Super-Star Effects in ATP Tennis Tournaments

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Abstract

This paper examines the effect of the presence of tennis “superstars” (notably Rafael Nadal, Novak Djokovic, Roger Federer) on the performance of other players in ATP tournaments. Using tournament theory and a comprehensive database covering more than 900,000 matches over 40 years, we combine econometric methods (fixed-effects models, logit, survival models, hurdle) and an evaluative approach by pairing to estimate the impact of star density on the performance of other players. The results show that the presence of stars significantly reduces the chances of victory of lower-ranked players, their progress in the tournament, as well as the number of sets won. These effects suggest a phenomenon of competitive deterrence, with heterogeneities depending on the players and the contexts.

1 Context and Problem

In high-level sports, iconic figures or “superstars” arouse considerable interest, both for spectators and for other competitors. In ATP tennis tournaments, the presence of players such as Federer, Nadal or Djokovic could influence the behavior and performance of other players. Tournament theory, introduced by Lazear and Rosen [1], postulates that individuals are motivated by relative rather than absolute gains. It predicts that the intensity of effort depends on the rewards but also on the perceived competition. A classic application of this theory examines the hypothesis that higher prizes and greater heterogeneity of skills among participants positively influence the efforts made by the players [2, 3]. In contrast to these traditional approaches, which focus mainly on financial incentives, an innovative approach documented in the literature aims to explore the non-financial effects of the presence of stars [4] [5, 6].

Thus, Brown [4] shows that the presence of Tiger Woods at golf affects the performance of other players. Stracke et al. [5] apply this approach to tennis and find that players modify their effort in the presence of superstars. The effect may depend on the level of the player, the type of tournament, and the frequency of confrontation with these superstars. The effects of the presence of stars, often called the “superstar effect”, suggests that the presence of exceptional players can have various effects on the performance of other competitors, ranging from incentive to disincentive [4]. The study of the presence of superstars in tennis tournaments thus remains a fertile area for research, with potential implications for understanding the dynamics of competition and the motivations of top-level players.

This work examines the : how does the presence of superstars affect the performance of other players? Do we observe incentive effects or, on the contrary, demotivation? The answer to these questions falls within the field of sports economics and contributes to the empirical evaluation of the dynamics of competition in the presence of stars [7, 4, 5]. Understanding these dynamics can help tournament organizers and tennis governing bodies adjust reward structures to maximize player competitiveness and engagement. Coaches and players can use this information to develop optimal tournament strategies. Finally, this study offers a unique perspective on competition and athletes’ motivations in the face of the elite.

2 Research Methodology

2.1 Data Presentation and Sources

The data used in this study comes from the public database compiled by Jeff Sackmann[1], which lists all ATP matches since 1968. This database includes detailed results for each match, player rankings, certain physical characteristics, and various performance statistics. An exploratory analysis revealed that **92% of the matches** are concentrated in less than **half of the tournaments**,

[1] Available at `https://github.com/JeffSackmann/tennis_atp`

which justifies the decision to restrict the analysis to the **150 tournaments** with the most data, without significant loss of information. In addition, **tournaments with fewer than 16 participants** were excluded, as were **Davis Cup** matches, in order to focus exclusively on individual competitions. After processing the missing values, the remaining variables with less than 1% missing data were imputed. The heights of the players were supplemented by the tournament average, while the missing surfaces were imputed by the most frequent modality. These choices limit the loss of information without introducing significant bias. In addition, certain modalities have been aggregated - in particular the grouping of dominant nationalities and the merging of *Grass* and *Carpet* surfaces - in order to guarantee statistically significant numbers for each modality and to reduce the total number of categories of qualitative variables.

After cleaning and pre-processing, the final database covers the period from **1990 to 2023** and contains approximately **14,710 matches**, spread over **218 unique tournaments**, focusing on the tournament levels most represented in volume (notably level A tournaments - ATP 250/500) as well as the most prestigious tournaments, such as the **G** (Grand Slam) and **M** (Masters 1000). Finally, several derived variables were constructed from the available data in order to address the research problem. The final database thus includes **quantitative**, **qualitative** and **dichotomous** variables, adapted to the different methods of analysis implemented in this study.

2.2 The variables

In order to understand and measure the competitive dynamics and motivations in ATP tennis tournaments, it is necessary to have variables that allow for a statistical description of these tournaments, the participants, and the matches in which these dynamics are expressed. A number of variables have been selected, identified or constructed from the available data. Table 1 presents these variables, including, for example, the type of surface, the winner's dominant hand, the level of the tournament, and the presence of stars. As the aim of this study is to measure the players' effort and the effects of the presence of stars on this effort, it was necessary, on the one hand, to define what is meant by **superstars** (explanatory variables of interest), and on the other hand, to specify the variables used to measure the players' effort (variables to be explained).

Definition of Superstars: A player is defined as a *superstar* if they simultaneously meet two criteria over a rolling period of 12 tournaments:

1. He regularly appears in the **Top 5** of the ranking in terms of cumulative points over 12 rolling tournaments.
2. He captures an **exceptionally high share of the available points**, statistically aberrant (according to robust methods: mean + standard deviation, 99th percentile, or IQR).

The cumulative points are calculated according to the official ATP formula:

$$\text{Rolling cumulative points} = \sum_{Tournaments=1}^{13} \text{Ranking points}_t$$

The points awarded to each player according to the level of the tournament and the round reached are summarized in table 2.

Measuring player effort Three complementary approaches are used to quantify a player's performance or effort:

- **Win (match) by lower ranked player** (`winner_lower_rank`): equal to 1 if the winner of the match is ranked lower than their opponent:

$$\texttt{winner\_lower\_rank} = \begin{cases} 1, & \text{if winner\_rank} > \text{loser\_rank} \\ 0, & \text{otherwise} \end{cases}$$

- **Sets won by the lower ranked player** (`sets_won_low`): Number of sets won by a lower ranked player in a match

$$\texttt{sets\_won\_low} = \sum_{s=1}^{Total\ sets} Lw_s$$

$$with \begin{cases} \text{Lw} = 1, & \text{if winner\_rank} > \text{loser\_rank} \\ 0, & \text{otherwise} \end{cases}$$

- **Survival in the tournament:** (`round_num`): number of rounds completed by the lower-ranked players before their elimination. The effort is measured using a survival model.
- **Dominant victories** (`victory_dominant`): a victory is said to be dominant if the player wins at least two sets with a score greater than or equal to 6 against a score of 2 or less for the opponent:

$$\texttt{victory\_dominant} = \not\Vdash \left[\sum_{s=1}^{S} \not\Vdash (w_s \geq 6 \wedge l_s \leq 2) \geq 2 \right]$$

where w_s and l_s refer to the scores of the winner and loser for set s respectively.

2.3 Analysis Method

To measure the effect of the presence of the stars, several approaches adapted to each measurement of the effort will be adopted:

Table 1: Variables selected for analysis and their description

Variable Name	Description
height_diff	Height difference between winner and loser (cm)
age_diff	Age difference between winner and loser (years)
num_stars_in_tournmnt	Number of superstars in the tournament
winner_hand	Winner's dominant hand (R, L)
surface	Surface type: Hard, Clay, Grass/Carpet
tourney_level	Level: G (Grand Slam), M (Masters), A (ATP250/500)
winner_ioc_grouped	Nationality of the winner (grouped)
draw_size_cat	Table size, in number of participants (categorized)
winner_age_cat	Winner's age category
winner_ht_cat	Winner's height category
round	Round reached (F, SF, QF, R16,...)
Rafael_Nadal_star	Presence of superstar Nadal (1=yes)
Roger_Federer_star	Presence of superstar Federer (1=yes)
Novak_Djokovic_star	Djokovic present superstar(1=yes)
victory_dominant	Dominant victory (1=yes)
winner_lower_rank	Lower ranked winner (1=yes)
sets_won_low	Number of sets won by the lower ranked player

Table 2: Point system for ATP tournaments

Round	Grand Slam	Masters 1000
Winner Final	2000	1000
Final	1200	600
Semi-final	720	360
Quarter-final	360	180
R16 (round of 16)	180	90
R32	90	45
R64	45	25
R128	10	10

2.3.1 Survival Model

In a descriptive approach, we will model the effect of the presence of stars on the survival time (in terms of rounds) of players in a tournament. The survival model can be specified as follows:

$$h(t|X) = h_0(t)\exp(\beta X)$$

where $h(t|X)$ is the hazard rate at time t, $h_0(t)$ is the baseline hazard rate, and X represents covariates such as the presence of stars, the player's ranking, etc. This descriptive model will make it possible to determine whether the presence of stars increases or decreases the chances of elimination of the other players at each round.

2.3.2 Hurdle model

To model the effort, represented by the players' victories or defeats in each match, we will use a Hurdle model. This model combines a binary component (Logit) to model the probability of exceeding the threshold (winning at least one match or set) and a counting component (Poisson or Negative Binomial) to model the number of matches or sets won among those that have crossed the threshold. The Hurdle model therefore consists of the following two parts:

- **Binary Component (Logit):** This component models the probability that the number of sets won is greater than zero:

$$\mathrm{P}(Y > 0|X)) = \frac{1}{1 + \exp\alpha_0 + \alpha_1 \mathrm{Stars} + \dots}$$

  where Y represents the number of sets won or lost, and X includes variables such as the presence of stars, the type of tournament, the opponent's ranking, etc.

- **Count Component (Truncated Poisson or Truncated Negative Binomial):** For observations where the number of sets won is greater than zero, this component models the number of matches or sets won Y :

$$\log(E(Y|Y > 0, X)) = \beta_0 + \beta_1\mathrm{Star} + \beta_2\mathrm{Tournaments} + \dots$$

  where Y represents the number of sets won, and X includes variables such as the presence of stars, the type of tournament, the opponent's ranking, etc.

This model allows us to treat separately the decision to cross the threshold (winning at least one match or set) and the number of sets or matches won among those who crossed this threshold, providing a more flexible and accurate representation of the data.

2.3.3 Fixed/random effects models

For the effort variables victory_dominant and sets_won_low, we used panel models to capture the effects specific to the players and the nature of the competitions over time. These models make it possible to control for unobservable effects that are constant over time, either through *fixed effects* (hypothesis of correlation between individual effects and explanatory variables) or through *random effects* (hypothesis of independence).

The generic specification is as follows:

$$\text{Effort}_{it} = \alpha_i + \beta_1 \text{Star}_{it} + \beta_2 X_{it} + \epsilon_{it}$$

2.3.4 Impact evaluation model: Matching approach

For each target variable, the estimated models (pooled OLS, fixed effects, random effects, fixed year effects) were compared using: the AIC/BIC criterion, the Hausman test: to choose between fixed and random effects, the Breusch-Pagan test: to choose between random effects and pooled model. In order to approach a causal interpretation of the relationship between the presence of stars and the performance of other players, a *propensity score matching method* was used. From an evaluative perspective, this approach consists of comparing the profiles of players who are similar in terms of their characteristics (covariables), but who differ only in whether or not they are stars in the tournament. The objective is to estimate its causal effect on different performance measures of non-star players, controlling for selection bias through propensity score matching.

To do this, it will be necessary to move from a *match-level* basis (row = match between two players) to a *player-level* basis (row = performance of a player in each match), via pivoting the dataset. Then it will be a question of estimating the **propensity scores** by logistic regression on the relevant covariates `X = heights, age group, rank, etc.`. The pairing of players (1 against 1) by nearest neighbor will be done according to the propensity scores. Finally, the effect of the `presence_star` treatment on the target variables `round_num`, `winner_lower_rank`, `victory_dominant` will be estimated using OLS or Logit models on the matched data. This method allows for a more robust causal measurement of the effects, by controlling for selection biases related to observable characteristics. It usefully complements the panel model analysis. The transformed *player-level* data were also used for the **survival models**, making it possible to measure the survival time of players in tournaments according to the presence of stars, using Kaplan-Meier curves and log-rank tests.

2.4 Expected Results and Outlook

The results of this work could improve our understanding of competitiveness and fairness in tennis tournaments, while offering valuable insights for other areas of sports management and economics. The expected results of this study include: an in-depth understanding of the effects of the presence of stars on the performance of other players; an evaluation of the impact of stars on the motivation and effort of players; recommendations for tournament organizers regarding the structuring of bonuses and the selection of participants.

3 Results and interpretation

3.1 Descriptive data analysis

Before estimating our models, a detailed descriptive analysis was carried out in order to understand the distribution of the main variables and to identify the regularities relevant to the analysis. Exploration of the tournaments shows that some events are over-represented in the database. Figure 1 shows the 50 most frequent tournaments, in proportion to matches. The *Grand Slam* tournaments (e.g. Australian Open, Roland Garros, Wimbledon, US Open) and the *Masters 1000* (e.g. Indian Wells, Miami, Rome) are consistently among the most represented, each totaling between 1.2% and 1.6% of the matches. This distribution reinforces the choice to focus the analysis on level tournaments,*A (ATP250/500)*, *G (Grand Slam)* and *M (Masters)* in the rest of the work, which offer significant volumes of data and maximum competitive intensity.

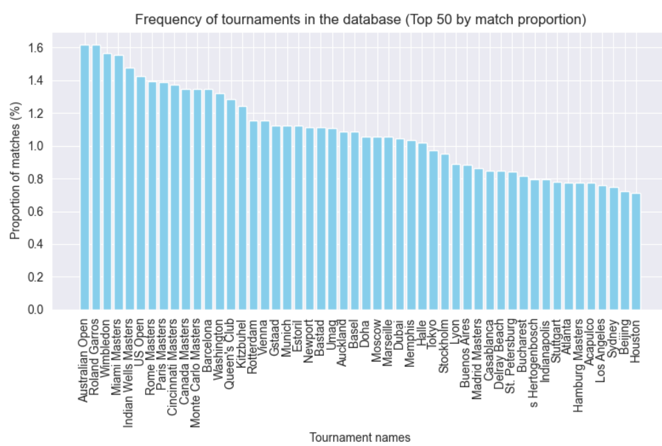

Figure 1: Frequency of tournaments in the database (Top 50 by proportion of matches)

Match profile: Figure 2 shows that the majority of matches were played on *hard* surfaces, accounting for almost 48% of matches, followed by *clay* surfaces with 35%, while *grass and carpet* surfaces accounted for 17%. Regarding the level of competition (Figure 2), *ATP (A)* tournaments make up 67% of the matches recorded, compared with 12% for *Masters (M)* and 6% for *Grand Slams (G)*. This distribution reflects the ATP calendar, which is largely dominated by ATP 250/500 tournaments. Furthermore, we see that nearly 46% of the tournaments have no stars (as defined by our ranking of dominant players), while 32% have five. This heterogeneity justifies a fine categorization of the number of stars in the analysis of their impact on the match outcomes. Figure 2 also compares the distribution of the **age** and **height** of winners and losers. Winners are on average slightly younger and slightly taller. The peak age is between **24 and 26**, a period corresponding to the peak of athletic performance. The average height of players is around **185 cm**, with no marked difference between winners and losers.

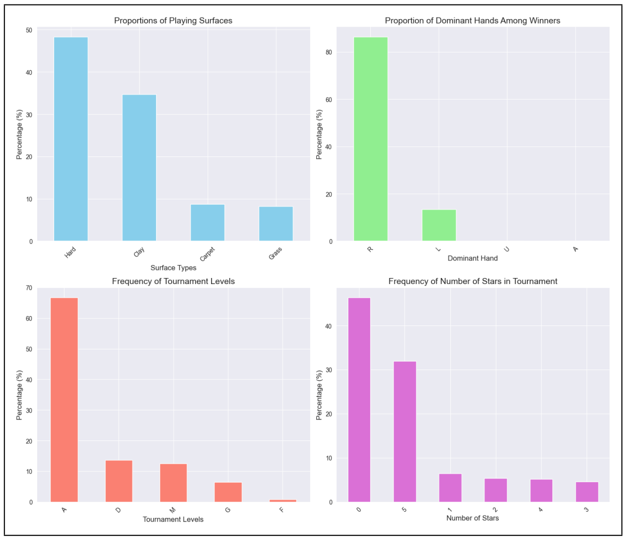

Figure 2: Distribution of playing surfaces, dominant hands, tournament levels, and number of stars per tournament

Figure 3 shows the proportion of victories by country over the period. The **United States**, **Spain**, and **France** dominate the list, accounting for around 27% of victories, followed by Germany, Argentina, and Sweden. This geographical concentration could reflect the structural strength of these nations in men's professional tennis.

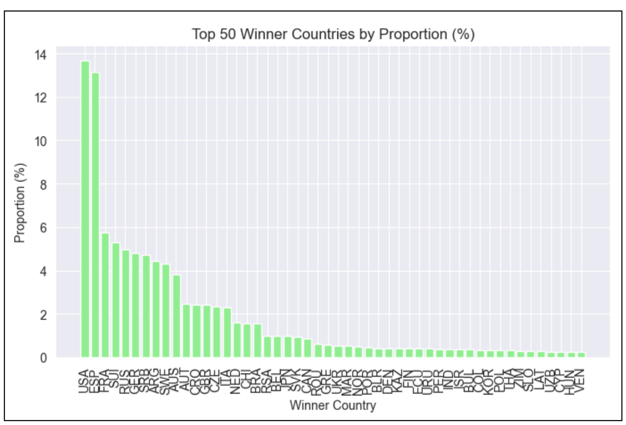

Figure 3: Top 50 countries by proportion of victories (%)

Furthermore, the longitudinal analysis of the cumulative points per player 4 reveals a marked concentration of performances around a handful of elite players, mirroring the geographical concentration. Notably **Novak Djokovic, Rafael Nadal, Roger Federer, Andy Murray, Pete Sampras, etc**.

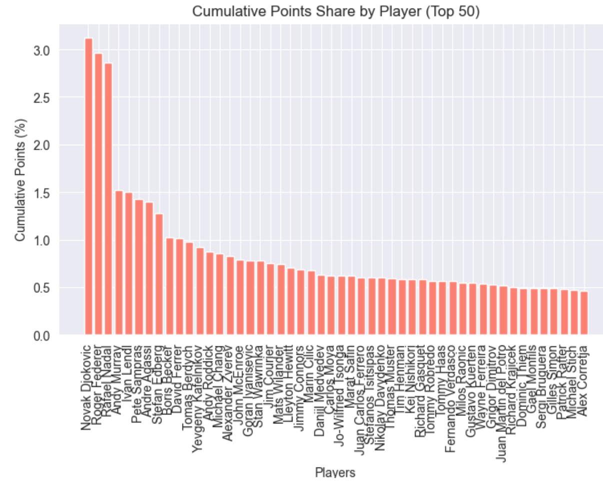

Figure 4: Cumulative share of points per player (Top 50, 1990-2024)

The domination of superstars: We have established that Novak Djokovic, Rafael Nadal and Roger Federer and a handful of players have concentrated the majority of points accumulated since 1990 (**figure 4)**. Looking at the number of appearances in the `Top 1/2/3 Star` ranking ranking over the period 1991-2024 (figure 5), and knowing that the **Top 3 worldwide** trio concentrates more than 10% of the total points each year, it is undeniably apparent that there is persistent domination by a small elite. Moreover, in this small group, we see that Djokovic, Federer, Nadal and Murray dominate very clearly. Collectively, they have a record number of appearances as `Top 1` (9, 8 and 6 times respectively), `Top 2` and `Top 3`. This hierarchy is reflected in Figure 4, which shows that these same players capture the highest share of cumulative points across the entire database, each reaching more than 2.5% of the total, far ahead of the other competitors.

We have identified our "Superstars" for the period in question!

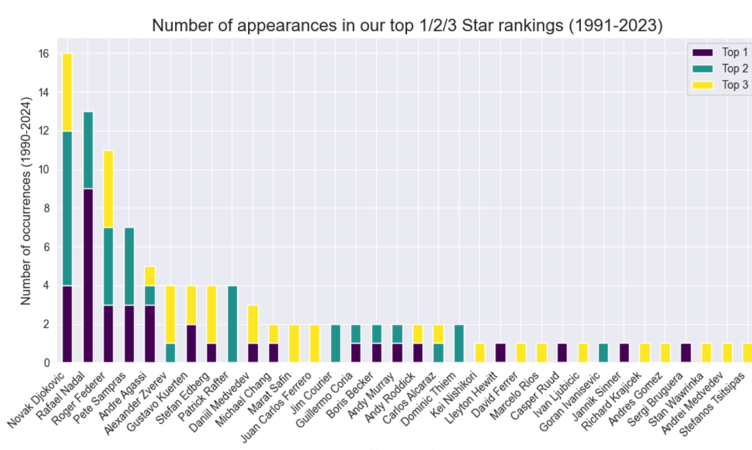

Figure 5: Number of appearances in the Top 1/2/3 Stars ranking (1991-2024)

This concentration can also be seen over time: Figure 6 illustrates the annual share of points won by the `Top 1`, `Top 2` and `Top 3` players. Between 2005 and 2020, the dominance of the best players has increased, with almost 20% of the points won each year by the `Top 1` alone, and around 35% by the `Top 3`. This dynamic highlights the rise of elitism in men's tennis, where a few players concentrate a large share of competitive resources.

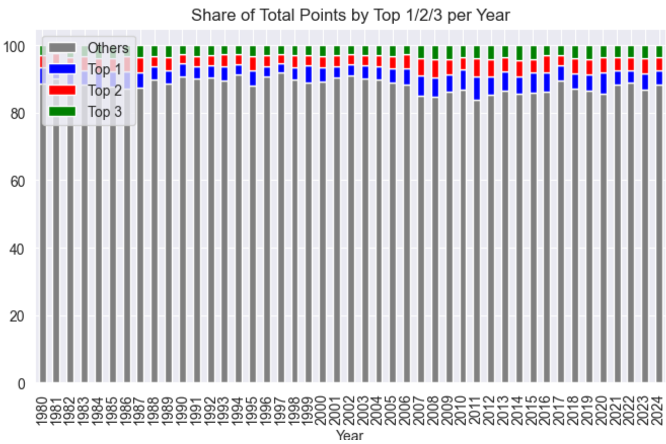

Figure 6: Annual share of points won by the Top 1/2/3 players (1980-2024)

Relative player performance: The descriptive analysis of the target variables reveals that, of all the matches analyzed, 45% are won by the player with the lowest rank (`winner_lower_rank`). On average, the lowest-ranked players win one set per match, with 17% of matches ending in a so-called *dominant* victory (clear victory). Furthermore, figure 7 shows that the proportion of *dominant victories* increases sharply with the presence of *5 stars* (14%), compared with only 6% to 9% when 0 to 4 stars are present. Conversely, figure 8 indicates that the proportion of **victories by lower-ranked players** decreases with the number of stars, going from 39% with 1 star to 23% with 5 stars. These observations suggest that the presence of stars has a dissuasive effect on the competitiveness of lower-ranked players.

These descriptive results show a high concentration of performance in men's professional tennis, in terms of nationalities, individuals and surfaces. The presence of stars seems to correlate with an increase in dominant victories and a reduction in the success of lower-ranked players, suggesting a potentially dissuasive tournament effect. These observations motivate the estimation of a model to precisely quantify this effect.

3.2 Survival analysis: Kaplan-Meier curves

The survival curves (figure 9 10) illustrate the probability of players remaining in the tournament (depending on

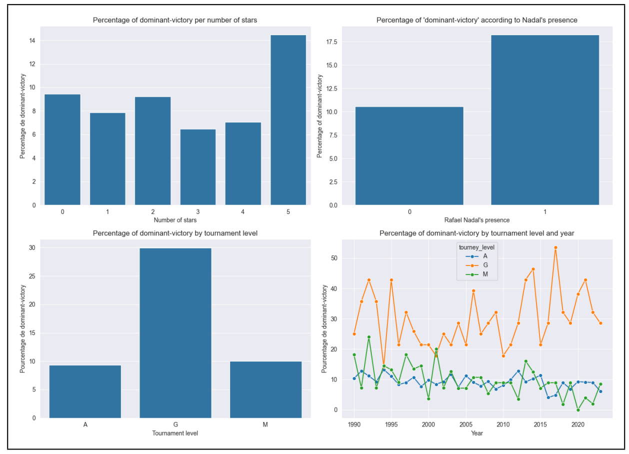

Figure 7: Proportion of dominant victories according to the number of stars, the presence of Nadal, the level and the year of the tournament

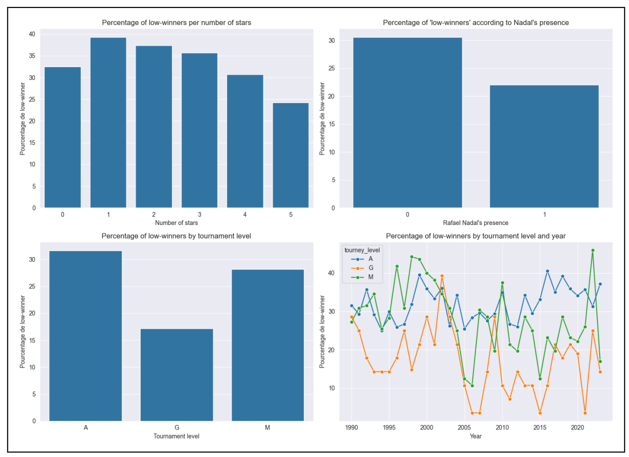

Figure 8: Share of victories of lower-ranked players by number of stars, presence of Nadal, level and year of tournament

the round reached), depending on whether or not a star is present. Log-rank tests are used to assess the significance of the differences observed. The first curve shows 9 **All players combined** shows that the presence of a star significantly reduces player survival ($p < 0.001$). The curves **By ranking quartiles** figure 10 show:

- 0–25% (lowest ranked players): strongly negative effect ($p < 0.001$).
- 25–50% and 50–75%: same trend ($p < 0.001$).
- 75–100% (highest ranked players): non-significant effect ($p = 0.422$).

The presence of stars negatively affects the progression of moderately or poorly ranked players, but not that of elite players.

The presence of stars negatively affects the progress of average and weak players, but not that of elite players.

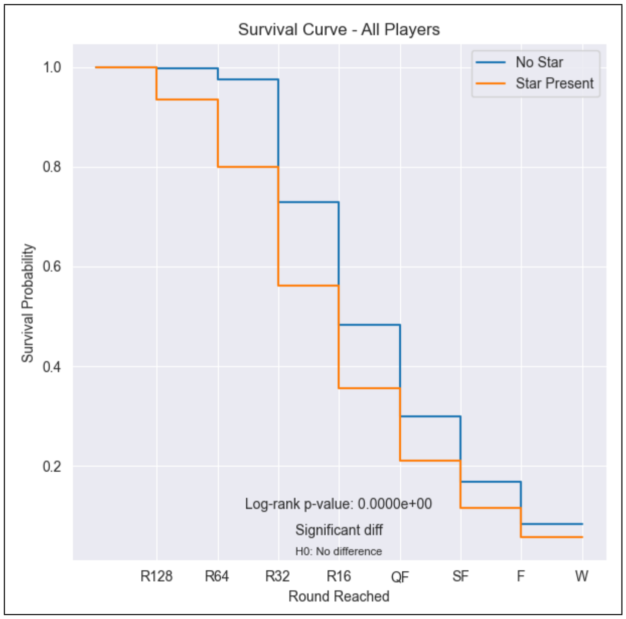

Figure 9: Maintenance curve for all players, depending on the presence or absence of a star

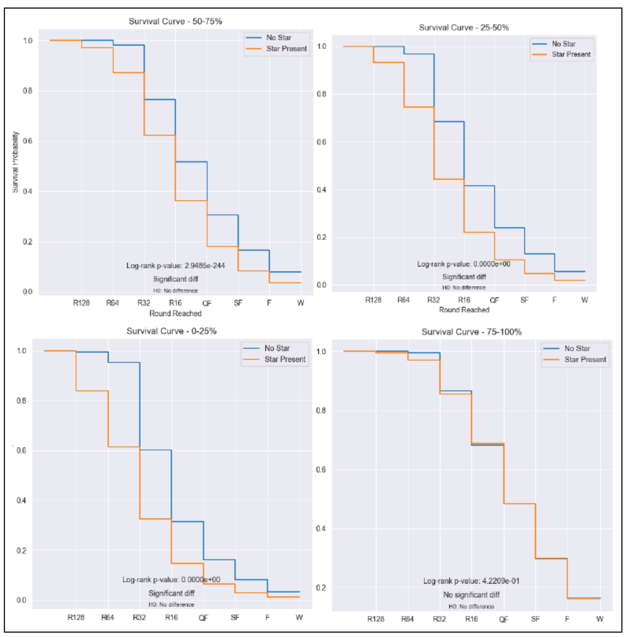

Figure 10: Player survival curve by ATP ranking quartiles, depending on the presence or absence of a star

3.3 Econometric Analyses:

3.3.1 Model Comparison: Statistical Tests of Choice

For each dependent variable, several econometric models were tested to identify the best specification (table 3). The criteria used are: *AIC (Akaike Information Criterion)* - the lower the value, the better the model fits; *Hausman test* - compares fixed and random effects; if significant, favor fixed effects. *Breusch-Pagan test* - compares random effects and OLS; if significant, favor random effects.

3.3.2 Panel model: round reached (`round_num`)

The results, table 4, confirm that the more stars a tournament attracts, the more difficult it is for players to progress: each additional star significantly reduces the probability of reaching an advanced round, with an increasing effect from 2 stars (`num_stars.2` : $coef. = -0{,}084$, `num_stars. 3` : $coef. = -0{,}106$, `num_stars.4` : $coef. = -0{,}182$, `num_stars.5` : $coef. = -0{,}237$ with $p < 0{,}01$). This confirms the hypothesis of increased competition at the top of the table.

The Hausman test confirms the relevance of the fixed effects ($\chi^2 = 48.91$, $p < 0.001$), while the Breusch-Pagan test demonstrates the heteroscedasticity of the individual effects ($\chi^2 = 523.39$, $p < 0.001$). The model explains approximately 26.5% of the intra-player variance ($R^2_{\text{Within}} = 0{,}2647$), which is notable in such a heterogeneous setting.

Furthermore, the individual effect of being a star remains positive (`is_star`: $+0{,}28$, $p < 0{,}001$), suggesting that the best players come out on top even in the most competitive environments.

3.3.3 Logit model: victory of the lowest-ranked player (`winner_lower_rank`)

The logit model explores the factors influencing the probability that a lower-ranked player will win a match. The results in table 5 indicate that the presence of Roger Federer or Novak Djokovic in a tournament significantly reduces this probability: their dissuasive effects are clear, with respective odds ratios of 0,62 ($p < 0{,}001$) each. Conversely, Rafael Nadal does not appear to have a significant effect on the chances of the underdogs ($p = 0.837$). Furthermore, each additional star present in a tournament slightly but significantly reduces the chances of victory of a lower-ranked player (OR = 0.95, $p < 0.00$), suggesting an overall strengthening of competition in the most prestigious tournaments.

3.3.4 Logit model: victory dominant (exttttvictory_dominant)

This logit model evaluates the determinants of a so-called “dominant” victory. The results (table 6) show that the presence of Roger Federer significantly reduces the chances of a dominant victory (OR = 0.55, $p < 0.001$), while Novak Djokovic tends to increase them (OR = 1.25, $p < 0.001$). On the contrary, Rafael Nadal seems to be associated with a reduced probability of a dominant victory (OR = 0.86, p ¡ 0.001).

Furthermore, the density of stars in a tournament has a positive, albeit moderate, effect: each additional star

Table 3: Model comparison for each dependent variable

Target variable	Preferred model	AIC	Hausman test
round_num	Time Fixed Effects	805688.05	Fixed Effects
winner_lower_rank	Logit/Probit	800721.06	–
victory_dominant	Fixed Time Effect	463470.14	Fixed Effects
sets_won_low	Fixed Time Effect	2159972.76	Fixed effects

Table 4: Effects of the stars on the round reached by the players (fixed effects model with year effects)

Explanatory variable	Coefficient	p-value
is_star	0.28	< 0.001
num_stars_in_tourn.2	-0.08	0.003
num_stars_in_tourn.3	-0.11	< 0.001
num_stars_in_tourn.4	-0.18	< 0.001
num_stars_in_tourn.5	-0.24	< 0.001
Constant	–	–
R^2 Overall	0.11	–
R^2 Within	0.27	–
AIC	284200	–
Hausman test	48.91	< 0.001
Breusch-Pagan test	523.39	< 0.001

Table 5: Effects of stars on the victory of the lowest ranked player (Logit)

Explanatory variable	Coefficient	OR	p-value
Rafael_Nadal_star	-0.002	1.00	0.837
Roger_Federer_star	-0.48	0.62	< 0.001
Novak_Djokovic_star	-0.48	0.62	< 0.001
num_stars_in_tourn.	-0.05	0.95	< 0.001
Pseudo R^2	0.2540	–	–
AIC	802040	–	–

slightly increases the probability of a dominant victory (OR $= 1.02$, $p < 0.001$), potentially reflecting an increase in intensity and a more pronounced affirmation of the best players.

Table 6: Effects of stars on the probability of dominant victory (Logit)

Explanatory variable	Coefficient	OR	p-value
Rafael_Nadal_star	-0.15	0.86	< 0.001
Roger_Federer_star	-0.6	0.55	< 0.001
Novak_Djokovic_star	0.22	1.25	< 0.001
num_stars_in_tourn.	0.02	1.02	< 0.001
Pseudo R^2	0.03	–	–
AIC	619362.10	–	–

3.3.5 Hurdle Model: sets won by the lowest ranked player (sets_won_low)

This hurdle model allows us to analyze two dimensions separately: the probability that a lower-ranked player will win at least one set (probit component), and the number of sets won when at least one set is won (negative binomial component).

Probit component (crossing the threshold): The results (table 7) indicate that the presence of the stars significantly increases the probability that an outsider will win at least one set. The coefficients associated with Federer, Djokovic and Nadal are all positive and significant ($p < 0.001$), suggesting an effect of competitive stimulation or increased motivation in the face of these renowned players.

Negative Binomial Component (number of sets won): On the other hand, Federer and Djokovic are associated with a decrease in the total number of sets won by lower-ranked players (significant negative coefficients), while Rafael Nadal is associated with the opposite effect, favoring a greater number of sets won by these players (table 8).

Table 7: Effects of the stars on the probability of winning at least one set (Probit)

Explanatory variable	Coefficient	p-value
Rafael_Nadal_star	0.07	< 0.001
Roger_Federer_star	0.13	< 0.001
Novak_Djokovic_star	0.14	< 0.001
num_stars_in_tourn.	0.01	< 0.001
Nickname R^2	0.11	–
AIC	1 074 303.39	–

Table 8: Effects of the stars on the number of sets won (Negative Binomial)

Explanatory variable	Coefficient	p-value
Rafael_Nadal_star	0.039	< 0.001
Roger_Federer_star	-0.032	< 0.001
Novak_Djokovic_star	-0.11	< 0.001
num_stars_in_tourn.	0.01	< 0.001
AIC	1 637 305.41	–

3.3.6 Causal estimation by matching: effect of the number of stars

The results are obtained by comparing the trajectories of "treated" players (who have played in tournaments with a high number of stars) and "control" players (tournaments with a low number of stars), after matching on a set of control variables (surface area, level of the tournament, demographic and sporting characteristics of the player, etc.). Three dependent variables were tested: progress in the tournament (`round_num`, OLS); the probability that the lowest-ranked player will win the match (`winner_lower_rank`, Logit); the number of sets won by the lowest-ranked player (`sets_won_low`, OLS).

Estimated effects of the treatment (presence of stars in the tournament):

- **On the probability of victory of the lowest ranked player**: the presence of a greater number of stars in the tournament is associated with a significant decrease in the probability that the lowest ranked player will win the match ($coef. = -0.05$, $p < 0.001$). This result suggests a deterrent effect or an increase in the overall level of competition in star-studded tournaments (table 9).
- **On the round reached in the tournament**: with similar characteristics, playing in a tournament with more stars is associated with a significant decrease in the round reached by the other players ($coef. = -0.06$, $p < 0.001$). This reinforces the idea of a higher competitive barrier when several stars participate in the tournament (table 9).
- **On the number of sets won by the lowest ranked player**: the effect is also negative and significant ($coef. = -0.01$, $p < 0.001$), indicating that the underdogs win fewer sets on average in tournaments with a strong presence of stars. This effect may reflect stronger dominance or fewer opportunities to express their game (table 9).

These estimates confirm that the massive presence of stars acts as a significant competitive context shock. By considering this factor as an exogenous treatment applied to non-star players, the matching analysis allows for a more credible estimate of the causal effect of star density in a tournament (table 9). These results are consistent with those obtained by the specifications of standard econometric models (table 10) and reinforce the robustness of the empirical conclusions.

3.4 Synthesis of results

All of the analyses – descriptive, econometric and causal – converge towards a robust conclusion: the presence of stars in a tournament significantly alters the behavior and performance of the other players, particularly those outside the elite (table 10).

The effects are particularly marked for outsiders and intermediate players, while elite players remain relatively insensitive to this additional pressure. Djokovic stands out as the only one to increase the probability of dominant victories, where Federer and Nadal have more ambiguous or defensive effects. The results as a whole support the idea of a competitive imbalance brought about by the presence of superstars: the latter focus attention and the stakes, and influence the mental and strategic dynamics of the other players.

4 Discussion and limitations of the study

Despite the wealth of data and the diversity of the models estimated, this study has several limitations. First, some relevant variables (e.g. injuries, recent physical fitness, weather conditions) are not observable, which can lead to an omission bias. Second, the models estimated (in particular the linear and logistic models) assume homogeneity of the coefficients over time and between individuals, which may not reflect the real dynamics.

Furthermore, old data may contain errors or gaps, particularly with regard to the first matches of the 1980s. The introduction of fixed effects and panel models attempts to correct for certain heterogeneities, but relies on strong assumptions (correlation between unobserved effects and explanatory variables). Finally, the strategy of causal identification by matching, although it strengthens the robustness of the estimates, cannot guarantee a complete absence of selection bias on unobserved variables.

5 Conclusion

This work highlights a significant and robust effect of the presence of stars in ATP tennis tournaments on the performance of other players. Beyond a simple correlation, the causal analysis suggests that the density of stars acts as a factor structuring the competition, modifying strategic behavior and performance trajectories.

These results make an original contribution to the literature on tournament effects, the economics of sport and motivation theory. They also open up practical perspectives for tournament organizers and broadcasters, insofar as the presence of stars influences the dynamics of competition and possibly the interest of spectators. Finally, extensions could include more advanced counterfactual methods (DID, synthetic control [8]) to refine causal analysis or more theoretical simulation methods (individual or collective dynamic models [9, 10]).

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Table 9: Estimated effects of the number of stars per pairing (processing: `num_stars_in_tourn`)

Dependent variable	Coefficient	p-value	Effect
`winner_lower_rank`	-0.05	< 0.001	Lower probability of victory for outsiders
`round_num`	-0.06	< 0.001	Slower progress in the tournament
`sets_won_low`	-0.01	< 0.001	Fewer sets won by the lower ranked player

Table 10: Synthesis of the effects of the presence of stars on player performance

Target variable	Effect of stars	Significant	Measure of effect
Survival (Kaplan-Meier)	$\downarrow$ *players out of Top 25%*	Yes	$p < 0.001$
`round_num`	*/average progression*	Yes	$coef. = -0.06$ (matching)
`winner_lower_rank`	*/underdog victory*	Yes	OR $\approx$ 0.6 (F/D)
`victory_dominant`	$\uparrow$ *Djokovic, strugglingFederer/Nadal*	Yes	OR = 1.25 / 0.55
`sets_won_low`	$\uparrow$ *probability of 1 set,*$\downarrow$ *total sets*	Yes	$coef. = -0.01$ (matching)

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