Winner effect in dynamic contests

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February 11, 2014

Abstract

We investigate the existence of a “winner effect” in dynamic contests as predicted by several contest models. Using a large data set of point by point ball tracking data from tennis matches over the period 2005-2008, we exploit the randomised variation in point results that occurs when balls bounce very close from the court’s line to estimate the causal effect of winning a point of the chance to win the next point. We find evidence of a substantial winner effect. Players have 5.58 percents more chances to win the next point after winning a point than after losing it. This effect goes up to 12 percents point at the most decisive points of the game.

1 Introduction

Tournaments are pervasive in society and economic organisations such as in promotion tournaments (Rosen 1986, O’Flaherty and Siow 1995, Dubey and Haimanko 2003, Gershkov and Perry 2009), patent races (Harris and Vickers 1985, Harris and Vickers 1987) and political races Klumpp and Polborn (2006). The study of tournaments in economics has made very important progresses since the seminal paper of Lazear and Rosen (1981) showing that tournaments are good incentive schemes to optimise the effort level of agents.

In particular, the empirical research on how agents do behave in strategic contests has flourished. Many study have used real contests, in particular sporting contests (Ferrall and Smith 1999, Taylor and Trogdon 2002, Walker and Wooders 2001, Chiappori, Levitt, and Groseclose 2002, Palacios-Huerta 2003, Hsu, Huang, and Tang 2007, Romer 2006, Bhaskar 2009, Malueg and Yates 2010). In addition, there is a fast growing literature using laboratory experiments to investigate agents’ behaviour in contests (for a survey, see: Dechenaux, Kovenock, and Sheremeta 2012). As part of this literature, recent experiments
recruited professional sport players to test economic predictions about strategic behaviour (Palacios-Huerta and Volij 2008, Wooders 2010, Levitt, List, and Reiley 2010). Beyond improving our understanding about how individuals behave in contests, these studies provide evidence on whether individuals react optimally to incentives and are able to approximate the optimal strategies. The complexity of contests with the strategic uncertainty which characterise them provide an interesting setting to study how close can agents’ behaviour and strategies be from optimal strategies derived from game theoretic models.

Dynamic contests, that is contests where agents make decisions based on past actions from them and/or other agents, are, in this light, particularly interesting. Most real life contests take place over time and the introduction of a time dimension makes optimal strategies often more computationally demanding (eg dynamic programming solutions). Understanding how the agents react to strategic variables in dynamic contests is therefore relevance to understand how contests and tournaments work in practice as incentive schemes.

While contests differs, several models have suggested that if agents react appropriately to incentives during a dynamic contest, a “strategic momentum” should appear. The perfect equilibria of races modelled by Harris and Vickers (1985) and Harris and Vickers (1987) lead to the leader of the race making greater effort than the follower. It is also a result found by Ferrall and Smith Jr (1999), Konrad and Kovenock (2008) and Malueg and Yates (2010) in the case of best-of-n contests and by Breitmoser, Tan, and Zizzo (2010) in the context of R&D races. On the other hand it has also been suggested that contestants follow a “hare-tortoise” heuristic where the “trailing contestant will exert more effort to catch up, whereas the leading contestant will slack off” (Tong and Leung 2002).

Outside economics, the notion of “psychological momentum” has been proposed as reflecting that winning may help enhance contestants’ confidence with the consequence that “success breeds success” (Dorsey-Palmateer and Smith 2004, Vallerand, Colavecchio, and Pelletier 1988).

The empirical evidence on such effects is mixed. A large body of literature in social psychology initiated by Gilovich, Vallone, and Tversky (1985) studied whether momentum in competition were real phenomena or just an illusion, with mixed empirical results with a tendency to lean towards an absence of any momentum Bar-Eli, Avugos, and Raab (2006). In economics, Ferrall and Smith Jr (1999) did not found any momentum in US sport championship series. On the contrary, Malueg and Yates (2010) and Page and Coates (2013) find support for the existence of a winner effect between sets of a tennis match and Klaassen and Magnus (2001) show that the iid hypothesis should be marginally rejected in tennis, with the possibility of a winner effect in some cases between points. In a laboratory experiment, Tong and Leung (2002) found results supporting a negative momentum effect such that trailing contestants expand more effort to catch up with leading contestants. This result is compatible with the study by Simon (1971) supporting a “back to the wall” effect. On the contrary, Mago, Sheremeta, and Yates (2012) found experimental evidence consistent with the existence of a strategic momentum.

The present paper contributes to this literature. It addresses the inherent
difficulties in estimating the existence of a winner effect in contest by using very large dataset on precise ball location during tennis matches of male players. This allows us to select a very small subset of points providing a quasi-experimental setting to study the causal effect of winning on future performance. Specifically, looking at the ball position when bouncing on the court, we use the court lines as the sources of discontinuity in the probability to win the present point. This discontinuity in probability can be used to estimate, via a fuzzy regression discontinuity design, the causal effect of winning a point on the probability to win the next point. Doing so, we find a significant winner effect: players are 5 to 10 percentage point more likely to win the next point after winning the present point. We also find evidence suggesting that the winner effect is stronger when contestants are close in terms of performance (as predicted by several models of dynamic contests). Looking at a smaller dataset for females we do not find evidence of a winner effect, which could point out to the existence of gender differences in strategic behaviour in dynamic contests.

The reminder of the paper is as follows: Section 2 presents and justifies our identification strategy, Section 3 describes the data, Section 4 presents the results, Section 5 presents the evidence justifying the identification hypothesis and section 6 discusses the results and concludes.

2 Identifying the effect of past performance on future performance

A fundamental difficulty in the identification of a momentum is that a given state in a dynamic contest is reached as a consequence of the opposition of contestants whose characteristics are never fully observed. Any unobserved difference in ability will not only influence future performance. It will also have influenced past performance and therefore lead to different positions in the contest. There is a fundamental endogeneity problem when trying to regress performance on relative positions in contest in order to estimate a momentum effects. Typically, the observation that a contestant leading in a competition has a higher level of performance than a trailing contestant does not prove the existence of a momentum as leading contestants are most likely to have a higher level of ability.

Importantly, this endogeneity problem exists durin a dynamic contest as the ability/fitness of the contestants can change over time. If a contestant ability was constant during a given contest, fixed effect estimators could be used to estimate the effect of different states in a contest controlling for the unobserved characteristics of the contestants. However, it is most likely that this hypothesis is unrealistic. In the example of a tennis match, a player may get worse if he gets a minor injury (strain, blisters) or get tired from the physical effort (muscle soreness, cramping), he/she may get better if he/she learns how to use the weaknesses of his opponent. Assuming wrongly the constance of the contestants’ ability will bias the estimated effect of previous performance
on current performance. For example, if a contestant ability is affected by random shocks over time and follows a moving average, unobserved ability will be characterised by positive serial auto-correlation over time and will create an illusion of “momentum”.

Following the seminal paper on the hot hand by Gilovich, Vallone, and Tversky (1985) many studies attempted to assess whether sequences of success and failures exhibits more streaks than what should be expected from a binomial model (Bar-Eli, Avugos, and Raab 2006). Such an approach does not allow to disentangle between a momentum effect and a positive autocorrelation in the individual variation in ability during a contest. More recent studies have used more compelling statistical approaches. Klaassen and Magnus (2001) used a dynamic binary panel model to assess if points in tennis are iid and found a small momentum effect where a player is slightly more likely to won a point just after winning a point. Ferrall and Smith (1999) have used a structural econometric model to assess the reality of the existence of a momentum in best-of-7 US championship series and did not find any evidence of strategic momentum. In two studies using tennis results, Malueg and Yates (2010) and Page and Coates (2013) found results supporting the existence of a momentum effect such that player winning the first set in a tennis match by a close margin have higher chances to win the second set. The first study used matches where the first set ended with less than two game differences and where the contestant had similar chances to win the match ex-ante (measured by betting odds), the second study used first set ending up in long tie breaks to compare winners and losers after a very close performance in the first set.

We propose here a new identification strategy which solves the identification problem in the estimation of momentum effect. To identify the effect of previous performance on current performance, one would ideally like to have an experimental setting where contestants are randomly allocated to different levels of previous performance. Such a situation is naturally impossible to find. However we can look for quasi-experimental situations. In sport matches, scorelines evolves differently around some threshold of performance. We use this to look at situation where contestants with very similar performance end up in different relative position to each other (ahead vs behind). This identification strategy is pushing further the approach adopted by Malueg and Yates (2010) and Page and Coates (2013) and makes it possible, via a regression discontinuity design to provide a clean identification of momentum effects in a contest with professional players.

Looking at tennis matches data, we use the fact that the probability of a player to win a point varies discontinuously as a function of the location of the ball on the court. When the ball is in, the player who hits the ball has a positive probability of winning the point. When the ball is out, the rules state that the player loses the point. Under the identification assumption that, for balls hit close enough to the line, there is no differences in average ability between players putting the ball slightly in and those putting the ball slightly out, the in/out position of the ball provides an exogenous variation of the probability to win the current point. We can use this exogenous variation to estimate the causal
effect of winning the current point on winning the next point, using a regression discontinuity design (Imbens and Lemieux 2008).

Tennis matches also provide another advantage relative to other sports as they only oppose individuals. For this reason, Ferrall and Smith Jr (1999) stressed that they are likely to offer better leverage to study winner effects emerging from strategic behaviour. In practice, tennis matches are divided in “games”, which are very similar to best-of-4 contests with the difference that to win the players needs at least two more points than his/her opponent. Such contests have formally been investigated by Walker, Wooders, and Amir (2011). Our identification strategy allows us to precisely test whether a winner effect exist in such contests.

3 Data

Our dataset corresponds to the official Hawk Eye data, for almost all the matches played at the international professional level between 2005 and 2008, where this technology was used. Hawk-Eye is a computer system used in tennis and other sports to record the trajectory of the ball. Most of the matches are either from Grand slam and ATP (Association of Tennis Players) tournament or lower level ITF (International Tennis Federation) tournaments: Challengers, Futures and Satellite. In addition, some matches are from diverse cups like the Davis Cup or the Olympic games and some exhibition tournaments. Overall the dataset contains 3,561 different matches played in single.

For each point we know the position of every bounces record by the Hawk-Eye, as well as the player serving, the current score, and the winner of the point. The Hawk-Eye estimates very precisely the location of ball bounces with a mean prediction error of 0.36cm. For a subsample of the matches the ATP ranking of the players as well as the odds given by the bookmaker prior to the match are available. In total, we are considering the location of balls on 1,640,058 bounces in all these matches.

Table 3 presents a description of the type of tournaments where the matches included in the dataset come from. Matches from both gender and from a wide range of competition are included in the dataset. As Hawk-Eye system is usually restricted to the main tournaments, the dataset contains a large proportion of matches from top tournaments (ie Grand Slams). Within tournaments, matches are more likely to feature top players as the system is used on the main courts and is often absent from minor courts. These aspects implies that the matches contained in the dataset are more likely to feature the best male and female

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1Some points where dropped due to discrepancies in the part of the scoreline which is entered by hand. We did not include game points in order to ensure that the server and receiver do not change at the next point. We also did not include points from tie-breaks, where the scoring rule differs. We otherwise include all points, including points where players “challenged” the ruling of the line judge about the position of the ball. In such cases, the challenge of the player may lead to the point being replayed. As the challenge is motivated by the visual perception from the player about the location of the ball’s bounce mark, excluding them could lead to a selection bias around the court lines.
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<tr>
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<tr>
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<th>ATP (Premier)</th>
<th>International</th>
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<th>Hopman Cup</th>
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<td>66</td>
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<td>36</td>
<td>66</td>
<td>30</td>
</tr>
</tbody>
</table>

| Total  | 1169               | 1994       | 3163     |

Table 1: Break down of the matches included in the dataset

players over that period. Any strategic effect to be found is therefore unlikely to be due to a lack of experience of the players.

For each bounce, the dataset records the location of a bounce mark which is an oval shape made of 51 different points. We use this bounce mark to to compute the exact distance between the ball impact and the court’s lines. We then use this distance as a running variable in regression discontinuity as the probability to win the point changes markedly around the line: in the tennis rules the players hitting the ball has a positive probability to win the point if the ball is just in but has null probability to win the point if the ball is just out.

4 Analysis and results

4.1 The estimate of a winner effect

Let \( d \) be the “distance” to the line with \( d \) being positive if the ball is inside the court and negative if the ball lands outside the court. Around \( d = 0 \), tennis rules imply a jump in winning probability for the player who hit the ball. This jump can be used to estimate the effect of winning the present point on the probability to win the next point. Let \( y_1 \in \{0, 1\} \) be a binary variable indicating whether the player wins the current point or not, and \( y_2 \in \{0, 1\} \) the variable indicating whether the player wins the following point. The causal effect of winning one point on the probability to win the next point is given by the Wald estimator:

\[
\tau_{FRD} = \frac{\lim_{d \downarrow 0} E(\Delta y_2|d) - \lim_{d \uparrow 0} E(\Delta y_2|d)}{\lim_{d \downarrow 0} E(\Delta y_1|d) - \lim_{d \uparrow 0} E(\Delta y_1|d)} = \tau_{SRD,y_2} \tau_{SRD,y_1}
\] (4.1)

6
As the effect of the ball being in and out is not fully deterministic, but instead produces a change in the probability to win the point, the fuzzy regression design estimator rescales the exogenous variation in the probability to win the next point to provide the full causal effect of winning one point.

Figure 4.1 shows the probability of winning the current point depending on how far the ball hits the court’s line. When the ball is inside the court, the probability of winning the point is positive, while when the ball is outside the court the probability is close to zero. Note that the probability of winning the point is not zero when the ball is just out of the court. This is due to the fact that when the ball is just out of the court but close to the line, line judges may make mistakes and rule “in” some balls which were actually out. Symmetrically, some balls which are just in are sometimes ruled “out” by line judges and this leads to a drop in probability to win the point when the ball is very close from the line. For balls right on the line there is a high probability of mistakes either way.

As a consequence, Figure 4.1 does not show a marked discontinuity in zero. Umpires’ mistakes may have two detrimental effects. First it blunts the discontinuity in zero which weakens the power of the fuzzy regression discontinuity estimation. Second, the sharp reduction in the probability to win the current point around the threshold may lead to a tendency for the point estimate of $\tau_{FRD}$ to inflate as the denominator in the ratio (4.1) tends towards zero.

To address this issue we implement a donut regression design whereby the observations in a small neighborhood of the threshold are excluded (Almond, Doyle, Kowalski, and Williams 2010, Barreca, Guldi, Lindo, and Waddell 2011, Lindo, Siminski, and Yerokhin 2013). This allows us to keep observations very close to the line.

Figure 4.1: Probability of winning a point depending on the distance from which the ball hits the court’s line. (in meters)

3 Note that when the ball gets close to the line overall the probability to win the point tend to increase, this is due to the fact that the ball is harder to play back when it is further away in the court. However, for balls very close to the line there is a drop induced by line umpires’ mistakes.
close to the line while not including the balls right on the line where there are too many umpires mistakes for the ball position to create differences in probabilities of winning the current point. We also look at the raw effect of the difference in probability to win the present point on the next point: $\tau_{SRD,wp}$. This estimator does not reflects the effect of a winning a whole point, but it is not affected by the shrinkage in the denominator’s ratio in (4.1) close to the threshold. We then compute a fuzzy regression discontinuity estimator $\tau_{FRD}$ using a local Wald estimator (Hahn, Todd, and Van der Klaauw 2001), with the different limits estimated by kernel regressions with unifrom kernels. This specification presents the interest to mitigate the importance of the points closest to the threshold and to avoid a too great shrinkage in the estimation of the jump in probability. It therefore gives a conservative estimate of the effect.

To ensure the validity of our identification assumption, we focus on the points where balls fell very close from the line. Our preferred definition of “very close” which we use in the text to comments results is a window of 5cm or less from the courts line. To give an order of comparison, tennis balls are designed with a diameter of approximately 6.7 cm. When they hit the court at high speed they make an oval shaped bounce mark. The biggest distances between antipodal points on such oval bounce mark is on average 9 cm in our dataset. As a comparison, the court’s lines are 5 cm wide. A distance of 5 cm is therefore roughly equal to half of the size of the mark made by the bounce of the ball on the court and it is similar to the width a the court line. Given that RD estimates are often sensitive to bandwidth choice we follow the recommendation from Imbens and Kalyanaraman (2012) to present results with different bandwidth. We present our results in graphical form presenting point estimates and confidence interval for a wide range of windows for the distance to the line: from 2cm to 10cm.

4.2 Overall effect of winning a point on the probability of the winning next one

We present the results below for a donut size of 5mm (results for donut sizes of 0cm and 1cm are included in Appendix). For each estimation we represent graphically the point estimates and 95% confidence intervals. We indicate with a points the estimates for a 5cm window which is our preferred estimate as

Such estimators have the drawback to have a boundary bias in short distance. In our case, the conditional expectation to win the next point is flat around the threshold which eliminates risks of such bias.

Note that our choice of a privileged 5cm window to discuss our results differs from the bandwidth proposed by Imbens and Kalyanaraman (2012) as a “reference point for assessing sensitivity to bandwidth choice in RD setting”, given its optimality properties. In our case, Imbens and Kalyanaraman (2012)’s suggestions give different bandwidths over different sub-samples. We chose here to focus on a unique bandwidth to comment estimates across different samples. We chose a very small bandwidth to ensure that the identification assumption is valid. In order to assess the sensitivity of our the RD estimator to the bandwidth choice, we present our results for a wide range of bandwidths. For completeness, we give in Appendix the results for the Imbens and Kalyanaraman (2012) bandwidth over each sample.
indicated in 4.1.

Figure 4.2: Effect of winning a point on the probability of winning the next one for different bandwidths using a OLS (right) and a Wald estimator (left).

The estimates of $\tau_{SRD,y2}$ suggests that putting a ball just in rather than just out has a positive effect on the probability to win the next point. The difference is significant at 5% for a wide range of bandwidths. It is equal to 2.72% (p=0.01) for a 5cm bandwidth. The existence of a significant difference is important here as it indicates that there is a relation between an exogenous variation in the probability to win a point and the chance to win the next point as predicted by the winner effect. The fuzzy regression discontinuity estimator (4.1) rescales this difference to estimate the full effect of winning one point on the chances of winning the next point. Using the local Wald estimator, results follow closely the pattern of $\tau_{SRD,y2}$. This effect is estimated to be between 3 and 7 percentage points. It is equal to 5.59 percentage points (p=0.015) for balls landing within 5cm from the court lines.

4.3 By scoreline

Table: 2, shows the effect of winning a point on the next one depending on the scoreline. Interestingly, the momentum effect changes with the score. The effect is much stronger when the scoreline is symmetrical, that is 0-0, 15-15, 30-30. Hence, the players experience a stronger effect when they win a point which put them in the lead, besides the effect gets stronger the closer the players are getting to the victory. More specifically, the effect is bigger when the players are two points from the victory (i.e a score of 30-30 or 40-40) than when they are three points (i.e 15-15) or four points (i.e 0-0) from the end of the game. Overall, when looking at all the situations where the players are on par on the scoreline, the winner effect is 8.5% (bandwidth=5cm, p=0.012).
### Table 2: Wald estimator in percents of the effect of winning a point on the probability of winning the next one depending on the scoreline. (with a bandwidth of 5 cm and a donut of 1 cm).

<table>
<thead>
<tr>
<th>Scoreline</th>
<th>Player 1</th>
<th>Player 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>−8.9 × 10^−3</td>
<td>3.38</td>
</tr>
<tr>
<td>15</td>
<td>6.0</td>
<td>10.27</td>
</tr>
<tr>
<td>0</td>
<td>4.74</td>
<td></td>
</tr>
</tbody>
</table>

1 The scores 30-30 and 40-40 are merged, since for both of them the players are two points from the end of the game.

### 4.4 By gender

Another interesting question is whether there are gender differences in winner effect. While most of our dataset is on male players we have data on 1169 female matches (290,793 bounces). Using this data we estimate the winner effect for females. Figure: 4.3 shows the corresponding results. There is no effect for which the effect is significant for females. The reduction in sample size should prompt us to be cautious when discussing this result. The lack of significance could be due to the lower statistical power. However, our result could also suggest a gender difference in reaction to incentives in a dynamic contests. This possibility would be worth investigating further in the light of the evidence about gender differences in the behaviour in competitive environments (Paserman 2007, Niederle and Vesterlund 2007).

![Figure 4.3: Effect of winning a point on the probability of winning the next one for different bandwidths for female players, using a OLS (right) a Wald estimator (left).](image)

Figure 4.3: Effect of winning a point on the probability of winning the next one for different bandwidths for female players, using a OLS (right) a Wald estimator (left).
4.5 Effect of winning a game

Our dataset gives us the possibility to investigate whether a winner effect exists at different level during the match. A tennis match is composed of sets which are composed of games each of them being composed of points. Using our data we can study whether there is a winner effect for these units of success as well. The previous analysis used the randomised variation in probability to win a point for balls landing very close to the line to study winner effects between points, within a game. We excluded game point (ie points whose outcome may lead to a player winning the game) as the player winning such a point also wins the game. However if instead we focus on game points, we can use the fact that balls landing close to the line provide here a randomised variation in probability to win the game. We can then extend our methodology to estimate the effect of winning a game on the chances to win the next game. This extension faces two difficulties, first focusing only on game points reduces very substantially our sample (N=162,843), second the jump in probability to win the game for balls close to the line on game point is not as high as the jump in probability to win the point itself (a player can lose the point and then win the game and vice versa). Both factors imply a loss in statistical power. In line with the results on the point data, we find results consistent with the existence of an effect for males, though most of the estimates are only significant at 10% with only few being significant at 5% for some bandwidths. Figure 4.4 presents these results. For all the balls landing within 5cm of the line, the estimated effect of putting the ball in rather than out is 4.26% (p=0.11). The full effect of winning a game on the chances to win the next game estimated with the local Wald estimator is 21.45% (p=0.134).

Figure 4.4: Effect of winning a game on the probability of winning the next one for male players (top) and female player (bottom).
5 Validity of the identification assumption

A possible confounding explanation would be the existence of a discontinuity in the quality of the players for bounces around the court lines with players putting the ball slightly in having higher ability than players putting the ball slightly out. A standard test of a possible discontinuity in unobserved variables around the threshold in a RD estimation is the presence of a discontinuity in the density of the running variable (Imbens and Lemieux 2008). A discontinuity in the density of the balls’ distance to the court lines would naturally arise if good players were able to precisely aim on the right side of the court lines. We use the test proposed by McCrary (2008) to control for such a possibility. This test consists in running a local linear regression in the values of a thinly binned histogram on each side of the threshold and to estimate the discontinuity at the threshold. Figure: 5.1 shows an absence of manipulation of the running variable. In this figure the bandwidth is set to 5 cm and the binwidth is chosen optimally by the algorithm \((b = 1.7 \times 10^{-3})\) the point estimate is 0.05 \((p = 0.31)\). This results is robust to different choices of bandwidths and binwidths, computations for other bandwidths and binwidths can be found in the Appendix. In practice it means that it does not look as if good players are able to put their ball significantly more in than out when they hit a ball close to the line. This therefore support our identification that when the ball is close to the line, there is no noticeable correlation between its position in or out and players characteristics. The balls’ positions provide in then an exogenous variation in the probability to win the point.

![Figure 5.1: McCrary test](image)

In addition to this first test, Imbens and Lemieux (2008) also recommends to test for discontinuity in other covariates which could have an influence on the result. We collected information on the relative ability of the players in the form of their ATP rankings and of their ex-ante winning odds for the match. Using these variables, it is possible to test if players putting the ball in very close to the line tend to have on average higher ranking and better betting odds.
than those putting the ball out.

Following Klaassen and Magnus (2001) we do not use directly the ATP ranking, because the quality difference between two top ranked player \((e.g.\) ranked 1 and 2) is greater than between two lower ranked player \((e.g.\) ranked 100 and 101). Hence, we use a smoother measure of ranking proposed by Klaassen and Magnus (2001) by transforming the ATP ranking of each player into a variable \(R\) as follows:

\[
R = 8 - \log_2(RANK_{ATP})
\]

The betting odds, give the equivalent winning probabilities \(p\) estimated ex-ante by the betting market. Numerous studies have confirmed that they are very good predictors of the winning probability.

The discontinuity in ability at \(d = 0\) can be estimated and Figure: 5.2 shows the absence of discontinuity for the variables \(R\) about the ranking of the players and for the winning probability \(p\). For each of these figures the bandwidth is 5 cm, the point estimate for the difference in ranking is \(-4.97\% \ (p = 0.563)\) and for the ex-ante probabilities the point estimates is \(-0.91\% \ (p = 0.423)\). This absence of discontinuity in the ability of players for ball landing close to the line between one that put the ball in and one that put the ball out supports the identification hypothesis.

\[
\text{Figure 5.2: No discontinuity in abilities}
\]

We provide further tests supporting the identification hypothesis in Appendix. In particular we run “placebo tests” showing that players putting the ball slightly in are no more likely to win the previous point than players putting the ball slightly out.

6 Discussion

Using a dataset tracking with great precision the play of professional tennis players we are able to isolate specific situations where the success of a player at some point in the contest can be considered as good as random. In such a
quasi-experimental setting we find evidence of a winner effect as predicted by several models of dynamic contests. Within a game, the player who just won a point is more likely to win the next one as a consequence.

Given the ubiquity of contests in economic organisations, much further investigation into this phenomenon would be needed in order to fully understand how exactly contestants’ performance is influenced by the state and the history of the contest. The factors influencing this effect would also be worth studying. Are these strategic considerations less important when teams are involved rather than single individuals? Our results also suggest that the winner effect may differ between gender with it being only significant for males. Given the evidence of gender differences in behaviour in competitive environments (Paserman 2007, Niederle and Vesterlund 2007) it would also be a possible difference worth investigating further.

References


Lindo, J., P. Siminski, and O. Yerokhin (2013): “Breaking the link between legal access to alcohol and motor vehicle accidents: evidence from New South Wales.”


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