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Discouragement effect and intermediate prizes in multi-stage contests: Evidence from Davis Cup[☆]

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ABSTRACT

The discouragement effect of being the lagging player in multi-stage contests is a well-documented phenomenon. In this study, we utilize data from 2447 Davis Cup matches in team tennis tournaments to test the effect of being behind or ahead on individuals' performance with and without intermediate prizes. Using several different strategies to disentangle the effect of being ahead in the interim score from the effect of selection, we find the usual discouragement effect. However, the discouragement effect disappears after the introduction of intermediate prizes in the form of ranking points. The lagging favorite had close to a 20-percentage point greater probability of winning compared to matches without such a prize. We show that this result is not driven by the selection of better players into tournaments with intermediate prizes. As predicted by previous theoretical studies, our empirical findings suggest that intermediate prizes may mitigate or even eliminate the ahead–behind effects that arise in multi-stage contests.

1. Introduction

One of the fundamental relationships in the economic environment in general and in tournament settings in particular is the relationship between incentives and performance. It has been well-documented that higher stakes enhance the performance of higher ability agents (Rosen, 1986; Ehrenberg and Bognanno, 1990; Lazear, 2000; González-Díaz et al., 2012; Jetter and Walker, 2015). Another important feature that is frequently found in multi-stage tournaments is ahead–behind asymmetry, where one contestant has an advantage over the other by having a better previous performance. Such situations may occur in R&D contests (Harris and Vickers, 1987), political campaigns (Klumpp and Polborn, 2006), job promotions (Tsoulouhas et al., 2007), and sports competitions (Malueg and Yates, 2010). This ahead–behind asymmetry creates a discouragement effect, according to which a lagging player has fewer incentives to exert costly efforts and therefore is more

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likely to lose in the following stages.[1] There is also a psychological explanation according to which ahead–behind asymmetry creates additional psychological pressure on the lagging player, which in turn harms his/her performance and reduces his/her probability of winning (Apesteguia and Palacios- Huerta, 2010; Genakos and Pagliero, 2012; Palacios-Huerta, 2014; Genakos et al., 2015; González-Díaz and Palacios-Huerta, 2016).

The combination between incentives and ahead–behind asymmetry was studied theoretically by Konrad and Kovenock (2009). They showed that intermediate prizes in multi-stage contests might mitigate the discouragement effect on the lagging player. The intuition behind their result is that a lagging player has more incentive to exert effort in every stage, because the player is competing for an additional prize that can be achieved regardless of the interim gap between the players. In a more recent theoretical study, Fu et al. (2015) investigated multi-stage contests, where individuals from two teams compete in pairwise battles. In their model, a team that wins the majority of battles receives a team prize and, additionally, the winner of each pairwise battle receives an individual prize. The authors established the so-called strategic neutrality, according to which the existence of an individual prize eliminates any ahead–behind effect and the probability of winning in every single battle depends only on the players' innate ability, not on the outcome of the past battles.

In general, studying the performance of individuals within a team framework is an important economic and managerial task because in most professions, teamwork is the rule rather than the exception. For example, a recent report by the European Foundation for the Improvement of Living and Working Conditions (Eurofound, 2014) holds that, in 31 out of 37 sectors, teamwork prevails in over 50% of activities. However, studying the performance of individuals in non-experimental contests between teams is not a trivial task because reality rarely creates situations that allow a clear view of the contribution of individuals to a team's output. Therefore, the empirical literature is scarce and based mostly on laboratory experiments.[2] A notable exception is the orange grove field experiment conducted by Erev et al. (1993), where the authors found that inter-group competition produced a significantly higher output than in the case where subjects were paid according to their individual output or when they received an equal share of the group's total output.

In this paper, we are motivated by the scant empirical evidence from non-experimental settings on the performance of individuals within a team framework, in general, and on the interactive role of incentives and ahead–behind asymmetry in particular. Therefore, the aim of this paper is to test empirically the effect of ahead–behind asymmetry on individuals' performance in multi-stage contests between teams with and without intermediate prizes using data from tournaments among highly competitive and extensively trained professionals. To that end, we utilized data from tennis matches in the Davis Cup tournament, which is the premier international team event in men's tennis. Each tie between two nations consists of five separate pairwise matches. A team that wins three matches wins the tie.[3] Therefore, by construction, before the second and fourth matches of the tie, one of the teams should have more wins than the other. This structure allows us to study the performance of the lagging/leading players.[4] More importantly, a change of tournament rules in 2009 makes it feasible to study the effect of intermediate prizes. According to this change, between 2009 and 2015, a player who won a single match in the World Group received individual ranking points. In other years and groups, there were no individual prizes for winning a single match.

Utilizing data from professional sports where contestants have strong incentives to win has several advantages. First, it eliminates any possible skepticism about applying behavioral insights obtained in a laboratory to non-experimental settings (Hart, 2005). Second, sports contests involve high-stake decisions that are familiar to the agents. Third, it provides a unique opportunity to observe and measure performance as a function of variables such as heterogeneity in abilities and prizes. Fourth, at each point in time, the contestants have complete information about the interim score and the status of the tournament. Indeed, as Kahn (2000) argues, sports data are very unique in that they embody a large amount of detailed information that can be used for research purposes.[5]

Since being ahead or behind in the interim score is not determined randomly (for example, home teams or stronger tennis nations have a greater probability of being ahead in the interim score), we use several different strategies to disentangle the effect of leading/lagging from the effect of selection. First, we estimate the average treatment effect of leading/lagging by using the distance-weighted radius matching approach with bias adjustments suggested by Lechner et al. (2011) that has

[1] For example, Klumpp and Polborn (2006) theoretically showed that in sequential elections between two candidates, the loser in the first district had less incentive to exert costly effort in the second district, thereby making it more likely for the winner in the first district to win again. Malueg and Yates (2010) found that the winner of the first set in a tennis match between equally skilled players was more likely to win the second set. Finally, Gill and Prowse (2012) documented the discouragement effect in an experimental sequential tournament by showing that the second mover reacted negatively to the effort of the first mover.

[2] For example, in experimental settings Van Dijk, Sonnemans and Van Winden (2001) showed that piece-rate and team payment schemes yield the same efforts, whereas a tournament scheme leads to greater effort. In another experimental study, Dohmen and Falk (2011) found that the output in a team's revenue-sharing scheme was higher than in a fixed-payment structure. For additional references on different aspects in team contests, see the comprehensive review of Sheremeta (2017).

[3] Obviously, in our analysis we use only matches with undecided ties in which no team won three single matches. See more details on the structure and rules of the Davis Cup competition in Section 2.

[4] It is worth mentioning the paper of Berger and Pope (2011) who showed that basketball teams have a greater probability of winning if they are lagging by a very small margin at half-time.

[5] Numerous studies have used sports data to explain economic behavior. For instance, Walker and Wooders (2001) used tennis matches to test the theory of mixed strategy equilibrium empirically. Palacios-Huerta (2003) tested the Minimax theorem using penalty kicks in professional soccer. Finally, Pope and Schweitzer (2011) provided evidence of loss aversion in professional golf.

been shown to have superior finite sample properties relative to a broad range of propensity score-based estimators (Huber et al., 2013). We also use Oster's (2019) recently proposed bias-adjusted estimator.

Based on the analysis of 2447 matches from 966 international ties, we find a significant ahead–behind influence on players' performance, which is mostly pronounced in match 4, which is likely because of the unique schedule of the tie. More specifically, we find that the favorite (higher ranked player) has about a 10-percentage point greater probability of winning a match if his team is leading. However, the main contribution of this paper is that we have a unique opportunity to study the performance of players in tournaments with and without intermediate prizes. As already mentioned, in 2009, the Association of Tennis Professionals (ATP) decided to assign ranking points to the winner of a single match in the Davis Cup. These points are taken into account in determining the World Ranking list. Based on this list, players enter the most prestigious tournaments with the possibility of earning large monetary prizes.[6]

Investigating matches in the World Group with and without intermediate prizes (ranking points, in our case), we find that before the decision to assign ranking points for winning a single match, a favorite from the leading team was more likely to win in match 4 than the favorite from the lagging team. However, from 2009 to 2015, the gap between the probabilities of the lagging and leading favorites' winning disappeared. We also show that this result is not driven by the selection of better players into the tournament after the change. Our findings suggest that the introduction of intermediate prizes mitigates and may even eliminates the ahead–behind effects that arise in multi-stage contests.

The remainder of the paper is organized as follows. Section 2 describes the Davis Cup setting. The data and descriptive results are detailed in Section 3. Section 4 describes the estimation strategy. In Section 5 we present the evidence about the ahead–behind effect. Section 6 reports the effect of intermediate prize. Finally, in Section 7 we offer concluding remarks.

2. Description of the Davis Cup

The Davis Cup is an international men's tennis team competition played annually between teams from participating countries. The tournament is structured into five hierarchical levels: World Group, Group 1, Group 2, Group 3, and Group 4. The World Group is the top competition level, comprised of 16 participating nations. Nations that are not part of the World Group compete in one of the lower four groups. Teams in World Group, Group 1 and Group 2 compete in elimination tournaments according to which the winning team advances to the next round and the losing team is eliminated. Groups 3 and 4 use a round-robin structure according to which teams play against each other in pairwise ties.[7]

A tie signifies a competition round between two competing countries. In the World Group, for example, the 16 nations play eight pairwise ties in the first round (the round of Last 16). The eight winners of this round compete in four Quarterfinal ties. The four winners play two Semifinal ties. Finally, the two winners play the Final tie.

Teams from World Group to Group 2 that lose in the first round face the possibility of being relegated to a lower group for next year's tournament. Promotion or relegation in the World Group is decided in Play-off rounds played between losers of the first round in the World Group and winners of Group 1. To be promoted from Group 2 to Group 1, a team needs to win in three different rounds. A team that loses in three different rounds in Groups 1 and 2 is relegated to a lower group.

Each tie in the World Group, Group 1 and Group 2 consists of five rubbers (matches), namely, four singles matches and one doubles match. Each team consists of several players who are seeded according to their individual World Rankings. On the first day of each tie, two matches are played between the first seeded player of one team and the second seeded of another team. The schedule of the first day is determined randomly. The doubles match is always scheduled as match number 3, which takes place on the second day of the tie. On the third day, the two top seeded players from each team always compete against each other in match 4 and two second seeded players from each team always compete in match 5.

The first team that wins three rubbers wins the tie and progresses to the next round to play a tie against another team. If the tie has not already been decided in favor of one team (no team won three rubbers), then the remaining rubbers are termed live rubbers, which are played in the form of best-of-five sets. Additionally, all dead rubbers are played in the form of best-of-three sets.[8] Finally, between 2009 and 2015 a player who won a single rubber in the World Group received ranking points as long as the rubber was defined as a live rubber. In other years and groups there were no individual prizes for winning a single rubber.

[6] To emphasize the importance of these points, it is worth mentioning that many players decided not to participate in the Rio 2016 Olympic tennis tournament in part because of the absence of ranking points in this tournament, which obviously reduced the incentives for participation. See for example, https://www.nytimes.com/2016/05/30/sports/tennis/points-and-prize-money-mean-more-to-olympic-tennis-holdouts.html (last accessed on 12/07/2017). For additional details on the importance of ranking points see Jetter and Walker (2017).

[7] It has been shown theoretically (Krumer et al., 2017a) and confirmed empirically (Krumer and Lechner, 2017) that the probability of winning depends on the schedule of the round-robin tournament. In addition, Krumer et al. (2017b) showed that the probabilities of the favorites' winning differ in round-robin and elimination tournaments. Therefore, we concentrate only on the elimination structure used in the World Group, Group 1 and Group 2.

[8] For additional details see https://www.daviscup.com/en/organisation/rules-regulations.aspx. Last accessed on 10/07/2017.

3. Data and variables

3.1. Data

As already stated, since there is a difference between the round-robin and elimination formats, our dataset consists of Davis Cup matches in the World Group, Group 1 and Group 2 that use the latter format. In addition, we consider only matches between individuals and do not use matches between doubles because, in most cases, players do not specialize in doubles and play these types of matches only occasionally.

The data were collected from several websites (see Appendix A for a list of all sources). All Davis Cup matches played between 2003 and 2015 are present in the datasets. For every match, information is available regarding the names of the players, their previous head-to-head victories and losses against the opponent, and each player's 52-week ranking prior to the beginning of each match. The ranking is used as a measure of the players' abilities and is calculated and updated weekly by taking into account all of the player's results in professional tournaments over the previous 52 weeks. Apart from individual level data, information on the location, group type, year, and tournament round for each tie is also available.

In all, the dataset consists of 4206 Davis Cup matches. However, we consider only live rubbers (i.e., matches that are still crucial in deciding which team wins the tie) because dead rubbers are in the form of best-of-three sets and usually substitute players compete in these matches. Therefore, 1198 dead rubber matches were eliminated. In addition, another 561 matches lacked information regarding the current ranking of one of the players, or were not played to completion, and therefore were eliminated as well.[9] Dropping all of these matches leaves 966 Davis Cup ties, consisting of 2447 matches.

3.2. Variables

For each match, we first define the higher ranked player as the favorite and the lower ranked one as the underdog. Then, we estimate the probability that the favorite will win the match. Accordingly, we assign the dependent variable a value of one if the favorite player won and zero otherwise.

It is important to note that a favorite is lagging if the interim score of the tie before the respective match is 0:1 or 1:2 in favor of the opponent's team. A favorite is leading if the interim score of the tie before the respective match is 1:0 or 2:1 in favor of his team. Therefore, to estimate the effect of being ahead/behind in the score, we coded a dummy variable that equals one if the *favorite is lagging* before the respective match and zero otherwise. Similarly, we coded a dummy variable that equals one if the *favorite is leading* before the respective match and zero otherwise.

The probability of the favorite beating the underdog is obviously a function of their relative strength. We use two different measures in order to control for the relative strength of the two players. The first one, *DiffRank*, is defined as $\log_2(FavoriteRank) - \log_2(UnderdogRank)$, where *FavoriteRank* and *UnderdogRank* are the most current World Rankings of the favorite and the underdog, respectively. The main advantage of this measure is that the differences in the players' quality are not linear but rather grow at an increasing rate as we move up the ranking. Thus, a difference of one position in the ranking list corresponds to a smaller difference in quality if the players are at the bottom of the list, but to a more substantial difference when we compare the top contestants (see also Klaassen and Magnus, 2001). Table 1 shows that the mean value of this measure is negative due to the fact that the favorite is associated with a lower ranking number. The second measure that may provide information about the differences in the abilities of the two players is the difference in head-to-head victories prior to the respective match. Thus, for each match we calculate the number of head-to-head victories in favor of the favorite. This variable, *DiffH2H,* is measured as the difference between the numbers of matches that the favorite and the underdog won in previous head-to-head matches against each other.

We also control for the home advantage, which was found to play a significant role in professional tennis (Koning, 2011). Thus, the variable indicating that the favorite has a home advantage receives the value of one if the favorite competes at home and zero otherwise. In addition, we include dummies for each round and type of group categories. Finally, since starting from 2009 a single win in a live rubber of the World Group guaranteed ranking points, we coded a dummy variable that equals one if the match was in the World Group after 2009 and zero otherwise. The descriptive statistics of our dataset are presented in Table 1. It indicates that, on average, the favorite wins in 68.1% of cases if his team is lagging. It also shows that if the favorite's team is leading, his probability of winning is 80.4%. Using a 95% confidence interval, Fig. 1 shows that the favorite's share of wins when his team is leading (1:0 or 2:1) is significantly higher than when the interim score is a draw (0:0 or 2:2) or when the favorite's team is lagging (0:1 or 1:2). However, Table 1 also indicates that if the favorite is leading, he also has more of a home advantage, better head-to head performance, and a lower ranking index, which is associated with greater relative ability. Thus, in order to obtain the causal effect of being ahead/behind, we will use several estimation strategies that control for selection into treatment (leading/lagging). We discuss these strategies in the following section.

[9] Out of 561 eliminated matches due to missing information or matches that were not completed, 19 matches were from the World Group, 88 matches were from Group 1 and 454 matches were from Group 2. In seven matches from the World Group, one of the players did not have World Ranking. The corresponding numbers for Group 1 and Group 2 were 69 and 427, respectively.

Table 1
Descriptive statistics.

Variable name	Favorite is lagging		Draw		Favorite is leading	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Favorite Wins	0.681	0.466	0.741	0.438	0.804	0.396
DiffRank=$\log_2$ (Favorite Rank)−$\log_2$ (Underdog Rank)	−1.540	1.307	−1.687	1.427	−1.847	1.476
DiffH2H=Head to Head Wins Favorite – Head to Head Wins Underdog	0.204	1.286	0.146	0.993	0.302	1.128
Home Advantage to Favorite	0.437	0.496	0.511	0.500	0.590	0.492
World Group	0.361	0.481	0.357	0.479	0.337	0.473
Group 1	0.291	0.455	0.311	0.463	0.315	0.465
Group 2	0.348	0.477	0.332	0.471	0.347	0.476
Last 16	0.124	0.330	0.122	0.327	0.110	0.313
Quarterfinal	0.203	0.402	0.202	0.401	0.205	0.404
Semifinal	0.231	0.422	0.224	0.417	0.209	0.407
Final	0.155	0.362	0.179	0.384	0.196	0.397
Playoff	0.231	0.422	0.222	0.416	0.236	0.425
Playoff in Group 2	0.057	0.233	0.052	0.222	0.043	0.203
World Group before 2009	0.178	0.383	0.162	0.369	0.144	0.351
World Group after 2009	0.183	0.387	0.195	0.396	0.194	0.395
Observations	646		1037		764	

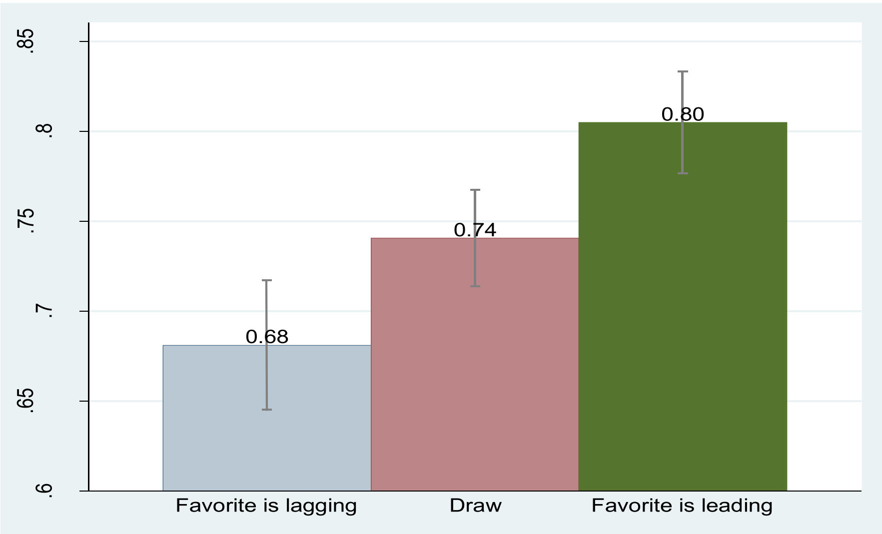

Fig. 1. Share of wins as a function of the status of the match.
Notes: This figure presents the means of the share of wins of a favorite at different statuses based on all data. 95% confidence interval is presented.

4. Estimation strategy

Studying whether being ahead or behind before a Davis Cup match gives an advantage to the favorite is a challenging task. A naïve approach of correlating a dummy variable for leading/lagging with the probability of winning a match will yield biased and inconsistent estimates because the status of being ahead or behind is not determined at random. Rather, as mentioned earlier, being ahead is a function of features specific to tennis such as home advantage, previous head-to-head meetings, and the difference in abilities between the other members of the teams. Furthermore, isolating an exogenous source of being ahead/behind in the score by using an instrumental variable approach seems unfeasible because any factor that might be associated with being ahead/behind is also likely to affect the probability of winning the match. In the absence of a valid instrument, we will use several alternative strategies to control for the endogeneity of leading or lagging in Davis Cup matches.

4.1. Radius matching estimator

Our main analysis is based on the radius-matching-on-the-propensity score estimator with bias adjustment (Lechner et al., 2011). Not only was it found to be very competitive among a range of propensity score related estimators, but also a later paper by Huber et al. (2013) actually demonstrated its superior finite sample and robustness properties in a large-scale empirical Monte Carlo study.[10] The main idea of this estimator is to compare treated and non-treated observations within a specific radius. The first step consists of distance-weighted radius matching on the propensity score. In contrast to standard matching algorithms where controls within the radius obtain the same weight independent of their location, in the radius matching approach, controls within the radius are weighted proportionally to the inverse of their distance to the respective treated observations to which they are matched. The second step uses the weights obtained from this matching process in a weighted linear or non-linear regression in order to remove biases due to mismatches. Because this approach uses all comparison observations within a predefined distance around the propensity score, it allows for greater precision than fixed nearest neighbor matching in regions in which many similar comparison observations are available.

4.2. Oster's bias-adjusted estimator

As a robustness check, we use Oster's (2019) bias-adjusted estimator. In order to isolate the selection bias and obtain the bias-adjusted treatment effect of leading/lagging, we use the following formula, which calculates the bias-adjusted treatment effect, β^*:

$$\beta^* = \tilde{\beta} - \delta\left[\beta^0 - \tilde{\beta}\right] \cdot \left(R_{\max} - \tilde{R}\right)/\left(\tilde{R} - R^0\right),$$

where $\tilde{\beta}$ and β^0 are the coefficients of the key variable in regressions with and without observed controls, respectively. $\tilde{R}$ and $R^0$are the R-squared values of these regressions, respectively. The bias-adjusted treatment effect calculated above is conditional on the size of two parameters: (1) the relative degree of selection on observed and unobserved variables (δ) and (2) the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls, $R_{\max}$. Like Altonji et al. (2005), Oster (2019) suggests that $\delta = 1$ may be an appropriate upper bound on δ. In addition, based on a sample of randomized papers from top journals, Oster determines that $R_{\max} = 1.3\tilde{R}$ may be a sufficient upper bound on $R_{\max}$. This criterion would allow at least 90% of randomized results from the above-mentioned papers to survive. Therefore, we follow the bounds on δ and $R_{\max}$ that Oster suggests and use them in our estimations.

5. Ahead–behind effect

5.1. Radius matching analysis

First, we conducted the analysis for the full dataset. As already discussed, there is a selection into being ahead/behind. Although the purpose of the propensity score estimation is only a technical one, namely, to allow the easy purging of the results from the effects of selection, it is nevertheless interesting to see which variables drive selection. In Table 2 we report the results for the propensity score estimation. We use two different specifications. In the first, we control for differences in rankings, previous head-to-head results and home advantage. In the second specification, we also control for specific features of the ties, such as the round of the tournament, the group, the year and whether the match is a World Group match before or after 2009. We can see that many variables are associated with being ahead/behind. This finding is not surprising because we would expect home players to be more likely to win and players from stronger countries have, on average, better teammates.

In Columns 1 and 2 of Table 3 we present the results for the radius-matching estimator where Panel A and Panel B report the average effects for lagging and leading, respectively. The clustered standard errors at the tie level are presented in parentheses. The results show that the effect of lagging is negative and significant. It reduces the favorite's probability of winning by about 5 percentage points. The effect of being ahead on the favorite's probability of winning is between 3.7 and 5.4 percentage points and also significant. This finding is in line with the ahead–behind asymmetry that has been found in soccer (Apesteguia and Palacios-Huerta, 2010; Palacios-Huerta, 2014) and chess (González-Díaz and Palacios-Huerta, 2016).

It is important to note that our results do not contradict those of Berger and Pope (2011) who found that being slightly behind (one point) at half-time has a positive effect on the probability of winning in basketball. However, being far behind is less likely to have a positive effect. Since in the Davis Cup there are only five matches, being one match behind is a much more significant lag than being one point behind in basketball, where teams score about 100 points per match. Therefore, we interpret lagging by one match in the Davis Cup as being further rather than slightly behind.

5.2. Oster's bias-adjusted treatment effect

It is important to note that the radius-matching-on-the-propensity score estimator is very flexible, without strict assumptions about the functional form. Nevertheless, as a robustness check we also use Oster's bias-adjusted estimator, which relies on a strict functional form, making it much less flexible than the semi-parametric matching estimator. In order to conduct the treatment effect of leading/lagging, in Columns 3 and 4 of Table 3, we present the results of the linear probability model (LPM) without and with the full set of controls respectively where standard errors clustered at the tie level appear in parentheses. Not surprisingly, we can see that the size of the coefficients of *Favorite is lagging* and *Favorite is leading* are

[10] See also Huber et al. (2015) who described this approach in detail and its implementation in different software packages such as Gauss, Stata and *R*.

Table 2
Propensity score estimation.

	Favorite is lagging		Favorite is leading	
	(1)	(2)	(3)	(4)
DiffRank	0.021***	0.022***	−0.019***	−0.023***
	(0.007)	(0.007)	(0.006)	(0.007)
DiffH2H	0.002	0.002	0.020**	0.021**
	(0.009)	(0.009)	(0.008)	(0.008)
Home Advantage to Favorite	−0.081***	−0.082***	0.090***	0.091***
	(0.020)	(0.020)	(0.017)	(0.017)
Group 1		−0.061**		0.072**
		(0.031)		(0.033)
Group 2		−0.042		0.072**
		(0.028)		(0.031)
Last 16		−0.037		0.048
		(0.048)		(0.057)
Quarterfinal		−0.047		0.054
		(0.044)		(0.053)
Semifinal		−0.031		0.034
		(0.040)		(0.048)
Final		−0.074*		0.073
		(0.041)		(0.048)
Playoff		−0.046		0.074
		(0.042)		(0.051)
World Group after 2009		−0.046		0.034
		(0.032)		(0.035)
Year dummies	No	Yes	No	Yes
Observations	2447	2447	2447	2447

Note: Logit average marginal effects are presented. In Columns 1 and 2 the dependent variable is a dummy of whether a favorite is lagging. In Columns 3 and 4 the dependent variable is a dummy of whether a favorite is leading. Clustered standard errors at the tie level are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 3
The effects of lagging/leading on the probability of winning a match.

	Radius matching		LPM		Oster
	(1)	(2)	(3)	(4)	(5)
Panel A					
Favorite is lagging	−0.049**	−0.050**	−0.087***	−0.049**	−0.037*
	(0.022)	(0.023)	(0.022)	(0.020)	(0.019)
Number of obs.	2447	2447	2447	2447	2447
Obs. in common support	2439	2441			
Panel B					
Favorite is leading	0.037*	0.054***	0.087***	0.048***	0.036**
	(0.021)	(0.020)	(0.018)	(0.017)	(0.017)
Number of obs.	2447	2447	2447	2447	2447
Obs. in common support	2426	2440			
No controls	N	N	Y	N	Y
Basic controls	Y	Y	N	N	Y
Full specification	N	Y	N	Y	Y

Notes: The dependent variable is a dummy of whether a favorite wins in the respective match. In Columns 1 and 2 the radius matching average effects of lagging/leading on the probability of a favorite's winning are presented. The results in Columns 1 and 2 of Panel A are based on the propensity score estimation presented in Columns 1 and 2 of Table 2, respectively. The results in Columns 1 and 2 of Panel B are based on the propensity score estimation presented in Columns 3 and 4 of Table 2, respectively. Clustered standard errors at the tie level are presented in parentheses. For these columns we also present the number of observations in common support.
The list of basic controls includes the difference in ranking indexes between a favorite and an underdog, whether a favorite has a home advantage, and the difference in the previous head to head results as presented in Columns 1 and 3 of Table 2. The full specification is presented in Columns 2 and 4 of Table 2.
In Columns 3 and 4 the coefficients from the LPM are presented. Standard errors clustered at the tie level are presented in parentheses.
In Column 5 we report the results of Oster's bias-adjusted treatment effect when the amount of selection on unobservables is recovered from the amount of selection on all observables. Standard errors in Column 5 are obtained from bootstrapping (499 replications). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

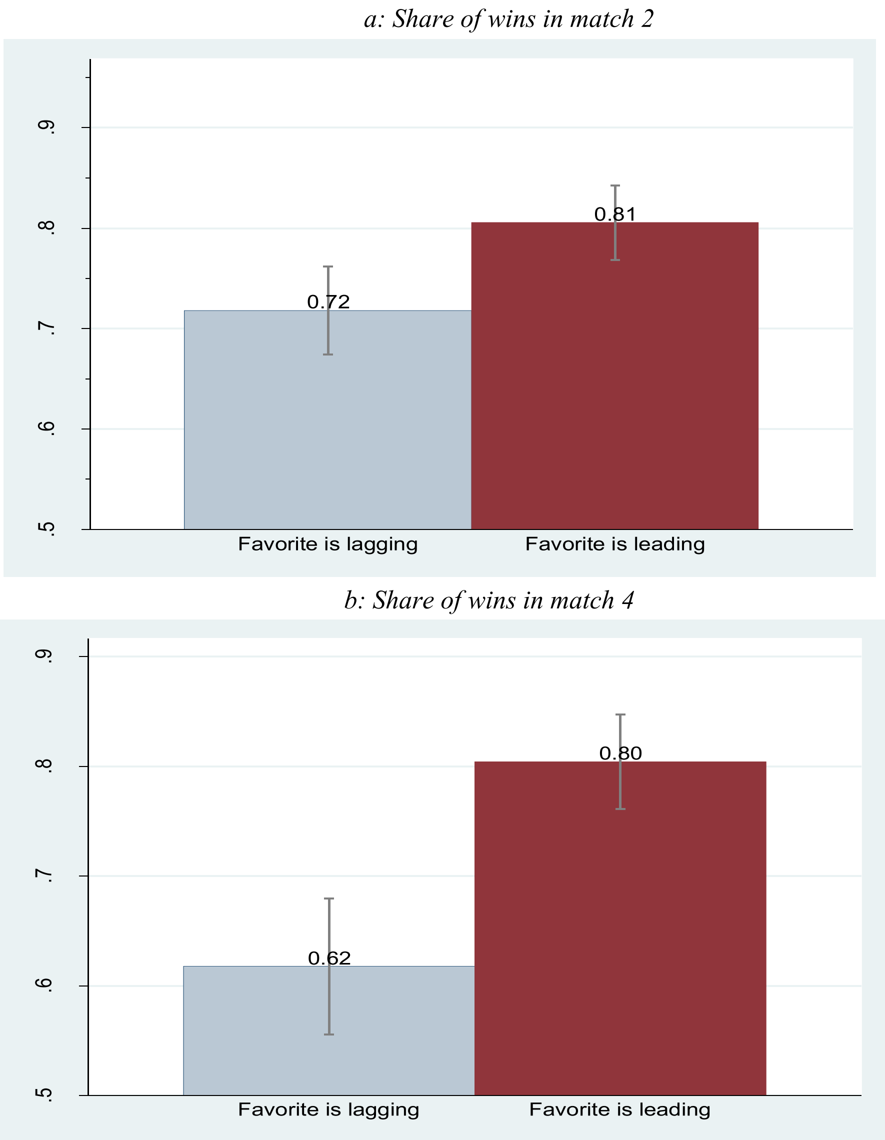

Fig. 2. (a) Share of wins in match 2. (b) Share of wins in match 4.
Notes: This figure presents the means of the share of wins of a favorite in match 2 (a) and match 4 (b) based on all of the tournaments. 95% confidence interval is presented.

much higher in the uncontrolled specification presented in Column 3 than in the specification with the full set of controls presented in Column 4.

In Column 5 we present the bias-adjusted treatment effect of lagging/leading. The standard errors obtained from the bootstrap are presented in parentheses. The results show that the estimated causal effect is closer to zero, but still significant. When a favorite is lagging, he is 3.7 percentage points less likely to win with a significance level of 5.3%. The positive effect of being ahead on the favorite's probability of winning is 3.6 percentage points with a significance level of 3.9%.[11]

5.3. Ahead–behind asymmetry in matches 2 and 4

In this subsection our aim is to investigate only matches where the score is asymmetric, namely matches 2 and 4, where by construction, one team is leading and the other is lagging before the beginning of the match. Fig. 2(a) and (b) shows that on average there is a much larger gap between the share of wins if a favorite is leading in match 4 compared to match 2.

[11] Note that in the case of lagging, our treatment is being behind compared to being ahead or even. Similarly, in the case of leading, our treatment is being ahead compared to being behind or even.

Table 4
The effects of leading in asymmetric scores.

	Radius matching		Oster	
	(1)	(2)	(3)	(4)
	Match 2	***Match 4***	***Match 2***	**Match 4**
Favorite is leading	0.031	0.097**	0.024	0.106***
	(0.033)	(0.041)	(0.031)	(0.037)
Number of obs.	845	565	845	565
Obs. in common support	837	562		

Notes: The dependent variable is a dummy of whether a favorite wins in the respective match. In Columns 1 and 2 the radius matching average effects of leading on the probability of a favorite's winning are presented. The results in Columns 1 and 2 are based on the propensity score estimation presented in Columns 1 and 2 of Appendix B, respectively. Standard errors are presented in parentheses. For these columns we also present the number of observations in common support.
In Columns 3 and 4 we report the results of Oster's bias-adjusted treatment effect when the amount of selection on unobservables is recovered from the amount of selection on all observables based on the same specifications as in Table 3. Standard errors in these columns are obtained from bootstrapping (499 replications). ** and *** denote significance at the 5% and 1% levels, respectively.

Our empirical analysis presented in Table 4 demonstrates that being ahead has a significant and positive effect on the probability of winning in match 4. We find no significant effect of being ahead in match 2.[12] This result is in line with several explanations. First, as already mentioned, matches 1 and 2 are played between the first seeded player of one team and the second seeded of another team, whereas match 4 involves the two top seeded players from each team. Thus, it is intuitive that a lagging favorite competes against a weaker opponent in match 2 compared to match 4. Therefore, the discouragement effect is less likely to appear in match 2, because being down 1:0 in a Davis Cup meeting is almost an expected event.

However, it is possible that the favorite player loses in the first match, which can have a different effect on the performance of the players in the second match. Therefore, in Appendix D we present the results of match 2 for cases in which a favorite won and lost in the first match. We find that if a favorite won in the first match, then being ahead in the second match has a positive effect on the probability of winning. However, this effect is not significant at conventional levels. We also observe a negative coefficient if the favorite lost in the first match. Nevertheless, the result is far from being significant.

There are some additional explanations for the difference in results between matches 2 and 4. For example, it is possible that a lagging player has much more to lose in terms of a team prize in match 4 compared to match 2 because if a lagging player loses in match 4, his team loses the entire tie. Therefore, such a situation may provoke choking under pressure of the lagging player and, as a result, harm his performance and reduce the likelihood of his winning.[13] Finally, it is also possible that the leading player values his win more than the lagging player in match 4 compared to match 2, which may also result in a difference in the probabilities of winning. This difference in valuations between the matches may be driven by simple egocentric motives. For example, the winner of the match that determines the tie gets more glory.

Although we cannot observe all of the possible prizes the players receive from winning a single match, in the next sub-section we use a unique opportunity to study the effect of the ahead–behind asymmetry in settings with and without intermediate prizes.

6. The effect of intermediate prizes

6.1. Introduction of ranking points in the World Group in 2009

In this section, we take advantage of the change in the rules introduced by the ATP. Up to 2009, players did not receive any ranking points for a single win. However, between 2009 and 2015, the winner of a live rubber of the World Group received ranking points. These points are taken into account in determining the World Ranking list. This list is very important because it determines the entries to the most important tournaments with the largest monetary rewards. In addition, players with a higher number of points may benefit from a better draw, because in the first rounds they play against weaker players. To put this decision into perspective, a win in a main tournament of the Davis Cup was worth 40–75 ranking points,

[12] In Appendix C we show that the effect of leading in match 4 is significantly higher than in match 2.
[13] See Ariely et al. (2009) who showed that large stakes might reduce performance. Additionally, Paserman (2010) found that the performance of tennis players deteriorates on more important points. Similarly, Cohen-Zada et al. (2017) documented that professional male tennis players lose more serves when the pressure is higher.

depending on the round. This means that two wins in Davis Cup matches were worth more than two wins in the first two rounds of Grand Slam tournaments (55 points), which are the most prestigious tennis tournaments.[14]

6.2. Theoretical framework

As discussed, theoretically, the intermediate prizes (ranking points) play a very important role in multi-stage contests. According to Konrad and Kovenock (2009), the introduction of positive intermediate prizes may increase the lagging player's probability of winning. Moreover, according to Fu et al. (2015), if there is an intermediate prize, which is common to both players, the interim score of a tie has no effect on the players' probability of winning in a single rubber. This probability depends only on the players' innate abilities.

In this sub-section, we introduce a very simple theoretical model of a contest between two symmetric players to illustrate how intermediate prize affect the probability of the lagging player's winning. We consider a sequential contest with two players denoted by $i = 1, 2$, and five stages (matches) denoted by $t = 1, 2, 3, 4, 5$. The players compete in sequential matches and a player who wins three matches wins the contest. Player *i's* value of winning the contest or type of player is V_i. Valuations are common knowledge. We assume symmetry between players, that is, $V_1 = V_2 = V$. For simplicity, assume that $V = 1$. Each player exerts an effort of x_i^t in stage t. These efforts are submitted simultaneously. Each player has a linear cost function $(x_i^t) = x_i^t$. Each match is modeled as a Tullock contest, where player *i's* probability of winning is the ratio between the effort he exerts and the total effort exerted by both players. In addition, there is an intermediate prize, k, for winning a single match, which is less than the value of winning the whole contest.

In Section 2 we noted that the last two matches involve the top seeded players from each team in match 4, and the two second seeded players from each team in match 5. In contrast, the first two matches always involve the first seeded player of one team and the second seeded of another team. Intuitively, match 4 is more symmetric than match 2. Indeed, in our dataset, the mean *DiffRank* value in match 2 equals -1.79, which is significantly lower than the mean *DiffRank* value in match 4, which equals -1.59 (two-sample mean comparison p-val=0.009). This result illustrates that match 4 is significantly more symmetric than match 2. Therefore, in our model between two symmetric players, we will present only the case of the last two matches, because they bear a closer resemblance to the empirical settings.

In order to analyze the equilibrium of this contest we begin with the last stage and move backwards to the previous stage. Therefore, we start our analysis from match 5. This match takes place only if each player won twice in the previous four matches. Therefore, if each player wins in this match, he receives the value for winning the entire contest as well as the intermediate prize of k. Thus, in match 5, the players maximize the following utility functions by choosing the optimal level of effort:

$$EU_1^5 = (1+k)\frac{x_1^5}{x_1^5 + x_2^5} - x_1^5$$

$$EU_2^5 = (1+k)\frac{x_2^5}{x_1^5 + x_2^5} - x_2^5$$

Solving the players' first-order condition, the players' efforts and their expected utilities are given by $x_1^5 = x_2^5 = \frac{(1+k)^3}{(2+2k)^2} = EU_1^5 = EU_2^5$. Obviously, in a symmetric case such as match 5, each player's probability of winning is 50%.

To solve the equilibrium in match 4, suppose that *Player 1* is leading and *Player 2* is lagging. If *Player 1* wins in that stage, he wins the entire contest and receives 1 as well as k for winning the specific match. If *Player 1* loses, he receives the expected payoff of the fifth match. Similarly, if *Player 2* wins, he gets the expected payoff of the fifth stage in addition to the intermediate prize of k. Thus, players maximize the following utility functions by choosing the optimal level of effort:

$$EU_1^4 = (1+k)\frac{x_1^4}{x_1^4 + x_2^4} + \left(\frac{(1+k)^3}{(2+2k)^2}\right)\left(1 - \frac{x_1^4}{x_1^4 + x_2^4}\right) - x_1^4$$

$$EU_2^4 = \left(\frac{(1+k)^3}{(2+2k)^2} + k\right)\frac{x_2^4}{x_1^4 + x_2^4} - x_2^4$$

Solving the players' first-order condition, the lagging player's (*Player 2*) probability of winning is given by $\frac{(1+k)^3 + k(2+2k)^2}{(2+2k)^2(1+2k)}$. Fig. 3 shows that the lagging player's probability of winning is increasing in k. In other words, we expect that the introduction of intermediate prizes should increase the probability of the lagging player's winning.

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[14] Two wins in the playoff of the Davis Cup were worth 15 points. For additional information see: https://en.wikipedia.org/wiki/Davis_Cup and https://en.wikipedia.org/wiki/ATP_Rankings#Points_distribution_.282009_.E2.80.93_present.29. Last accessed on 07/07/2017.

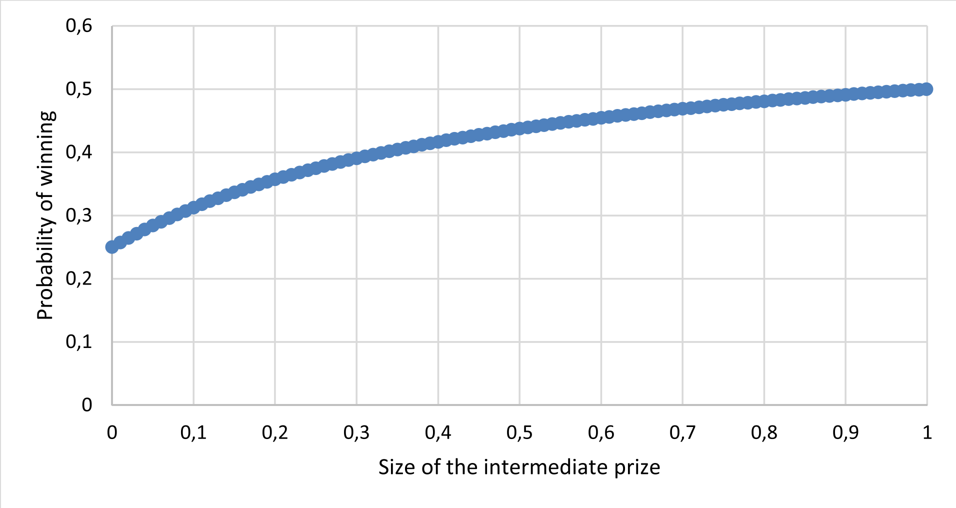

Fig. 3. Lagging player's theoretical probability of winning in match 4 as a function of the intermediate prize.
Notes: This figure presents the lagging player's probability of winning in match 4, as derived from the Tullock contest success function, where players' values for winning the entire contest are equal to one.

Table 5
Rankings of the players in match 4 in the World Group before and after 2009.

	Before 2009 (1)	After 2009 (2)	Difference (3)
Log_2 Favorite ranking	3.410	3.567	−0.157
	(1.835)	(1.759)	(0.256)
Log_2 Underdog ranking	5.431	5.579	−0.148
	(1.474)	(1.532)	(0.213)
DiffRank	−2.021	−2.012	−0.009
	(1.439)	(1.420)	(0.204)

Columns 1 and 2 present the average value of each of the characteristics in the World Groups' match 4 before and after 2009, respectively. Standard deviations are in parentheses. Results from univariate regressions of each of the variables in this table on a dummy variable indicating whether the match is before 2009 appear in Column 3. Standard errors are in parentheses.

6.3. Empirical evidence

Although our empirical settings do not fully resemble our theoretical model or the theoretical settings of Fu et al. (2015) and Konrad and Kovenock (2009), we still wish to test whether starting from 2009, the probability of winning is affected by the state of the contest (whether a player is leading or lagging). Based on the World Group ties, Fig. 4(a) shows that the gap between the probabilities of winning when one is leading in match 4 compared to being behind was, on average, 28 percentage points before the change in the rules in 2009.[15] However, as Fig. 4(b) illustrates, this gap declined dramatically to only 8 percentage points after 2009.

6.3.1. Selection issue

One possible concern, however, is that the introduction of the ranking points may attract better players. Therefore, the greater probability of the lagging favorite's winning might be attributed to selection rather than to intermediate prizes. To obviate this concern and show that the players' rankings are not differently distributed before and after 2009, we use the following two-step procedure. First, we partitioned the data into two parts, where one set contains the World Groups' match 4 before 2009 and the other the World Groups' match 4 after 2009. In Table 5 we report the average value of the $\log_2$ of the ranking of the favorite, the underdog and the differences between them on the match level, separately for each period. In parentheses we present their standard deviations. Column 1 refers to the matches before 2009, while Column 2 refers to the matches after 2009. We can see that the $\log_2$ of the players' rankings is even somewhat higher after

[15] As before, we observed no significant differences between the probabilities of winning in match 2. The results are available upon request.

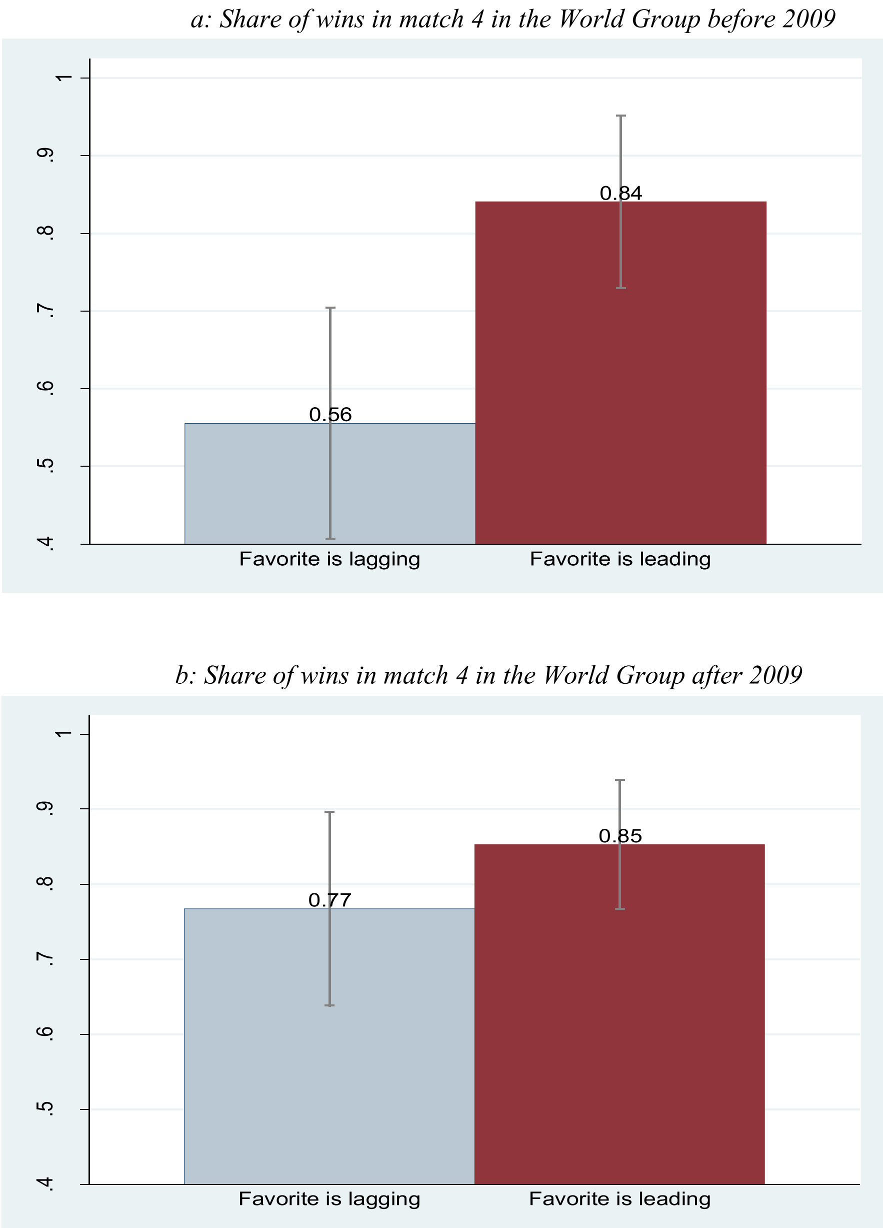

Fig. 4. (a) Share of wins in match 4 in the World Group before 2009. (b) Share of wins in match 4 in the World Group after 2009.
Notes: This figure presents the means of the share of wins of a favorite in match 4 in the World Group before 2009 (Fig. 3(a)) and after 2009 (Fig. 3(b)). 95% confidence interval is presented.

2009, implying the rankings of those with less ability. Then, we run a set of univariate regressions of each of the variables presented in Table 5 on a dummy variable indicating whether the specific observation was before 2009. The coefficient of this dummy variable and its standard error are presented in Column 3. The results show that none of these players' characteristics differ significantly between the two periods. This finding indicates that the players' $\log_2$ of rankings and their differences do not differ before and after 2009. Therefore, we can conclude that selection into the sample is not a concern.

6.3.2. Radius matching analysis

In Table 6, we present the effects of leading in match 4 on the probability of the favorite player's winning before and after 2009. The radius-matching estimator presented in Column 1 implies that there is a significant and positive effect of being ahead before 2009, which is much smaller and not significant after 2009.

Table 6
The effects of leading in match 4 in the World Group before and after 2009.

	Radius Matching	LPM		Oster
	(1)	(2)	(3)	(4)
Panel A: Before 2009				
Favorite is leading	0.222**	0.178*	0.180*	0.181
	(0.096)	(0.095)	(0.090)	(0.118)
Number of obs.	89	89	89	89
Obs. in common support	86			
Panel B: After 2009				
Favorite is leading	0.137	0.039	0.056	0.066
	(0.086)	(0.077)	(0.077)	(0.089)
Number of obs.	111	111	111	111
Obs. in common support	100			
Controls that were significant in propensity score	N	Y	Y	Y
Full specification	Y	N	Y	Y

Notes: The dependent variable is a dummy of whether a favorite wins in the respective match. In Column 1 the radius matching average effects of leading on the probability of a favorite's winning are presented. The results before and after 2009 are based on the propensity score estimation presented in Columns 1 and 2 of Appendix E, respectively. Standard errors are presented in parentheses. For these columns we also present the number of observations in common support.
In Column 2 we present the results of the LPM controlling for variables that were significant in the propensity score estimation presented in Appendix E as part of the identification strategy. Before 2009, the *DiffRank* and *Year2008* are included in both the controlled and uncontrolled regressions. After 2009, the *DiffRank* is included in both the controlled and uncontrolled regressions. Robust standard errors are presented in parentheses. In Column 4 we report the results of Oster's bias-adjusted treatment effect. Standard errors are obtained from bootstrapping (499 replications). * and ** denote significance at the 10% and 5% levels, respectively.

Table 7
The effects of an intermediate prize on the probability of a lagging favorite's winning match 4.

	Radius matching	LPM		Oster
	(1)	(2)	(3)	(4)
After 2009	0.184*	0.212**	0.209**	0.208*
	(0.103)	(0.099)	(0.104)	(0.109)
Number of obs.	88	88	88	88
Obs. in common support	86			
No controls	N	Y	N	Y
Full specification	Y	N	Y	Y

Notes: The dependent variable is a dummy of whether a favorite who was lagging before match 4 wins in the respective match. In Column 1 the radius matching average effect of the post-2009 period on the probability of a favorite's winning is presented. This result is based on the propensity score estimation presented in Appendix F, where we use the full specification. Standard errors are presented in parentheses. For Column 1 we also present the number of observations in common support.
In Columns 2 and 3 the coefficients from the LPM are presented. Robust standard errors are presented in parentheses.
In Column 4 we report the results of Oster's bias-adjusted treatment effect when the amount of selection on unobservables is recovered from the amount of selection on all observables. Standard errors in Column 4 are obtained from bootstrapping (499 replications). * and ** denote significance at the 10% and 5% levels, respectively.

Finally, we test whether the intermediate prizes increase the probability of the lagging player's winning, as indicated in Fig. 4(a) and (b). In Table 7, we compare the probabilities of the lagging favorites' winning in match 4 before and after 2009. In total, we have 45 such cases before 2009 and 43 after. The results of the radius-matching estimator presented in Column 1 imply that the effect of the intermediate prizes on the probability of the lagging favorite's winning is 18.4 percentage points with a significance level of 6%. It is important to note that similar to the results presented in Table 5, in the case with the lagging favorite as well, none of the characteristics significantly differs between the two periods, before and after

2009. In fact, as Appendix F indicates, none of the variables has a p-value lower than 0.31. This result serves as additional evidence that selection into the sample is not a concern.[16]

6.3.3. Oster's bias-adjusted treatment effect

As previously, we use Oster's bias-adjusted estimator as a robustness check. In Columns 2–3 of Table 6 we present the LPM's coefficients of *Favorite is leading* in match 4 in the World Group before and after 2009, where robust standard errors appear in parentheses. Given the very small number of observations, the R-squared is very sensitive to the inclusion of any additional variable. Therefore, we follow Oster (2019) who also offers an adjusted procedure for evaluating the bias-adjusted treatment effect when some variables are considered part of the identification strategy and thus appear in both the controlled and uncontrolled regressions. The idea is to assess the amount of selection on the observables conditional on including these variables in the estimation. Because some of the variables are significant in the propensity score estimation presented in Appendix E, it is worthwhile assessing the amount of selection conditional on these variables being included in the estimation as part of our identification strategy. Therefore, in Columns 2 and 3 of Panel A in Table 6, which represents the matches before 2009, the *DiffRank* and *Year2008* are included in both the controlled and uncontrolled regressions. Similarly, since *DiffRank* is significant in the propensity score estimation (Column 2 in Appendix E), in Panel B of Table 6, we include it in both the controlled and uncontrolled regressions (Columns 2 and 3).

We can see that the coefficients are significant before 2009 and even somewhat higher when including the controls (Columns 2 and 3 of Panel A in Table 6). Therefore, by definition, Oster's bias-adjusted coefficient has to be even farther from zero, as we can see in Column 4 of Panel A in Table 6. However, the bootstrapping procedure in the dataset that includes 89 observations only increases the standard errors and the *p*-val to 0.125. Nevertheless, the most important result in this case is that Oster's bias-adjusted coefficient becomes even larger compared to the LPM. When testing the effect of leading after 2009, we can see that according to all of the estimators (Columns 2–4 of Panel B in Table 6), the effect of leading in match 4 is much closer to zero and highly insignificant.

Finally, in order to conduct Oster's bias-adjusted treatment effect of playing after 2009 on the lagging player's probability of winning, we use the results of the LPM with and without the full set of controls as presented in Columns 2 and 3 of Table 7, respectively. We can see that the effect of the post-2009 period is not sensitive to the inclusion of the controls. Its size is about 20 percentage points with a significance level of 3.6% and 4.7% in Columns 2 and 3, respectively. Not surprisingly, Oster's bias-adjusted coefficient, presented in Column 4, is almost the same as in the LPM, with a significance level of 5.6%.

Taken together, our results suggest that the introduction of incentives for winning a single match is likely to affect the performance of players. Although our empirical settings do not fully match the theoretical settings of Fu et al. (2015) and Konrad and Kovenock (2009), our finding that the probability of winning is not affected by the state of the contest when an intermediate prize is introduced is in line with these theoretical predictions. In general, our empirical results emphasize the importance of the strategic allocation of efforts in multi-stage contests that is well known in the theoretical literature. Although we cannot rule out the possibility of some other psychological effects, our findings suggest that the introduction of intermediate prizes may mitigate or even eliminate the ahead–behind effects that arise in multi-stage contests.[17]

7. Conclusion

In this paper, we used tournaments among highly competitive and extensively trained professionals to test the effect of ahead–behind asymmetry on individuals' performance in multi-stage contests between teams with and without intermediate prizes. As in previous studies, we find that being ahead provides players with a greater probability of success. However, the main contribution of this paper is that it empirically shows that intermediate prizes eliminate the usual ahead–behind effect that may arise from psychological as well as from strategic considerations.

Our results, obtained from contests between high-profile professionals, underscore the role of strategic motives in individual performance. This is especially important on the team level, because teamwork is probably the most prevalent form of economic activity. Our findings suggest that non-monetary incentives alone, such as a team's pride, are probably not enough to maximize an individual's output. This result may be of great importance in situations that involve a choice between individual and social benefits. Nevertheless, it is important to note that we did not investigate the effect of team-based incentives on individual performance. Therefore, it will be interesting to study whether the introduction of team-based incentives instead of individual-based incentives will also lead to improved performance.

Furthermore, individual incentives may improve the utility of other teammates of the lagging team because such incentives do not affect the winning probabilities of leading favorites, who are likely to win the decisive match regardless

[16] One possible concern is about superstar effects in the way incentives affect lagging favorites. For example, superstars may have different preferences about Davis Cup tournaments. However, excluding the top four players (Roger Federer, Rafael Nadal, Novak Djokovic and Andy Murray) who have been in the top 10 most of the time since the mid-2000s, we find similar results. There are also no different effects on lagging favorites' winning match 4 among superstars. These results are not presented, but are available upon request.

[17] See Cohen-Zada et al. (2017) for a discussion about the coexistence of psychological and strategic motives in multi-stage contests.

of the incentives. It is rather the lagging favorite who benefits from additional individual rewards. In addition, his teammates benefit from the greater probability of winning the entire contest. This may explain why companies in difficulty are ready to pay extra salaries to high-profile workers, who are able to stabilize the firm's cash flows or profits. However, other workers who do not receive an additional individual reward may also benefit from the increased stability of their workplace.

Finally, it is important to note that despite the fact that our findings are in line with the common ahead–behind effects and with previous theoretical studies on the effect of intermediate prizes, the results of this paper were obtained from the sport of tennis, which is mostly an individual sport. Playing in teams in the Davis Cup is not the usual competitive format for most players. Therefore, it is possible that our results would be different in other settings, where individuals are used to performing in teams. It is also possible that those who are not used to large monetary rewards would also behave differently. Therefore, we call for additional empirical research to test the interactive effect of intermediate prizes and ahead–behind asymmetry in various other environments.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2019.06.001.

Appendix A: List of sources

www.daviscup.com
www.atpworldtour.com
www.itftennis.com
www.tennisabstract.com
www.tennis-data.co.uk
www.bet365.com/extra/en/betting/tennis
www.tennisbetsite.com
www.tennisexplorer.com

Appendix B: Propensity score estimation for matches 2 and 4

Table B.1
Propensity score estimation for matches 2 and 4.

	(1) Match 2	(2) Match 4
DiffRank	-0.032^{***}	-0.067^{***}
	(0.012)	(0.017)
DiffH2H	0.000	0.017
	(0.017)	(0.016)
Home Advantage to Favorite	0.170^{***}	0.111^{***}
	(0.032)	(0.039)
Group 1	0.099	0.149^{*}
	(0.068)	(0.080)
Group 2	0.050	0.145^{**}
	(0.062)	(0.072)
Last 16	0.063	0.104
	(0.105)	(0.127)
Quarterfinal	0.083	0.103
	(0.095)	(0.114)
Semifinal	0.060	0.056
	(0.085)	(0.103)
Final	0.067	0.216^{**}
	(0.086)	(0.105)
Playoff	0.097	0.103
	(0.091)	(0.109)
World Group after 2009	0.022	0.120
	(0.071)	(0.084)
Year dummies	Yes	Yes
Observations	845	565

Note: Logit average marginal effects are presented. The dependent variable is a dummy of whether a favorite is leading in the respective match. Standard errors are presented in parentheses. ** and *** denote significance at the 5% and 1% levels, respectively.

Appendix C: Comparison between the effects of leading

Table C.1
Comparison between the effects of leading in matches 2 and 4.

	LPM		Oster
	(1)	(2)	(3)
Favorite is leading in match 4	0.099**	0.094**	0.092*
	(0.047)	(0.045)	(0.049)
Number of obs.	1410	1410	1410
Main effects	Y	Y	Y
Full specification	N	Y	Y

Notes: The dependent variable is a dummy of whether a favorite wins in the respective match. In Column 1 we present the results of the LPM controlling for main effects only (a dummy of whether a favorite is leading and a dummy of whether a match is match 4 or not (match 2)). In Column 2 we use our full set of controls as presented in Column 4 of Table 2. Clustered standard errors at the tie level are presented in parentheses.
In Column 3 we report Oster's bias-adjusted treatment effect. We treat the main effects as part of the identification strategy and thus recover the amount of selection on unobservables from the amount of selection on all of the other observed characteristics, where the main effects are included both in the uncontrolled and controlled regressions presented in Columns 1 and 2, respectively. Standard errors are obtained from bootstrapping (499 replications). * and ** denote significance at the 10% and 5% levels, respectively.

Appendix D: The effect of leading in match 2 depending on the outcome in match 1

Appendix D.1
The effects of leading in match 2 depending on the outcome in match 1.

	Radius matching		Oster	
	(1) Favorite won in the first match	(2) Favorite lost in the first match	(3) Favorite won in the first match	(4) Favorite lost in the first match
Favorite is leading	0.046	−0.026	0.044	−0.039
	(0.038)	(0.058)	(0.036)	(0.065)
Number of obs.	639	206	639	206
Obs. in common support	629	199		

Notes: The dependent variable is a dummy of whether a favorite wins in the respective match. In Columns 1 and 2 the radius matching average effects of leading on the probability of a favorite's winning are presented. Standard errors are presented in parentheses. For these columns we also present the number of observations in common support.
In Columns 3 and 4 we report Oster's bias-adjusted treatment effect when the amount of selection on unobservables is recovered from the amount of selection on all observables based on the same specifications as in Table 3. Standard errors in these columns are obtained from bootstrapping (499 replications).

Appendix E: Propensity score estimation for match 4

Table E.1
Propensity score estimation in match 4 in the World Group before and after 2009.

	(1) Before 2009	(2) After 2009
DiffRank	−0.088***	−0.071**
	(0.034)	(0.035)
DiffH2H	0.002	0.026
	(0.035)	(0.026)

(continued on next page)

Table E.1 (*continued*)

	(1) Before 2009	(2) After 2009
Home Advantage to Favorite	0.155	−0.052
	(0.101)	(0.096)
Last 16	0.010	0.085
	(0.127)	(0.108)
Quarterfinal	0.068	0.156
	(0.157)	(0.132)
Semifinal	−0.067	0.029
	(0.170)	(0.185)
Final	0.214	−0.193
	(0.234)	(0.235)
Year 2004	0.041	
	(0.177)	
Year 2005	0.125	
	(0.168)	
Year 2006	0.144	
	(0.182)	
Year 2007	0.123	
	(0.168)	
Year 2008	0.332*	
	(0.173)	
Year 2010		−0.088
		(0.184)
Year 2011		0.063
		(0.171)
Year 2012		−0.019
		(0.170)
Year 2013		0.017
		(0.167)
Year 2014		0.034
		(0.174)
Year 2015		0.052
		(0.160)
Observations	89	111

Note: Logit average marginal effects are presented. The dependent variable is a dummy of whether a favorite is leading in the respective match. Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Appendix F: Propensity score estimation for post-2009 period

Table F.1
Propensity score estimation in match 4 in the World Group before and after 2009.

DiffRank	0.023
	(0.047)
DiffH2H	0.031
	(0.030)
Home Advantage to Favorite	0.102
	(0.106)
Last 16	−0.061
	(0.126)
Quarterfinal	0.002
	(0.173)
Semifinal	−0.164
	(0.188)
Final	−0.045
	(0.268)
Observations	88

Note: Logit average marginal effects are presented. The dependent variable is a dummy of whether match 4 in which a favorite was lagging was played before or after 2009 (dummy equals one if the match is after 2009). Standard errors are presented in parentheses.

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