is approximately equal to the artificial cut. I.e. the
normalization captures the same range as my neoclassical model. This strengthens the
assumption that my theoretical model gives a comparable view of the sought out
relationship.

Another notational fact is the imperfect data on scoring average and age. The
main reason is due to that data on such variables are not always presented on the PGA-
tour website and hence not fully collectable. In forthcoming sections I evaluate if this is a potential threat to identification and present the relationship in a graphical depiction.

**Graphical Depiction**

Averaging the variance in strokes by outcome day one returns the relationships I sought to investigate. The result from this procedure is presented in Graph 3 below.

**Graph 3. Risk Day 2 by Outcome Day 1**

Comment: Dependent variable: Variances in strokes during day two, by position day one. The data has been normalized around the predicted cut for comparability across tournaments. Each bin represents the average outcome for a given position day one.

Each point in Graph 3 represents the average variance for a given position day 1 in relation to the artificial cut. The red line indicates the artificial cut; hence to the right of this line represent the being within this artificial cut. Going left in the graph indicates a worse position day 1. One can conclude that basically all observations in the dataset are captured within a ten-positions/outcome deviation from the average observation, which approximately corresponds to the artificial cut. Graph 3 also gives a clear indication of a kink in the slope at the artificial cut and hence that this threshold
seem to effect what risk players choose to adopt. This gives support for what Prospect Theory predicts regarding reference dependence in risk preferences.

A clarification is that the data in Graph 3 is presented on the aggregate, while the theoretical predictions is formulated for how individual preferences are formed. So I cannot causally claim that a player’s preference for risk is affected by the artificial cut. To be able to make such a claim, I need to be able to assume that players around the artificial cut are at least as if randomly distributed and hence, comparable. The following section presents the quasi-experimental regression kink design that under reasonable assumption allow for a causal interpretation of the evident kink in the data.

**Identification and Regression Kink Design**

Graph 3 depicts the relationship between the variance amongst players of the same position day one. Hence, it gives no direct prediction of a given individuals response to the artificial cut, due to the aggregation of the data. To make such a transition, from the aggregate to the individual, I now present my empirical strategy.

To get a causal interpretation of the slope shift at the artificial cut I need a reliable way of handling potential endogeneity bias. The optimal case for investigating the causal effect of the artificial cut on risk adoption, would be to randomly assign players a day one position. Then, measure the average risk by position during day two. In absence of the time and monetary resources to perform such an experiment I turn to the next best thing, the quasi-experiment regression kink design.

This quasi-experiment relies on the assumption that entities just around a threshold are as if randomly distributed and hence comparable. In my case I need to assume that players just outside my artificial cut is a valid estimate of the counterfactual outcome of those within. To give further support for the claim that this approach induce estimating a causal effect, I follow direction of Card et al. (2015) & Engström et al. (2015). Thereby, the procedure of claiming the effect as causal boils down to: 1) being able to disregard any cofounding effect of underlying covariates, and 2) estimate a statistically significant kink at the artificial cut. Before presenting tests for claiming these points to be handled, I present the main specification for my estimations.
Empirical Specification

In accordance with arguments from Gelman & Imbens, (2018) I disregard from controlling for higher order global polynomials and estimate the following linear parametric model

\[ E[Y_{its}|X_1 = x_1] = a_0 + \beta_0(x_1 - k) + \beta_1(x_1 - k) \cdot I + X + \omega \]

where \((x_1 - k) \leq h\)

Where \(I\) is an indicator variable equal to \(1(x_1 > k)\), and \(k\) is the kink point at zero or more precisely, the artificial cut. The parameter \(\beta_1\) is what is of interest to my analysis as it measures the change in the derivative at the artificial cut. \(a_0\) is a constant and \(X\) a vector of controls on tournament level added for precision. \(\beta_0\) is an estimate of the underlying relationship and \(h\) is the prevailing bandwidth selection.

Even if players just around the artificial cut is likely to be comparable, \(\omega\) is entity fixed effects that will be specified either on tournament or player level. Fixed effects on either of these levels allow me to disregard from any potential confounding factor either across tournament or players.

Before turning towards the results, I now present an evaluation of point 1.

Comparability and Validity

With any quasi-experiment one needs to rely on a valid counterfactual. In my case I need to assume that players just outside the artificial cut are such a counterfactual for those within. A potential issue with such a claim is if players just outside my threshold are systematically different to those within. I.e. potential differences in terms of any unobserved factor that covariates with preference towards risk. A simple test for this threat of endogeniety is to look at the distribution of player over positions after day one. If there is evidence of any drastic change or bunching in the distribution at any side of my artificial cut, it is likely that players within the artificial cut are not comparable to those outside it. In Graph 4 below, the result of this test is presented. In absence of any drastic change around the threshold this indicates that players around the threshold are presumably comparable.
Graph 4. Density Plot

Comment: The plot depicts the frequency distribution of players over the first day outcome. The red line indicates the artificial cut. Each bin represents a given position.

Even though Graph 4 gives an indication of comparability, there still might be a threat of selection. If player characteristics that also affect preference towards risk differ between players around the artificial cut, there could still be selection bias. To investigate this potential threat I continue by looking at the distribution of underlying covariates. In Graph 5 I plot age and average scoring previous year against outcome day one. The choice of age is based on the common practice of age as a predictor for risk preference (Jianakoplos, & Bernasek, 2006) and the lag of scoring average as it can be seen as a good predictor of the relative quality of the player (Rosenqvist & Nordström Skans, 2015). The use of scoring average might not be an empirically stated factor in terms of players’ preferences for risk. On the other hand, a reasonable assumption is that the quality of a player would affect what risk they assert. A relatively better player would likely feel less induced to play risky if ending up just outside the artificial cut compared to a relatively less good player. Hence, I find it reasonable to look at the distribution of this variable.
Comment: Left graph. Dependent variable: Age. Right graph: One year lagged scoring average by player. The data has been normalized around the predicted cut for comparability across tournaments. Each bin represents the average outcome for a given position day one and the red line the artificial cut.

In Graph 5 I plot the average age and lagged scoring average (my quality measure) by position after day one. The reader finds age on the left hand side and scoring average at the right. As in Graph 3, being to the left of the red line (that marks the artificial cut) indicates being outside the artificial cut and to the right within. Evident is that neither age nor quality shows the tendency to jump or kink at the threshold. Hence any threat of selection around the threshold that could confound my estimations seems absent. This gives further evidence for the reliability of assuming that my specification estimates the causal effect of the artificial cut.

To get a statistical measure of this depicted relationship in Graph 5, I run a version of my main specification with an added dummy variable equal to one for being within the artificial cut. Results from this are presented in Table 2 with age and Table 3 with lagged scoring average. Marked by “Jump at Threshold” is the estimate for the dummy variable indicating being within the artificial cut. The kink represents the slope change at my artificial cut, $\beta_1$ in my main specification. As a robustness check of my estimations I also let the bandwidth vary from as much as $\pm 8$-position deviation to $\pm 2$.

A larger bandwidth allows for more observations and increased precision. At the same time, players become presumably less comparable the further away they are positioned from the artificial cut, hence inducing a loss of identification. Taking this into account and investigating Table 2, one can observe a significant negative kink in age at the threshold, down to bandwidth of $\pm 6$. At this bandwidth there is even a significant positive jump in the distribution at a 10% level. This pattern disappears
when inference is drawn from a lower bandwidth and ostensibly more comparable players. From a bandwidth of +5 down to +2, age neither kinks nor jumps at the artificial cut, strengthening the assumption of comparability at these bandwidths.

Table 2. Smoothness in Covariates - Age

<table>
<thead>
<tr>
<th></th>
<th>(1) Age</th>
<th>(2) Age</th>
<th>(3) Age</th>
<th>(4) Age</th>
<th>(5) Age</th>
<th>(6) Age</th>
<th>(7) Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jump at Threshold</td>
<td>0.253</td>
<td>0.262</td>
<td>0.278</td>
<td>0.198</td>
<td>0.103</td>
<td>-0.0499</td>
<td>-0.00349</td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.159)</td>
<td>(0.163)</td>
<td>(0.181)</td>
<td>(0.210)</td>
<td>(0.253)</td>
<td>(0.353)</td>
</tr>
<tr>
<td>Kink</td>
<td>-0.142**</td>
<td>-0.158**</td>
<td>-0.152**</td>
<td>-0.0757</td>
<td>-0.0502</td>
<td>0.0120</td>
<td>0.0699</td>
</tr>
<tr>
<td></td>
<td>(0.0673)</td>
<td>(0.0701)</td>
<td>(0.0711)</td>
<td>(0.0860)</td>
<td>(0.101)</td>
<td>(0.132)</td>
<td>(0.298)</td>
</tr>
<tr>
<td>Obs.</td>
<td>19,241</td>
<td>18,997</td>
<td>18,544</td>
<td>17,676</td>
<td>16,227</td>
<td>13,750</td>
<td>10,228</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.007</td>
<td>0.007</td>
<td>0.006</td>
<td>0.006</td>
<td>0.005</td>
<td>0.005</td>
<td>0.007</td>
</tr>
<tr>
<td>Tour.Fix</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Comment: Dependent variable is age. Controls and tournaments fixed effect are added in all specifications and robust standard errors clustered on tournament level in parenthesis. Controls are course, region and country. */**/*** significant at the 10/5/1 % level.

Table 3 reproduce the procedure as in Table 2 but with lagged scoring average as the dependent variable (my quality measure). These estimations indicate no significant jump at the threshold, which strengthens the view that players are comparable in terms of quality. Hence making any causal claim of an effect of the artificial cut, on the risk player use, more reliable. A result that argues against this is found in specification (6) at bandwidth +3, where there is a significant negative kink at a 10 % level. This estimate becomes insignificant at a +2 bandwidth but still, to some extent, weakens the assumption that my following estimations captures the causal effect of the artificial cut on the risk players’ adopt. A further evaluation of this threat will be captured in a sensitivity analysis in a forthcoming section.
### Table 3. Smoothness in Covariates - Lagged Scoring Average

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Jump at Threshold</td>
<td>0.00819</td>
<td>0.0103</td>
<td>0.0112</td>
<td>0.00258</td>
<td>-0.00628</td>
<td>0.000965</td>
<td>0.0145</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
<td>(0.0190)</td>
<td>(0.0192)</td>
<td>(0.0199)</td>
<td>(0.0211)</td>
<td>(0.0275)</td>
<td>(0.0344)</td>
</tr>
<tr>
<td>Kink</td>
<td>-0.00566</td>
<td>-0.00353</td>
<td>-0.00545</td>
<td>0.00112</td>
<td>-0.0248*</td>
<td>-0.0181</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00634)</td>
<td>(0.00642)</td>
<td>(0.00695)</td>
<td>(0.00804)</td>
<td>(0.00997)</td>
<td>(0.0134)</td>
<td>(0.0308)</td>
</tr>
<tr>
<td>Obs.</td>
<td>12,898</td>
<td>12,764</td>
<td>12,486</td>
<td>11,954</td>
<td>11,018</td>
<td>9,404</td>
<td>6,999</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.052</td>
<td>0.052</td>
<td>0.050</td>
<td>0.047</td>
<td>0.044</td>
<td>0.041</td>
<td>0.045</td>
</tr>
<tr>
<td>Tour.Fix</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Comment: Dependent variable is age. Controls and tournaments fixed effect are added in all specifications and robust standard errors clustered on tournament level in parenthesis. Controls are course, region and country. */**/*** significant at the 10/5/1 % level.

I can conclude that differences in player quality and age that could potentially confound the comparability between players within and outside the threshold seem negligible. Despite this, one could make the argument that even at the threshold, differences across tournament or players not captured by previous tests makes the estimations biased. I.e. certain tournaments or player characteristics not induced by the artificial cut could drive the relationship in Graph 3. To clear out for any potential unobserved variation across tournaments or players my estimations also include, as stated, fixed effects on either of these levels.

To support point 1) I was in need of reliable evidence for the assumption that the kink that is evident in the data is not due to inherent and systematic differences between players on either side of the threshold. The graphical and statistical analysis indicates, with some exceptions, such a claim. With a presumably valid confirmation of 1), I turn to point 2). First by presenting the results of my specification and then by investigating general robustness checks of my estimates.

### RKD Estimates

Table 4 below presents estimations of running my specification with the measure for risk adoption as the dependent variable. Specification (2) – (4) add tournament fixed effect, controls, and covariates respectively. Lastly, specification (5) is a replica of specification (4) despite that the entity fixed effects are now on a player level. Standard errors are clustered by tournament and an estimate for Outcome Day 1
(overall relationship) represents $\beta_0$ and the Kink $\beta_1$. The estimate of interest here is the Kink that indicates the slope change. The bandwidth used is a $\pm 5$ position deviation.

### Table 4. Main results – Risk adoption

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
</tr>
<tr>
<td>Outcome Day 1</td>
<td>-0.719***</td>
<td>-0.709***</td>
<td>-0.708***</td>
<td>-0.697***</td>
<td>-0.694***</td>
</tr>
<tr>
<td>Kink</td>
<td>0.685***</td>
<td>0.682***</td>
<td>0.681***</td>
<td>0.678***</td>
<td>0.662***</td>
</tr>
<tr>
<td></td>
<td>(0.122)</td>
<td>(0.119)</td>
<td>(0.119)</td>
<td>(0.133)</td>
<td>(0.127)</td>
</tr>
<tr>
<td></td>
<td>(0.184)</td>
<td>(0.182)</td>
<td>(0.182)</td>
<td>(0.199)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Obs.</td>
<td>18,488</td>
<td>18,488</td>
<td>18,488</td>
<td>11,877</td>
<td>11,877</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.045</td>
<td>0.114</td>
<td>0.114</td>
<td>0.110</td>
<td>0.081</td>
</tr>
<tr>
<td>Tour.Fix</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Covariates</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Play.Fix</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Comments: Controls: Course, Country and Region. Standard errors are clustered on tournament level. **/***/*** significant at the 10/5/1% level.

The main conclusion for Table 4 is that the estimate $\beta_1$ is seemingly stable across specifications and always significant at a 1% level. This indicates that the artificial cut has a significant effect on the risk a player adopts during the second day of a tournament. Hence, these estimates give additional support for the artificial cut as a salient reference point. And in extension, that even a professional golf player’s preferences towards risk are reference dependent.

To give this statistical measure of how the artificial cut affects risk an economic intuition, one can compare the relative slopes on either side of the threshold. By adding the estimate for the kink to the estimate for the underlying relationship (Outcome Day 1) one gets an estimate for the slope, within the artificial cut. Then, taking the ratio between the overall relationship (Outcome Day 1) and the slope estimate for the domain within the artificial cut, one gets a relative measure of the difference in the change in risk across positions when outside the artificial cut compared to within. Constructing such an analysis using figures from specification (4) yields an estimate of $\beta_0 = -0.697$ (underlying relationship) and $\beta_1 = 0.678$ (the slope shift at the artificial cut). Adding these equals $-0.019$, which correspond to the change in risk by position within the
artificial cut. The way to interpret this number depends on your perspective. One way to see this is that the change in risk during day two decreases with 0.697 each position closer (from the left) to the artificial cut. The same position change for a player within the artificial cut, but now each position further away from it, indicate a decreases in risk by 0.019 on average. Taking the ratio of these returns a relative measure of how a change in position affects the change in risk adoption on either side of the artificial cut. This ratio equals approximately 36.7, indicating that in relative terms, the change in terms risk across positions outside the threshold compared to within, is about 37 times as large. Or in other words, the average difference in risk across positions outside the artificial cut is in relative terms 37 times as large as the same difference within the artificial cut. Therefore, in my perspective, the effect of the artificial cut estimated in Table 4 is also economically significant.

To give an additional feature of the stability of the estimates in Table 4, Table 5 depicts the same estimation as specification (4) in Table 4 when the bandwidth is allowed to vary. Starting with a +8-position deviation from the artificial cut in specification (1) to a +2 in specification (7). Evident from this procedure is that the results from Table 4 hold down to a bandwidth of +3 although now significant at a 5% level. At the narrowest bandwidth where inference is drawn from players within only two positions from the artificial cut, the estimate is no longer significant. Hence, there seems to be an evident fragility in the estimated effect of the artificial cut.

<table>
<thead>
<tr>
<th>Table 5. Bandwidth Alteration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Outcome</td>
</tr>
<tr>
<td>Day 1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Kink</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Obs.</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
<tr>
<td>Tour.Fix.</td>
</tr>
<tr>
<td>Controls</td>
</tr>
<tr>
<td>Covariates</td>
</tr>
</tbody>
</table>

Comment: Controls: Course, Country and Region. Standard errors are clustered on tournament level. **/***/***significant at the 10/5/1% level.
Evident from Table 5 is that the estimated kink at the artificial cut lost significance with a reduction in bandwidth to a +2 deviation. The procedure of reducing the bandwidth does on one hand increase identification, because now the analysis is based on a presumably more comparable set of players. On the other hand, this comes at a loss of precision. Hence, an effect at this bandwidth demands a lot from my estimations. Evident when comparing specification (1) and (7) is that the sample size reduces by almost a half and the standard errors increase to about twice the size. Indicating a loss in precision.

Together with a non-significant estimate of a kink at the artificial cut at a bandwidth of +2, Table 3 indicated a significant kink in quality amongst players even at a bandwidth of +3. Hence, even if the estimates in Table 4 are in line with Prospect Theory’s prediction, any causal claim of the artificial cut on the level of risk a player asserts can be questioned. In the following sensitivity analysis I give an implicit clarification to the idea that the artificial cut works as a reference point that alters what risk players use.

**Sensitivity Analysis**

The results from Table 4 gives a stable indication of what Prospect Theory would predict. A significant kink in risk adoption at the artificial cut which signals that players use this reference point to decide what risk to assert the second day of a tournament. What was evident from Table 5 was that when reducing the bandwidth to a two-position deviation, the estimate of a kink became insignificant. To strengthen the view that there is no omitted factor that confounds my results, I construct two alternative procedures to look at the effect of my artificial cut on the risk players assert.

The first procedure is reconstructing my normalized running variable and create placebo cuts. The reasoning for this procedure follows from that if the estimate peaks somewhere else in the distribution, there might be some other factor than the artificial cut that contribute to the relationship present in the data. Each placebo kink is constructed at a +3 bandwidth as specification (6) in Table 5. This returns seven placebo kinks on each side of the artificial cut. In Graph 6 below I track the magnitude in these placebo kinks together with the estimate of the kink from specification (6) in Table 5. Each marker in the graph represents the size of the estimate at the
corresponding kink point. Blue markers indicate a non-significant estimate and the red a significant estimate. Estimates that construct Graph 6 are found in Appendix 1.

Two estimates in Graph 6 are significant, at the artificial cut and at placebo kink +1. The overall evolution of the magnitude in the estimate also indicates a peak at the real threshold. One deviation is the placebo kink at +7, where the estimated kink skyrocketed. As the estimate is not significant I disregard from giving this pattern any further analysis. Thereby, the results from this placebo analysis indicates that it is the artificial cut that driver the shift in risk adoption. Hence, this strengthens the viewpoint of the artificial cut as a reference point, dictating a player’s preference towards risk.

**Graph 6. Sensitivity Analysis – Placebo Cuts**

![Graph 6. Sensitivity Analysis – Placebo Cuts](image)

Comment: Placebo kink analysis. Each marker represents an estimate for a placebo kink at corresponding placebo threshold. A blue marker indicates a non-significant estimate and a red a significant.

Secondly, I also utilize what was preciously presented as the “no-cut”-tournaments. The theoretical reasoning why the artificial cut would be a reference point is because players perceive a position outside it as a loss, and as a result have a relatively higher preference towards risk. If no actual cut exists in a tournament, the importance of the artificial cut disappears, as no actual treat of being cut exists. If I then see that there is no significant kink at the artificial cut in this sample, it gives an implicit indication that players use the artificial cut as a reference point. Hence, supporting evidence that players actually do have reference dependent preference towards risk. Results from this analysis are presented in Table 6 below and graphical evidence in
Appendix 2. As in Table 5 I allow the bandwidth to vary over the range +8 to +2 and the estimations are specified similarly.

**Table 6. Sensitivity Analysis – No-cut Tournaments**

<table>
<thead>
<tr>
<th></th>
<th>(1) Variance Day 2</th>
<th>(2) Variance Day 2</th>
<th>(3) Variance Day 2</th>
<th>(4) Variance Day 2</th>
<th>(5) Variance Day 2</th>
<th>(6) Variance Day 2</th>
<th>(7) Variance Day 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome Day 1</td>
<td>-0.0118</td>
<td>-0.0134</td>
<td>-0.0670</td>
<td>-0.240</td>
<td>0.0642</td>
<td>-0.213</td>
<td>-0.218</td>
</tr>
<tr>
<td></td>
<td>(0.209)</td>
<td>(0.229)</td>
<td>(0.246)</td>
<td>(0.370)</td>
<td>(0.525)</td>
<td>(0.957)</td>
<td>(0.976)</td>
</tr>
<tr>
<td>Kink</td>
<td>-0.187</td>
<td>-0.188</td>
<td>-0.121</td>
<td>0.126</td>
<td>-0.589</td>
<td>0.0848</td>
<td>-0.516</td>
</tr>
<tr>
<td></td>
<td>(0.364)</td>
<td>(0.354)</td>
<td>(0.377)</td>
<td>(0.523)</td>
<td>(0.809)</td>
<td>(1.309)</td>
<td>(1.594)</td>
</tr>
<tr>
<td>Obs.</td>
<td>1.210</td>
<td>1.204</td>
<td>1.199</td>
<td>1.167</td>
<td>1.098</td>
<td>955</td>
<td>729</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.109</td>
<td>0.113</td>
<td>0.113</td>
<td>0.119</td>
<td>0.124</td>
<td>0.114</td>
<td>0.175</td>
</tr>
<tr>
<td>Tour.Fix.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Covariates</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>No-Cut</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Comment: Controls: Course, Country and Region. Standard errors are clustered on tournament level. **/**/**** significant at the 10/5/1 % level.

The conclusion from Table 6 is that the data rejects that risk adoption kinks at the artificial cut when no cut exists. Comparing these results with previous estimations gives an additional implicit indication that the artificial cut after day one matters when facing the threat of being cut. This strengthens the view that the artificial cut does alter a player’s preference towards risk.

**Concluding Remarks**

In this thesis I evaluate if there is evidence of reference dependent preference towards risk even amongst experienced agents. This question describes the discrepancy between what the neoclassical and the behavioural approach would predict.

By investigating the response in risk adoption around an artificially constructed cut the data speaks for the behavioural approach, through Kahneman & Tversky’s Prospect Theory (1979). As this behavioural model predicts that an individual evaluate risky decisions in terms of gains and losses and have higher preferences towards risk when facing a comparable loss. With data on professional golfers my results also indicate that even experienced agents do not act as the Homo economicus that the
neoclassical approach would proclaim. Thereby, rejecting findings by List (2003) of market experience inducing no difference between what we do and what we should do.

To get a causal estimate of the evident kink in risk adoption at my artificial cut, I employed a regression kink design. My main specifications indicate that the slope shift at the threshold is of a causal nature. On the other hand, these estimations proved somewhat sensitive to bandwidth alteration and become insignificant when using a sample of the most comparable player’s at +/-2 position deviation. Hence a causal interpretation is questionable.

As my results are somewhat inconclusive in claiming the evident kink as a causal shift in risk preference, I perform a sensitivity analysis. First, by a placebo cut analysis, which indicate a peak in the estimate at my artificial cut. Second, I analyse tournaments that does not have a real cut and find no evidence of a kink at the artificial cut. Both of these tests indicate that the shift in risk the second day of a tournament evident in my main sample, is driven by the artificial cut. Hence, strengthening the viewpoint that the artificial cut is a salient reference point and that a player’s preferences towards risk shift in relation to this point.

In line with Pope & Schweitzer (2011) I find evidence that market experience does not eliminate behavioural anomalies. It is these anomalies of individual behavioural that distinguish actual behaviour from optimal behaviour, at least in a neoclassical perspective. A contribution of my analysis is that contrary to Pope & Schweitzer (2011), I evaluate how a salient reference point affects risk directly. A limitation on the other hand is that my data is aggregated over position. Hence, I need to a greater extent rely on the assumption that players on either side of my threshold are comparable, as I do not directly follow an individual’s response in risk. To this, the theoretical argument of reference dependent preference from Prospect Theory is argumentative in my setting. And instead of confirming this theoretical perspectives prediction, I construct a model of the theoretical counterpart and reject it. With this in mind I leave it to future research to support the conclusion that experienced agents act in accordance to a model based on preferences in terms of risk being reference dependent.

This thesis adds to existing literature that claims preferences being reference dependent even amongst experienced agents. In a general sense I would consider it interesting for further research to give this question a gender perspective, as preference and perception of risk are commonly seen to differ amongst the sexes.
Reference List


Appendix 1

**Placebo Kinks: Positive**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
<td>Variance day 2</td>
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<tr>
<td>Placebo +1</td>
<td>-0.325**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Placebo Kink +1</td>
<td>0.363*</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.217)</td>
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<td></td>
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Observations: 8,766 7,436 5,762 3,915 2,307 1,204 516
R-squared: 0.122 0.105 0.107 0.120 0.153 0.184 0.443
Bandwidth: [+3]  [+3]  [+3]  [+3]  [+3]  [+3]  [+3]
Tour.Fix: Yes Yes Yes Yes Yes Yes Yes
Controls: Yes Yes Yes Yes Yes Yes Yes
Covariates: Yes Yes Yes Yes Yes Yes Yes

Comment: Controls: Course, Country and Region. Standard errors are clustered on tournament level.
***/*** significant at the 10/5/1 % level.
## Placebo Kinks: Negative

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<th>Placebo Kink -3</th>
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<tr>
<td>Placebo -1</td>
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<td>0.536 (0.382)</td>
<td>-0.763* (0.383)</td>
<td>0.277 (0.445)</td>
<td>-0.136 (0.346)</td>
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<td>0.563 (0.665)</td>
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<td>-0.0240 (1.596)</td>
<td>0.0602 (2.332)</td>
<td>0.136 (2.418)</td>
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</table>

Observations: 9,174 8,142 6,597 4,963 3,375 2,121 1,213
R-squared: 0.135 0.133 0.120 0.115 0.106 0.145 0.188
Bandwidth: [+3] [+3] [+3] [+3] [+3] [+3] [+3]
Tour.Fix: Yes Yes Yes Yes Yes Yes Yes
Controls: Yes Yes Yes Yes Yes Yes Yes
Covariates: Yes Yes Yes Yes Yes Yes Yes

Comment: Controls: Course, Country and Region. Standard errors are clustered on tournament level.

*/**/*** significant at the 10/5/1 % level.
Appendix 2

Risk Day 2 by Position Day 1 – No-cut Sample

Comment: Dependent variable: Variances in strokes during day two, by position day one. The data has been normalized around the predicted cut for comparability across tournaments. Each bin represents the average outcome for a given position day one.