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

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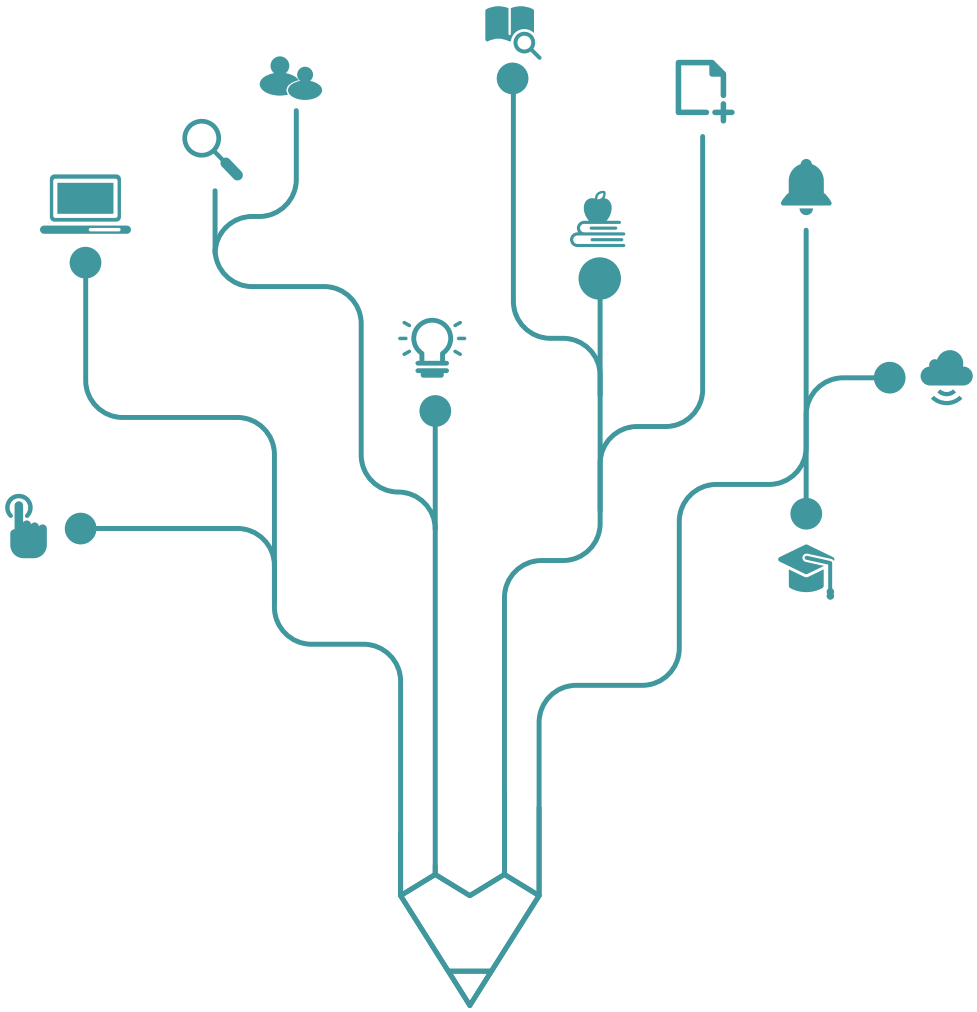

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# Strategic Pairings in Professional Doubles Tennis: The Role of the Strongest and Weakest Players*

Jeong Yeol Kim, David Sungho Park, Chungeun Yoon

**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. Considering the strategic interactions between these player pairings, we analyze their offensive and defensive positioning and scoring probabilities using a simplified $2 \times 4$ game.

The Nash equilibrium analysis reveals a distinct strategic tendency based on the defensive team composition. When the team consisting of the strongest and weakest players is on defense, the opposite team shows a tendency to concentrate their strategy on only targeting the area where the weakest player is positioned, resulting in a Pure Nash equilibrium. In contrast, when the team composed of the second- and third-strongest players is on defense, the attacking team adopts a mixed Nash equilibrium, distributing their offensive strategy between the unoccupied spaces and the area where weakest player is positioned.

Furthermore, when teams alternate between offense and defense, a comparison of equilibrium payoffs demonstrates that the team comprising the strongest and weakest players consistently achieves a higher equilibrium payoff than the team formed by the second- and third-strongest players. The results of the equilibrium analysis demonstrate that variations in individual player abilities within a doubles team fundamentally alter the strategic approaches of teams with larger and smaller ability gaps in both offense and defense, also impacting each team's equilibrium payoff.

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.

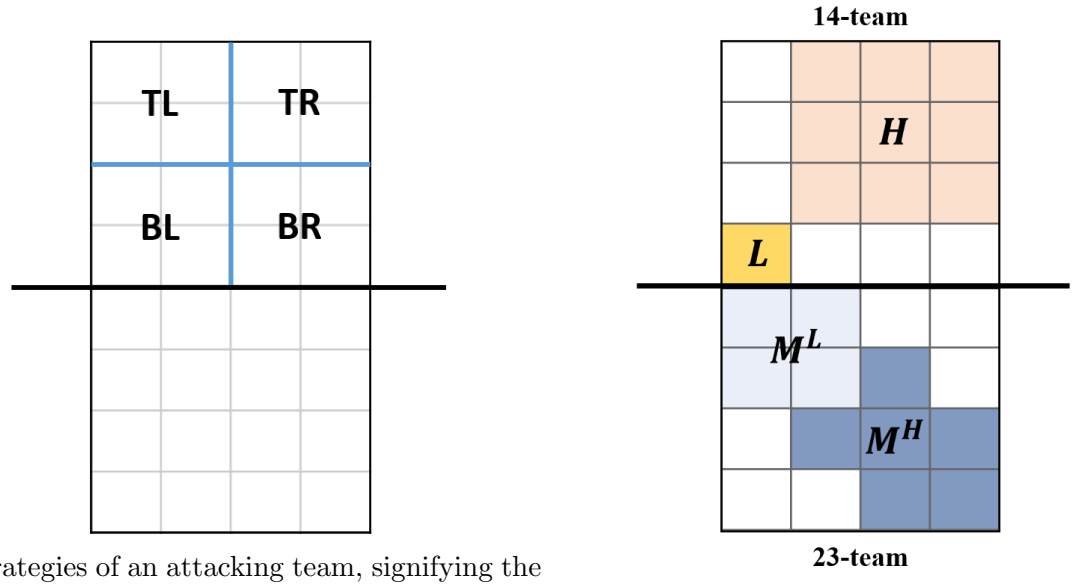
The rest of our paper is organized as follows. In Section 2, we introduce the conceptual framework based on a model where a team comprising the strongest and the weakest player competes against a team of the second- and third-strongest players. Section 3 describes the data and the empirical strategy 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"

We model a doubles tennis match as a game in which two teams engage in offensive and defensive actions on a tennis court. In this game, the team on offense selects a specific area within the court to target, while the team on defense designates one of its players to respond defensively. The payoffs for each team are determined by the probabilities of successful offense and defense.




(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

Before explaining each team's offensive and defensive strategies, we first simplify the spatial aspects of the game. We assume that each team's tennis court is a single large square.[1] In this game, a team which is attacking selects one of four quadrants: Top-Left (TL), Top-Right (TR), Bottom-Left (BL), or Bottom-Right (BR). Each quadrant consists of four smaller squares, making the entire court a grid of 16 squares. Figure 1 illustrates the game court and the designated attack areas.

[1] 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 for simplification.

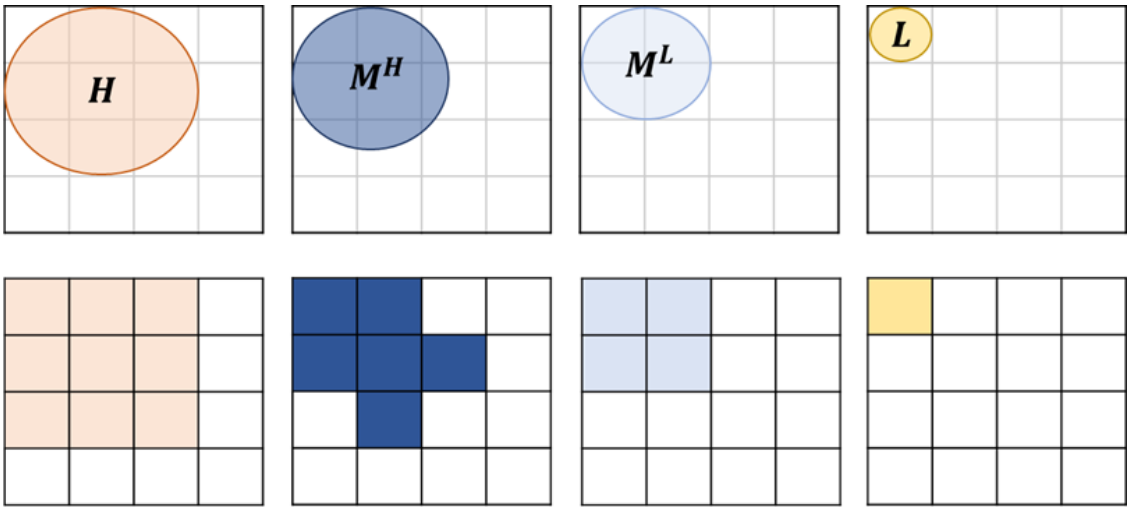



Figure 2: Defensive Coverage Range by Character (Ability)

*$H$ and $L$ form the 1+4 team, and $M^H$ and $M^L$ form the 2+3 team.

Each of the two teams participating in the doubles tennis match consists of two characters. These four characters are categorized based on their abilities as High ($H$), Middle-high ($M^H$), Middle-low ($M^L$), and Low ($L$). In this game, a player's ability is defined by the range of court areas they can cover while defending. All other conditions of the players are assumed to be identical.

The top four illustrations in Figure 2 represent the defensive coverage range of each character. For instance, $H$ covers a wide area, while $M^H$ covers a slightly smaller region. Similarly, the defensive range decreases progressively from $M^L$ to $L$. The bottom part of Figure 2 simplifies these coverage areas by representing them in block form instead of circles.

In this framework, the $H$ player is capable of defending 9 out of the total 16 squares, $M^H$ can cover 6 squares, $M^L$ can defend 4 squares, and $L$ is restricted to a single square. Based on these defensive capacities, two teams are formed: the "1+4 team," consisting of players $H$ and $L$, and the "2+3 team," composed of players $M^H$ and $M^L$. Each team possesses an equivalent total defensive coverage, with both the 1+4 team and the 2+3 team covering 10 squares (1+4 team: 9+1 squares; 2+3 team: 6+4 squares).

In this game, each team is considered a player operating two characters. The primary strategic decisions involve the selection of an attack zone when on offense and the designation

of a defending player when on defense. Building on this spatial structure, Sections 2.2 and 2.3 will provide a detailed analysis of the strategic interactions between teams in both offensive and defensive scenarios.

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

We first examine a defensive scenario involving the 1+4 team. In the first stage, the 1+4 team positions its H and L characters on the court to establish their defensive formation. The possible configurations are illustrated in Figure 3 and are assumed to be as follows: (1) H is positioned on the top right and L on the bottom left. (2) H is positioned on the top left and L on the bottom right, (3) H is positioned on the bottom right and L on the top left, and (4) H is positioned on the bottom left and L on the top right.

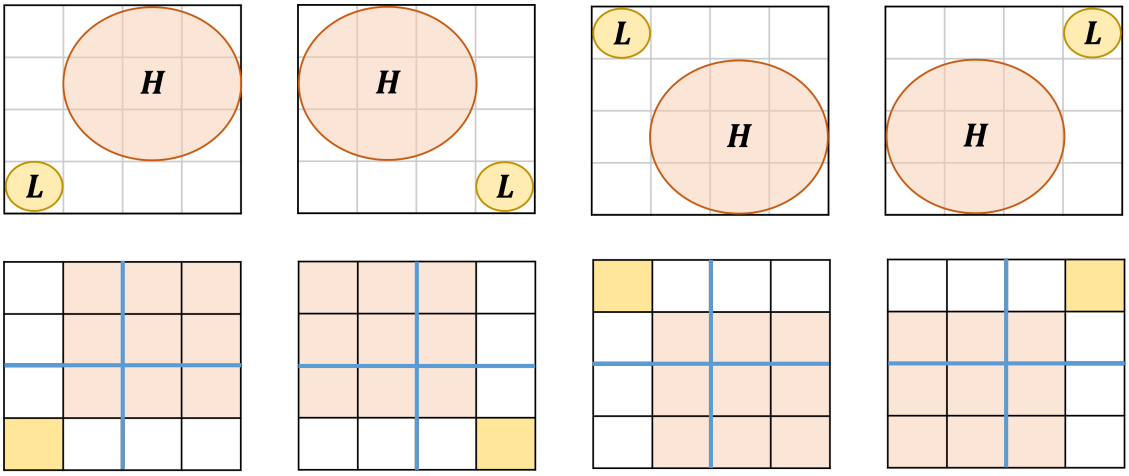
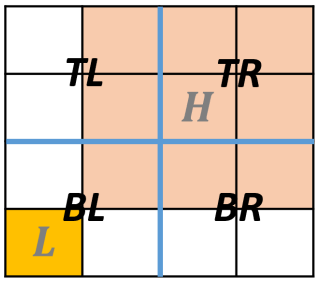


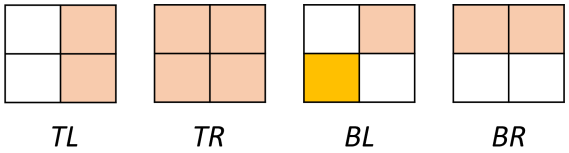

Figure 3: The four possible defensive formations for the 1+4 team.

*$H$ and $L$ form the 1+4 team, and $M^H$ and $M^L$ form the 2+3 team.

We consider the case where the 1+4 team selects the formation shown in the first column of Figure 3, with $H$ positioned at the front-right and $L$ positioned at the bottom-left. The 2+3 team, after observing the defensive positioning of the 1+4 team, chooses one of the four attack zones: $TL, TR, BL$, and $BR$. However, the 2+3 team does not know which character from the 1+4 team will defend. Similarly, the 1+4 team must decide which character, $H$ or $L$, will defend without knowing which attack zone the 2+3 team has chosen.




(a) H at Top-Right, L at Bottom-Left




(b) Four Quadrants for 2+3 Team

Figure 4: A case of 1+4 Team's Defensive Positionings and Four Quadrants

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

At this stage, the payoffs are determined as shown in Table 1, based on the attack zone selected by the attacking team and the defensive coverage of each character. For example, if the 2+3 team selects $TL$ and the 1+4 team assigns the $H$ character for defense, the resulting payoffs are (2+3 team's payoff, 1+4 team's payoff) $= (0.5, 0.5)$. This outcome arises because, as illustrated in Figure 4, the defensive coverage of the H character spans 2 of the 4 squares in the $TL$ region, allowing a 50% probability of failure. Consequently, each team receives a payoff of 0.5. However, if the 2+3 team selects $TL$ while the 1+4 team assigns the character $L$ for defense, the payoffs are $(1, 0)$. In this case, the character $L$ does not cover any of the 4 squares in the $TL$ region, ensuring that the 2+3 team scores while the 1+4 team gains nothing.

By summarizing the payoffs for all possible scenarios, Table 1 is constructed. Considering the payoffs between the two teams, the Nash equilibrium for the case where $H$ is positioned at the upper right and $L$ at the bottom left is $\{BL, H\}$, with an equilibrium payoff of $(0.75, 0.25)$. By examining the cases in the second, third, and fourth columns of Figure 3, the Nash equilibrium and equilibrium payoff for each case can be formulated as the following proposition.

**Proposition 1.** *When the 1+4 team defends against the attack of the 2+3 team, the 2+3 team chooses the area where L is positioned, and the strategy for the 1+4 team is to make H defend. This constitutes a pure NE for each case, and the equilibrium payoff is* $(0.75, 0.25)$.

| | | 1+4 team | |
|---|---|---|---|
| | | ***H*** | ***L*** |
| **2+3 team** | ***TL*** | (0.5, 0.5) | (1, 0) |
| | ***TR*** | (0, 1) | (1, 0) |
| | ***BL*** | (0.75, 0.25)* | (0.75, 0.25) |
| | ***BR*** | (0.5, 0.5) | (1, 0) |

Table 1: The Payoff Table: H at Top-Right, L at Bottom-Left

* The payoffs indicate (2+3 team's payoff, 1+4 team's payoff) and $(BL, H)$ is the pure Nash equilibrium for the case where 1+4 team set their defense positioning as the picture of the first column in Figure 3.

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

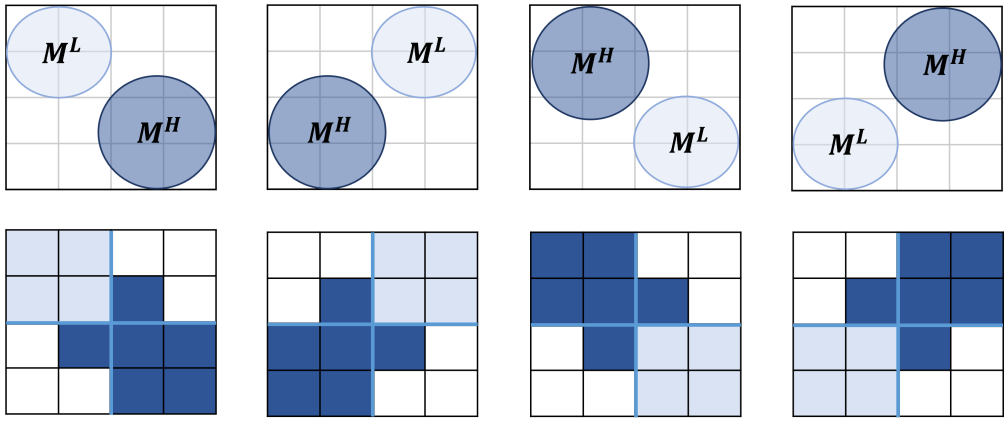
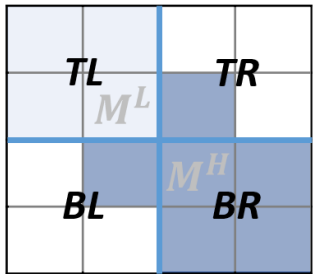



Figure 5: The four possible defensive formations for the 1+4 team.

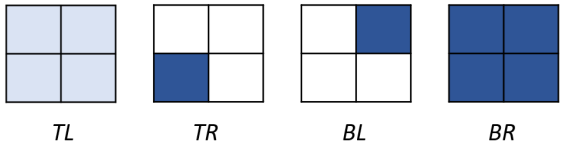
*$H$ and $L$ form the 1+4 team, and $M^H$ and $M^L$ form the 2+3 team.

In Section 2.2, we examined the defensive scenario of the 1+4 team and analyzed its Nash equilibrium and equilibrium payoff. In this section, we discuss the defensive scenario of the 2+3 team. Since the defensive coverage of the two characters in the 2+3 team, $M^H$ and $M^L$, differs from that of the 1+4 team, the equilibrium and payoff structure of the game also change.

Figure 5 illustrates the four possible defensive formations of the 2+3 team, which are assumed to be as follows: (1) $M^L$ is positioned in the top-left and $M^H$ in the bottom-right, (2) $M^L$ is positioned in the top-right and $M^H$ in the bottom-left, (3) $M^L$ is positioned in the bottom-right and $M^H$ in the top-left, and (4) $M^L$ is positioned in the bottom-left and $M^H$ in the top-right.




(a) $M^L$ at Top-Left, $M^H$ at Bottom-Right




(b) Four Quadrants for 1+4 Team

Figure 6: A case of 2+3 Team's Defensive Positionings and Four Quadrants

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

We now consider the case where the 2+3 team selects the formation shown in the first column of Figure 6, with $M^L$ positioned in the top-left and $M^H$ positioned in the bottom-right. Following the same procedure as in Section 2.2, the 1+4 team observes the defensive positioning of the 2+3 team and selects one of the four attack zones: $TL, TR, BL$, and $BR$. Meanwhile, the 1+4 team must determine which character, either $M^H$ or $M^L$, will defend without knowing which attack zone the 2+3 team has chosen.

Table 2 presents the possible payoffs based on the attack zone selected by the 1+4 team and the defending character chosen by the 2+3 team for the case depicted in the first column of Figure 4. For example, if the 1+4 team selects TL and the 2+3 team assigns $M^L$ as the defender, the 2+3 team successfully defends with 100% probability, resulting in payoffs of (2+3 team's payoff, 1+4 team's payoff) = (1,0). Conversely, if the 1+4 team selects TL while the 2+3 team assigns $M^H$ as the defender, the payoffs are (0,1). In this manner, Table 2 details the payoffs corresponding to the scenario where $M^L$ is positioned in the top-left and $M^H$ in the bottom-right.

| | | 1+4 team | | | |
|---|---|---|---|---|---|
| | | ***TL*** | ***TR*** | ***BL*** | ***BR*** |
| **2+3 team** | $M^H$ | (0, 1) | (0.25, 0.75) | (0.25, 0.75) | (1, 0) |
| | $M^L$ | (1, 0) | (0, 1) | (0, 1) | (0, 1) |

Table 2: The Payoff Table: $M^L$ at Top-Left, $M^H$ at Bottom-Right

* The payoffs indicate (2+3 team's payoff, 1+4 team's payoff) and there is no pure Nash equilibrium but exists mixed Nash equilibria for the case where 2+3 team set their defense positioning as the picture of the first column in Figure 5.

In this case, no pure Nash equilibrium exists. Considering the mixed Nash equilibrium, let the probabilities of selecting TL, TR, BL, and BR be denoted as $q_{TL}$, $q_{TR}$, $q_{BL}$, and $q_{BR}$, respectively, such that $q_{TL} + q_{TR} + q_{BL} + q_{BR} = 1$. Similarly, let the probabilities of selecting $M^H$ and $M^L$ be denoted as $p_{M^H}$ and $p_{M^L}$, respectively. By ensuring the uniformity of expected payoffs and maintaining consistency among these probabilities, the equilibrium can be determined.[2]

The mixed Nash equilibrium is given by:

$$\{(p_{M^H} = 0.8, p_{M^L} = 0.2; q_{TL} = 0.2, q_{TR} = x, q_{BL} = 0.8 - x, q_{BR} = 0) \mid 0 \leq x \leq 0.8\}.$$

That is, the probability of selecting TL is fixed at 0.2, while the probabilities for TR and BL are distributed arbitrarily such that their combined probability remains 0.8. This constitutes the 1+4 team's mixed Nash equilibrium. Meanwhile, the 2+3 team assigns probabilities of 0.8 and 0.2 to $M^H$ and $M^L$, respectively.

From these probabilities, the equilibrium payoff is computed as $(2+3$ team's payoff$, 1+4$ team's payoff$) = (0.2, 0.8)$, leading to the following result:

**Proposition 2.** *When the 2+3 team defends against the attack of the 1+4 team, the mixed equilibria occur when the 2+3 team assigns probabilities of 0.8 and 0.2 to the locations of $M^H$ and $M^L$, respectively, while the 1+4 team assigns a probability of 0.2 to the region where the*

[2]See Appendix 5

*$M^L$ player is located and a combined probability of 0.8 to the remaining two regions where neither $M^H$ nor $M^L$ are positioned. The equilibrium payoff is (2 + 3 team's payoff, 1 + 4 team's payoff) = (0.2, 0.8).*

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) = (0.95, 1.05), indicating that the 1+4 team has a higher likelihood of advantage in the match. Thus, the equilibrium payoffs indicate that in a strategic interaction where the 2+3 team and the 1+4 team engage in offensive and defensive play, the 1+4 team achieves a higher expected payoff, reflecting its relative advantage in the equilibrium outcome.

# 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.[3] We specifically rely on a repository designed for scraping tennis-related data from the ATP World Tour's web pages.[4] 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.[5] These match results are organized and presented in Table 3.

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

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

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

[5] 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.

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 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 3: 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 4 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.

Table 4: 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.

## 3.3 Empirical strategy

We first run the following specification on the full sample:

$$Win_{imtr} = \beta_1 Strongest_{itmr} + \beta_2 Weakest_{itmr} + \beta_3 Strongest_{itmr} \times Weakest_{itmr} + \phi_t + \lambda_r + \theta X_i + \varepsilon_{imtr}, \quad (1)$$

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. $\phi_t$ and $\lambda_r$ are tournament and round fixed effects, respectively. $X_i$ is a vector of team characteristics, including the variables in Table 4. 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:

$$Y_{imtr} = \beta 14Team_{itmr} + \phi_t + \lambda_r + \theta X_i + \varepsilon_{imtr}, \tag{2}$$

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 5 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.

Table 5: 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.

## 4.2 Do the dynamics differ in high-stakes matches?

In Table 6, 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.

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 6: 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 7, 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 7: 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.

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# Appendix A. Mixed Equilibria and Equilibrium payoffs

In this section, we derive the mixed Nash equilibria and their corresponding payoffs as presented in Section 2.3. The strategy set of the 2+3 team, as shown in Table 2, is given by $\{M^H, M^L\}$, while the strategy set of the 1+4 team consists of $\{TL, TR, BL, BR\}$. Let $p$ denote the probability with which the 2+3 team selects $M^H$, and let $1-p$ be the probability of selecting $M^L$. Similarly, let $q_{TL}$, $q_{TR}$, $q_{BL}$, and $q_{BR}$ represent the probabilities with which the 1+4 team selects TL, TR, BL, and BR, respectively, satisfying the constraint:

$$q_{TL} + q_{TR} + q_{BL} + q_{BR} = 1.$$

We first consider the expected payoffs of the 2+3 team. If the 2+3 team selects $M^H$, its expected payoff is given by:

$$U_{\text{2+3 team}}(M^H) = 0.25q_{TR} + 0.25q_{BL} + q_{BR}.$$

If the 2+3 team selects $M^L$, its expected payoff is:

$$U_{\text{2+3 team}}(M^L) = q_{TL}.$$

Thus, the following equilibrium condition must hold:

$$0.25q_{TR} + 0.25q_{BL} + q_{BR} = q_{TL}.$$

Next, we analyze the payoffs of the 1+4 team for each strategy. The expected payoffs corresponding to each column are as follows:

$$U_{\text{1+4 team}}(TL) = p,$$

$$U_{\text{1+4 team}}(TR) = 1 - 0.25p,$$
$$U_{\text{1+4 team}}(BL) = 1 - 0.25p,$$
$$U_{\text{1+4 team}}(BR) = 1 - p.$$

Based on these values, we compare the optimal responses across strategies. First, comparing TL and TR, if $p < 0.8$, selecting TR yields a higher payoff, while if $p > 0.8$, selecting TL is optimal. When $p = 0.8$, both strategies yield identical payoffs. Second, the payoffs of TR and BL are always equal at $1 - 0.25p$. Third, comparing BR with TR and BL, since $1 - p$ is always lower than $1 - 0.25p$ for $p > 0$, the expected payoffs of TR and BL always exceed that of BR.

Considering these conditions, we verify the consistency of probabilities to ensure that both teams are simultaneously indifferent in the mixed strategy equilibrium.

Next, we consider three cases:

**Case 1:** If $p < 0.8$, then $U_{\text{1+4 team}}(TL) < U_{\text{1+4 team}}(TR) = U_{\text{1+4 team}}(BL)$, implying that only TR and BL are played with positive probability. Thus, $q_{TL} = 0$, $q_{BR} = 0$, and $q_{TR} + q_{BL} = 1$. However, under these conditions, the expected payoffs of the 2+3 team

satisfy:

$$U_{2+3 \text{ team}}(M^H) = 0.25, \quad U_{2+3 \text{ team}}(M^L) = 0.$$

This implies $p = 1$, contradicting the assumption $p < 0.8$.

**Case 2:** If $p > 0.8$, then $U_{1+4 \text{ team}}(TL) > U_{1+4 \text{ team}}(TR) = U_{1+4 \text{ team}}(BL) > U_{1+4 \text{ team}}(BR)$, implying that TL is the only strategy played with positive probability. Thus, $q_{TL} = 1$ and $q_{TR} = q_{BR} = q_{BL} = 0$. In this case:

$$U_{2+3 \text{ team}}(M^H) = 0, \quad U_{2+3 \text{ team}}(M^L) = 1.$$

This leads to $p = 0$, contradicting the assumption $p > 0.8$.

**Case 3:** If $p = 0.8$, then the payoffs satisfy:

$$U_{1+4 \text{ team}}(TL) = U_{1+4 \text{ team}}(TR) = U_{1+4 \text{ team}}(BL) = 0.8, \quad U_{1+4 \text{ team}}(BR) = 0.2.$$

Thus, $q_{TL} + q_{TR} + q_{BL} = 1$ and $q_{BR} = 0$. Since the 2+3 team must also be indifferent,

$$U_{2+3 \text{ team}}(M^H) = 0.25q_{TR} + 0.25q_{BL} + q_{BR} = U_{2+3 \text{ team}}(M^L) = q_{TL}.$$

Solving for probabilities, we obtain $q_{TL} = 0.2$ and $q_{TR} + q_{BL} = 0.8$. Consequently, the mixed Nash equilibria are given by:

$$\{(p_{M^H} = 0.8, p_{M^L} = 0.2; q_{TL} = 0.2, q_{TR} = x, q_{BL} = 0.8 - x, q_{BR} = 0) \mid 0 \leq x \leq 0.8\}.$$

Thus, when the 2+3 team positions $M^L$ at the top-left and $M^H$ at the bottom-right (the first case in Figure 5), the 2+3 team selects $M^H$ with probability 0.8 and $M^L$ with probability 0.2, while the 1+4 team assigns probability 0.2 to TL, distributes 0.8 between TR and BL, and assigns 0 probability to BR. Similarly, by deriving the mixed equilibria for the remaining cases in Figure 5 (second, third, and fourth column cases), we obtain results consistent with those stated in Proposition 2.

Furthermore, using the mixed Nash equilibria above, the equilibrium payoffs can be computed as follows:

$$\begin{aligned} &U_{2+3 \text{ team}}(M^H) = U_{2+3 \text{ team}}(M^L) = 0.2, \\ &U_{1+4 \text{ team}}(TL) = U_{1+4 \text{ team}}(TR) = U_{1+4 \text{ team}}(BL) = U_{1+4 \text{ team}}(BR) = 0.8. \end{aligned}$$

Thus, the mixed Nash equilibrium payoffs for the two teams are:

$$(2 + 3 \text{ team's payoff}, 1 + 4 \text{ team's payoff}) = (0.2, 0.8).$$

# 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.