The momentum effect in competitions: field evidence from tennis matches
Working paper

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Abstract

It is often suggested that there is a psychological advantage to be leading in a competition. It is, however, hard to identify such an effect econometrically. Using a Regression Discontinuity Design over a large dataset of tennis matches (N=634,095) the present paper exploits the randomised variation in first set results that occurs when the first set is decided by a close tie break (N=72,294). I find that winning the first set has a significant and strong effect on the result of the second set. A player who wins a close first set tie break will, on average, win one game more in the second set. I discuss the likely economic and psychological explanations of this phenomenon.

1 Introduction

Does leading in a competition give a psychological edge? Folk psychology suggests numerous (and often contradictory) ways in which relative positions in competition may affect performance. It is often said that winning players may "feel in the zone", have a "hot hand" or a "psychological momentum" but at the same time it is also thought that winning players may "rest on their laurels". On the other side, trailing competitors may have a tendency to "throw in the towel" but they can also have "nothing to lose" and increase their performance when they have their "back to the wall". Compared to the numerous ideas in folk psychology about individual behaviour in competition, the scientific study is still faced with lots of uncertainty about the reality of such phenomena. One of the reason for this is the difficulty to disentangle all the possible behavioural explanations in dynamic competitions.

The study of competitions 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 the agents. Given that tournaments are pervasive in organisation, the theoretical and empirical study of these incentive schemes present a clear interest. In this context, sports competitions offer an ideal setting to study competitor behaviour in tournaments since they typically provide large samples of identical situations where individuals/teams have to make choices with real incentives. Early studies of real sport tournaments have shown that, indeed, contestants performance is influenced by the incentive structure of the tournament (Ehrenberg and Bognanno 1990, Craig and Hall 1994). Taylor and Trogdon (2002) even found the compelling results that when a competition provides an incentive to finish last some teams are indeed more likely to lose to get this reward. More recently numerous papers have used sports competitions to assess if competitors not only react to incentives but adopt optimal strategies. Chiappori, Levitt, and Groseclose (2002) and Palacios-Huerta (2003) showed for instance that footballers use Nash mixed strategies in penalty kicks, and Walker and Wooders (2001) and Hsu, Huang, and Tang (2007) found an equivalent result in tennis for the choice of location for the first serve. On the other hand, Romer (2006) argued that American football teams fail to optimise when choosing on fourth down between trying for a first down and kicking. Bhaskar and Park (2004) also present evidence that cricket teams fail to optimise when they have the choice to bat first or second after the toss.

The present paper contributes to the literature on the study of behaviour in competitions by looking at how competitors performance is influenced by their relative standing in the competition. While there is a rich set of ideas about this issue in folk psychology, the study of this question is still in its early stage in economics. This study aims to bring more insight into the agent's psychology in competitive situations and to improve our understanding of how relative positions affect agents' behaviour in competitions.

In the present paper, I use a regression on discontinuity design (Hahn, Todd, and Klaauw 2001, Imbens and Lemieux 2008) to study the effect of relative standing in competition on current performances when the relative standing has been determined almost randomly by a very close result in an early round. Regression over discontinuity is a useful tool to circumvent the inconvenience of field data (Manski 1995).

The reminder of the paper is as follows: Section 2 presents the model and defines the notions of state and path dependency in dynamic competition and the literature related to them while Section 3 presents the identification strategy. Section 4 describes the data, section 5 presents the results and section 6 discusses the results and concludes.

2 Behaviour in best-of-n competitions: Theory and evidence

2.1 General framework

I consider a "best-of-n" competition where competitors are opposed in a series of n one shot opposition stages (eg. games/matches/set). A competitor wins the competition as soon as he/she has won $(n+1)/2$ confrontations. A best-of-n competition may be represented with a tree like the one depicted in Figure 1

$$
\begin{tikzcd}
V & V & \\
(1,0) \arrow[u] \arrow[r] & (1,1) \arrow[u] \arrow[r] & D \\
(0,0) \arrow[u] \arrow[r] & (0,1) \arrow[u] \arrow[r] & D
\end{tikzcd}
\qquad
\begin{tikzcd}
V & V & V & \\
(2,0) \arrow[u] \arrow[r] & (2,1) \arrow[u] \arrow[r] & (2,2) \arrow[u] \arrow[r] & D \\
(1,0) \arrow[u] \arrow[r] & (1,1) \arrow[u] \arrow[r] & (1,2) \arrow[u] \arrow[r] & D \\
(0,0) \arrow[u] \arrow[r] & (0,1) \arrow[u] \arrow[r] & (0,2) \arrow[u] \arrow[r] & D
\end{tikzcd}
$$

Figure 1: Best-of-3 and best-of-5 competitions

which represents a best-of-3 and a best-of-5 competition. Each contestant/team begins at the state (0,0) and moves up if he/she/it wins the current stage/round or right if the other contestant/team wins it. In the tree V and D denotes respectively victory and defeat.

Let's consider a basic framework to model the decision making problem of the competitor. Any agent a opposed to an agent b in a dynamic competition has to solve at each period t a problem of the form:

$$\max_{e_{at}} P(e_{at}, e^*_{bt})\Delta V_{at} - c(e_{at}) \tag{1}$$

This is a natural extension in the dynamic case of the Dixit (1987) model in the one period contest. The agent a chooses her level of effort e_{at} anticipating the best response e_{bt} from the opponent b. The effort level e_{at} and e_{bt} should therefore be a Nash equilibrium (pure or mixed) in each period.

The value ΔV_{at} is the difference in expected gain for a from winning the current stage in the competition. It is clear that ΔV_{at} depends on the actions of the contestant at later stages. As the optimisation program is identical at each stage, it can be rewritten as a recursive optimisation problem. Let s_a and s_b be the score of player a and b and s'_a and s'_b their score at the next period. The Bellman equation of the problem is:

$$V_a(s_a, s_b) = -c(e_a) + \max_{e_a} \mathbb{E}(V_a(s'_a, s'_b)) \tag{2}$$

The expected value of the value function may be written explicitly as a function of the probability of winning the stage/round and the values for the player of the next round if they win the present round, $V_a(s_a+1, s_b)$, or lose it $V_a(s_a+1, s_b)$.

$$\begin{aligned} V_a(s_a, s_b) = \quad & -c(e_a) \\ & + \max\nolimits_{e_a} P(e_a, e^*_b)V_a(s_a+1, s_b) + (1 - P(e_a, e^*_b))V_a(s_a, s_b+1)) \end{aligned}$$

In this problem the scoreline in the competition s_a, s_b is the only state variable and the effort level e_a is the only control variable. The problem is quite complex as it presents both a dynamic and a strategic dimension. However, if there is a unique equilibrium for this problem on one period, one can deduce by backward induction that there is a unique subgame perfect equilibrium for the whole game. Several papers have studied such a problem and used different functional forms for $P(e_a, e_b)$ and $c(e_a)$ for which there is unique Nash equilibrium strategy, which in some cases is a mixed strategy (Ferrall and Smith 1999, Klumpp and Polborn 2006, Konrad and Kovenock 2008).

This framework will help us to address two intuitions about the behaviour of contestant in competition which we will describe as state dependency and path dependency.

2.2 State dependent performances

In a short paper, Simon (1971) noticed that baseball World Series tends to end more often than should be expected in 7 games (maximum). Simon wondered about the existence of a “back to the wall effect” such that the team on the verge of losing raises its level of performance to stay in competition. While more recent studies do not support this idea, this paper is a good example of what is a state dependence in performance. State dependency in performance exists when competitors performance is influenced by the scoreline or the relative standing in the competition. Typically, a player leading could play better or worse *because* of his/her leading position in the competition.

Let y_t be the performance of a player at period t, for example in a set from a tennis match y_t may be measured by the number of games scored by the player. The difference of performance between players a and b at stage t may be written $\Delta_{(a,b)}y_t$. For simplicity let's write this difference Δy_t, and let's $w_t = (s_a, s_b)$ be the state of the competition (scoreline) at period t between a and b. One can then define state dependency as:

Definition 1 (State dependency in performance) *There is a state dependence if for two players with identical ability, there exists some states w_t such that*

$$E(\Delta y_t | w_t = (s_a, s_b)) \neq 0$$

2.2.1 State dependency in the standard model

In the model (2), a state dependency will exist if the state of the competition creates an *asymmetry* in the program solved by each contestant. If the parameters in the equation (1) are identical for a player leading and a player trailing there is no reason for an asymmetry in performance to appear.

However, given the dynamic nature of the game, the value of winning a set ΔV_{at} depends on what will happen next. If players are at opposite points in the game tree, they do not face the same games ahead if they win or lose the current set and therefore there is no reason a priori for the value of winning a set to be identical. It can actually be shown that, without any specific assumption on the functional form of $P(e_a, e_b)$ and $c(e_a)$, there will be necessarily such an asymmetry in terms of incentives at the end of a best-of-n competition between the leading and trailing contestant.

Proposition 1 (Incentive asymmetry at the end of the competition) *In a best-of-n competition where agents solve the program (1), and where the marginal cost of effort is positive, the value of winning the current set for a player leading* $(\frac{n-1}{2}, \frac{n-1}{2} - 1)$ *will be higher than the value of winning the same set for the player trailing* $(\frac{n-1}{2} - 1, \frac{n-1}{2})$

Proof. See appendix ■

Proposition 1 means that in a best-of-5 match a player leading (2,1) will give a greater value to winning the set (giving him the victory) than the player trailing (1,2). Identically, in a best-of-3 match, the player leading (1,0) will give a higher value to winning the set than the player trailing (0,1). Given that there is an asymmetry at the end of the game, it is most likely that the asymmetry spreads out to the whole game by backward induction. It is however not possible to predict how without specifying some functional form for the probability function and the cost function. It should also be noted that it is not possible to determine how this asymmetry in incentive will affect the performance without making some assumptions on the functional forms of $P(e_a, e_b)$ and $c(e_a)$.

Several papers have addressed this problem, sometimes independently from each other. In a seminal paper, Ferrall and Smith (1999), derived a Nash equilibrium for the problem (1) to study "best of 7 games" in the final series in Basketball, Baseball and Hockey in the United States. Klumpp and Polborn (2006) used this framework to model the sequential race to the primaries and Konrad and Kovenock (2008) proposed a theoretical analysis of best-of-n competition when each stage is modelled as an all-pay auction. Table 1 presents the functional forms proposed in each paper in the case of contestants with identical abilities.

	$P(e_a, e_b)$	$c(e_a)$	Nash equilibrium for one stage
Ferrall and Smith, 1999	$P(e_a - e_b + \varepsilon > 0)^\dagger$	$e^{e_a/r}$	Pure or mixed
Klumpp and Polborn, 2006‡	$\frac{e_a}{e_a+e_b}$	e_a	Pure
Konrad and Kovenock, 2008	$\mathbb{1}_{\{e_a>e_b\}}$	e_a	Mixed

† Where ε is a stochastic term, typically gaussian.

‡ The "effort" is the money spent in the race for the primaries.

Table 1: Functional forms adopted in previous papers

The theoretical results of these papers are concordant and they indicate that a contestant in the lead will be more likely to have an interest in expending more effort than a trailing contestant. As a consequence the leading contestant has a higher probability to win the current stage of the competition.

However, the empirical results in the literature differ somewhat. Ferrall and Smith estimated the parameters of the model from data from US championship series and found an absence of state dependency in these competitions. Teams seem to play each game as well as they can. On the contrary, Klumpp and Polborn found some evidence of "momentum" in the race for the primaries and stress that the importance given to the first primary in the New-Hampshire could stem from the existence of such a momentum. One noticeable difference between the present study and the current papers is that previous studies looked at the behaviour of teams of individuals (sport teams and political party) while the present paper focuses on individual decisions. In any case, the evidence of state dependency in performance in best-of-n competitions is limited, partial and not fully concordant.

2.2.2 State dependency from behavioural models

In the standard model (2), a state dependence appears because the maximisation program of the agent depends on the relative standing of the agent in the competition. Another possibility is that the relative standing in the competition plays a role for behavioural reasons which are not usually taken into account in standard models of decision making[1].

First, there is a huge literature on reference dependent preferences. While most studies have usually assumed that the reference point of the agent is the status quo, a recent effort has been made to generalise the notion of reference point to situations where it is higher than the status quo (Koszegi and Rabin 2006, Rayo and Becker 2007). In the domain of performance Heath, Larrick, and Wu (1999) proposed that goals may act as reference points and for this reason, the goal level may have an effect on the agent performances. Some prediction of this model seem confirmed by empirical studies (See, Heath, and Fox 2003, Bothner, Kang, and Stuart 2007, Amir and Ariely 2008). Overall, it is possible that if agents have reference dependent preferences, their reference point is influenced by their standing in the competition. This, in particular, is the case if we assume that this reference point should be the expectation of victory of the agent (Koszegi and Rabin 2006).

Second, a recent paper by Apesteguia and Palacios-Huerta (2008) found that the performance in penalty shoot-outs in Association Football is state dependent because the relative position in the standing may create a pressure which can alter the performance ability of the agents trailing. For this reason, Apesteguia and Palacios-Huerta argue that there is an advantage to shoot first in football as the pressure is then on the trailing team to catch up. This idea is also put forward in tennis where it is often argued that players serving first in the set have an advantage as the pressure is on the other player to catch up

[1] Beyond the case of best-of-n competitions, when the choice does not only concern the effort level but also the level of risk seeking, the relative standing in the competition may also give an advantage because it allows the leading team/performer to adopt a more conservative strategy. This is in particular the case if a conservative strategy can It is for instance what is found by Rigotti and Rustichini (1998) in the case of Association Football. For a similar reason, when contestants have to score in turn, scoring second may give an advantage since the resolution of the uncertainty allows the contestant to adopt an optimal level of risk seeking with more information than their opponent (Preston and Thomas 2000, Bhaskar and Park 2004).

(in particular toward the end of the set). Magnus and Klaassen (1999) studied this phenomenon and found that players serving first tend to win the set more often but their result was not statistically significant. In psychology, the effect of pressure on performance has been extensively studied (Ericsson, Charness, Feltovich, and Hoffman 2006, Beilock 2007, Ariely, Gneezy, Loewenstein, and Mazar 2008). This literature stresses on the negative role of pressure on performance. A recent paper by Paserman (2007) on performance in tennis matches tends to confirm the possible role of pressure in high stakes situations. Paserman finds a gender difference such that females do not play as well on important points than males. This can be related to another finding of Magnus and Klaassen (1999) which found that the performance of unseeded players tend to be worse on important points than the performance of seeded players (which stays roughly constant). These elements could suggest that performance can be state dependent because the state of the competition creates different levels of pressure for each player.

2.3 Path dependent performances

Folk psychology arguments often raise the idea that the very last performance has an impact on current performance. To define precisely the notion of path dependency in performance let's $\mathcal{S}_{(s_a,s_b)} = \{w_k\}_{k=1}^{k=t}$ be the set of sequence of scores leading to $w_t = (s_a, s_b)$. An element $s \in \mathcal{S}_{(s_a,s_b)}$ is a sequence $\{w_k\}_{0\leq k\leq t}$ such that the state of the competition in period t is $w_t = (s_a, s_b)$. It is first possible to determine a path dependency as the fact that current performance is determined by previous performances.

Definition 2 (Path dependency in performance) *There is a path dependency if for two players with identical ability*

$$E(\Delta y_t | s = \{w_k\}_{0\leq k\leq t}) \neq 0$$

However, it is clear from this definition that it also includes state dependent performances. It is therefore useful to define more restrictive notions. First a *strict state dependency in performance*:

Definition 3 (Strict state dependency in performance) *There is a strict state dependency if for two players with identical ability,*

$$E(\Delta y_t | w_t) \neq 0$$

and if for any two elements s and s' of $\mathcal{S}_{(s_a,s_b)}$,

$$E(\Delta y_t | w_t, s) = E(\Delta y_t | w_t, s')$$

A strict state dependency implies that once the state of the competition is known the path which has been followed to reach it does not add any relevant information to predict the performance of the competitors.

Symmetrically, one can define a *strict path dependency* as:

Definition 4 (Strict path dependency in performance) *There is a strict path dependency if for two players with identical ability and a given state w_t of the competition, there are two elements s and s' of $\mathcal{S}_{(s_a,s_b)}$ such that:*

$$E(\Delta y_t|w_t, s) \neq E(\Delta y_t|w_t, s')$$

It will be difficult to disentangle between a state and a path dependency effect since w_t and $\{w_k\}_{0\leq k\leq t}$ are jointly determined. However, these effects are clearly different. A strict path dependency implies that the history of the game matters, while a strict state dependency implies that the scoreline is the only relevant variable. For instance in a best-of-5 tennis match, if there is only a state dependency, a score of 2 set to 1 will have the same effect whatever the way this score was reached by both players. If there is a path dependency, it will typically make a difference if for instance the player leading won the first two sets and lost the third one (negative momentum) or if he lost the first set and won the last two sets (positive momentum). An interesting type of situation which allows us to discriminate between strict path dependency and strict state dependency are symmetrical scorelines.

Proposition 2 (Path dependency and symmetrical scorelines) *From Definition 4 we can infer that:*

i *If there is no strict path dependency,the expected performance of two players in a state with a symmetrical scoreline $w_t = (k, k)$ will be identical.*

$$E(\Delta y_t|w_t = (k, k)) = 0$$

ii *If there is a strict path dependency, a difference in performance can be observed between two players with identical ability in a symmetrical scoreline situation $w_t = (k, k)$, due to the different paths s and $s' \in \mathcal{S}_{(k,k)}$ they took to reach this scoreline.*

$$E(\Delta y_t|w_t = (k, k), s) \neq 0$$

The notion of strict path dependency has not been much studied in economics. From the point of view of the model (2) there is no reason a priori for the existence of any path dependency. The scoreline (s_a, s_b) is the only state variable and it summarizes all information from the past that is needed for the forward-looking optimization problem (Adda and Cooper 2003). Once the scoreline is known, the way this scoreline was reached should not have any influence of the current stage of the competition.

The idea of path dependency in performance has on the contrary been the origin of large strand of research in psychology. Psychologists have in particular studied the argument that players may feel in the "zone" when successfully scoring several times in a row. In a seminal study, Gilovich, Vallone, and Tversky

(1985) critically examined the argument that such an effect exists in Basketball (a belief which suggests that players should pass the ball to players who have been successful in the last shots as they are more likely to score, having a "hot hand"). An important literature has been written on the hot hand hypothesis, and there is still some disagreement over the reality of this effect, some papers arguing for it (Larkey 1989, Albert 1993, Stern and Morris 1993, Brown and Sauer 1993, Stern 1995, Wardrop 1999) and some against it (Siwoff, Hirdt, and Hirdt 1987, Camerer 1989, Albright, Albert, Stern, and Morris 1993, Koehler and Conley 2003, Ayton and Fischer 2004). Overall, there is still an uncertainty about the reality of this phenomenon (Bar-Eli, Avugos, and Raab 2006). More generally, a large literature on "psychological momentum" has studied the effect of position/recent performance on current performance. There is however still a huge uncertainty about the reality and reasons of such a phenomenon (Burke, Edwards, Weigand, and Weinber 1997).

In the case of dynamic competitions, Klaassen and Magnus (2001) show that good points are more likely to be followed by good points in an analysis of 90,000 points played at Wimbledon. However, even if a departure from pure randomness can be found statistically, it is hard to attribute this to a psychological state of the competitors. It is possible instead that the relative form of the player fluctuates slightly during the game. If one player feels good at some point of the game and bad at some other point it is clear that an analysis would find that when this player won a point he was more likely to win the next one. In some extreme cases, the shape of the player can change due to physical problems (injuries, cramps, blisters). Therefore a departure from randomness does not automatically means that the result of the last point had a causal effect on the next point.

3 Identification strategy

The empirical identification of the effect of previous performance/current scoreline on present performance face a natural endogeneity problem. The difference in performance Δy_t observed during one period of a competition may be a function of the difference in performance at the previous period Δy_{t-1} and the current scoreline w_t, but it will also be a function of the difference in ability of the players which will necessarily be imprecisely observed by the researcher. Any unobserved difference in ability will affect both the present difference in performances Δy_t and the past difference in performances Δy_{t-1}. As a consequence the current state of the competition w_t will also be influenced by these unobserved differences in ability.

Any empirical relationship observed between Δy_t and Δy_{t-1}, w_t will be suspected of being spurious and due to the unobserved differences in ability of the players. The difficulty of this problem is that arguably it will never be possible to measure the exact shape of the competitors. Current rankings are a useful information, but they do not precisely indicate the current form of the player in the very recent period, or even the precise day of the match. Even within the match the relative strength of the players can change due to physical strain or injuries. For this reason, it is hard to disentangle a possible causal effect of Δy_{t-1} and w_t on Δy_t from a possible spurious correlation due to an unobservable heterogeneity in competitors' ability.

3.1 State dependency

Let's consider the case of state dependency. In order to study state dependency in performance, one would ideally like to have an experimental setting where contestants are randomly allocated to different levels of relative standing w_t. Alternatively one may look for a situation where relative standings have been determined in an almost random way. The argument made in this paper is that tennis matches provide such a situation since the first set may be determined in a very close tie break where arguably the final result is fairly random. I will consider here primarily the effect of winning the first set on the second set result.

Let W_{10} be a binary variable taking the value 1 if player a won the first set and zero otherwise. To study the effect of a win in the first set on performance in later set, one would ideally need to compare what the winner of the first set does in the later set to *what he would have done if he had lost the first set*. This counterfactual is naturally never observed. Let's define $\Delta y_2(1)$ be the difference in performance between competitor a and b in the second set if player a won the first set ($W_{10} = 1$), and $\Delta y_2(0)$ the difference in performance if a lost the first set. The effect of winning the first set is therefore $\Delta y_2(1) - \Delta y_2(0)$.

This situation is a classical problem in the treatment evaluation literature. Several techniques have been proposed to circumvent the problem of absence of counterfactual and to try to estimate the effect of the treatment variable (here W_{10}). One of them is the regression over discontinuity design, which uses situations where a discontinuity in the treatment variable exists around a threshold of a variable predicting the treatment. In the *sharp design* version which I am using here, the treatment is completely determined by the position relative to the threshold.

Let's consider tie breaks. Results may be more or less "close" in a tie break. Typically a close tie break is a tie break where the result could easily have been the other way, for example when both players got an opportunity to win it. I will define the "closeness" of the tie break results as a function of their length. The intuitive argument behind this definition is that the longer the tie-break the more likely that the players were of roughly identical ability in the game, and the more likely it is that both of them got one or more set points during the tie break. Given that there is a part of randomness in the result of every point, the result of a long tie break may be seen as more random since the difference in ability of the players was not large enough for them to end the set earlier and the set is likely to have been decided by chance in the game. Let's define a measure of the closeness of the result: if pt_a and pt_b are the points scored in the tie breaks by each players, the closeness of the victory/defeat can be measured by:

$$d = \frac{pt_a - pt_b}{pt_a + pt_b}$$

Formally, d is equal to the difference between the estimates $\widehat{p}_a$ and $\widehat{p}_b$ of the probability of each players to win a point in the tie break. When the tie break length increases, $d \to 0$ and $\widehat{p}_a - \widehat{p}_b \to 0$ The treatment (a victory in the first set) is determined by the cut-off point zero for the variable d:

$$W_{10} = d > 0$$

The RD estimate of the effect of winning the first set is given by:

$$\lim_{d \downarrow 0} E(\Delta y_2 | d) - \lim_{d \uparrow 0} E(\Delta y_2 | d)$$

And

$$\tau_{RD} = E(\Delta y_2(1) | d = 0) - E(\Delta y_2(0) | d = 0)$$

For the RD strategy to be valid, several conditions must be met. First, the conditional expectations $E(\Delta y_2(1)|d)$ and $E(\Delta y_2(0)|d)$ must be continuous in d.

Second, if z is a variable having an effect on Δy_2,

$$E(z | W_{10} = 1, d = 0) - E(z | W_{10} = 0, d = 0) = 0$$

It must be noted that it is not necessary to assume that observed competitors are strictly identical on both sides of the cut-off point, but only that at the limit in the cut-off points there is no difference in the competitors. This should be the case in the present situation, as the probability that players have different winning probabilities decreases toward zero as the duration of the tie-break increases and $d \to 0$.

The parameter τ_{RD} is typically estimated non parametrically as the difference between the end point values of two non parametric estimates of the conditional expectation of the dependent variable on both sides of the cut-off point. In order to limit boundary bias (Hardle 1994), local linear regression is preferred to kernel regression and the estimator of the conditional expectation is given by:

$$\min_{\alpha,\beta} \sum_{j}^{n} (\Delta y_2 - \alpha - \beta(d_j - d))^2 K\left(\frac{d_j - d}{h}\right)$$

Where the weighting function K is an Epanechnikov kernel giving higher weight to observations close to the point where the regression curve is estimated.

The estimator τ_{RD} depends on the chosen bandwidth for the local linear regression, and as suggested by Imbens and Lemieux (2008) I implement a leave one out cross validation technique to determine the optimal level of bandwidth. For each observation I estimate:

$$\widehat{m}_{h,j} = \frac{1}{n}$$

$$CV(h) = \frac{1}{n}\sum_{j=1}^{n}(\Delta y_2 - \widehat{m}_{h,j})^2$$

The optimal bandwidth is then:

$$h_{CV}^{opt} = \arg\min_{h} CV(h)$$

3.2 Path dependency

If it is empirically hard to identify precisely a state dependency effect, it is even harder to discriminate it from a possible path dependency effect. One of the problem is that a recent win changes the state of the scoreline. To identify the effect of a path dependency, the effect of a recent success in scoring, must be calculated relative to the counter factual: the failure to score. However, both situations lead to different scorelines. Winning versus losing the first set in tennis typically places the player in a leading or a trailing situation. For this reason, any path dependency will produce some apparent state dependency (and vice versa). It is therefore unclear if any observed effect following a win in the first set is due to a state dependency or due simply to the fact of having won the previous set.

One way to look into path dependency is however to try to assess if the condition for strict state dependency is respected. That is: when a relative standing in the competition is known is the path which has been followed irrelevant to predict the next performances? For instance, one solution would be to take all the 2-1 sets situations and see if the way to reach this score has an influence on later performance. However, such an identification strategy cannot control for possible changes in players shape during the match (tiredness, cramps, physical injury). When at 2-1, having won the last set could be correlated with a better form in the last set which is likely to be associated with a better form on average in the current set.

Ideally one would like to observe random variations in path leading to a scoreline. But such random variations cannot be observed in the field and in any case the RD identification strategy cannot be strictly implemented here as it is not possible to observe quasi random variations in path for a given scoreline. It is however possible to try to mimic the previous identification strategy by looking at matches where the result of each points in the path have been almost randomly determined. Let's take the example of a tennis match at 1-1 before the 3rd set. Under strict state dependency, two players with equal ability should have the same probability to win the 3rd set. It is possible to focus on matches where both sets were determined almost randomly in close tie breaks. One should expect players in these matches to have very close ability level and therefore, under strict state dependence, no systematic difference in performance should be observed between players having won the first set and players having won the second set.

The conclusion of such an analysis will not be as robust than for the regression over discontinuity since a selection takes place after the first set and only a minority of matches reach a second set tie break after a first set tie break. One could wonder about possible systematic differences in ability and this will have to be checked carefully.

4 Data

Our dataset contains an almost exhaustive list of all the matches played at the international professional level between 1991 and 2008. Most of the matches are either from Grand slam and ATP tournament or lower level 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. The dataset includes some matches in double, and a small minority of matches played in the best of 5 sets. Overall the dataset contains 634,095 observations. For consistency, I will use the matches played in best of 3 sets in singles, except when mentioned otherwise. Table 2 shows the breakdown of the matches in the dataset.

Type of competition	Nb obs
Single - best of 3 sets	515,980
Single - best of 5 sets	12,464
Double - best of 3 sets	104,190
Double - best of 5 sets	1,461
Total	634,095
ATP	185,586
Davis Cup	7,613
Challenger	117,614
Futures	309,936
Total	634,095

Table 2: Breakdown of the dataset

Figure 2 shows the breakdown of matches depending on the first set result. From this whole dataset the analysis will focus on the matches where the first set ended in a tie break (N=73,318) and in particular the matches for whom the precise breakdown of points in these tiebreaks is available (N=72,294). Figure 3 presents the breakdown of points in the tie break for the matches ending in the tie break in the first set.

Obviously one of the concerns is that players may have different levels of ability. To measure ability, seeding numbers may be used as a proxy to measure differences in ability. The seed of the player indicates the quality of the players and provides a good approximation of the relative ranking of the seeded players. Typically a quarter of the players are seeded. Since seeded players tend to win

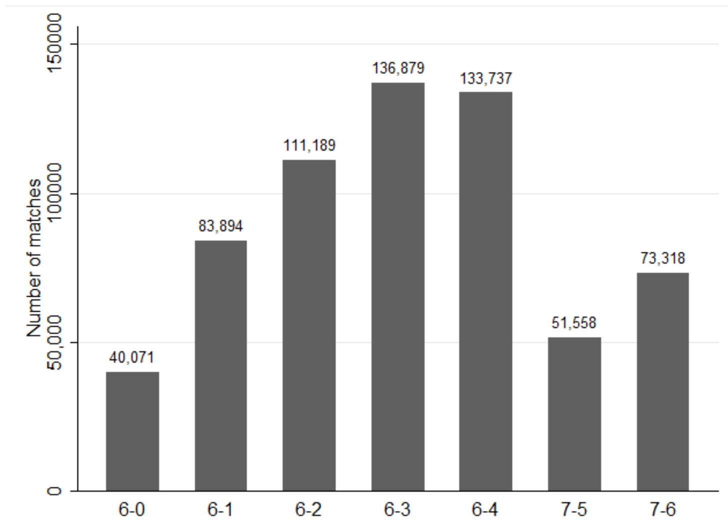

Figure 2: Break down of results for the first set

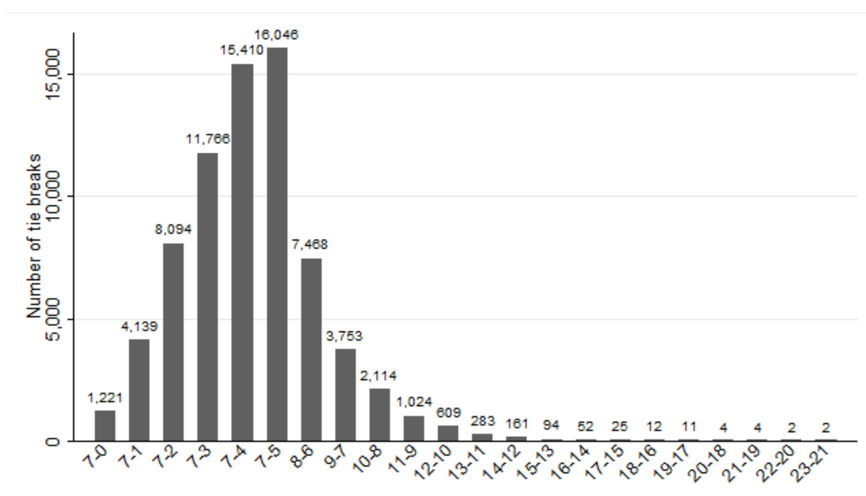

Figure 3: Break down of the tie breaks for the first set

more matches in a tournament than unseeded players, they are more represented at later stages in the tournament and they represent more than a quarter of the players in the dataset.

This seeding information is used to build a variable q indicating the relative ability of the player. First q equals the seeding number for seeded players. Second, I give to the unseeded players a number equal to the difference between the seeded number of the lowest ranked player and the total number of players entering the tournament. For example in a tournament with 64 players and 16 seeded players, the variable q takes values between 1 and 16 for the seeded players, and a value of 40 for the unseeded players.

The variable q has the advantage to be available for most of the matches from the dataset. In addition I collected for a sub-sample of matches on the ATP circuit a much more precise information about the relative ability of both players thanks to the betting odds of each players prior to the match (N=25,000). These betting odds, give the equivalent winning probability p estimated ex-ante by the betting market. Numerous studies on betting odds have confirmed that they are very good predictors of the winning probability

5 Results

5.1 State dependency

As advised by Imbens and Lemieux (2008) it is useful to check how the average of the outcome variable Δy_2 varies over a set of bins close to the cut-off value. Table 3 shows this for the different possible ends of the first set. As one would expect, closer results in the first set are associated with closer results in the second set. However, the difference in results in the second set seems to stay significant even for very close results in the first set. A close look on the table shows that while Δy_2 decreases systematically between a result of 6-0 to a result of a tie break 7-4, it does look to decrease as much afterwards. This would be consistent with the idea that for such results players are on average of equal ability and that the persistent difference is due to the state dependency per se.

For the regression over discontinuity, the optimal bandwidth has to be estimated first. As suggested by Imbens and Lemieux, I restrict the estimation sample for this computation to the observations relatively close in order for the estimate not to be influenced by observations far from the cut-off point. The sample to estimate was therefore restricted to all the matches ending with a tie break in the first set. The calculation of the optimal bandwidth gives 0.7. Figure 4 shows the result of the regression over discontinuity using the optimal bandwidth this discontinuity. Overall winning versus losing the first set creates a very significant difference of one game in the second set ($p < 0.01$ by bootstrap over 400 replications).

Score in the firs set	$\overline{\Delta y_2}$	N
6-0	3.57***	35,190
6-1	2.63***	70,308
6-2	2.11***	90,789
6-3	1.44***	108,676
6-4	1.15***	105,441
7-5	1.17***	40,875
Tie break		
7-0	1.32***	954
7-1	1.22***	3,178
7-2	0.99***	6,173
7-3	0.92***	8,932
7-4	0.88***	11,783
7-5	0.67***	12,183
8-6	0.70***	5,678
9-7	0.63***	2,821
10-8	0.66***	1,602
11-9+	0.67***	1,733

Significant at † 10%, * 5%, ** 1%, *** 0.1%.
p-values calculated with a t-test

Table 3: Difference in the second set by results in the first set

While the optimal bandwith should be used for the point estimate, the result should also be robust to different bandwiths (Imbens and Lemieux 2008). Table 4 shows the result of the estimation of τ_{RD} for different bandwith lengths. Results do not change significantly across different levels of bandwidths. This indicates that the result is robust and not linked to a very specific selection of matches around the threshold $d = 0$: τ_{RD} is consistently significant.

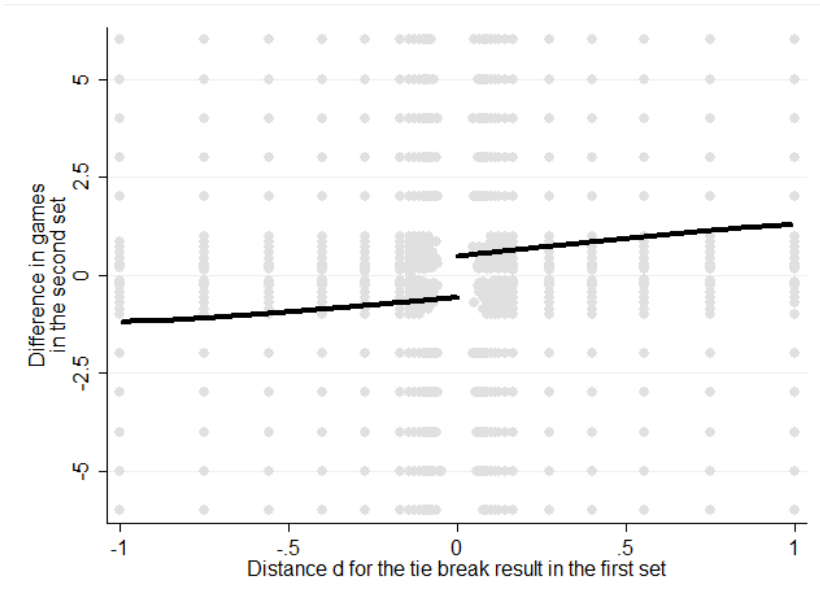

Figure 4: Effect of a close win in the first set on the result of the second set (local linear regression)

Bandwith	$E(\Delta_{y_2} \vert d > 0)$
$.7^{CV}$	1.01^{***}
.15	1.16^{***}
.2	1.27^{***}
.3	0.95^{***}
.4	0.85^{***}
.5	0.93^{***}
.6	0.97^{***}

Significant at † 10%, * 5%, ** 1%, *** 0.1%.
p-values calculated by bootstrap.

Table 4: Robustness of the result to different bandwidth

A natural concern is that even very close tie breaks could systematically be determined in a non random way. Typically the underlying problem is the possible existence of a discontinuity in the quality of the players between players winning versus losing very close tie breaks. Using the seeding information from the dataset and the ex-ante winning probability from the betting odds on the subsample, it is possible to test if players winning very close tie breaks tend to have on average better seeding numbers indicating a higher ranking. First, like for the difference in results in Table 3, Table 5 presents the average difference in seeding number Δq for each score in the first set (with the difference in results for comparison purposes). In accordance with the identification assumption, the average difference in seeding numbers decreases a lot with the duration of the tie break and becomes insignificant for tie breaks won in 11 points or more. The last columns of Table 5 present the equivalent calculations for the difference in results and winning probabilities in the subsample of ATP matches for which betting odds are available. Here again winning probabilities decrease and become insignificant for tie break won with more than 10 points. These descriptive statistics fully support the identification of the RD estimation.

Score in the firs set	Subsample with seeding nbs			Subsample with odds		
	$\overline{\Delta y_2}^a$	$\overline{\Delta s}^b$	N	$\overline{\Delta y_2}^a$	$\overline{\Delta p}^c$	N
6-0	3.28***	−11.23***	21,490	1.79***	0.28***	546
6-1	2.43***	−9.62***	47,634	1.57***	0.26***	2,115
6-2	1.97***	−8.84***	64,042	1.37***	0.20***	3,333
6-3	1.36***	−6.45***	79,970	1.02***	0.17***	5,777
6-4	1.10***	−5.18***	78,812	0.82***	0.11***	5,845
7-5	1.12***	−4.48***	30,568	0.98***	0.12***	2,216
Tie break						
7-0	1.26***	−3.80**	697	1.29***	0.12*	70
7-1	1.15***	−4.59***	2,423	0.46*	0.02	234
7-2	0.98***	−3.77***	4,729	0.72***	0.12***	499
7-3	0.88***	−3.71***	6,811	0.78***	0.08***	681
7-4	0.85***	−2.98***	8,790	0.76***	0.06***	940
7-5	0.65***	−1.97***	9,203	0.51***	0.05***	1,009
8-6	0.67***	−2.38***	4,368	0.48***	0.08***	452
9-7	0.63***	−2.87***	2,197	0.72***	0.08**	229
10-8	0.67***	−2.02*	1,277	0.75**	−0.03	129
11-9+	0.62***	0.90	1,293	0.86***	0.02	135

Significant at † 10%, * 5%, ** 1%, *** 0.1%. p-values calculated with a t-test

[a] Difference in score in the second set for comparison with Table 1

[b] Difference in seeding numbers (lower seeding numbers indicate higher ability)

[c] Difference in winning probability from betting odds

Table 5: Difference in players' ability depending on the score in the first set

The discontinuity in ability at $d = 0$ can be estimated and Figure 5 shows the absence of discontinuity for the variables q about the seeding of the players and for the winning probability p. For each of these figures the optimal bandwidth is calculated by cross validation (0.7 and 0.285 respectively). The results indicate that there is no jump in players quality at the cut-off point with asymptotic differences of 1.05 ($p = 0.23$) and 0.02 ($p = 0.64$) at $d = 0$. This absence of discontinuity in the ability of players for very close tie breaks between winners and losers fully supports the identification hypothesis.

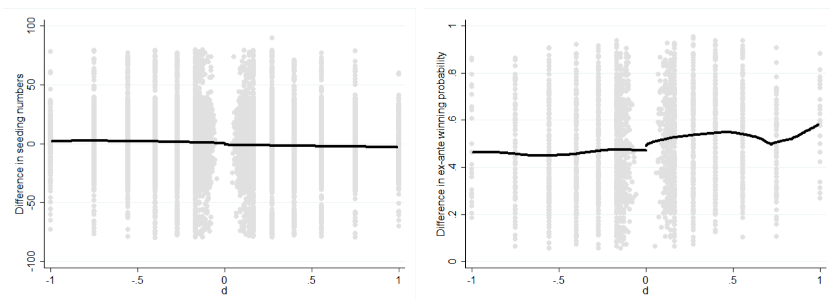

Figure 5: No discontinuity in ability

Seeding numbers give a good indication about the relative ability of the players and ex-ante winning probabilities from betting odds should incorporate a large amount of information to estimate the fitness of the players (eg. recent results, news of injuries, relative skill of the player on the surface). However, one may still argue that while these variables are very good measures of the relative ability of the players it is never possible to observe fully the fitness of the player during the match. Potentially, there is still some variations in ability which could not be predicted by betting odd. A player could feel better or worse on a given day for instance. If Δq is the difference in ability measured with the observable measures of ability and Δu the difference in unobservable ability between players, we can make sure that Δq is not significantly different from 0 for very close tie breaks however it could well be that players winning tie breaks are still better relative to this unobserved ability.

A convincing way to test for a possible hidden difference in ability is to run a placebo regression over discontinuity. If players winning a very close tie break are more likely to be better players, then, when they win any set in a very close tie break, they should be more likely to win any other set. It is therefore possible to discriminate between a state dependency effect and a difference in ability between players winning and losing very close tie breaks because the state dependency requires the effect to be observed only from one set to the next.

Let's consider the first two sets, if the precedent result is due to a state dependency, one should expect that winning or losing a very close tie break in the second set has no effect on the first set. On the contrary if winners of very close tie breaks are better players, then winners of very close tie break in the second set should have better results in the first set in the same way that winners of very close tie breaks in the first set have better results in the second set. Figure 6 shows the result of this placebo regression of the effect of winning a very close second set on the result in the first set. The value of the difference between the curves at the discontinuity (the equivalent of τ_{RD}) is slightly negative and not significant. There is indeed no (positive) discontinuity in the average result of the first set when the second set was won in a very close tie breaks. This suggests that the identification assumption is respected and we can assume that there is no discontinuity on observable and unobservable characteristics between players playing a very close tie break.

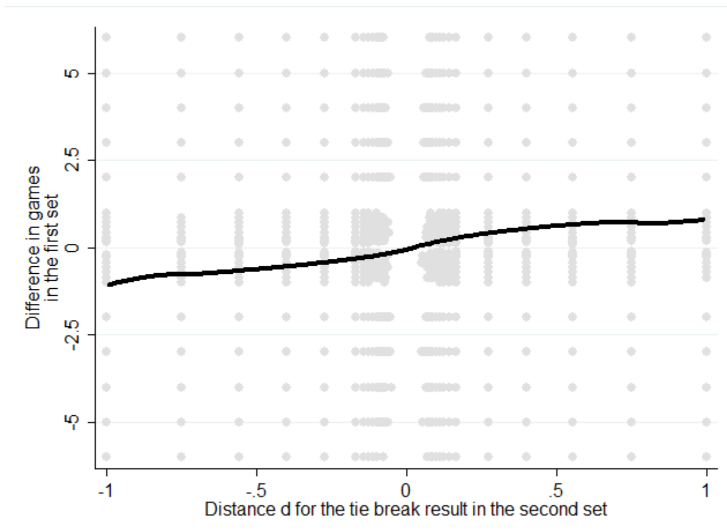

Figure 6: Average difference in the first set for a close win in the second set (local linear regression)

5.2 Factors influencing the effect

The size of the dataset allows us to study if the effect differs across different competitions or type of matches. Table 6 shows the difference in second set results for very close results in the first set (tie breaks won 11-9 or more). There are differences across competitions and match types.

To check this further, it is possible to run a parametric version of the RD design where:

$$
\begin{aligned}
E(\Delta y_2(\mathbb{1}_{\{d>0\}})) = \quad & \beta_0 + \beta_1 d + \beta_2 s + \beta_3 dble + \beta_4 bestof5 + \beta_5 atp + \beta_6 prize \\
& + \mathbb{1}_{\{d>0\}} \times (\beta_7 + \beta_8 dble + \beta_9 bestof5 + \beta_{10} atp + \beta_{11} prize)
\end{aligned} \tag{3}
$$

Score in the firs set	Tie breaks won 8-6 or higher		Tie breaks won 11-9 or higher	
	Average difference in the 2nd set for the winner of the first set	Nb obs	Average difference in the 2nd set for the winner of the first set	Nb obs
ATP	0.54***	3,451	0.47***	515
Challengers	0.64***	7,305	0.62***	1,060
Futures	0.69***	8,667	0.73***	1,216
Davis Cup	0.66***	223	0.53	39
Best of 3	0.70***	14,662	0.70***	2,129
Best of 5	0.53***	472	0.23	67
Single	0.67***	12,214	0.65***	1,783
Double	0.50***	3,270	0.49***	473

Significant at † 10%, * 5%, ** 1%, *** 0.1%. p-values calculated with a t-test

Table 6: Difference in the second set by results in the first set

And then $\tau_R D = E(\Delta y_2(1)|d=0) - E(\Delta y_2(0)|d=0) = \beta_7 + \beta_8 \mathbb{1}_{\{dble=1\}} + \beta_9 \mathbb{1}_{\{bestof5=1\}} + \beta_1 0 \mathbb{1}_{\{atp=1\}}$ in the linear equation (3). Table 7 shows the result of such an estimation. The first two columns report the result for two sets of covariates on the whole sample. The results indicate that there is a significant difference across competitions with the effect being lower for ATP matches where the quality of the players is higher. There is no significant difference in the effect between single and double matches. The differences between matches in best-of-3 and best-of-5 is not clear as it could be due to unobserved heterogeneity between best-of-3 and best-of-5 matches. Typically best-of-5 matches oppose better players than best-of-3 matches because they occur in final of events and in Grand slam (in addition to the Davis Cup). The column (4) restrict the estimation to Grand Slam, the point estimate of the difference between best-of-3 and best-of-5 matches decreases and is insignificant but is still negative and close to its value in other estimations. The inclusion of prize money in column (3) for a sub-sample for which it is available, suggests that the effect is not influenced by the monetary incentive linked to the competition.

Beyond this comparison across competitions, it is also possible to assess if the effect is larger when players are close in ability or when there is an important asymmetry in the players ability. It is, for instance, often argued that it is more important for low seeded players to win the first set as the loss of the first set is likely to strike a blow to their motivation. To answer this question it is possible to use the information on the players ability, in particular on the sub-sample for which the estimation of the ex-ante winning probability is estimated by the betting odds.

Figures 7 shows the average result in the second set as a function of the winning probability ex-ante when the first set is won or lost on a tie break 7-5 or higher. As expected, players winning the tie break have on average a better result in the second set, however this difference is higher for players with roughly equal probability and lower (even negative) for players with very distinct probabilities.

Figure 7 is naturally symmetric relative to 0.50 as a match won by a player

Table 7: Difference of the first set effect across competitions

Δy_2	(1) Δy_2	(2) Δy_2	(3) Δy_2	(4) Δy_2
Win first set	1.326***	1.558***	1.401***	1.400***
	[5.534]	[6.387]	[5.065]	[4.322]
Best of 5		0.435**	0.257	0.185
		[2.555]	[0.754]	[0.735]
Double		-0.0249	-0.0451	
		[-0.375]	[-0.635]	
ATP		0.151**	0.107	
		[2.236]	[1.029]	
Prize money			1.52e-08	
			[0.209]	
Win1 × Best5		-0.690***	-0.633	-0.456
		[-2.882]	[-1.316]	[-1.205]
Win1× ATP		-0.275***	-0.302**	
		[-2.899]	[-2.061]	
Win1× Double		0.0337	0.0349	
		[0.360]	[0.349]	
Win1× Prize			5.34e-08	
			[0.516]	
d	-0.449	-0.516	-0.123	0.371
	[-0.558]	[-0.636]	[-0.133]	[0.748]
Δq	-0.0209***	-0.0208***	-0.0235***	-0.00838***
	[-19.79]	[-19.55]	[-19.06]	[-4.744]
Constant	-0.628***	-0.754***	-0.667***	-0.553***
	[-5.173]	[-6.054]	[-4.717]	[-2.655]
Observations	24781	24257	18751	1176
R^2	0.054	0.064	0.067	0.073

t statistics in brackets

*** p<0.01, ** p<0.05, * p<0.1

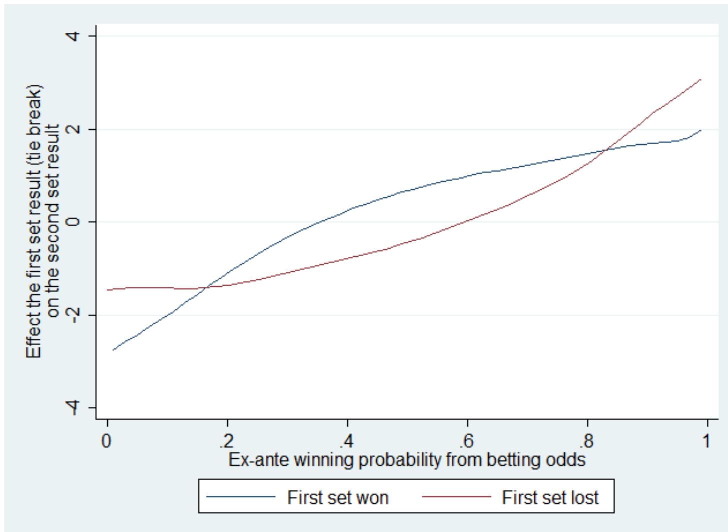

Figure 7: Effect of tie break result in the first set on the second set as a function of the probability of winning the match

with a winning probability p is equivalent to a match lost by a player with a winning probability $1 - p$. Figure 7 opposes therefore matches with opponents with an equal ability to matches where there is an asymmetry in the ability of the players. Figure 8 presents the point estimate of the difference between the two curves of Figure 7 depending on the proximity between the two contestants (the figure uses the winning probability of the favourite as the horizontal axis). A confidence interval is estimated by percentile bootstrap following the method suggested by Hardle (1994). The effect of a win in the first set tie break is maximum when both players have roughly equal chances to win the match, it however decreases and become insignificant when players are highly unmatched in terms of winning chances.

This result is at first sight not intuitive, but it is not fully incompatible with the model (1). The optimal effort from the contestant is naturally a function of his relative ability compared to his opponent. With two different parametrisations of the model (1), Ferrall and Smith (1999) and Klumpp and Polborn (2006) found that the better contestant will tend to expend a higher level of effort. Let Δ_q be the difference in quality between the contestants a and b and Δ_s be the difference in score between them. Let $e_a^*(\Delta_p, \Delta_s)$ and $e_b^*(\Delta_p, \Delta_s)$ be the optimal effort of each contestant. The difference in optimal effort $\Delta e^* = e_a^* - e_b^*$ may be concave in Δ_p and Δ_s such that $\partial \Delta e^*(\Delta_s, \Delta_p)/\partial \Delta_s$ is lower for higher values of Δ_p.

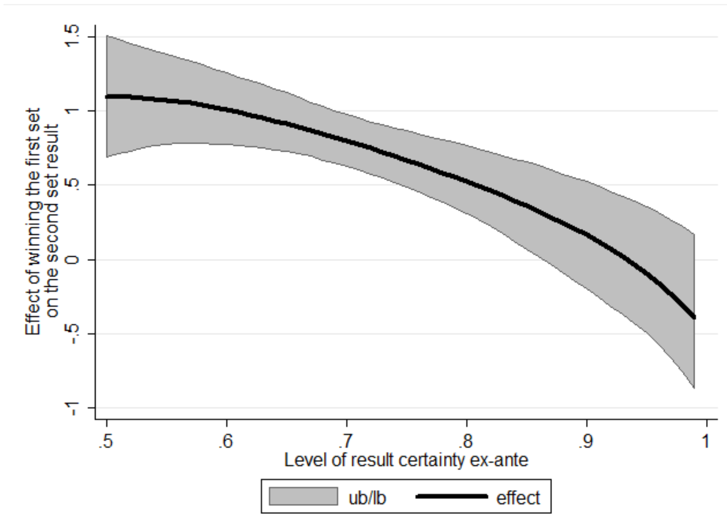

Figure 8: Effect of tie break win in the tie break as a function of the ex-ante probability of winning the match

5.3 Path dependency

In the precedent analysis. The effect observed can be due to a strict state dependence (effect of being in a leading position) or to a path dependency (effect of having won the previous set). To assess further if there is a strict path dependency, let's consider matches at 1-1: does having won the second set help win the third set? Following the same approach, I focus on matches where the order of the set is almost random: matches where both sets where decided in close tie breaks: 7-6 6-7 or 6-7 7-6. Table 8 shows the result of this analysis and indicates that the previous path of performance per se matters to predict future performance. This result holds even when possible differences in ability are controlled for using the variable q on seeding numbers. The same analysis can be done for matches at 2-2 in 5 sets matches. While the number of matches available decreases sharply making results non significant, the sign is still positive and with the same magnitude than for the 1-1 situation suggesting that winning the last set gives an advantage to win the next one.

These results suggest that there may well be a "path dependency" in results. In their analysis of 90,000 points played at Wimbledon, Klaassen and Magnus (2001) found a path dependency in points such that good points tend to be followed by good points. The present analysis suggests such path dependency at the set level: winning a set tends to give an advantage to win the next one. The advantage of the present analysis is that these results cannot be driven by some unobserved changes in the shape of the player. Such unobserved changes would tend to create a positive correlation between points within the match. However because this study focuses on sets which were won on close tie

Matches at 1-1	Expected difference in the 3d set for the winner of the second set			
Difference in 1st and 2nd sets	Simple difference	N	Correcting for players' seeds	N
2 games difference	0.56***	41,886	0.55***	40,752
Any tie breaks	0.63***	4,606	0.59***	4,479
Tie break 7-5 or closer	0.53**	966	0.46*	939
Tie break 8-6 or closer	0.87*	259	0.83*	250
Tie break 9-7 or closer	0.92	83	0.76	80
Matches at 2-2	**Expected difference in the 5th set for the winner of the 4th set**			
Difference in 3rd and 4th sets	Simple difference	N	Correcting for players' seeds	N
2 games difference	0.57†	369	0.88*	268
Any tie breaks	0.55	49	1.24	36
Tie break 7-5 or closer	0.22	12	0.71	9

Table 8: Effect of winning the previous set

breaks, the winner of the last set has on average the same ability than the other contestant.

6 Discussion and conclusion

The results presented here indicate that the player in the lead has a higher probability of winning the next stage of the competition. The precision of the dataset used makes it possible to test for state dependency and path dependency in performance. I find a state dependency, compatible with rational models of competitions. Such a state dependency is hard to find and Ferrall and Smith (1999) did not find any in their studies of championships. They concluded that "strategical" consideration were absent from such competition and that teams performed each time to their best. The present results indicate otherwise. In the situation of tennis matches, there is a strong state dependency in performance with the leader tending to outperform significantly the contestant trailing. This difference in their results could be due to several factors. The competitions are different with teams of several players involved and several days between each match while in tennis there are only one or two players and the sets are played in a row. The difference may also come from the different technique, Ferrall and Smith use a maximum likelihood estimator which is downward biased and correct for the bias by bootstrap. Such a correction may fail when the variability of the bootstrap estimation may be quite high relative to the bias (Efron and Tibshirani 1993).

The present results however raise new questions. From the model (1) one could expect a state dependency in performance to arise from the optimal behaviour of contestants. However, no path dependency should be expected a priori. It would obviously be easy to introduce path dependency in the model by adding new hypotheses to the model regarding the effect of past performance on the cost of effort or on the probability function. Path dependency is however not a natural result from the model. From the analysis of tennis players performances it appears that there is a state dependency, however it also looks like there is a path dependency which contradicts the idea of *strict state dependency*. As a consequence, one could wonder if the state dependency observed in the first place is just the result of a strict path dependency: the winner of the first set could have an advantage in the second because he won the first set and not because he is ahead in the competition. To my knowledge, no economic model explains such a phenomenon which is described in psychology as the momentum effect.

Overall this study suggests that state and path dependency exists in competitions. Given the ubiquity of competitions in economic organisations, much further investigation into these phenomena would be needed in order to fully understand how contestants' performance is influenced by the state of the competition. The factors influencing this effect would also be worth studying. Are these strategic considerations lower when teams are involved rather than single individuals? or when there is a third party coaching the contestants?

A appendix

Proof of Proposition 1. Without loss of generality, let's assume that the value of a victory is 1 and the value of a defeat is 0. In a best-of-n competition, the current set is decisive when the scoreline is $(\frac{n-1}{2}, \frac{n-1}{2})$, the program for each player is then:

$$\max_e P(e, e^*) - c(e)$$

As the problem is symmetrical for both players, they will have ex-ante the same expected level of effort. As a consequence, since they have the same ability, they will have a probability 1/2 to win the set. It is then possible to deduce that the value of winning the last set is $V(\frac{n-1}{2}, \frac{n-1}{2}) = 1/2 - c(e^*) < 1/2$. Going backward, the player ahead during the last set when the scoreline was $(\frac{n-1}{2}, \frac{n-1}{2} - 1)$ gives the following value to winning: $\Delta_{(\frac{n-1}{2}, \frac{n-1}{2}-1)}V = 1 - V(\frac{n-1}{2}, \frac{n-1}{2}) > 1/2$. Instead, the value of winning the next set for the player trailing is $\Delta_{(\frac{n-1}{2}-1, \frac{n-1}{2})}V = V(\frac{n-1}{2}, \frac{n-1}{2}) - 0 < 1/2$.

As a consequence, there is an asymmetry between the player leading and the player trailing such that: $\Delta_{(\frac{n-1}{2}, \frac{n-1}{2}-1)}V > \Delta_{(\frac{n-1}{2}-1, \frac{n-1}{2})}V$.

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