9-1-2018

Revisiting loss aversion: Evidence from professional tennis

Nejat Anbarci
Durham University Business School

K. Peren Arin
Zayed University, kerim.arin@zu.ac.ae

Torben Kuhlenkasper
Hochschule Pforzheim

Christina Zenker
Zayed University

Revisiting loss-aversion: Evidence from Professional Tennis*

Nejat Anbarci,[a] K. Peren Arin,[b] Torben Kuhlenkasper,[c] Christina Zenker[b]

[a]Deakin University, Australia
[b]Zayed University, UAE
[c]Pforzheim University, Germany

September 22, 2017

Abstract

We provide further evidence for the existence of loss-aversion in a high-stakes context: professional tennis. Our contribution to the literature is threefold: (1) We provide a theoretical framework as a basis of our investigation, (2) we test the predictions of our model by using a novel dataset for both male and female players from the Dubai Tennis Championships 2013 that not only includes the serve speed but also the serve location, and (3) we employ semiparametric Additive Mixed Models to include smooth one-, two- and three-dimensional interaction eects for modelling the serve speed and placement. By doing so, we provide additional evidence for the existence of loss-aversion for both males and females, but we show that loss-aversion kicks in much later for females compared to males. We also document that male players take more risks in the final, when the stakes are highest. Our results imply significant gender differences for both risk-taking and loss-aversion.

(3) *Keywords*: Tennis, risk aversion, loss-aversion, semiparametric methods
JEL Classification: C14, D03, D81, L83

*The authors would like to thank Peter Dicce and James Smith for providing access to the data as well as to Zaid Al-Mahmoud and Blagoj Gegov for valuable research assistance. We would like to thank the editor and an anonymous referee for their constructive comments and suggestions. Corresponding author: Torben Kuhlenkasper; Tiefenbronner Str. 65, 75175, Pforzheim, Germany; torben.kuhlenkasper@hs-pfrozheim.de; Tel: +49 7231 28 6331.

1 Introduction

In their seminal paper regarding the Prospect Theory, Kahneman and Tversky (1979) argue that economic agents place a different weight on losses than on gains. Despite assigning more weight on losses than on gains, agents are risk seeking in the loss domain and risk averse in the gains domain. While numerous studies provided evidence that loss-aversion exists, many scholars remain skeptical.[1]

More recently, Pope and Schweitzer (2011) use data from professional golf to demonstrate that players are indeed loss averse – as they are more focused while playing in the loss domain. We take the aforementioned paper as a starting point and test prospect theory in another setting – namely, in professional tennis. Contrary to golf where a player has full control of every shot, in tennis the only action where a player has full control is the serve, particularly the serve speed and placement/location. Specifically, players take higher risks when they serve faster and go for a precise location closer to the T-line.[2] Given that the data on serve speed and location have recently become available by Hawk-eye technology that measures the serve speed and location for selected matches, professional tennis provides us a unique opportunity to test prospect theory in a competitive setting, with large stakes and very experienced agents.[3]

We test the implication of our model that a server will be less risk averse in his/her serve speed and in trying to serve closer to the center of the T-line when behind in score than when ahead in score using novel data from the Dubai Duty Free Tennis Championships in 2013, by utilizing advanced semi-parametric econometric methods. We build upon Anbarci et al. (2017) by also explicitly taking the serve location into account. We can therefore test loss-aversion in a multi-dimensional setting with the use of our state-of-the-art empirical methodology that can account for interaction between our variables of interest. With the latter, we model multivariate and non-linear functional effects impacting the serve speed. Our results provide further evidence that loss-aversion significantly influences behavior, even after controlling for the stakes and experience. However, we also show that the timing of loss-aversion differs by gender, and while males are loss-averse within a game, females are

[1] Loss-aversion has been documented in many laboratory and field settings. See, for instance, Knetsch (1989), Kahneman, Knetsch and Thaler (1990), Tversky and Kahneman (1991), Camerer et al. (1997), Gneezy and Potters (1997), Thaler et al. (1997), Odean (1998), Genesove and Mayer (2001), List (2003), Mas (2006), Fehr, Goette and Zehnder (2007), Abeler et al. (2011), Crawford and Meng (2011), Hossain and List (2012), Heffetz and List (2014). The sceptics include, List (2003), Hart (2005), Levitt and List (2008). In particular, List (2003) suggests that experience and large stakes may eliminate decision errors. Kahneman and Tversky's (1979) "prospect theory" is at the root of other important phenomena such as the endowment effect (Thaler, 1980), the status quo bias (Samuelson and Zeckhauser, 1988), disappointment aversion (Gul, 1991), and reference-dependent preferences (Kőszegi and Rabin, 2006), among others.

[2] The T-line refers to the T-shape formed by the service and center-service line. See Figure 2 for the layout of a tennis court.

[3] Hawk-Eye is computer system used in various sports to measure the trajectory, speed and placement of the ball.

loss-averse when they are behind in sets. Moreover, we also document that, when the stakes are the highest (i.e., in the final), the serve speed is significantly higher for male players.

The remainder of the paper is organized as follows: Section 2 provides a theoretical framework as a basis of our empirical investigation, Section 3 reviews data, Section 4 presents the empirical methodology, and the empirical results are provided in Section 5. Finally, Section 6 concludes.

2 Conceptual Framework

Kahneman and Tversky's (1979) "prospect theory" triggered a vast literature by providing evidence on the prominence of "loss-aversion"(i.e., on the phenomenon that individuals weigh (and respond to) losses more than identical gains with respect to a salient reference point). Loss-aversion implies that agents' "value function" is kinked at the reference point with a steeper gradient for losses than for gains; in addition, agents are risk seeking in the loss domain and risk averse in the gain domain. That is, the utility function is convex in the loss quadrant and concave in the gain quadrant. Similar to Pope and Schweitzer (2011) model, we develop a simple conceptual framework to describe the influence that loss-aversion may have on first and second serves when players are ahead or behind in score. Similar to golf, there is also a reference point in tennis, which is a tied score in a game, set and the match. Players are "at par" if the game score is tied in a game or if the set score is tied after equal numbers of games or if equal numbers of sets are won by players; they are not at par otherwise.

Our paper makes an important contribution to the literature by documenting loss-aversion in another competitive field setting – namely in professional tennis – with large stakes, very experienced agents and a well-defined reference point. In a sense, our paper complements Pope and Schweitzer (2011) and our results serve as a strong robustness check of Pope and Schweitzer's results specific to golf, since tennis and golf are very different in their competitive nature, as in golf one competes against the whole field (open play), while in tennis one opponent is taken one at a time (match play).[4]

In tennis (and unlike golf), the only shot over which a player has full control is the serve. Therefore, the serve is very critical and the server has a distinct incentive to put great effort into the serve, especially in terms of the speed and the location/placement of the serve. This also brings up the issues related to risk taking and a higher cognitive effort of aiming the serve over the net and inside the service box, preferably with a precise location close to the side of the service box which are the hardest ones to reach for the returner. The returner's

[4]This difference has very important implications. Laband (1990) compared golf and tennis and showed that the open play nature of golf tournaments leads to a lack of dominance by one or a few players, whereas in contrast the match play nature of tennis tournaments is conducive to dominance by one or a few players being the usual outcome; specifically, Laband (1990) found under match play, the probability that a top-ranked player finishes first is about four times greater than in open play against the field.

effort too is important since he/she has to react as quickly as possible to a faster serve that lands on a side line of the service box with a significant physical and cognitive effort; besides, a point cannot continue without a return that is placed back into the server's court.

Consider any probability function where the probability of winning a point is strictly concave in the serve and the serve is strictly concave in effort and risk taking (i.e., given that the latter is fixed/given for an individual, it is not a strategy variable). The serve success depends on the speed and location. The serve speed depends on physical effort and risk taking, and the serve location depends on cognitive effort and risk taking.

One can model interactions between a serving player and the returner in various ways. One way is to model it at a very general level by considering the probability of winning a point as a function of server's effort, which is endogenously set by him/her as follows:

$$P_s\big(\text{win the point while serving}\big) = f_s(e_s, e_r, z_s, z_r) + \epsilon \tag{1}$$

where e_s represents the amount of effort exerted by the server on the serve, e_r represents the amount of effort exerted by the returner and ϵ is random noise. The vectors z_s and z_r contain player characteristics (e.g., ranking, height, weight) of the server and returner, respectively.

Note that the function f_s is positive w.r.t. e_s while f_s is negative w.r.t. to e_s. That is, additional effort strictly increases the probability of winning a point, and $f_s(\cdot)$ is strictly concave in effort.

Alternatively, one may consider a more specific probability function incorporating the interaction between players into consideration in the form of a contest success function (e.g., Tullock (1980)). This indicates that winning is a probabilistic event, depending on the relative efforts of contestants:

$$P_s\big(\text{win the point while serving}\big) = g_s(e_s, e_r, \alpha, \beta) = \frac{e_s^{\alpha}}{e_s^{\alpha} + e_r^{\beta}} \tag{2}$$

where e_s again represents the amount of effort exerted by the server on the serve and e_r represents the amount of effort exerted by the returner. $\alpha(z_s)$ and $\beta(z_r)$ are such that $1 > \alpha$, $\beta > 0$ and they depend on who the server is as well as on z_s and z_r.

Since $1 > \alpha > 0$, g_s is positive w.r.t. e_s and g_s being negative w.r.t. e_s. Additional effort strictly increases the probability of winning a point and $g_s(\cdot)$ is strictly concave in effort.

Note that regardless of whether one considers the general functional form f or the specific functional form g, the level of effort and of risk-taking determine the speed of each serve as well as its placement.

Let T_s denote the score of the server (in terms of points or games or sets) and T_r denote the score of the returner. To incorporate loss-aversion, we will utilize the value functions for a winning score (w), a losing score (l) and a tied score (t) with both a "degree of loss-aversion" separate risk preference parameters, γ and δ, for the gain and loss domains, respectively:

$$V(w) = (T_s - T_r)^\gamma \quad \text{if} \quad T_s > T_r$$
$$V(l) = -\lambda(T_r - T_s)^\delta \quad \text{if} \quad T_r > T_s$$

Let

$$(T_s - T_r) = \Delta_s$$

and

$$(T_r - T_s) = -\Delta_r$$

where $\Delta_s = \Delta_r \equiv \Delta$ if and only if $T_s - T_r = -(T_r - T_s)$.

$$V(w) = \Delta_s^\gamma \quad \text{if} \quad T_s > T_r \tag{3}$$
$$V(l) = -\lambda \left(-\Delta_s^\delta\right) \tag{4}$$
$$V(t) = 0 \tag{5}$$

Due to $\lambda > 1$, the difference in value between winning a service game and a tied score is smaller than the difference in value between a tied score and losing a point. Note that $1 > \delta \geq \gamma > 0$ allows for "diminishing sensitivity" in score difference such that incremental gains in Δ_s above the reference point (i.e., the tied score) result in progressively smaller utility improvements and, conversely, incremental reductions in Δ_r that are below the tied score result in progressively smaller declines in utility.

There is a cost of effort for the server, $c_s(e_s)$, which is strictly increasing in effort e_s with c_s being positive w.r.t. e_s and c_s being positive w.r.t. to e_s as well. That is, additional effort strictly increases the cost of effort and $c_s(\cdot)$ is strictly convex in effort.

Each server's utility is equal to the values placed on winning and losing a point weighted by their probabilities and subtracting the cost of effort. For our purposes of establishing loss-aversion, we only need to compare payoffs of servers when they are ahead or behind. A serving player derives the following expected utilities U and V depending on which one of the probability functions, for g, is used respectively, when he/she has advantageous score (e.g., 40-30) serving for the game (or set or match). When it is a game (or set or match) point favoring the server, where W denotes this state, we have the following:

$$\begin{aligned} U_s(W) &= \Big[f_s(e_s, e_r, z_s, z_r) + \epsilon\Big] \cdot V(W) + \Big[1 - f_s(e_s, e_r, z_s, z_r) + \epsilon\Big] \cdot V(t) - c_s(e_s) \\ &= f_s(e_s, e_r, z_s, z_r) + \epsilon - c_s(e_s) \end{aligned} \tag{6}$$

$$
\begin{aligned}
V_s(W) &= \Big[g_s(e_s, e_r, \alpha, \beta)\Big] \cdot V(W) + \Big[1 - g_s(e_s, e_r, \alpha, \beta)\Big] \cdot V(t) - c_s(e_s) \\
&= g_s(e_s, e_r, \alpha, \beta) - c_s(e_s) \\
&= \left[\frac{e_s^\alpha}{e_s^\alpha + e_r^\beta}\right] \cdot V(W) + \left[1 - \frac{e_s^\alpha}{e_s^\alpha + e_r^\beta}\right] \cdot V(t) - c_s(e_s) \\
&= \frac{e_s^\alpha}{e_s^\alpha + e_r^\beta} - c_s(e_s)
\end{aligned} \tag{7}
$$

Likewise, a serving player derives the following expected utilities U and V depending on which one of the probability functions, f or g, is used respectively, when he/she has a disadvantageous score (e.g., 30-40) serving for the game (or set or match). When it is a game (or set or match) point favouring the returner, where L denotes this state, we have the following:

$$
\begin{aligned}
U_s(L) &= \Big[f_s(e_s, e_r, z_s, z_r) + \epsilon\Big] \cdot V(t) + \Big[1 - f_s(e_s, e_r, z_s, z_r) + \epsilon\Big] \cdot V(l) - c_s(e_s) \\
&= \Big[1 - f_s(e_s, e_r, z_s, z_r) + \epsilon\Big](-\lambda) - c_s(e_s)
\end{aligned} \tag{8}
$$

$$
\begin{aligned}
V_s(L) &= \Big[g_s(e_s, e_r, \alpha, \beta)\Big] \cdot V(t) + \Big[1 - g_s(e_s, e_r, \alpha, \beta)\Big] \cdot V(l) - c_s(e_s) \\
&= \Big[1 - g_s(e_s, e_r, \alpha, \beta)\Big](-\lambda) - c_s(e_s) \\
&= \left[\frac{e_s^\alpha}{e_s^\alpha + e_r^\beta}\right] \cdot V(t) + \left[1 - \frac{e_s^\alpha}{e_s^\alpha + e_r^\beta}\right] \cdot V(l) - c_s(e_s) \\
&= \left[1 - \frac{e_s^\alpha}{e_s^\alpha + e_r^\beta}\right](-\lambda) - c_s(e_s)
\end{aligned} \tag{9}
$$

Maximizing the utility functions in (6) and (8) yields the following first-order conditions:

$$
\begin{aligned}
c_s'/f_s' &= \Delta_s^\gamma \quad \text{when the state is } W \\
c_s'/f_s' &= \lambda\Delta_s^\delta \quad \text{when the state is } L
\end{aligned} \tag{10}
$$

Likewise, maximizing the utility functions in (7) and (9) yields the following first-order conditions

$$
\begin{aligned}
c_s'/g_s' &= \Delta_s^\gamma \quad \text{when the state is } W \\
c_s'/g_s' &= \lambda\Delta_s^\delta \quad \text{when the state is } L
\end{aligned} \tag{11}
$$

The first-order conditions in (10) and (11) (which, incidentally, are identical to those of Pope and Schweitzer (2011)) indicate that a server chooses an optimal level of effort, e_s^*, by setting the marginal cost of effort equal to the marginal benefit of effort when serving. When behind in score, the server chooses a higher optimal effort level, which equates the ratio of the marginal cost and benefit of effort to λ, than when ahead, which equates the ratio of the marginal cost and benefit of effort to 1. Thus, the first-order conditions imply that a server chooses higher effort level in the loss domain than he/she does in the gain domain. We then obtain the following result.

Proposition 1. *Controlling for individual characteristics, z_s and z_r leading to α and β, a loss averse server will be more risk averse in terms of the serve speed and the location of the serve when ahead in score than when behind in score.*

In addition, the curvature of these utility functions induces a server to exert less effort when he/she is significantly ahead (e.g., 40-0 in his/her serve game, 5-0 in a set and 2-0 in sets in a grand-slam tournament) than when he/she is slightly ahead (e.g., 40-30 in his/her serve game, 5-3 in a set and 0-0 in sets) and much more effort when he/she is drastically behind (e.g., 0-40 in his/her serve game, 0-5 in a set and 0-2 in sets in a grand-slam tournament) than when he/she is slightly behind (e.g., 30-40 in his/her serve game, 3-5 in a set and 0-0 in sets).

Observe that when $\Delta_s = \Delta_r \equiv \Delta$, the first-order conditions still imply that a server chooses higher effort level in the loss domain than he/she does in the gain domain for the same score differential. In addition, $c_s'/f_s' = \Delta_s^\gamma$ or $c_s'/g_s' = \Delta_s^\gamma$ implies that a server will put more effort into his/her serve in terms of speed and placement when slightly ahead in score than significantly ahead in score, while $c_s'/f_s' = \lambda\Delta_s^\delta$ or $c_s'/g_s' = \lambda\Delta_s^\delta$ implies that a server will put more effort into his/her serve in terms of speed when slightly behind in score than when significantly behind in score. Further, note that, with $\lambda > 1$ and $\delta \geq \gamma$, the first-order conditions also allow that a more loss averse server with γ and δ will put more effort into his/her serve in terms of speed and placement at a closer losing score than a less loss averse server with $\gamma' < \gamma$ and $\delta' < \delta$ will at the same or more disparate losing score.

Thus, we have the following result:

Proposition 2. *Controlling for individual characteristics, z_s and z_r leading to α and β, (1) a loss averse server will put more effort into his/her serve in terms of the speed and the location of the serve, (i) when slightly behind in score than when significantly behind in score, and (ii) when slightly ahead in score than significantly ahead in score. (2) compared to a less loss averse server, a more loss averse server will put more effort into his/her serve in terms of the speed and the location of the serve at any losing score.*

As a result of both the loss-aversion and diminishing sensitivity components of prospect theory, loss averse servers in the domain of gains will be more likely to choose risk averse serves and locations than loss averse servers in the domain of losses. This leads to our final result:

Proposition 3. *Controlling for individual characteristics, z_s and z_r leading to α and β, a loss averse server will be more risk averse in terms of the serve speed and the location of the serve when ahead in score than when behind in score.*

3 Data

The data consists of 32 matches of the Dubai Duty Free Tennis Championships in 2013 for which Hawk-Eye technology was available. Of these, 19 were matches by male and 13 by female players. It is a $2 million ATP (Association of Tennis Players) tournament, a so-called *ATP 500 tournament*, and a $2 million WTA (Women's Tennis Association) tournament, a so-called *Premier Event*.[5] Due to its prestige and money prizes, the tournament manages to attract the best players in the world. For instance, both the number 1 ranked female and male players in the world, Novak Djokovic from Serbia and Victoria Azarenka of Belarus, were also the top seeds in the tournament for males and females, respectively. After Azarenka's withdrawal with injury, World Number 2 Serena Williams from the USA was promoted to be the top seed.

The dependent variable – serve speed – was obtained from Hawk-Eye Innovations, which uses ball tracking technology to measure it. The Hawk-Eye technology has been used for all ATP, WTA and ITF tournaments since 2002. The serve speed is measured in miles per hour (mph) for every serve in the match. During the Dubai Duty Free Tennis Championships, Hawk-Eye technology recorded all matches played on the center court. Only serves that were counted *in* were included in the dataset, since the Hawk-eye technology does not measure the serve speed for serves that are ruled as *out*. Our first category of independent variables uses the serves that are ruled *in*: The serve-speed data was also used in Anbarci et al. (2017). However, Hawk-Eye also captures the location of the service in the field of the receiver. Thus, one contribution of this paper is to extend the aforementioned dataset by incorporating information regarding the serve location coordinates. These spatial coordinates allow us to include the positioning of the service in the model. According to Figure 1, the serves must be placed in the green shaded area by the server from the diagonal opposite side. The variables are summarized in Table 1. Figure 2 shows the observed locations of the services.

The second category is made up of player characteristics. We thereby use the age, height and weight of each player. Additionally, we control for the rank of each male and female player from the official ATP and WTA sites, respectively. The resulting variables are defined in Table 2. In addition to these personal characteristics, we include variables capturing the different characteristics of the currently observed match. The definitions for the latter group of variables are presented in Table 3. In Table 4 and 5, we provide summary statistics for

[5] Since its inauguration in 1993, the tournament has been hosted in the Dubai Duty Free Tennis Stadium.

male and female players, respectively. For two of the female matches (Stosur vs. Makarova and Putintseva vs. Robson) data was unavailable, although the Hawk-Eye technology was installed for these matches.

4 Methodology

We model the speed of serve t from server i to receiver j for females by

$$
\begin{aligned}
\text{Serve Speed}^f_{ijt} &= \beta_0 + \beta_1 \cdot \text{Second Serve}_{ijt} \\
&+ \beta_2 \cdot \text{Round } 2_{ijt} + \beta_3 \cdot \text{Round } 3_{ijt} + \beta_4 \cdot \text{Round } 4_{ijt} + \beta_5 \cdot \text{Round } 5_{ijt} \\
&+ \beta_6 \cdot D_{2\ ijt} + \beta_7 \cdot D_{3\ ijt} + \beta_8 \cdot D_{4\ ijt} \\
&+ \beta_9 \cdot (\text{Round } 5_{ijt} \cdot D_{4\ ijt}) \\
&+ g\left(\text{Longitude}_{ijt}, \text{Latitude}_{ijt}\right) \\
&+ b\left(\text{Height}_{ijt}, \text{Weight}_{ijt}, \text{Age}_{ijt}\right) \\
&+ f_1\left(\text{Rank}_{ijt}\right) \\
&+ f_2\left(\text{Point Difference}_{ijt}\right) + f_{2|M}\left(\text{Point Difference}_{ijt}\right) \cdot \text{Male}_{ijt} \\
&+ f_3\left(\text{Game Difference}_{ijt}\right) + f_{3|M}\left(\text{Game Difference}_{ijt}\right) \cdot \text{Male}_{ijt} \\
&+ \gamma_i + \eta_j + \epsilon_{ijt}
\end{aligned} \tag{12}
$$

and for males by

$$
\begin{aligned}
\text{Serve Speed}^m_{ijt} &= \beta_0 + \beta_1 \cdot \text{Tie-Break}_{ijt} + \beta_2 \cdot \text{Second Serve}_{ijt} \\
&+ \beta_3 \cdot \text{Round } 2_{ijt} + \beta_4 \cdot \text{Round } 3_{ijt} + \beta_5 \cdot \text{Round } 4_{ijt} + \beta_6 \cdot \text{Round } 5_{ijt} \\
&+ \beta_7 \cdot D_{2\ ijt} + \beta_8 \cdot D_{3\ ijt} + \beta_9 \cdot D_{4\ ijt} \\
&+ g\left(\text{Longitude}_{ijt}, \text{Latitude}_{ijt}\right) \\
&+ b\left(\text{Height}_{ijt}, \text{Weight}_{ijt}, \text{Age}_{ijt}\right) \\
&+ f_1\left(\text{Rank}_{ijt}\right) \\
&+ f_2\left(\text{Point Difference}_{ijt}\right) \\
&+ f_3\left(\text{Game Difference}_{ijt}\right) \\
&+ \gamma_i + \eta_j + \epsilon_{ijt}
\end{aligned} \tag{13}
$$

In (12) and (13) we include γ_i as the random effect for server $i = 1, \ldots, 36$ and η_j as the random effect for receiver $j = 1, \ldots, 36$. In addition to the parametric effects $\beta_0, \ldots, \beta_9$ for the binary-coded variables, our models contain three types of nonparametric components.

First, the univariate functional effect $f_1(\text{Rank}_{ijt})$ captures the (possible) nonlinear effect of the ranking from player i on his or her serve speed. $f_1(\cdot)$ is a priori unspecified and estimated with a data-driven approach. To obtain a nonlinear but also sufficiently smooth effect $\hat{f}_1(\cdot)$, we employ penalized spline smoothing. In our method, the P-splines are built upon B-spline bases. The idea traces back to Eilers and Marx (2010). To achieve the smoothness for this type of effect, the approach uses the squared derivative of the function. The latter represents the variability of the function by focusing on its curvature. By penalizing a wiggly and unsmooth function with the second derivative, we use

$$\lambda \int \left(f_1(x)\right)^2 dx$$

with λ being the parameter steering the smoothness. For more details, we refer to Fahrmeir et al. (2013). In (12) and (13), we use the same approach for $f_2(\cdot)$ and $f_3(\cdot)$.

The functional effect $g(\cdot,\cdot)$ captures in an a priori unspecified form the location of the serve by assuming a joint effect of the longitude and the latitude. The resulting bivariate interaction surface from $\hat{g}(\cdot,\cdot)$ is obtained by using tensor product bases in the first step. Due to the spatial character of this effect, we assume an isotropic structure of the two location variables. With this flexible form, we allow for both non-linear joint effects of the positioning and interactions of the two variables. By isotropic, we mean that rotation of the covariate co-ordinate system will not change the result of smoothing. This is especially useful for geographic variables with the same dimension of values.[6]

Finally, the body-characteristics of each player are included with a three-dimensional function $b(\cdot,\cdot,\cdot)$. We allow the weight, the height and the age of the player to be combined simultaneously to one trivariate effect and to affect the serve speed again in a nonlinear and smooth way. Although tensor products are again used to obtain the bases for this nonparametric effect, we do not assume an isotropic structure of the three variables in $b(\cdot,\cdot,\cdot)$: our variables for the body-characteristics are measured on different scales. For an application of trivariate nonparametric effect, we refer to Berlemann, Enkelmann and Kuhlenkasper (2015). With the two random effects γ_i and η_j, our models (12) and (13) are (semiparametric) Additive Mixed Models. The estimation is conducted in R.[7]

5 Empirical Results

Our discussion of the empirical results starts with Table 6, which provides coecient estimates for the parametric parts of models (12) and (13). Our results, consistent with Anbarci et al. (2017), show that both male and female players serve significantly slower in their second

[6]See Fahrmeir et al. (2013) and Wood (2006) for more information regarding this procedure.
[7]See R Core Team (2016)) with the function `gamm4` from the package `gamm4`. Also, see Wood and Scheipl (2016).

attempt. Moreover, serve speed for males is significantly higher in the final round of the competition, when the stakes are the highest. This result is consistent with previous studies examining the incentive eect of tournaments, which show that subjects increase their effort in response to an increase in the winner's prize (Harbring and Irlenbusch, 2005, 2008; Falk, Fehr and Huffman, 2008). However, this does not hold for female players, which points out an important gender-difference in risk-taking

Our main variables of interest are the three dummy variables which we use to test for incidence of loss-aversion. Once again, we document remarkable gender differences with respect to risk-taking behaviour. The negative and significant coefficient for the D3 variable for males, and the positive and significant coefficient for females for the same variable imply that male players serve slower when they are ahead in sets, while female players do the exact opposite by serving faster. Interestingly, the positive and significant coefficient for the D4 variable for males is somewhat consistent with the pioneering study of Pope and Schweitzer (2011), show that the serve speed is significantly lower when the score is tied in terms of sets. Nevertheless, it is important to emphasize that if one looks at serve speed when players are a set behind, female players exhibit consistent behaviour in terms of loss-aversion theory, while male players do not.

However, this result can be explained with the *timing* of loss-aversion, as documented by Anbarci et al. (2017). In order to investigate this we have a closer look at how the point difference in a game and how the game difference in a set affects the serve speed for male and female players. In Figure 11 we can analyse the partial eect of the point dierence within a game, and Figure 12 shows the partial eect of the game dierence within the current set of the match.

The top half of Figure 11 shows loss-aversion within a game for female players and the bottom half shows the same for male players. We observe opposite patterns for the two genders. In the very short run (i.e., within a game), female players do not show any loss-aversion when behind in the game. This can be seen by the positive eect on the serve speed on the left-hand side of the response function. Conversely, for male players, there is evidence for immediate loss-aversion, especially if they are significantly behind in a game. This result confirms our initial suspicion that loss-aversion exists for both genders, but kick in at different times: male players become "loss-averse" much earlier compared to female players.

Figure 12 shows the eects for what we call the medium run (i.e., within a set). Once again we observe an opposing pattern for the two genders. If females are – slightly as well as significantly – behind in the set, the serve is significantly slower compared to when they are ahead. For males, on the other hand, the opposite can be observed: being behind in the set leads to higher serve speed (more so when slightly behind) and therefore to higher risk taking in the serve. This behaviour is consistent with what we observe in the short-run, i.e. within a game.

In a nutshell, our results provide evidence that loss-aversion exists for both genders. However, the "timing" of loss-aversion is different for male and female players. The results also show that, within a match, the risk-taking behaviour changes over time. We believe this result is very important and has never been documented before.

In the next step, we present the estimated bivariate partial effect $\hat{g}$ (Longitude, Latitude) as a two-dimensional contour graph in Figure 3 and as three-dimensional perspective graphs in Figures 4 and 5. For the Figures 3 to 9, we use the heat colorscheme. The latter indicates higher partial effects on the serve speed by brighter colors and lower and even negative partial effects with darker colors. Our results for this bivariate spatial effect clearly show that the selected location by the server affects his/her speed. In other words, the players can serve faster by positioning their serves closer to the center of the T-line or the outer border of the T-field.

The partial effect of the body characteristics $\hat{b}$ (height, weight, age) are displayed in a two-dimensial graph in Figures 6 and 8 and as a three-dimensial graph in Figures 7 and 9. We show the partial trivariate eect by holding age constant. Our results show that the interaction of physical characteristics is very important in terms of serve speed. For instance, our results for the oldest age group (34) show that only shorter players with very low or very high weight serve faster compared to other players.

In addition to the trivariate body-characteristics, Figure 10 shows the smooth partial effects of the ranking on the serve speed. We document that players lower in the world rankings serve statistically significantly faster on average. This result is consistent with the findings of Kräkel, Nieken and Przemeck (2014), who posit that the underdog (in our case the player with lower probability of winning) should strictly benefit from taking higher risks since he has nothing to lose, and good luck may compensate for the competitive disadvantage. Interestingly, once again, this result does not hold for female players.

6 Conclusion

In this paper, we provide additional evidence for the existence of "loss-aversion" in the highly competitive context of professional tennis. Interestingly, the influence of loss-aversion is visible in three dierent settings. First, when players are behind in score, we show that they are more likely to take risks in their serve speed, although the timing of the loss-aversion is different between male and female players. Second, we also document that male players are more willing to take risks when the stakes are highest; namely, they take more risks in the final, when also in monetary terms there is much more to lose. Third, we also document that lower-ranked male players for whom the opportunity cost of a loss is much higher, risk taking is higher as well. For many lower-ranked players, entrance to the main draw of the next tournaments is highly dependent on their performance in the previous tournaments.

Further exploration of these results in dierent sports as well as in other fields seem to be very beneficial for deeper understanding of loss-aversion and its origins.

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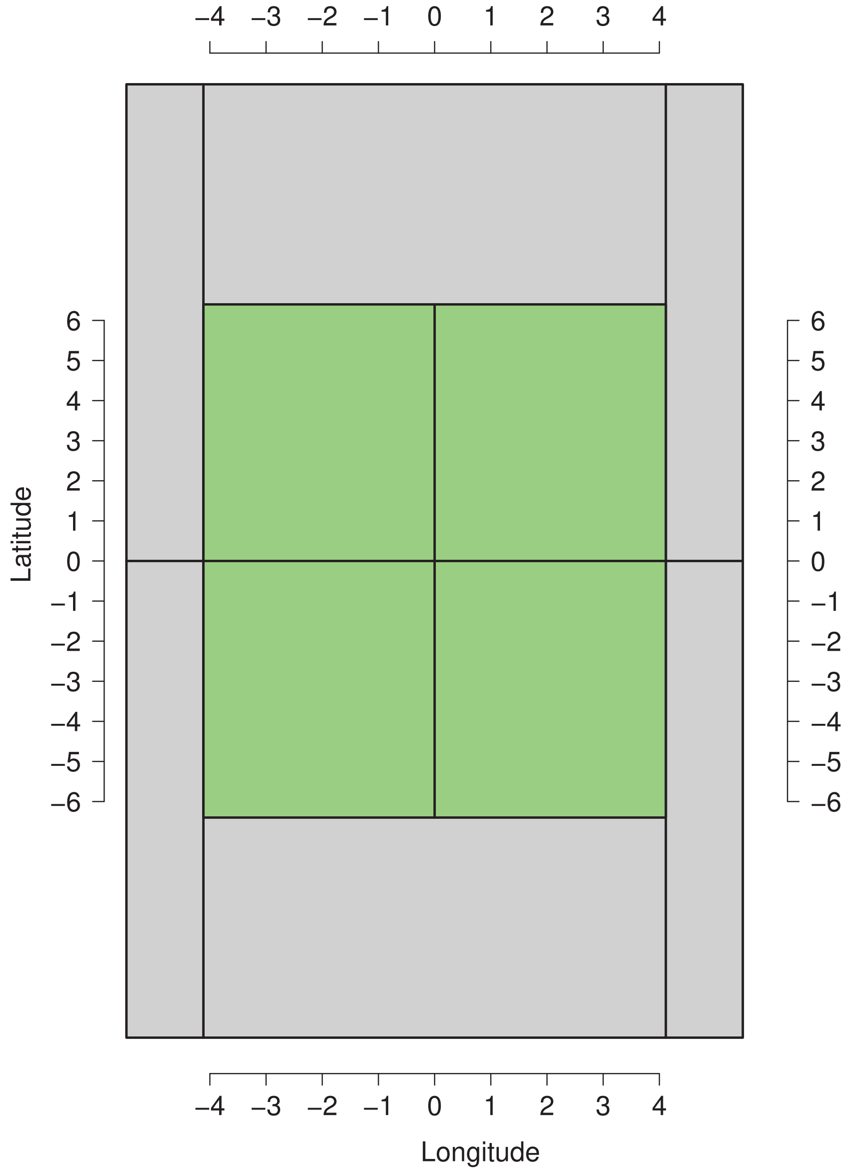

Figure 1: Scheme of a tennis court with units for the longitude and latitude.

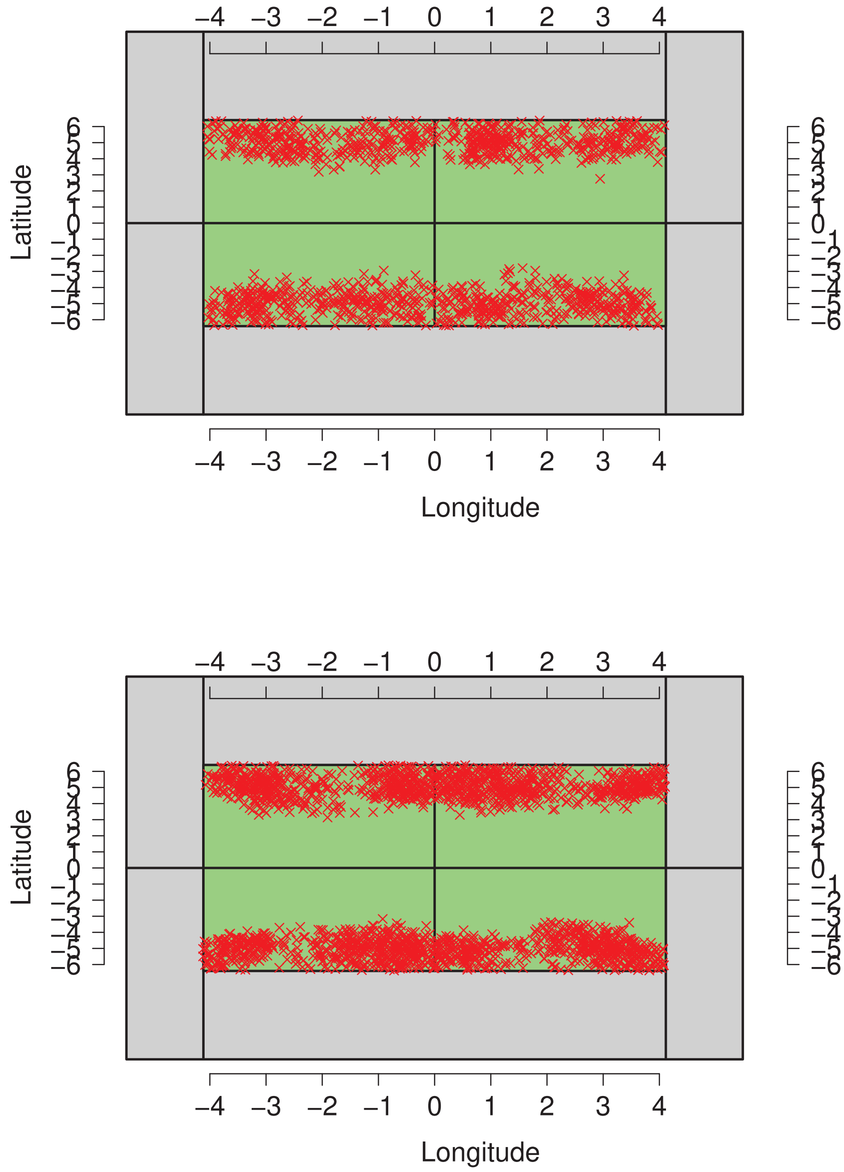

Figure 2: Scheme of a tennis court with observed locations of services for females (top) and males (bottom)

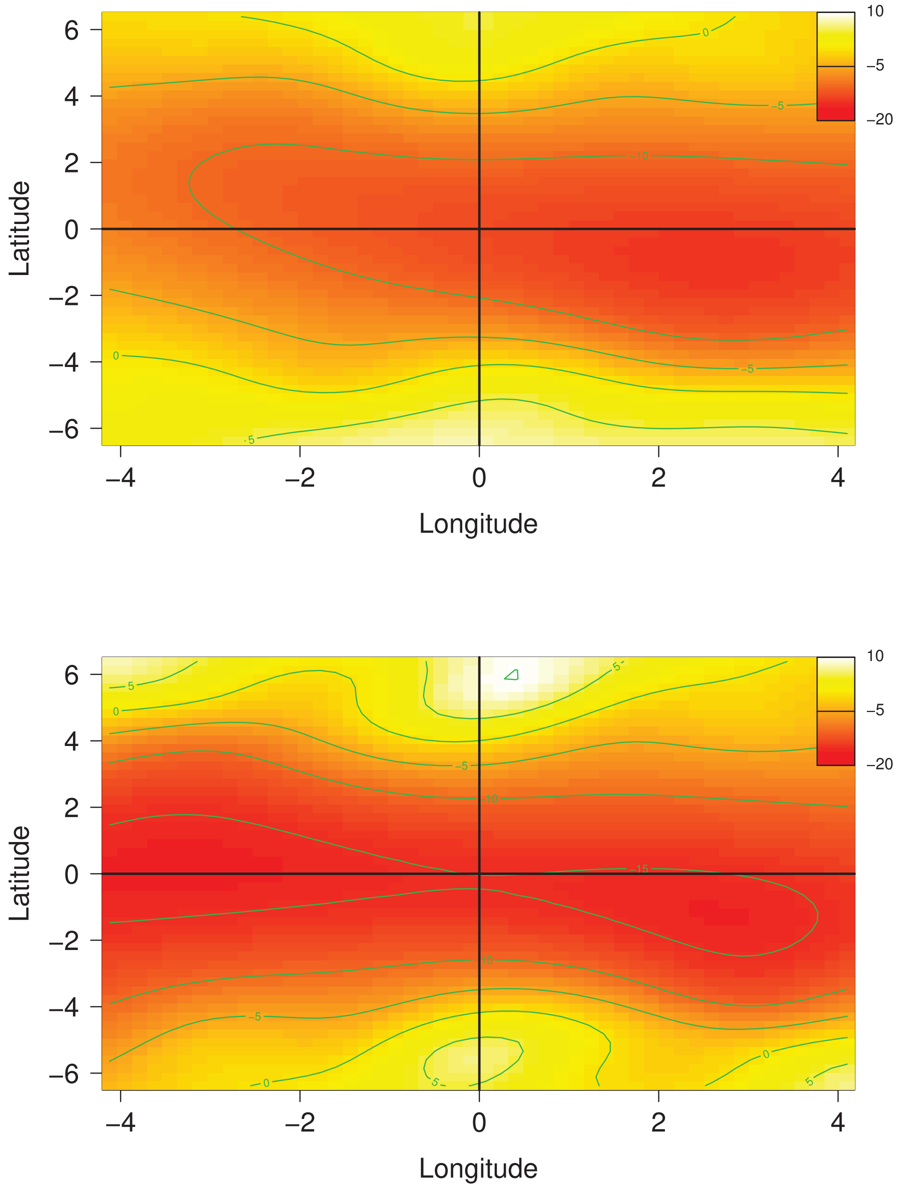

Figure 3: Two-dimensional visualization of the simultaneous isotropic partial effect of the positioning of the service on its speed for females (top) and males (bottom)

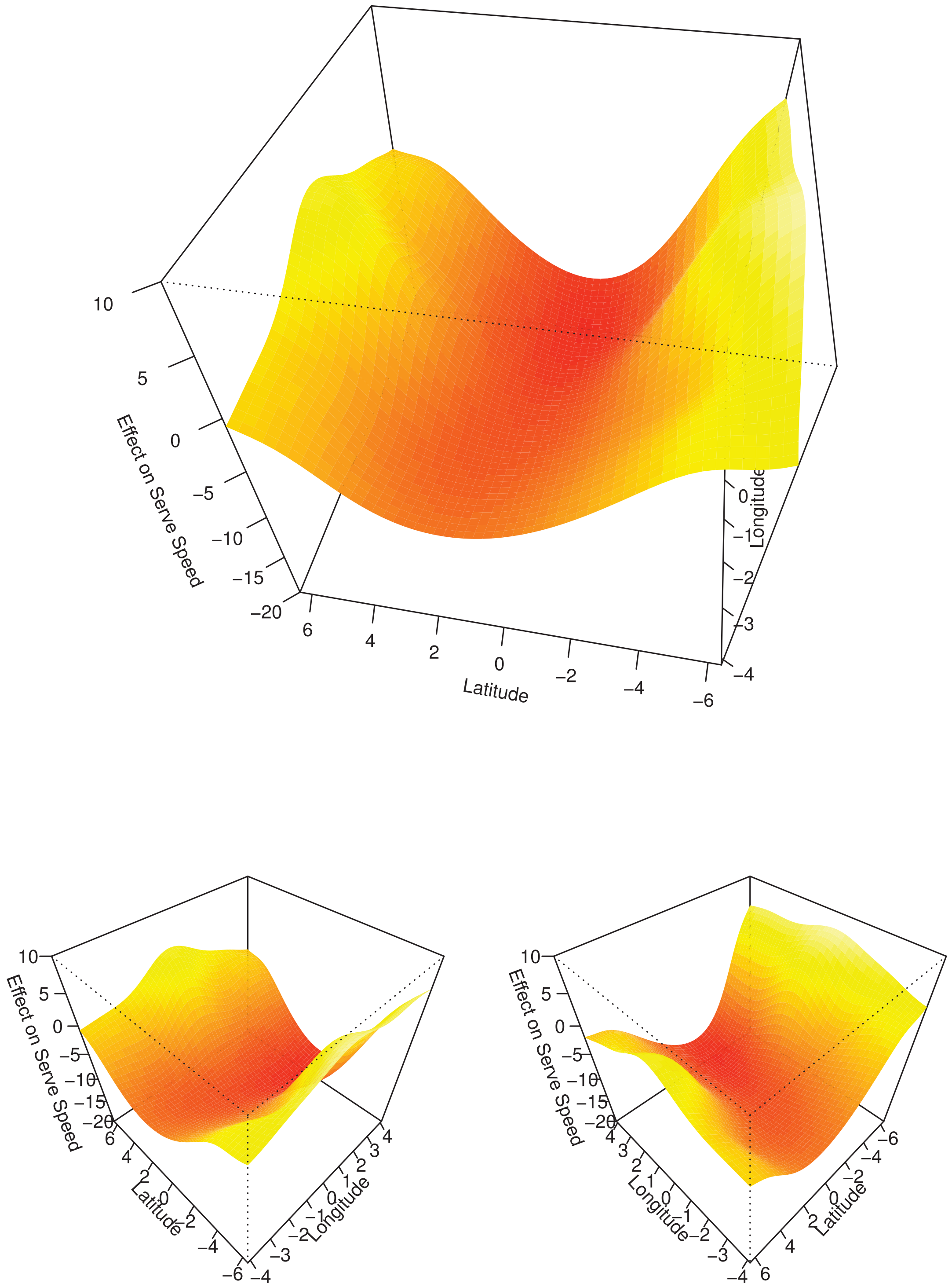

Figure 4: Three-dimensional visualization of the simultaneous isotropic partial effect of the positioning of the service on its speed from different perspectives for females

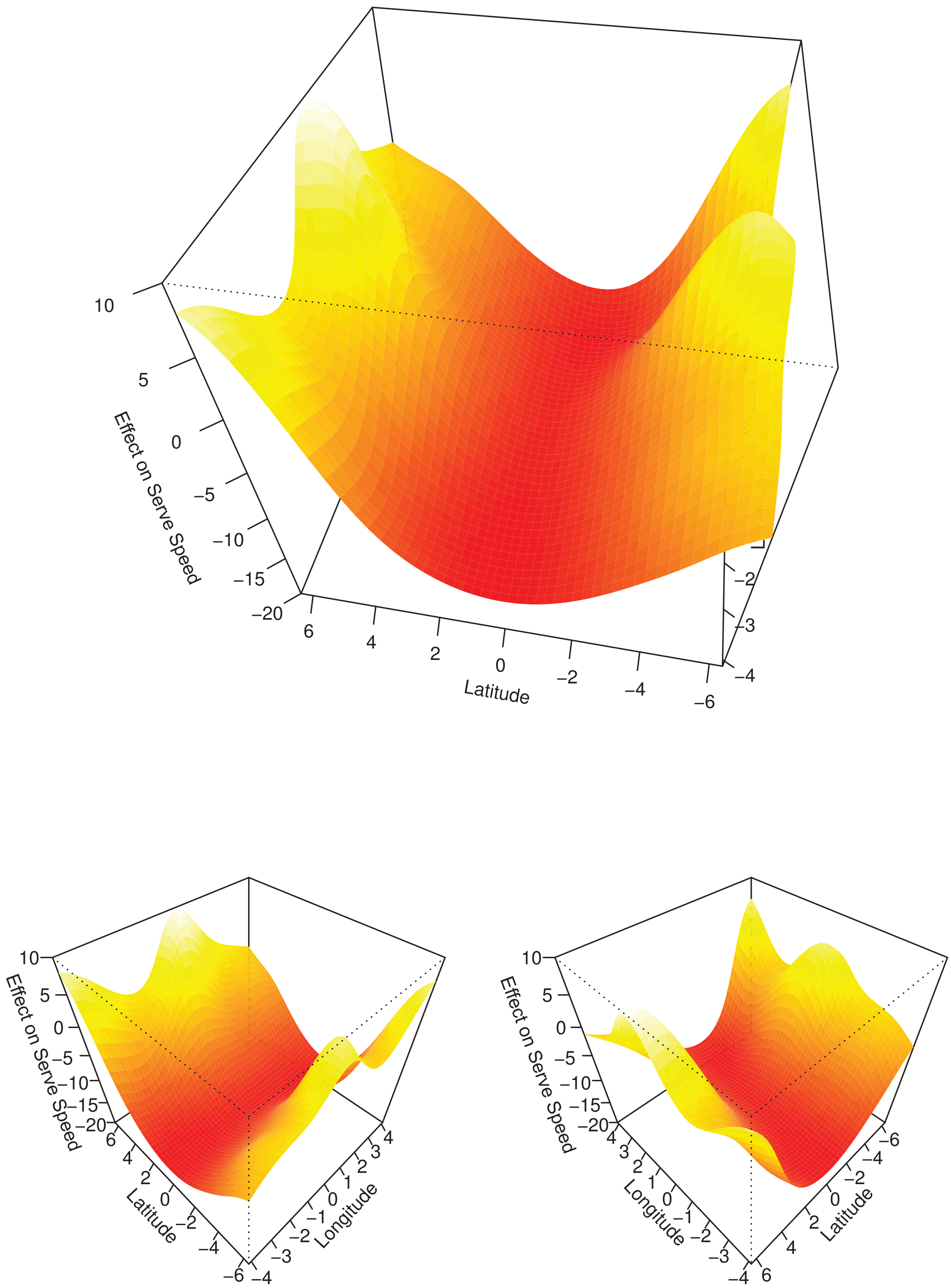

Figure 5: Three-dimensional visualization of the simultaneous isotropic partial effect of the positioning of the service on its speed from different perspectives for males

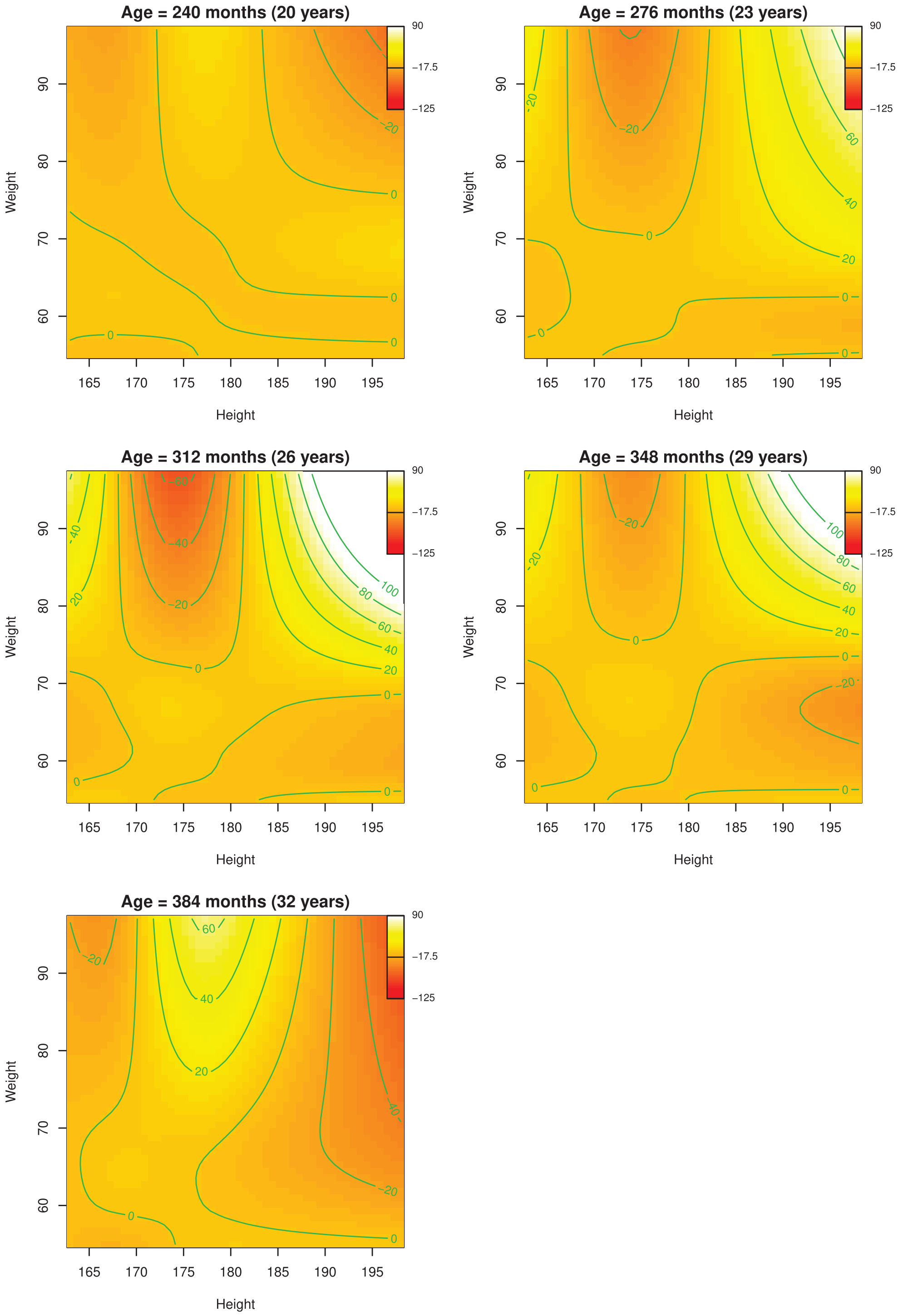

Figure 6: Two-dimensional visualization of the simultaneous partial effect of weight, height and age on the serve speed by holding age constant for eight selected values for females

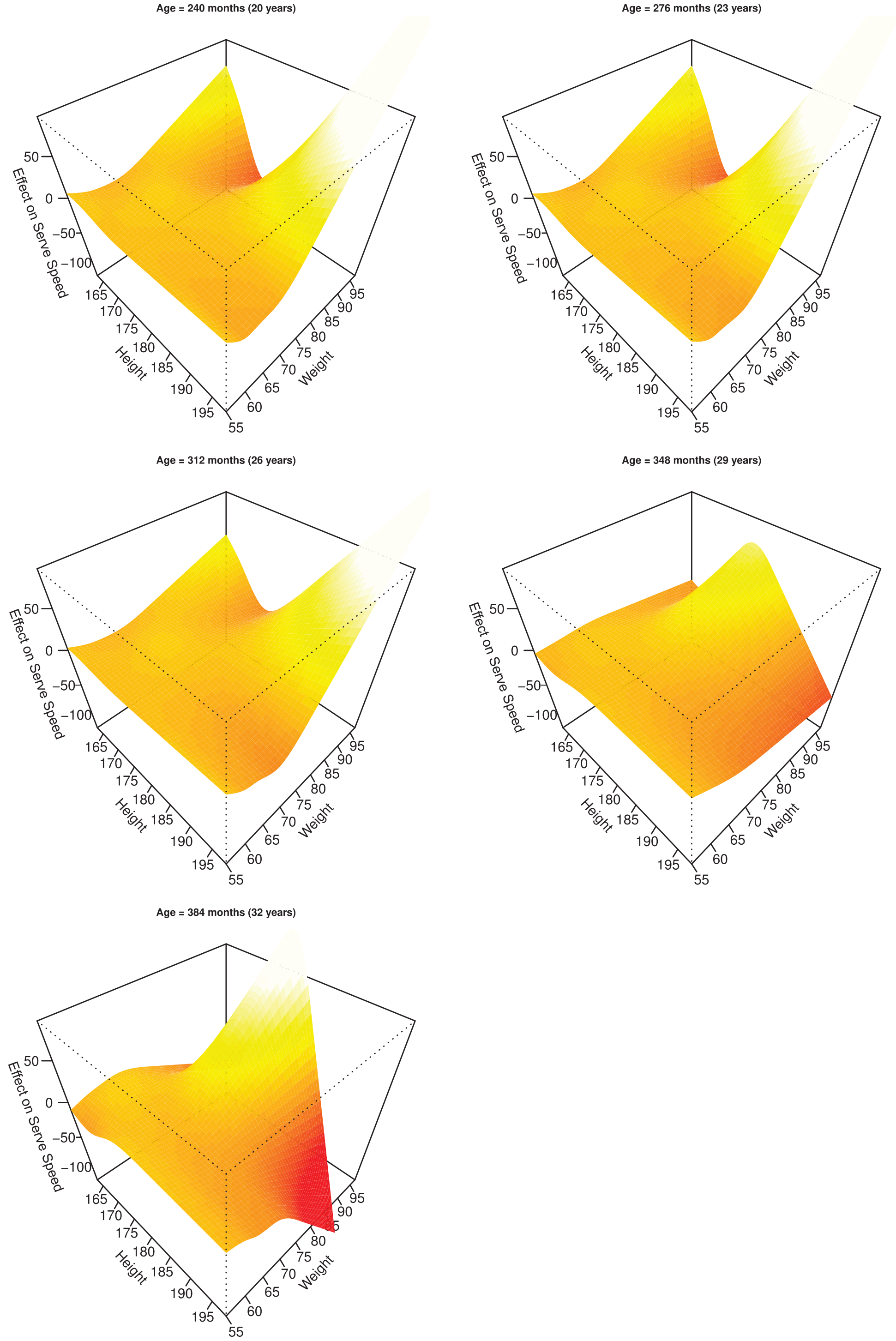

Figure 7: Three-dimensional visualization of the simultaneous partial effect of weight, height and age on the serve speed by holding age constant for eight selected values for females

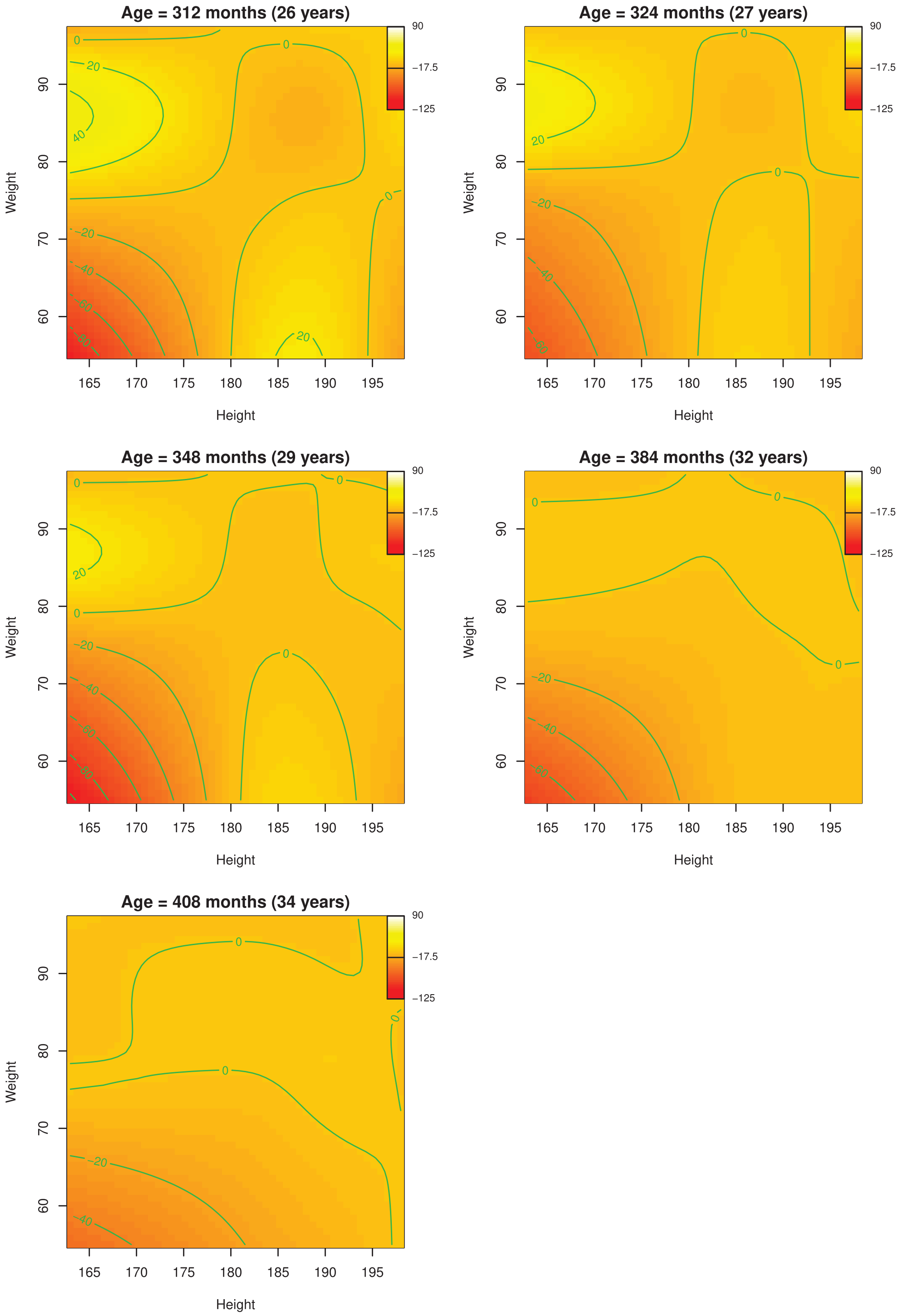

Figure 8: Two-dimensional visualization of the simultaneous partial effect of weight, height and age on the serve speed by holding age constant for eight selected values for males

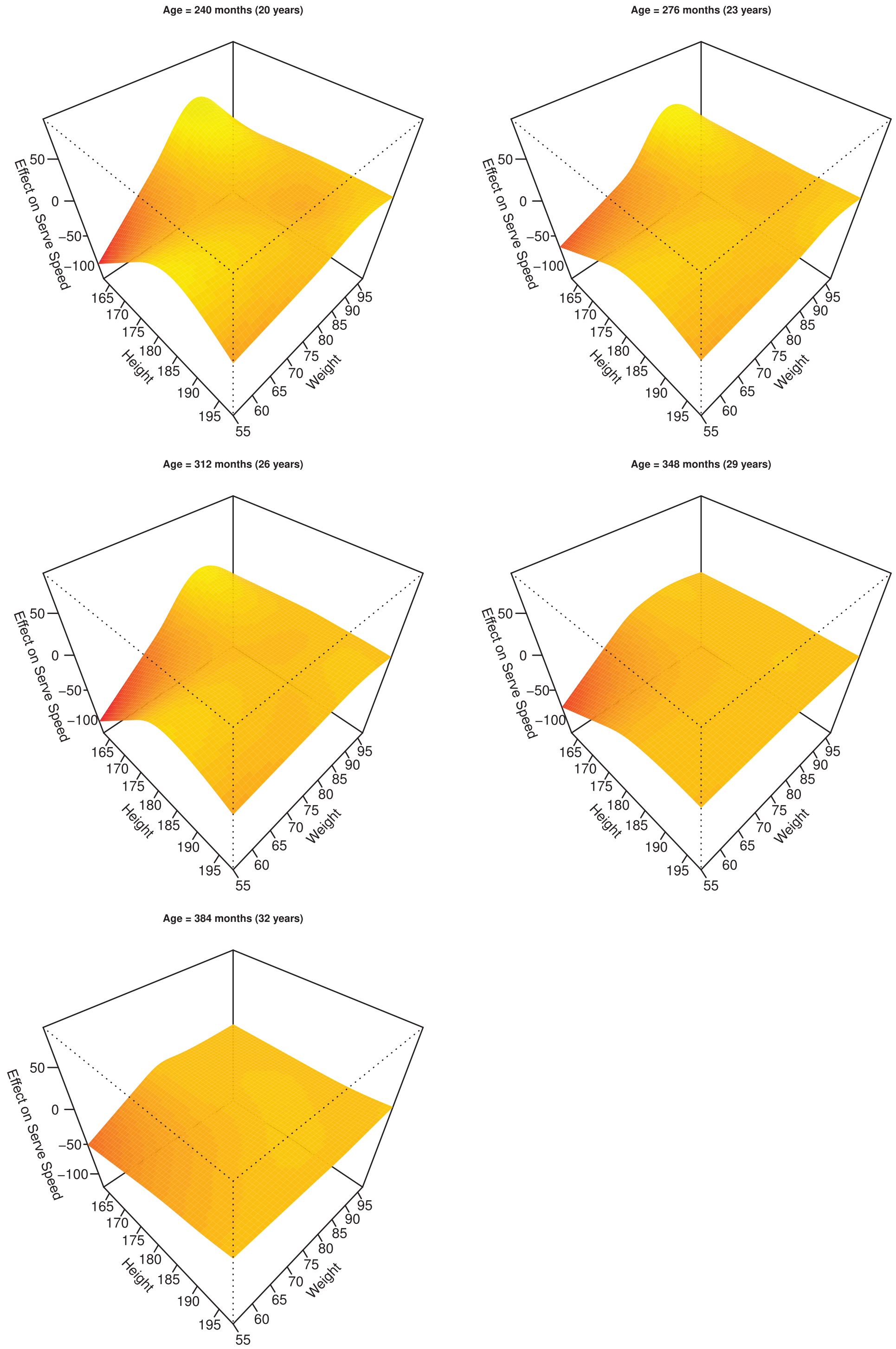

Figure 9: Three-dimensional visualization of the simultaneous partial effect of weight, height and age on the serve speed by holding age constant for eight selected values for males

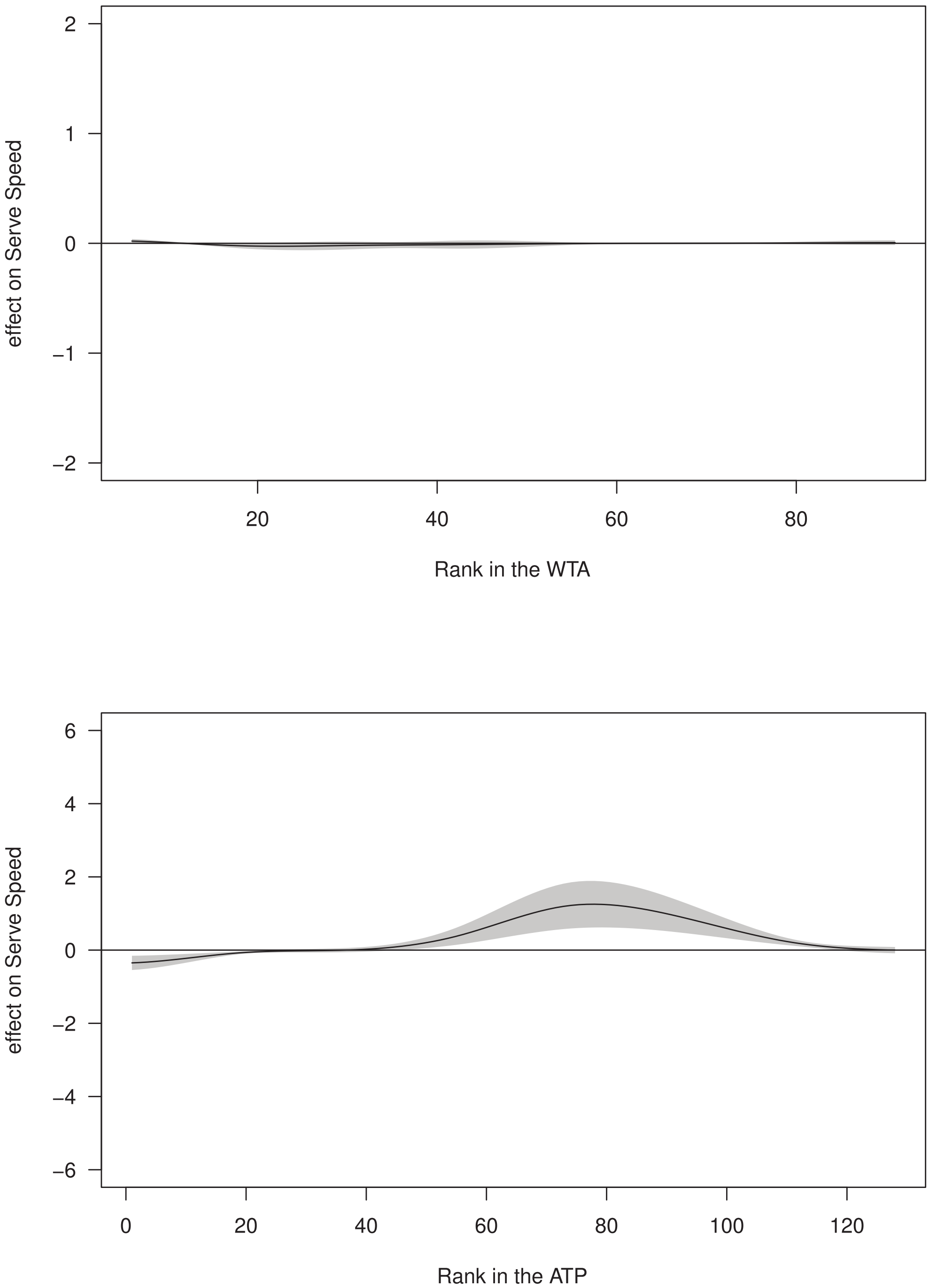

Figure 10: Smooth partial effect of the ATP / WTA position on the serve speed with pointwise 95% confidence bands for females (top) and males (bottom)

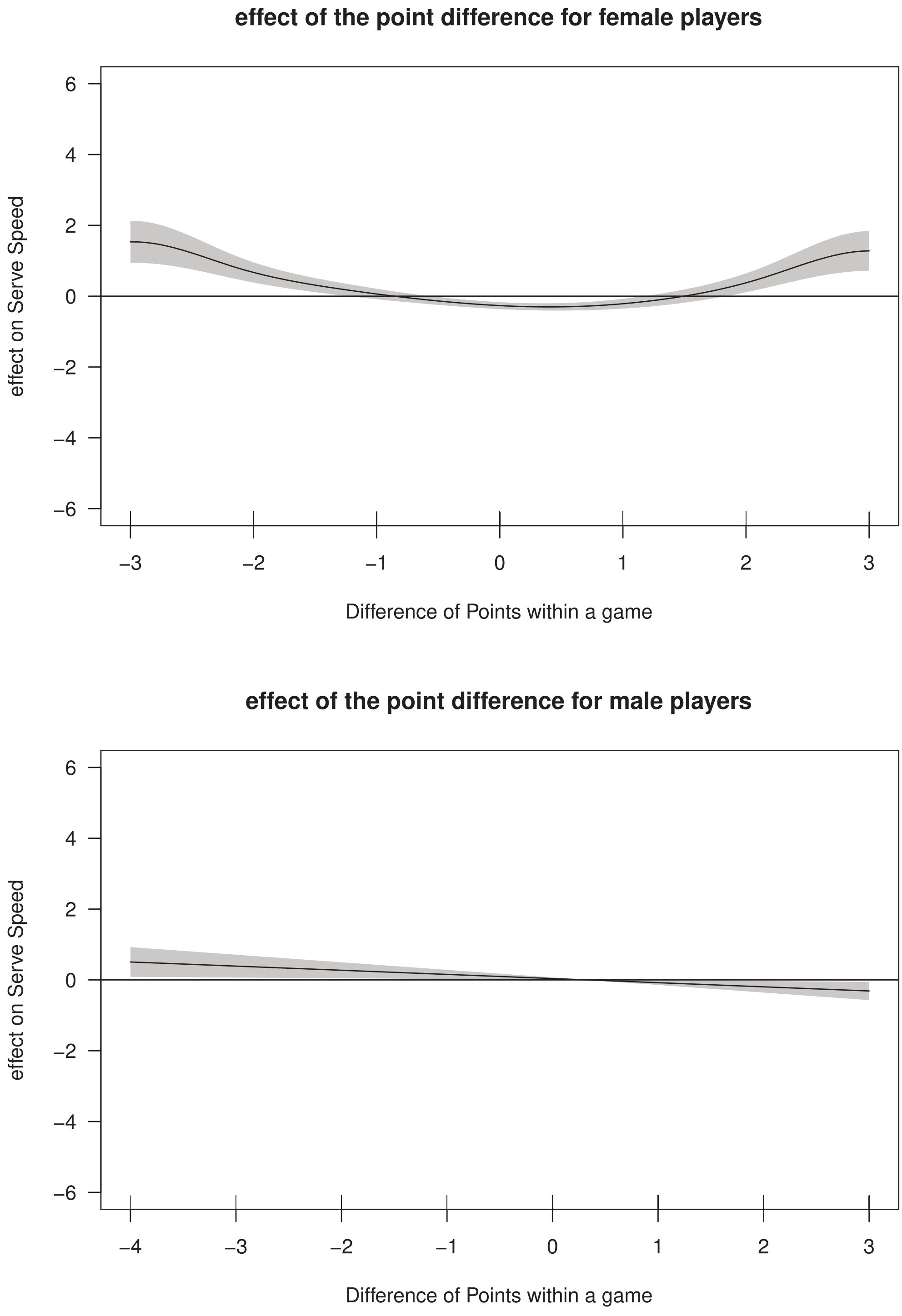

Figure 11: Smooth partial effect of the point difference within a game on the serve speed with pointwise 95% confidence bands for females (top) and males (bottom)

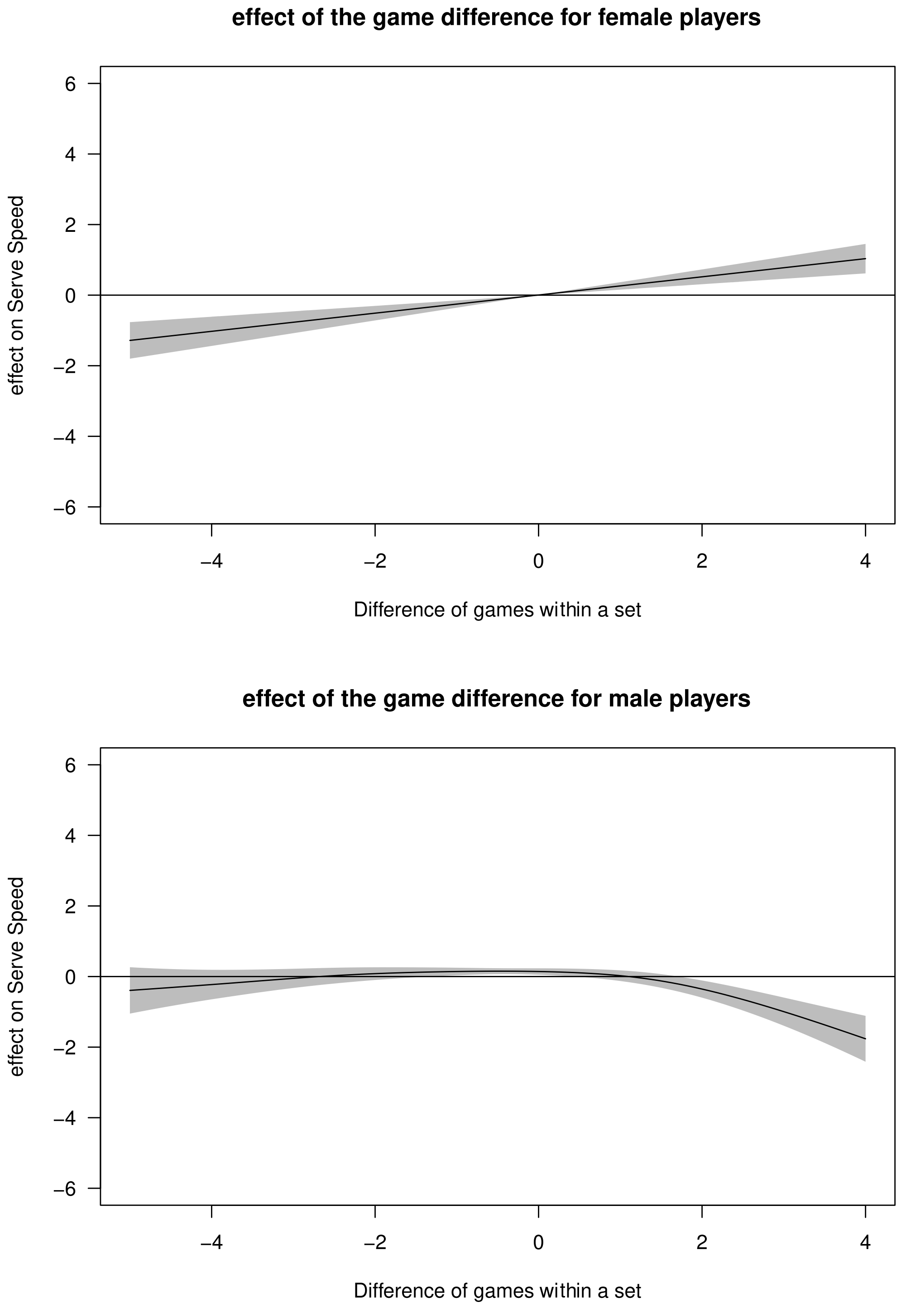

Figure 12: Smooth partial effect of the game difference within a set on the serve speed with pointwise 95% confidence bands for females (top) and males (bottom)

Table 1: Definition of the spatial variables

Variable	Definition
Longitude	The final position of the serve in the horizontal perspective from the server. The values are centered around the middle line and have a range of 8.223 meters
Latitude	The final position of the serve in the vertical perspective from the server. The values are centered around the net and have a range of 12.764 meters

Table 2: Definition of the variables for player characteristics

Variable	Definition
Rank	The ATP or WTA World-Rank of the player. The value is captured one week prior to the start of the tournament from the ATP or WTA website.
Age	The age of the player, measured in months. The value is captured one week prior to the start of the tournament from the ATP or WTA website.
Height	The height of the player, measured in centimeters. The value is captured from the ATP or WTA website.
Weight	The weight of the player, measured in kilograms. The value is captured from the ATP or WTA website.

Table 3: Definition of the match variables

Variable	Definition
Round	The stage of the tournament with 1 being the lowest value for the first round of matches and 5 being the highest possible value for the final match. We define dummy variables for the rounds > 1 yielding round 1 to be the reference.
Tie-Break	Dummy variable which takes the value of 1 if the serve takes place during a Tie-Break and 0 otherwise (only observed for males)
Second Serve	Dummy variable which takes the value of 1 if the serve is "second serve". This implies that the player made an error during his/her first serve. This serve is then the last chance before he/she is penalized by a point.
D_1	Dummy variable that takes the value of 1 if the set score is tied at 0,0.
D_2	Dummy variable that takes the value of 1 if the set score is 0,1. The serving player is behind.
D_3	Dummy variable that takes the value of 1 if the set score is 1,0. The serving player is ahead.
D_4	Dummy variable that takes the value of 1 if the set score is tied at 1,1.
Point Difference Game	The number of points won by the player who is currently serving minus the number of points won by the receiver in the current game. The numbers are taken prior to the serve.
Game Difference Set	The number of games won by the player who is currently serving minus the number of games won by the receiver in the current set. The numbers are taken prior to the serve.

Table 4: Summary statistics for male players

variable	full sample (n=2191)				D_1 (n=978)				D_2 (n=504)				D_3 (n=473)				D_4 (n=236)			
	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max
Serve Speed	105.4	14.3	72	134	105.1	14.5	74	134	106.0	14.1	74	132	104.6	13.8	78	132	106.9	14.8	72	132
Rank	35.3	50.1	1	315	40.3	54.8	1	315	33.9	32.3	2	167	28.6	58.9	1	315	30.6	38.1	2	128
Age	351.6	29.8	308	408	353.9	29.7	308	408	344.6	27.1	308	395	352.5	30.8	308	408	354.8	31.0	308	393
Height	187.7	6.3	178	198	187.4	6.4	178	198	189.2	6.6	178	198	187.0	5.1	178	198	187.4	6.9	178	198
Weight	82.8	7.6	70	97	82.5	7.6	70	97	83.6	8.6	70	97	81.4	6.0	70	97	85.2	7.1	73	97

Table 5: Summary statistics for female players

variable	full sample (n=21312)				D_1 (n=618)				D_2 (n=255)				D_3 (n=242)				D_4 (n=197)			
	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max	mean	std.	min	max
Serve Speed	85.6	12.0	54	114	85.7	11.6	54	114	88.1	11.9	58	114	81.4	11.3	54	110	87.4	12.6	54	114
Rank	18.5	17.7	6	91	19.1	18.7	6	91	23.9	23.9	6	91	15.4	10.1	7	38	13.5	7.3	7	30
Age	322.4	41.1	232	387	323.6	40.1	232	387	319.0	45.9	232	383	325.2	39.7	254	387	319.5	39.2	254	383
Height	170.4	6.2	163	182	170.5	6.4	163	182	171.8	5.8	163	178	167.7	6.1	163	182	171.5	5.5	164	182
Weight	61.8	4.4	55	74	61.7	4.2	55	62.7	62.7	4.9	5.7	74	60.4	3.2	55	70	62.9	4.7	59	74

Table 6: Summary of model (12)

Dep. Var. *Serve Speed*	Estimates Females	Estimate Males
Constant	$\mathbf{91.87}^{***}$ $(\mathbf{34.65})$	$\mathbf{113.30}^{***}$ $(\mathbf{118.73})$
Tie-Break	—	-0.97 (-0.96)
Second Serve	$\mathbf{-13.08}^{***}$ $(\mathbf{-32.97})$	$\mathbf{-18.48}^{***}$ $(\mathbf{-47.09})$
Round 2	-0.78 (-0.35)	-1.79 (-1.62)
Round 3	-0.16 (-0.08)	-0.33 (-0.39)
Round 4	2.41 (0.74)	0.43 (0.69)
Round 5	3.96 (1.16)	$\mathbf{2.73}^{*}$ $(\mathbf{2.00})$
D_2	-0.33 (-0.60)	0.46 (0.97)
D_3	$\mathbf{-1.38}^{**}$ $(\mathbf{-2.43})$	$\mathbf{1.07}^{*}$ $(\mathbf{2.20})$
D_4	$\mathbf{-2.37}^{***}$ $(\mathbf{-3.67})$	-0.47 (-0.76)
$D_4 \times$ Round 5	0.90 (0.54)	—
$\widehat{Var}(\gamma)$	43.88	8.81
$\widehat{Var}(\eta)$	5.59	1.00
R_c^2	0.71	0.82

Data Source: Hawk-Eye. Robust standard errors. t-statistics in parentheses. Bold faced coefficients are statistically significant. $^{\cdot}$, *, ** and *** respectively indicate significance at the 10%, 5%, 1% levels and almost 0% levels.