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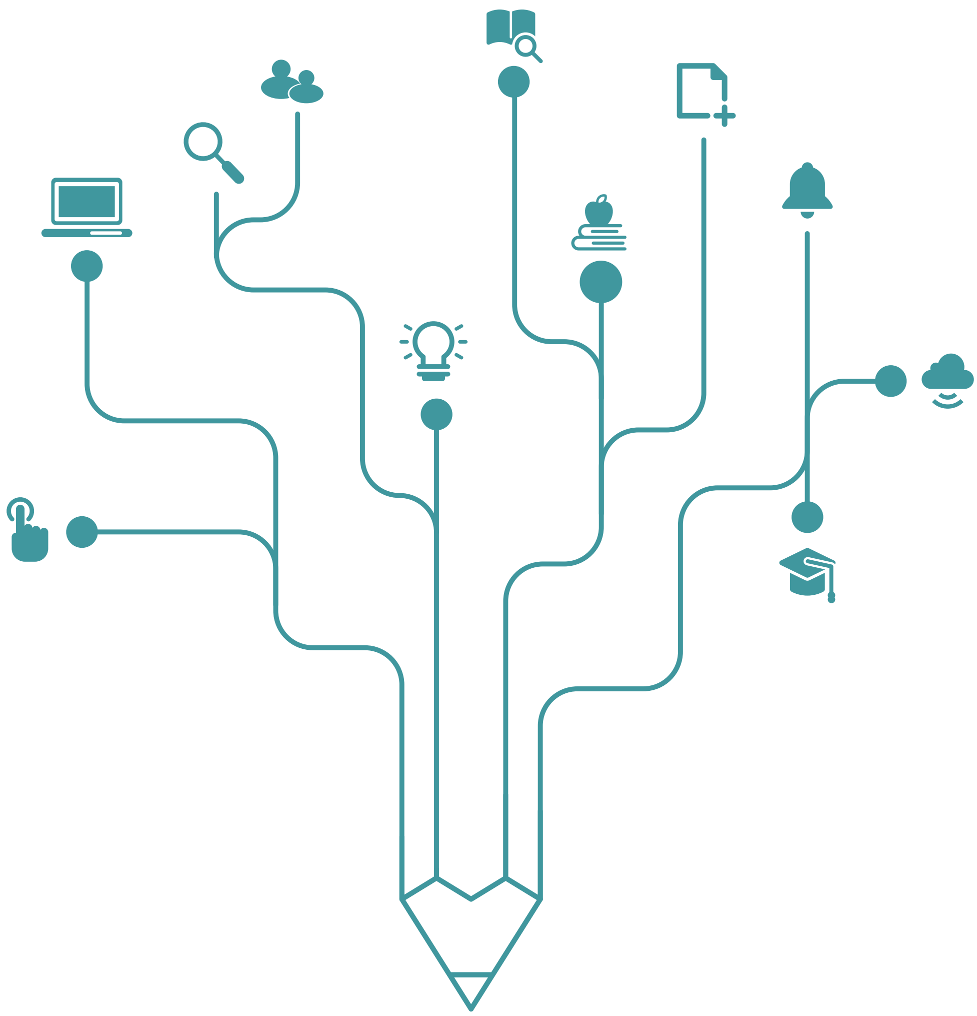

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Strategic Pairings in Professional Doubles Tennis: The Role of the Strongest and Weakest Players*

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Abstract

This paper examines the dynamics of team composition in doubles tennis, exploring the strategic impact of player selection and the relative influence of the strongest and weakest players on a partnership's performance. Employing a game-based theoretical framework and analyzing data from ATP World Tour doubles matches (1976–2017), we investigate whether outcomes are more influenced by "hard-carrying," where a top-tier player significantly elevates a team's victory chances, or the "weakest link," where the least skilled player potentially poses a detriment. Our findings reveal that partnerships that include the strongest player in a match have a higher likelihood of winning, particularly when there is a notable skill disparity between the partners. This suggests that the presence of key high performers can elevate team outcomes.

JEL Codes: C72, J24, L83, M52

Keywords: team composition, game theory in sports, team dynamics, performance optimization

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1 Introduction

Interactions among team members are crucial in determining team performance, especially in team sports where these outcomes may depend upon the relative impact of the strongest and weakest players. This dynamic poses an intriguing question in sports psychology and strategy: Is the strength of a team determined by its most skilled player or its least skilled player? One school of thought advocates the concept of "hard-carrying," where a standout player's exceptional abilities are seen as pivotal in steering the team towards victory. In such instances, the superior skills of this top player are believed to compensate for the weaker capabilities of their teammates.

Another viewpoint emphasizes the critical role of the team's least skilled player. This perspective posits that a team's overall capacity is determined by the performance of its weakest member, echoing the notion that a chain is only as strong as its weakest link. One implication under this theory is that a substantial skill gap within a team is thought to present a disadvantage, and it is suggested that maintaining a balanced skill level among all members is essential for overall success. This dichotomy highlights the complex interplay of individual skills and collective strategies in team sports, inviting further exploration into how these factors converge to influence game outcomes.

The interaction between doubles tennis partners provides a unique context in which to explore these competing theories. Unlike singles tennis or any other individual sports, doubles tennis requires a delicate balance of individual prowess and collaborative synergy. Additionally, relative to team sports where there are more players, doubles tennis presents a more intimate context, facilitating a detailed examination of the influence of the strongest and weakest player on overall team strength and performance within a constrained team dynamic.

We first develop a game-based theoretical framework to elucidate the intricate dynamics of the roles of the strongest and weakest players on a doubles team. This framework is grounded in a simplified game model, which strategically pairs the strongest player with the weakest player against a team composed of the second- and third-strongest players. In this model, each player's ability is quantified in terms of their capacity to defensively cover a specific range on the tennis court. To analyze the strategic interactions and outcomes of these pairings, we employ the concept of the Perfect Bayesian Nash Equilibrium (PBNE). Our model's PBNE analysis shows that the equilibrium payoff for a team comprising the strongest player and the weakest player is consistently higher than that of a team formed by the second and third players. This theoretical finding indicates that the presence of a top-tier player is more crucial to the match outcome than the average combined skill level of the team.

To shed further light on this debate, we empirically investigate the relative impacts of the strongest and weakest players on a team's performance. Specifically, we collect data from the ATP World Tour website, focusing on male doubles matches played from 1976 to 2017. This comprehensive dataset of ATP tournament details includes the match scores and statistics as well as individual players' rankings and profiles.

We have three main empirical findings. First, we find that a partnership that includes the strongest player in a match has a significantly higher chance of winning that match. Having the strongest among four players is associated with winning probabilities that are 14-20 percentage points higher, while having the weakest player decreases the chances of winning by 13-18 percentage points. The net effect of having both the strongest and weakest players is 3-4 percentage points. This finding supports the hypothesis of a "hard carry" effect in doubles tennis; having the highest-performing player outweighs the potential negative impact of having the least skilled player.

Second, to directly validate the theoretical prediction of our conceptual framework, we limit the analysis to matches where a team consisting of the "strongest and weakest players" competes against a team made up of the "second and third players." We find that the winning probabilities of the "strongest and weakest" teams are 3-8 percentage points higher ("1+4 team" effect), even when we control for team characteristics, including average individual rankings. This finding validates the propositions of our conceptual framework that the payoff for the team with the strongest players is consistently higher. We further investigate whether these dynamics differ in high-stakes matches, where a victory grants higher ranking points. While we don't find any evidence for differential effects in high-stakes tournaments like the Grand Slams, we find the "hard carry" effects are stronger for finals, semi-finals, or quarter-finals in a given tournament.

Third, in further investigating the mechanisms of these effects, we observe that they are driven by the teams with top-ranked individual players. The hard carry effect is 5-6 percentage points for teams where the strongest player is ranked in the top 100 individually, while the effect is about 1 percentage points (statistically insignificant) for teams where the strongest player is not ranked in the top 100. Notably, these interaction effects intensify in scenarios where the disparity in rankings within a team is greater. For matches where the within-team rank differences are above median, the interaction effect with having a top 100 player escalates to 6-7 percentage points, compared to the 4 percentage points without (insignificant). This evidence underscores the pivotal role of skill level disparity, as indicated by individual rankings, in shaping the strongest player's influence on match outcomes. Partnerships that include a player in the top 100, especially partnerships where there is a substantial within-team ranking gap, exhibit an increased likelihood of victory. This highlights the profound impact that a single highly skilled player can exert in doubles tennis.

In conclusion, this study illuminates the strategic nuances of player selection in doubles tennis, offering a fresh perspective on team composition. Contrary to traditional strategies that emphasize the combined skill levels of team members, our findings suggest that the presence of a top-tier player may significantly determine the aggregate abilities of a duo. This revelation could revolutionize the approach to team formation and strategy development in professional doubles tennis. In essence, our research, underpinned by a robust conceptual model and solid empirical evidence, reframes our understanding of professional doubles tennis dynamics. It not only calls into question established beliefs but also paves the way for innovative exploration of strategic pairings and player selection within the sport.

Our research contributes to several streams of the existing literature, particularly those that emphasize the pivotal role of team composition strategies and peer effects in team sports. For example, Cohen-Zada et al. (2023) highlights the significant role of effort spillovers in team production in soccer, where a single player's effort can substantially affect overall team effort and performance. Similarly, Weimar and Wicker (2017) examine the impact of effort on soccer team performance, showing that increases in effort measures increase the likelihood of winning a match. In another context, Arcidiacono et al. (2017) use basketball data to demonstrate peers' roles in productivity, also showing significant productivity spillovers in teams. Gould and Winter (2009) investigate how athletes' efforts affect the productivity of their teammates in baseball, finding that in production, efforts are complementary, and whether teammates affect each other positively or negatively depends on whether they are substitutes or complements. Brave et al. (2019) focus on Major League Baseball, applying advanced techniques to measure team synergy and finding that about 40% of the variation in team performance can be explained by teammate interactions. On the other hand, Guryan et al. (2009) examine peer effects in golf and find no significant impact of playing partners' ability on performance, challenging the existing evidence on peer effects in other settings. Our study extends the existing literature by providing an explanation of team dynamics in doubles tennis and insights that could help sports analysts, coaches, and players optimize team performance.

Explorations of peer effects and team composition have extended beyond sports, as evidenced by studies in educational settings (Angrist and Lang, 2004; Azoulay et al., 2010; Boucher et al., 2014; Hoxby, 2000; Jackson and Bruegmann, 2009; Sacerdote, 2001), labor markets (Amodio and Martinez-Carrasco, 2018; Bandiera et al., 2009; Brune et al., 2022; Cornelissen et al., 2017; Mas and Moretti, 2009; Oreopoulos, 2003), and other contexts (Angrist, 2014; Caeyers and Fafchamps, 2016; Herbst and Mas, 2015), which have produced mixed results regarding the impact of peer characteristics and interactions. Our research adds to this diverse body of literature by demonstrating how peer characteristics and interactions influence performance outcomes in the specific context of doubles tennis.

Our conceptual framework contributes to the literature on team composition by introducing a model based on doubles partnerships. Our framework complements the studies of Budak et al. (2018) and Budak and Kara (2022), who proposed a model linking team harmony and player performance to optimal team composition, and Cao et al. (2022), who developed a graph theory and model focusing on doubles table tennis. Our paper distinguishes itself by demonstrating the strategic interactions and decision-making processes specific to doubles play. The utility of our model is not confined to tennis; it can be adapted to other doubles sports, such as badminton.

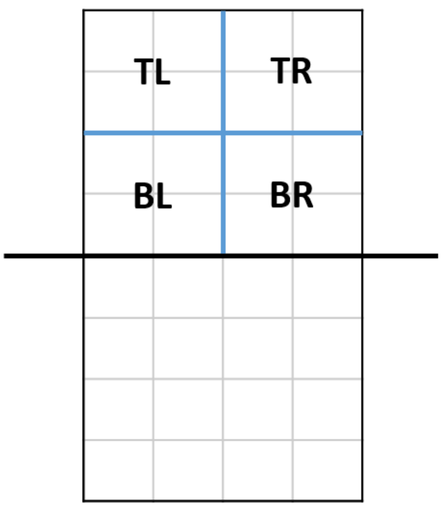
Finally, our study contributes to the tennis sports literature. There is a substantial body of research on tennis, including studies on player rankings, performance metrics, and the strategic aspects of the game (Bozóki et al., 2016; Gerdin et al., 2018; T et al., 2020; Irons et al., 2014; Loffing et al., 2012; Malueg and Yates, 2010; Radicchi, 2011; Reid et al., 2010; Reid and Morris, 2013; Ruiz et al., 2013). For example, Walker and Wooders (2001) developed the minimax hypothesis, which explained win rates for both the serve and return plays of top professional tennis players. While there has been growing interest in the dynamics of tennis doubles (Blickensderfer et al., 2010; Borderias et al., 2022; Martínez-Gallego et al., 2019, 2021; Raue et al., 2020), the influence of team composition in terms of player rankings on winning rates in doubles matches has not been explored. Our research fills this void by specifically investigating how the rankings of individual players in a doubles partnership correlate with the partnership's winning rates. This approach allows us to investigate team dynamics in doubles tennis, considering not only the individual skills of the players, but also how their combined rankings may predict match outcomes. In sum, our study provides insight into strategic team formation in doubles tennis, offering both theoretical and practical implications for players, coaches, and analysts in the sport.

The rest of our paper is organized as follows. In Section 2, we introduce the conceptual framework based on a model where a team comprising the strongest and the weakest player competes against a team of the second- and third-strongest players. Section 3 describes the data and the empirical strategy employed in our analysis. In Section 4, we present our empirical findings, highlighting the key results and interpreting their implications within the context of doubles tennis. In Section 5, we conclude our paper with a summary of our findings and their broader implications.

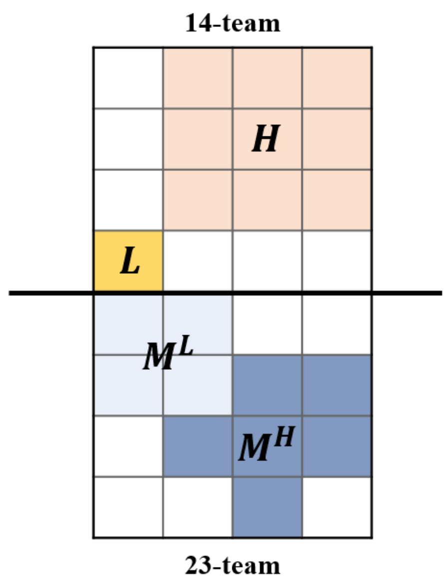
2 Conceptual Framework

2.1 "1+4 team" vs. "2+3 team"

To begin, we develop a simplified game model based on a doubles tennis match. We designate the skill ranking of each player from 1 through 4, naming them H for player H, M for player M^H, N for player M^L, and L for player L. Now, for the sake of convenience, we explore scenarios where Players H and L team up as the "1+4 team," while Players M^H and M^L form the "2+3 team." Each team's overall ability is the sum of their players' abilities, and the overall abilities of the 1+4 team and the 2+3 team equal each other. Here, "each player's ability" signifies their capacity to cover a range of the tennis court for defensive purposes, assuming all other factors remain constant, ceteris paribus.



(a) Strategies of an attacking team, signifying the ability to attack within each court quadrant



(b) An example of illustrating a defensive team's coverage configuration tailored to player abilities

Figure 1: The court for 1+4 vs. 2+3 double tennis game

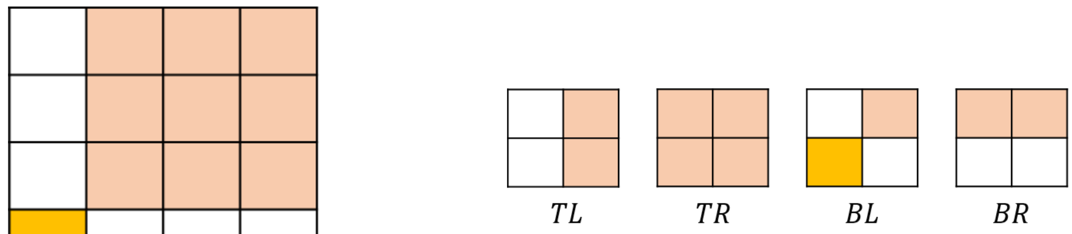
* In this game, there are four players, H, M^H, M^L, and L, belonging to two teams based on their ability order. 1+4 team consists of players H and L, while 2+3 team comprises the others. Each team can either attack or defend. The court is divided into four regions: TL, TR, BL, and BR. The attacking team selects one region from the four available. The defending team establishes their coverage, influencing the payoffs by determining the probabilities of successful attacks and defenses."

To represent each player's abilities within the game, we first define the court's regions. In actual tennis, the court dimensions for each team are approximately 10.97 meters in width and 11.89 meters in length, with the length slightly exceeding the width. In our game model, we treat each team's side of the court as a large square. We can divide the court into four quadrants: top-left (TL), bottom-left (BL), top-right (TR), and bottom-right (BR). Each of these quadrants can be further subdivided into four squares. In essence, the court can be broadly divided into four quadrants of 4 squares each, resulting in a total of 16 squares. In the court consisting of 16 squares, the abilities of teams 1+4 and 2+3 are equal. Assume that H can cover 9 squares, M^H can cover 6 squares, M^L can cover 4 squares, and L can cover 1 square.

The game comprises three stages. In the first stage, the defensive team determines which squares each player will defend based on their respective abilities. The configuration of this area is common knowledge. In the second stage, the offensive team decides to target one of the four areas, TL, BL, TR, or BR, and at this point, the defensive team cannot predict where the attack will occur. In the third stage, the defensive team decides which of their two players will receive the ball. The rewards for each team vary depending on the decisions made in each stage.

2.2 When the "1+4 team" defends against the attack of the "2+3 team"

Figure 1 represents one example of how players H and L can be positioned in the first stage when the 1+4 team is defending their court. H occupies 9 of the 16 squares in the upper right corner, while L takes the bottom-left square. This, in turn, determines the probabilities that each player will receive the ball in the TL, BL, TR, and BR areas. These probabilities determine the expected values of the rewards. In the second stage, the 2+3 team chooses one of the four quadrants to attack, TL, TR, BL, or BR. In the third stage, unaware of which quadrant the 2+3 team has selected, the 1+4 team decides which partner will receive the ball. Figure 2 illustrates the second and third stages. Let's assume TR is chosen for the attack. If H of the 1+4 team receives the ball in the third stage, they can defend with a 100%



(a) Example of Court Occupation for the 1+4 team

(b) Positioning by Zones for the 1+4 team

Figure 2: One example among the 1+4 team's defense strategies

*In (a), the beige-colored area with 9 cubes represents the region chosen by player H for defense, while the yellow-colored area with 1 cube represents the region chosen by player L.

chance of success, whereas if L is chosen to defend, they cannot do so at all. Representing the expected values of the scores with probabilities, if H receives, (2+3 team's payoff, 1+4 team's payoff) = (0, 1); if L receives, this becomes (1, 0). In this manner, the payoffs for each case are depicted in Figure 2.

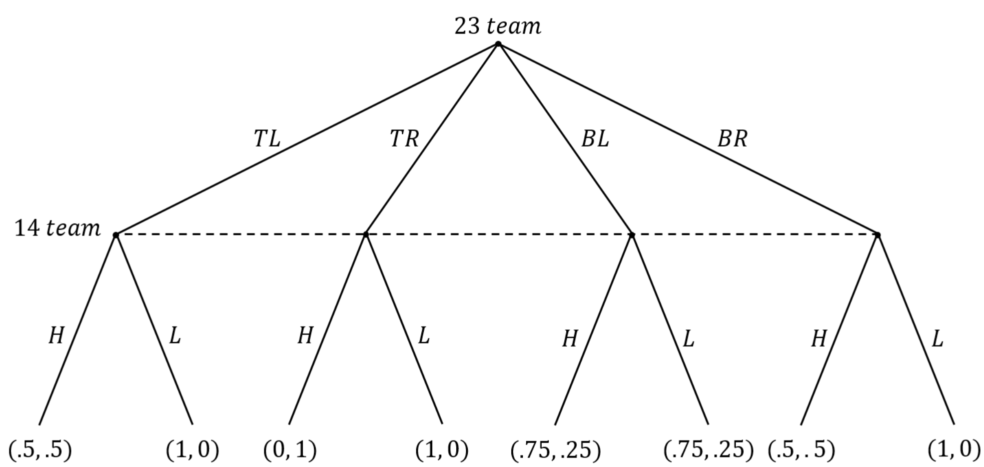


Figure 3: The game tree of the example in Figure 1(a)

*The payoffs indicate (2+3 team's payoff, 1+4 team's payoff) in the above.

To find the Perfect Bayesian Nash Equilibrium (PBNE), consider the example in Figure 2. For team 1+4's beliefs about the decisions of the 2+3 team, assign $(1 - \mu_1 - \mu_2 - \mu_3)$ to TL, μ_1 to TR, μ_2 to BL, and μ_3 to BR. In this case, the expected payoffs for the 1+4 team depending on the receiver are as follows:

$$E(\pi_{14}(H)) = .5(1 - \mu_1 - \mu_2 - \mu_3) + \mu_1 + .25\mu_2 + .5\mu_3 = .5 + .5\mu_1 - .25\mu_2 \quad (1)$$

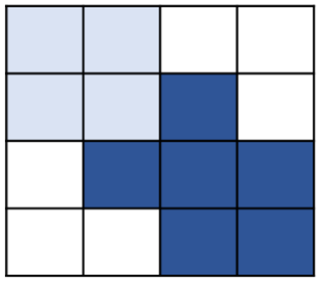
$$E(\pi_{14}(L)) = .25\mu_2 \quad (2)$$

Following equations (1) and (2), $E(\pi_{14}(H)) \geq E(\pi_{14}(L))$ for all $\mu_i \in [0, 1]$. H is selected by the 1+4 team and the 2+3 team chooses BL. Thus, the PBNE for Figure 2 is (BL, H for any $\mu_1 \in [0, 1]$). The PBNE can also be established in the same way when the 1+4 team selects their defensive positions differently. In Figure 1, with the area chosen by Player H fixed, when Player L chooses 1 square in either TL or BR, the payoffs in Figure 2 change accordingly, but the PBNE remains (BL, H for any $\mu_1 \in [0, 1]$). The two players of the 1+4 team, H and L, can select 10 squares out of 16 in various combinations. However, in each case, the optimal strategy for the 2+3 team is to choose the area selected by L, and the optimal strategy for the 1+4 team is to select H as the receiver, regardless of their beliefs about the location selected by their opponents. This is the PBNE, and the equilibrium payoffs of the 2+3 team and the 1+4 team are (.75, .25). The Appendix A1 introduces other possible cases, including the solution for obtaining a PBNE for each case.

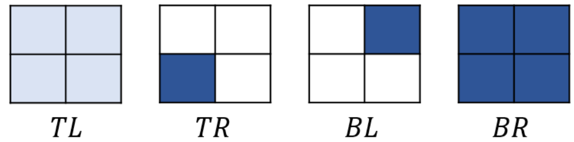
Proposition 1. *When the 1+4 team defends against the attack of the 2+3 team, the 2+3 team chooses the area selected by Player L, and the strategy for the 1+4 team is for Player H to receive, regardless of their beliefs. This constitutes a PBNE, and the equilibrium payoff is (.75, .25).*

2.3 When the "2+3 team" defends against the attack of the "1+4 team"

In a scenario where the 2+3 team is defending, the abilities of Players M^H and M^L differ from those of the 1+4 team's players, changing the game's equilibrium and payoffs. Figure 4 illustrates one example of the possible defensive positions that the 2+3 team can choose. As demonstrated in Section 2.2, Figures 4 and 5 can be used as an example to derive a PBNE.



(a) Example of Court Occupation for the 2+3 team



(b) Positioning by Zones for the 2+3 team

Figure 4: One example among the 2+3 team's defense strategies

*In (a), the dark blue-colored area with 6 cubes represents the region chosen by player M^H for defense, while the light blue-colored area with 4 cubes represents the region chosen by player M^L.

In Figure 4 (a), M^H has selected 6 squares to defend, while M^L has chosen 4 squares, and the defensive capabilities for each of the 4 areas are shown in Figure 4 (b). Say that in the first stage, the 2+3 team positions themselves in the defensive formation depicted in Figure 4. Figure 5 depicts the decision-making and payoffs that follow for each team in the second and third stages.

To establish an equilibrium in the scenario described above, we can assign the beliefs about which quadrant the 1+4 team will target as follows, for ease of computation: ρ_1 to TL, $1-\rho_1-\rho_2-\rho_3$ to BL, ρ_2 to TR, and ρ_3 to BR. The expected payoffs for the 2+3 team's decisions as to whether M^H or M^L should receive the ball are as follows:

$$E(\pi_{23}(M^H)) = .25(1-\rho_1-\rho_2-\rho_3)+.25\rho_2+.\rho_3 = .25-.25\rho_1+.75\rho_3 \tag{3}$$

$$E(\pi_{23}(M^L)) = \rho_1 \tag{4}$$

In equations (3) and (4), the equilibria vary depending on the beliefs. Comparing the expressions for $E(\pi_{23}(M^H))$ and $E(\pi_{23}(M^L))$ in equations (3) and (4), we can determine that when $1+3\rho_3 \geq 5\rho_1$, the optimal strategy for the 2+3 team is to choose M^H; otherwise, the optimal strategy is to choose M^L.

Accordingly, in the former case, targeting TL is the optimal strategy for the 1+4 team,

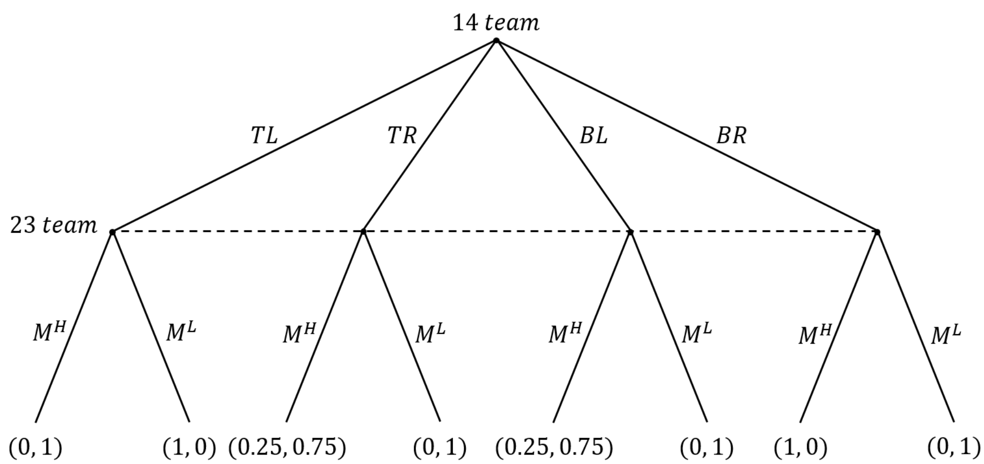


Figure 5: The game tree of the example in Figure 3

*The payoffs indicate (2+3 team's payoff, 1+4 team's payoff) in the above.

while in the latter case, targeting one of the other 3 quadrants (TR, BL, BR) is the optimal strategy for the 1+4 team. Therefore, the PBNE are (TL, M^H with $1 + \rho_3 \geq 5\rho_1$) and (TR or BL or BR, M^L with $1 + \rho_3 < 5\rho_1$). The equilibrium payoff (2+3 team's payoff, 1+4 team's payoff) always = (0,1). Appendix A1 shows other defensive strategies of the 2+3 team, each of which has an equilibrium payoff of (0,1).

Proposition 2. *When the 2+3 team defends against the attack of the 1+4 team, each team's equilibrium strategy varies depending on beliefs about the targeted quadrant, but the equilibrium payoff is (0, 1) indicating (2+3 team's payoff, 1+4 team's payoff).*

Thus, Propositions 1 and 2 suggest that when the two teams engage in both offense and defense, the sum of their expected payoffs is as follows: (2+3 team's payoff, 1+4 team's payoff) = (0.75, 1.25), indicating that the 1+4 team has a higher likelihood of advantage in the match. That is, the equilibrium payoffs suggest that in a competitive scenario where the "2+3 team" and the "1+4 team" engage in offense and defense, the "1+4 team's" expected payoff is higher.

3 Data and Empirical Strategy

The theoretical predictions from Section 2 indicate that in real doubles tennis matches where team abilities are similar, the team with the strongest player has a higher likelihood of winning. This section discusses the data for an empirical analysis based on these theoretical predictions and strategies to further investigate this phenomenon.

3.1 Data

We collect data from the ATP World Tour website.[1] We specifically rely on a repository designed for scraping tennis-related data from the ATP World Tour's web pages.[2] This dataset contains information related to ATP tournaments, match scores, match statistics, player rankings, and player profiles. Within this extensive dataset, our primary focus is male doubles match results from 1976 to 2017.[3] These match results are organized and presented in Table 1.

To analyze the dynamics of male doubles teams in tennis matches, we categorize these teams by the pairings of ranked players. For instance, "1+4" represents teams where the highest-ranked player and the lowest-ranked player of the four players playing a match. Conversely, "2+3" signifies teams comprising the other two players, i.e. the second-ranked and third-ranked players from the same group of four players. "1+4 team vs. 2+3 team" describes the specific matchups between these two pairs. We also calculate the average between the two players individual doubles rankings, denoted as "Doubles Ranking Mean." This is derived from the time-varying doubles rankings of individual players at the precise moment they participated in the matches. We also consider the nationalities of players who are paired on a team using the "Same Nationality" variable, which reveals whether a team is composed of players from the same country. Furthermore, our dataset takes into account the experience factor, which is based on the number of matches played by unique

[1] https://www.atptour.com/

[2] https://github.com/serve-and-volley/atp-world-tour-tennis-data, https://datahub.io/sports-data/atp-world-tour-tennis-data

[3] We restrict our analysis to male doubles matches due to the availability of comprehensive and consistent historical data for this category, which allows for a robust and detailed statistical examination of team dynamics and performance trends over an extended period.

team pairings. Under the "Major Championships" variable, we identify the Grand Slam tournaments, namely the Australian Open, the French Open, Wimbledon, and the US Open.

Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) Min.	(4) Max.	(5) Observations
Panel A. Team-level characteristics					
Doubles ranking mean	113.81	136.27	1	1,653	117,210
Doubles ranking difference	58.38	106.24	0	1,620	117,210
Having Top 100 player in team	0.74	0.44	0	1	117,210
Teammates from same country	0.50	0.50	0	1	117,210
Number of double games played together	44.03	115.46	0	1,023	117,210
Number of unique pairs					32,595
Number of unique tournaments					3,031
Panel B. Match-level subsamples					
Number of 1+4 team vs. 2+3 team matchups					16,487
Number of Major Championship matches[a]					19,804

Note: This table presents the summary statistics of match results for male doubles between the years 1976 and 2017 from the ATP World Tour website.
[a] These indicate matches in one of the four Grand Slam tournaments namely (Australian Open, the French Open, Wimbledon, and the US Open).

3.2 Team characteristics and winning

In order to examine potential factors that influence match outcomes in male doubles tennis, we initially investigate the extent to which team characteristics predict the likelihood of winning a match. Table 2 presents the regression results. The dependent variable in both columns is the percentage chance of winning a match—i.e., the variable is coded as 100 if the match is won, and 0 otherwise. In order to account for variations in tournament conditions and rounds within tournament, in column 1, we include the tournament fixed effects, and in column 2, we add the round fixed effects.

For individual player's doubles ranking, the within-team mean and differences are significantly correlated with winning probabilities. Yet the magnitudes are very small, so we'd rather be cautious in attributing substantial practical significance to this finding.

On the other hand, the presence of a Top 100 player in a team substantially enhances the chances of winning, the effect quantified at 7.4-8.7 percentage points. This finding aligns with the concept of "hard-carrying," where a single highly skilled player can tilt the balance in favor of their team. Also, the status of being a Top 100 player in tennis holds considerable significance, as it not only reflects a high level of skill but also markedly influences team performance and success in competitive matches.

Interestingly, teams composed of players from the same country are found to have a lower probability of winning, with a decrease of 2.6-2.7 percentage points. This might reflect cultural or strategic nuances that impact team dynamics in doubles tennis, which is a potential subject of future research.

Additionally, the analysis reveals a small but positive correlation between the number of double games played by a team and their winning chances. Each additional game played increases the winning probability by approxmately 0.2 percentage points, indicating the benefits of experience. The squared term of the number of games played shows a close-to-zero association with winning probability, suggesting returns with increasing experience neither increases nor diminishes.

Overall, these results provide suggestive findings on the intricate interplay of individual skills, team composition, and experience in determining the success of doubles teams in professional tennis.

3.3 Empirical strategy

We first run the following specification on the full sample:

$$Win_{imtr} = \beta_1 Strongest_{itmr} + \beta_2 Weakest_{itmr} + \beta_3 Strongest_{itmr} \times Weakest_{itmr} + \phi_t + \lambda_r + \theta X_i + \varepsilon_{imtr}, \quad (5)$$

where Win_{imtr} is the match result for team i in match m in round r of tournament t. $Strongest_{imtr}$ indicates whether the team has the highest-ranked player among the four players, and $Weakest_{imtr}$ indicates that it has the lowest-ranked player. ϕ_t and λ_r are tournament and round fixed effects, respectively. X_i is a vector of team characteristics,

Table 2: Team Characteristics and Winning Probability

	(1)	(2)
	Percentage of winning match	
Doubles ranking mean	-0.054***	-0.061***
	(0.001)	(0.001)
Doubles ranking difference	0.008***	0.008***
	(0.002)	(0.002)
Having Top 100 player in team	7.425***	8.735***
	(0.452)	(0.453)
Teammates from same country	-2.564***	-2.673***
	(0.302)	(0.300)
Number of double games played	0.220***	0.238***
	(0.003)	(0.003)
Number of double games played squared	-0.000***	-0.000***
	(0.000)	(0.000)
Overall mean	50.00	50.00
Tournament FE	Yes	Yes
Round FE	No	Yes
Observations	117,210	117,210

Note: Sample at match level. Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

including the variables in Table 2. We employ heteroskedasticity-robust standard errors.

To empirically validate our conceptual framework from Section 2, we restrict the sample to matches where the team with the "Strongest (1st rank among four players) + Weakest (4th rank)" competes against the team with the "Second (2nd rank) + Third (3rd rank)," and we run the following:

$$Y_{imtr} = \beta 14Team_{itmr} + \phi_t + \lambda_r + \theta X_i + \varepsilon_{imtr}, \tag{6}$$

where $14Team_{itmr}$ is an indicator for the pair made up of the "Strongest (1st-ranked) + Weakest (4th-ranked)" players.

4 Results

In this section, we present and interpret the core findings of our study, focusing on the influence of the strongest and weakest players within teams. Central to our analysis is the examination of the effects arising from partnerships composed of the "strongest + weakest" players. This investigation is pivotal in validating the propositions set forth in the conceptual framework we outlined earlier. We meticulously analyze how the combination of the highest- and lowest-ranked players within a team impacts match outcomes, offering empirical evidence that supports our theoretical predictions.

4.1 Influence of the strongest and weakest players

Our analysis begins by investigating the impact of having the strongest and weakest players on a doubles tennis team's probability of winning a match. This inquiry is central to understanding the dynamics within partnerships and how individual player ability influences overall team performance.

Utilizing the regression specification outlined in our empirical strategy, we examine the full sample of matches to discern the effects of having the highest-ranked (strongest) and lowest-ranked (weakest) players among four players. The key variables of interest are the indicators for the presence of the strongest or weakest player, along with their interaction term. The regression model also controls for tournament and round fixed effects, as well as other team characteristics.

The results from Panel A of Table 3 reveal compelling findings. The presence of the strongest player is associated with a substantial increase in a partnership's chances of winning, with coefficients ranging from 14.0 to 20.3 percentage points across different model specifications, all statistically significant at 1% level. This positive effect emphasizes the pivotal impact of a top player on team performance.

Conversely, the presence of the weakest player in a team has a significant negative impact on a partnership's probability of winning, with coefficients indicating a decrease in the likelihood of winning of between 12.5 to 17.8 percentage points. This finding aligns with the intuition that lower-ranked players could potentially decrease a team's overall strength.

The interaction term between the strongest and weakest players exhibits a statistically significant effect in column 3 (our preferred specification), and the inclusion of the strongest and weakest players predicts an increase of around 4 percentage points in the probability of winning (numerically summing up all three coefficients). These results corroborate the "hard carry" hypothesis, indicating that the influence of having the highest-performing player on a team is more critical in determining victory than the possible detrimental effect of having the least skilled player.

In Panel B, in order to empirically investigate the theoretical predictions derived from our conceptual framework, we focuses on the subsample of matches between a "1+4 team" (made up of the first- and fourth-ranked players) competes against a "2+3 team" (made up of the second- and third-ranked players in a match). Here, we observe that the "1+4 team" has a consistently higher probability of winning, with coefficients ranging from 2.5 to 7.7 percentage points across models. To support the validity of our results, we conduct a robustness check using logit regression analysis. The dependent variable is a binary indicator of whether the team wins or not, making logit regression applicable. We measure the effect using this method and find consistent results, as shown in Table B1.

In summary, the results support our hypothesis of a "hard carry" effect in doubles tennis. The empirical evidence suggests that having the strongest player on a team significantly boosts that team's chances of winning and outweighs the negative impact of having the weakest player. This finding not only validates the propositions of our conceptual framework but also provides valuable insights into strategic player selection in professional doubles tennis.

4.2 Do the dynamics differ in high-stakes matches?

In Table 4, we extend our analysis, examining whether these dynamics remain consistent under high-pressure scenarios such as Grand Slam tournaments or advanced stages of competitions like finals, semi-finals, or quarter-finals.

In Panel A, for tournaments that grant the highest ranking points, namely Grand Slams, ATP Finals, and ATP 1000 tournaments, we do not find any statistically significant effects, let alone linearity across tournaments.

Table 3: Strongest and Weakest Players on Winning Matches

	(1)	(2)	(3)
	Percentage of winning match		
Panel A. Full sample			
Strongest player	20.33***	20.33***	14.02***
	(0.59)	(0.61)	(0.61)
Weakest player	-17.82***	-17.83***	-12.54***
	(0.59)	(0.61)	(0.61)
Strongest × Weakest	0.01	0.01	2.99***
	(0.83)	(0.88)	(0.87)
Mean: No Best × No Worst	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	117,210	117,210	117,210
Panel B. Matches of 14 team vs. 23 team			
1+4 team	2.52***	2.53***	7.72***
	(0.78)	(0.85)	(1.04)
Mean (2+3 team)	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,481	16,481

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Panel B focuses on critical match stages within a tournament: finals, semi-finals, and quarter-finals. Many of the interaction terms display statistically significant differences from lower-stage matches. These findings align with the results from the logit regression analysis presented in Table B2. This suggests that the strategic advantage of having the strongest and weakest player combination does significantly change during these crucial stages of a tournament. One explanation for these results is that across rounds within tournaments, the pairing is more exogenous because changing a doubles partner within tournament is often not allowed. Therefore, the differential effects across rounds can be interpreted as the overweighing impact of the strongest player is stronger for these high-stakes matches.

Table 4: Strongest and Weakest Players in High-stakes Matches

	(1)	(2)	(3)
	Percentage of winning match		
Panel A. High-stakes tournaments			
1+4 team	2.90***	3.12***	8.19***
	(0.85)	(0.98)	(1.17)
1+4 team × Grand Slams	-1.75	-2.41	-3.08
	(1.95)	(2.61)	(2.58)
1+4 team × ATP Finals	5.83	11.16	19.62
	(11.18)	(16.73)	(16.04)
1+4 team × ATP 1000	-1.48	-2.59	-0.94
	(1.75)	(2.62)	(2.60)
Mean (2+3 team)	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,481	16,481
Panel B. Finals, semi-finals, quarter-finals			
1+4 team	0.70	0.71	5.06***
	(0.98)	(1.07)	(1.26)
1+4 team × Finals	4.26	4.42	7.07**
	(3.21)	(3.51)	(3.41)
1+4 team × Semi-finals	8.10***	8.10***	9.88***
	(2.53)	(2.77)	(2.74)
1+4 team × Quarter-finals	3.40*	3.37	4.44**
	(2.03)	(2.22)	(2.20)
Mean (2+3 team)	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,481	16,481

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

4.3 Mechanisms driving the "1+4 team" effect

In this subsection, we delve into the underlying mechanisms driving the observed "1+4 team" effect, particularly focusing on the presence of a top-ranked player on the team.

In Panel A of Table 5, we show that the "1+4 team" effect is more pronounced for teams that feature a player ranked in the top 100. For teams without a top 100 player, the effects are approximately 1.0 percentage points (insignificant). In contrast, for teams that do include a top 100 player, this effect—calculated as the numerical difference between the coefficient of the interaction term and the standalone "Top 100 player" term—is about 2.2 percentage points. This suggests that the strategic advantage of pairing the strongest player with the weakest player is enhanced when the team includes a top 100 player.

Panel B extends this analysis to teams with large disparities between the members' rankings. We restrict the analysis to those with above-median differences in team members' rankings. This approach allows us to explore the dynamics of teams where the skill gap between the strongest and weakest players is particularly pronounced. This targeted examination is crucial to understanding how the "1+4 team" effect operates in scenarios where the disparity in skill levels is more extreme. By isolating teams with greater ranking disparities, we can assess whether the impact of having a top 100 player is amplified in the context of a wider skill gap within the team.

We find that the "1+4 team" effect is even more striking in such cases. The interaction term shows an even larger positive effect, with coefficients of 5.9-7.2 percentage points, while the standalone "Top 100 player" effect is insignificant. These results indicate that the impact of having a top player in a partnership is further magnified in scenarios where the disparity in the rankings of the two partners is greater. These findings are consistent with the results from the logit regression analysis shown in Table B3.

In summary, our findings highlight the critical influence of individual player rankings, especially the presence of top-tier players, on doubles tennis outcomes. The data shows that partnerships that include a top 100 player, and particularly partnerships with substantial skill disparities, have a higher probability of winning. This analysis not only confirms the significant impact of highly skilled players but also demonstrates how skill level disparities within a team can be strategically leveraged to enhance performance in professional doubles tennis.

Table 5: Weakest Player Paired with Strongest Player of Top 100

	(1)	(2)
	Percentage of winning match	
Panel A. Top 100 player		
1+4 team	1.02	0.96
	(2.09)	(2.09)
1+4 team × Top 100 player	5.35***	5.55***
	(1.49)	(1.51)
Top 100 player	3.16**	3.40**
	(1.58)	(1.62)
Mean (2+3 team × Non-Top 100)	47.51	47.51
Round FE	Yes	Yes
Tournament FE	No	Yes
Observations	16,481	16,481
Panel B. Top 100 player in high gap teams[a]		
1+4 team	4.16	3.99
	(2.85)	(2.85)
1+4 team × Top 100 player	5.88**	7.24***
	(2.44)	(2.47)
Top 100 player	0.18	1.38
	(3.31)	(3.33)
Mean (2+3 team × Non-Top 100)	47.33	47.33
Round FE	Yes	Yes
Tournament FE	No	Yes
Observations	7,732	7,732

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.
[a] Sample is restricted to teams above the median in terms of within-team ranking differences.

5 Conclusion

We investigate the dynamics of team composition and strategy in professional doubles tennis and explore the "hard-carry" hypothesis. Our findings confirm that a top-tier player can indeed significantly improve a team's chances of victory, often outweighing the negative impact of a less skilled teammate. This "hard-carry" effect is more pronounced when the stakes are higher, such as finals within a tournament, or when the "1+4 team" includes a top 100 player.

In our theoretical framework, we employ the Perfect Bayesian Nash Equilibrium (PBNE) and demonstrate that teams with a significant skill disparity, particularly those consisting of both the strongest and weakest players in a match, are more likely to succeed than teams that pair the second- and third-strongest players. This finding not only supports our hypothesis but also provides insights into strategic pairings and team formation. Our research marks a significant step in understanding the dynamics of team sports, specifically in the context of professional doubles tennis. We also offer a new perspective for players, coaches, and analysts on how team composition based on player ranking differences impacts the chance of winning.

However, it is crucial to acknowledge the limitations of our study. We have exclusively focused on professional doubles players on ATP World Tours, leaving the dynamics of amateur tennis and other related sports relatively unexplored. This gap presents a promising direction for future research, and similar studies can be conducted in other sports and at other levels of play to enhance our understanding of team dynamics and the applicability of the "hard-carry" effect. Our findings not only illuminate the strategic importance of individual players in doubles tennis but also invite broader consideration of how player selection impacts team performance in sports. As we look to the future, we anticipate that our study will inspire further research, leading to a more nuanced understanding of team composition and strategy across different sporting disciplines.

References

Amodio, F. and M. A. Martinez-Carrasco (2018). Input allocation, workforce management and productivity spillovers: Evidence from personnel data. *The Review of Economic Studies 85*(4), 1937–1970.

Angrist, J. D. (2014). The perils of peer effects. *Labour Economics 30*, 98–108.

Angrist, J. D. and K. Lang (2004). Does school integration generate peer effects? evidence from boston's metco program. *American Economic Review 94*(5), 1613–1634.

Arcidiacono, P., J. Kinsler, and J. Price (2017). Productivity spillovers in team production: Evidence from professional basketball. *Journal of Labor Economics 35*(1), 191–225.

Azoulay, P., J. Graff Zivin, and J. Wang (2010). Superstar extinction. *The Quarterly Journal of Economics 125*(2), 549–589.

Bandiera, O., I. Barankay, and I. Rasul (2009). Social connections and incentives in the workplace: Evidence from personnel data. *Econometrica 77*(4), 1047–1094.

Blickensderfer, E. L., R. Reynolds, E. Salas, and J. A. Cannon-Bowers (2010). Shared expectations and implicit coordination in tennis doubles teams. *Journal of Applied Sport Psychology 22*(4), 486–499.

Borderias, M., M. Crespo, R. Martínez-Gallego, and E. Baiget (2022). Comparison of the game structure and point ending during grand slam women's doubles tennis. *International Journal of Sports Science & Coaching 18*, 1248 – 1255.

Boucher, V., Y. Bramoullé, H. Djebbari, and B. Fortin (2014). Do peers affect student achievement? evidence from canada using group size variation. *Journal of applied econometrics 29*(1), 91–109.

Bozóki, S., L. Csató, and J. Temesi (2016). An application of incomplete pairwise comparison matrices for ranking top tennis players. *European Journal of Operational Research 248*(1), 211–218.

Brave, S. A., R. A. Butters, and K. A. Roberts (2019). Uncovering the sources of team synergy: Player complementarities in the production of wins. *Journal of Sports Analytics 5*(4), 247–279.

Brune, L., E. Chyn, and J. Kerwin (2022). Peers and motivation at work: evidence from a firm experiment in malawi. *Journal of Human Resources 57*(4), 1147–1177.

Budak, G. and I. Kara (2022). A multiobjective mathematical model to form the best team at sports clubs: team harmony and player performance objectives. *Team Performance Management: An International Journal*.

Budak, G., İ. Kara, Y. T. İç, and R. Kasımbeyli (2018). Optimization of harmony in team formation problem for sports clubs: a real-life volleyball team application. *Int. J. Appl. Sci. Eng 8*(2).

Caeyers, B. and M. Fafchamps (2016). Exclusion bias in the estimation of peer effects. Technical report, National Bureau of Economic Research.

Cao, Y., Y. Peng, Z. Shen, H. Chen, B. Peng, and X. Yan (2022). Application of tactics in technical and tactical analysis of table tennis mixed doubles based on artificial intelligence graph theory model. *Journal of Environmental and Public Health 2022*.

Cohen-Zada, D., I. Dayag, and N. Gershoni (2023). Effort peer effects in team production: Evidence from professional football. *Management Science*.

Cornelissen, T., C. Dustmann, and U. Schönberg (2017). Peer effects in the workplace. *American Economic Review 107*(2), 425–456.

Gerdin, G., M. Hedberg, and C.-A. Hageskog (2018). Relative age effect in swedish male and female tennis players born in 1998–2001. *Sports 6*.

Gould, E. D. and E. Winter (2009). Interactions between workers and the technology of production: Evidence from professional baseball. *The Review of Economics and Statistics 91*(1), 188–200.

Guryan, J., K. Kroft, and M. J. Notowidigdo (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics 1*(4), 34–68.

Herbst, D. and A. Mas (2015). Peer effects on worker output in the laboratory generalize to the field. *Science 350*(6260), 545–549.

Hoxby, C. M. (2000). Peer effects in the classroom: Learning from gender and race variation.

Irons, D. J., S. Buckley, and T. Paulden (2014). Developing an improved tennis ranking system. *Journal of Quantitative Analysis in Sports 10*(2), 109–118.

Jackson, C. K. and E. Bruegmann (2009). Teaching students and teaching each other: The importance of peer learning for teachers. *American Economic Journal: Applied Economics 1*(4), 85–108.

Loffing, F., N. Hagemann, and B. Strauss (2012, 11). Left-handedness in professional and amateur tennis. *PLOS ONE 7*(11), 1–8.

Malueg, D. A. and A. J. Yates (2010). Testing contest theory: evidence from best-of-three tennis matches. *The Review of Economics and Statistics 92*(3), 689–692.

Martínez-Gallego, R., M. Crespo, J. Ramón-Llín, S. Micó, and J. F. Guzmán (2019). Men's doubles professional tennis on hard courts: Game structure and point ending characteristics. *Journal of Human Sport and Exercise*.

Martínez-Gallego, R., S. M. Salvador, J. F. G. Luján, M. Reid, J. Ramón-Llín, and M. Crespo (2021). Challenging serve myths in doubles tennis. *International Journal of Sports Science & Coaching 16*, 1305 – 1311.

Mas, A. and E. Moretti (2009). Peers at work. *American Economic Review 99*(1), 112–145.

Oreopoulos, P. (2003). The long-run consequences of living in a poor neighborhood. *The quarterly journal of economics 118*(4), 1533–1575.

Radicchi, F. (2011). Who is the best player ever? a complex network analysis of the history of professional tennis. *PloS one 6*(2), e17249.

Raue, C., D. Dreiskämper, and B. Strauss (2020). Do we agree on who is playing the ball? developing a video-based measurement for shared mental models in tennis doubles. *PLoS ONE 15*.

Reid, M., D. McMurtrie, and M. Crespo (2010). The relationship between match statistics and top 100 ranking in professional men's tennis. *International Journal of Performance Analysis in Sport 10*(2), 131–138.

Reid, M. and C. Morris (2013). Ranking benchmarks of top 100 players in men's professional tennis. *European Journal of Sport Science 13*(4), 350–355.

Ruiz, J. L., D. Pastor, and J. T. Pastor (2013). Assessing professional tennis players using data envelopment analysis (dea). *Journal of Sports Economics 14*(3), 276–302.

Sacerdote, B. (2001). Peer effects with random assignment: Results for dartmouth roommates. *The Quarterly journal of economics 116*(2), 681–704.

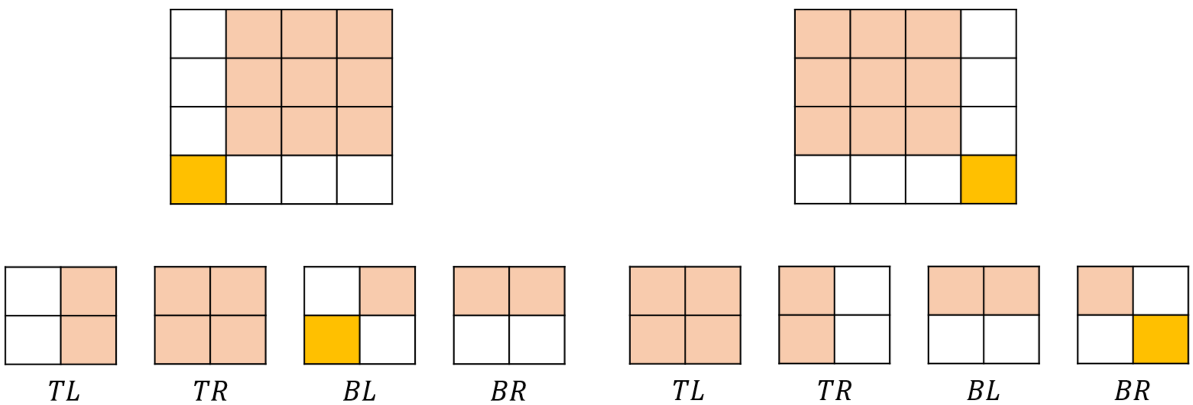
T, K., J. Carboch, C. M, and K. J (2020). Tactics in tennis doubles: analysis of the formations used by the serving and receiving teams. *International Journal of Physical Education, Fitness and Sports*.

Walker, M. and J. Wooders (2001, December). Minimax play at wimbledon. *American Economic Review 91*(5), 1521–1538.

Weimar, D. and P. Wicker (2017). Moneyball revisited: Effort and team performance in professional soccer. *Journal of Sports Economics 18*(2), 140–161.

Appendix A. Possible cases for 1+4 team vs. 2+3 team

In this chapter, we examine the possible scenarios for each team's attack and defense in the game described in Section 2. While the cubes that can be covered depend on the abilities of each player, what ultimately matters in the game is the combination of payoffs that may occur in different scenarios. In other words, as shown in the two scenario of Figure A2 below, the payoff for each team's success or failure in attack and defense varies based on which cubes players choose to cover. However, the composition of payoffs can be expressed within a few representative scenarios.



(a) scenario 1 (b) scenario 2

Figure A1: Two scenarios considered as equivalent with the same payoff combination for 1+4 team

*The case 1 shows when H selects cubes in the upper-right section, and L selects the only lower-left cube and the case 2 shows when H selects cubes in the upper-left section, and L selects the only lower-right cube. The payoff for the strategy of the 2+3 team differs in two scenarios, but ultimately, the possible combinations of payoffs are the same.

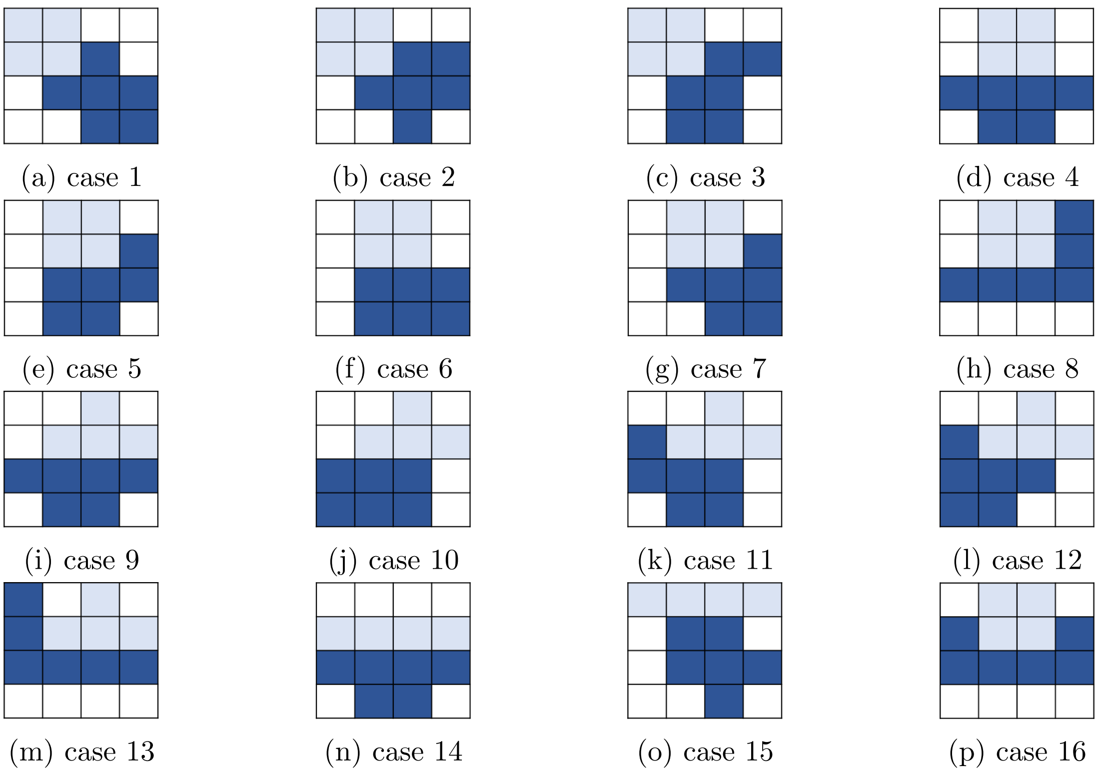
As explained in Section 2, Figure A1 illustrates the probability of success in defense for players H and L from the 1+4 team against the 2+3 team's strategies TL, TR, BL, and BR. For example, in the scenario 1, TR indicates that the 1+4 team's H has a 100% probability of successful defense, while in the scenario 2, TL shows that H can defend with 100% probability. As seen in these two cases, the combination of defense probabilities for each player is the same, its order is different only. Thus, the two scenarios can be considered as one representative case that H selects a square of 9 cubes and L player chooses a corner cube.[4] Figure A2 provides representative cases for the 1+4 team's defense, and Figure A3 shows representative cases for the 2+3 team's defense. In the game framework outlined in

[4] We have excluded impractical scenarios in the appendix. For example, consider the case where the 1+4 team's H player selects 9 cubes in one-side half of the court (8 cubes) and 1 cube. In this scenario, one of the four regions (TL, TR, BL, and BR) must be empty, resulting in a disadvantage for the 1+4 team compared to scenarios where the H player chooses a square-shaped 9 cubes. Thus, we have omitted cases that are naturally impractical for each team, as they do not contribute to the maximum payoff for them, regardless of the opposite team's beliefs.

Section 2, various combinations for double tennis are feasible for each case. The Perfect Bayesian Equilibrium payoffs are determined as follows: (1+4 team's payoff, 2+3 team's payoff) = (0.25, 0.75) in the 1+4 team's defense and (1, 0) in the 2+3 team's defense. This outcome remains consistent across all cases.

(a) case 1 (b) case 2

Figure A2: Possible cases for 1+4 team's defense



(a) case 1 (b) case 2 (c) case 3 (d) case 4 (e) case 5 (f) case 6 (g) case 7 (h) case 8 (i) case 9 (j) case 10 (k) case 11 (l) case 12 (m) case 13 (n) case 14 (o) case 15 (p) case 16

Figure A3: Possible cases for 2+3 team's defense

Appendix B.

Table B1: Strongest and Weakest Players on Winning Matches - Logistic Regressions

	(1)	(2)	(3)
	=1 if winned the match		
Panel A. Full sample			
Strongest player	0.85***	0.85***	0.58***
	(0.02)	(0.02)	(0.03)
Weakest player	-0.75***	-0.75***	-0.51***
	(0.02)	(0.02)	(0.03)
1+4 team	0.00	0.00	0.13***
	(0.03)	(0.04)	(0.04)
Mean: No Best × No Worst	0.49	0.49	0.49
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	117,210	117,210	117,210
Panel B. Matches of 14 team vs. 23 team			
1+4 team	0.10***	0.10***	0.32***
	(0.03)	(0.03)	(0.04)
Mean (2+3 team)	0.49	0.49	0.49
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,479	16,479

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B2: Strongest and Weakest Players in High-stakes Matches - Logistic Regressions

	(1)	(2)	(3)
	Percentage of winning match		
Panel A. High-stakes tournaments			
1+4 team	0.12***	0.12***	0.34***
	(0.03)	(0.04)	(0.04)
1+4 team × Grand Slams	-0.07	-0.10	-0.13
	(0.08)	(0.10)	(0.10)
1+4 team × ATP Finals	0.24	0.45	0.93
	(0.46)	(0.62)	(0.69)
1+4 team × ATP 1000	-0.06	-0.10	-0.03
	(0.07)	(0.10)	(0.10)
Mean (2+3 team)	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,479	16,479
Panel B. Finals, semi-finals, quarter-finals			
1+4 team	0.03	0.03	0.21***
	(0.04)	(0.04)	(0.05)
1+4 team × Finals	0.17	0.18	0.30**
	(0.13)	(0.13)	(0.13)
1+4 team × Semi-finals	0.32***	0.33***	0.42***
	(0.10)	(0.10)	(0.10)
1+4 team × Quarter-finals	0.14*	0.13*	0.19**
	(0.08)	(0.08)	(0.08)
Mean (2+3 team)	48.74	48.74	48.74
Round FE	Yes	Yes	Yes
Tournament FE	No	Yes	Yes
Controls	No	No	Yes
Observations	16,487	16,479	16,479

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B3: Weakest Player Paired with Strongest Player of Top 100 - Logistic Regressions

	(1)	(2)
	=1 if winned the match	
Panel A. Top 100 player		
1+4 team	0.04	0.04
	(0.08)	(0.08)
1+4 team × Top 100 player	0.21***	0.22***
	(0.05)	(0.06)
Top 100 player	0.13**	0.14**
	(0.06)	(0.06)
Mean (2+3 team × Non-Top 100)	0.48	0.48
Round FE	Yes	Yes
Tournament FE	No	Yes
Observations	16,479	16,479
Panel B. Top 100 player in high gap teams[a]		
1+4 team	0.17	0.16
	(0.11)	(0.11)
1+4 team × Top 100 player	0.25***	0.32***
	(0.09)	(0.09)
Top 100 player	0.01	0.06
	(0.12)	(0.12)
Mean (2+3 team × Non-Top 100)	0.47	0.47
Round FE	Yes	Yes
Tournament FE	No	Yes
Observations	7,115	7,115

Note: Heteroskedasticity-robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

[a] Sample is restricted to teams above the median in terms of within-team ranking differences.