The Superstar Effect: Evidence from Chess*

Eren Bilen[†] Alexander Matros[†,‡]

January 4, 2021

Abstract. "Superstars" exist in many places – in classrooms, or in workplaces, there is a small number of people who show extraordinary talent and ability. The impact they have on their peers, however, is an ongoing research topic. In competition, they might intimidate others; causing their peers to show less effort. On the other hand, superstars might encourage higher effort, as their existence in a competition encourages them to "step up" their game. In this study, we analyze the impact of a superstar on their peers using evidence from chess. The existence of a contemporary superstar (and the current World Chess Champion) Magnus Carlsen, as well as, past world champions such as Garry Kasparov, Anatoly Karpov, or Bobby Fischer enables us to identify whether the existence of a superstar in a chess tournament has a positive or an adverse effect on other chess players' performance. We identify errors committed by players using computer evaluation that we run on our sample with 35,000 games and 2.8 million moves with observations from 1962 to 2019, and estimate position complexity via an Artificial Neural Network (ANN) algorithm that learns from an independent sample with 50,000 games and 4 million moves. The results indicate that the effect depends on the intensity of the superstar. If the skill gap between the superstar and the rest of the competitors is large enough, an adverse effect exists. However, when the skill gap is small, there may be slight positive peer effects. In terms of head-to-head competition, the evidence shows that players commit more mistakes against superstars in similarly-complex games. Understanding the effect of superstars on peer performance is crucial for firms and managers considering to introduce a superstar associate for their team.

JEL classification: M52, J3, J44, D3
Keywords: superstar, tournament, effort, chess

*We would like to thank seminar participants at the Laboratory Innovation Science at Harvard, University of South Carolina and Lancaster University, and participants in the Contests Theory and Evidence conference at the University of East Anglia for their questions and suggestions.

[†]Department of Economics, University of South Carolina, Columbia, SC 29208. Email: eren.bilen@grad.moore.sc.edu, alexander.matros@moore.sc.edu

[‡]Department of Economics, Lancaster University, Lancaster, LA1 4YX, United Kingdom Email: a.matros@lancaster.ac.uk

1. Introduction

> *"When you play against Bobby [Fischer], it is not a question of whether you win or lose. It is a question of whether you survive."*
>
> –Boris Spassky, World Chess Champion, 1969 - 1972.

Maximizing their employees' effort is one of the chief goals of the firm. To this extent, firms typically encourage competition among their employees and allocate bonuses according to their performance and effort. At the same time, firms want to hire the best workers – preferably, the ones who are "superstars" in their fields. For this reason, it is not unusual to see million-dollar hiring contracts among the Forbes top 500 firms.

However, there might potentially be unintentional side effects of hiring a superstar employee. The seminal work done by Brown (2011) took a new and creative approach to analyze these potential side effects. She considered a famous superstar from golf: Tiger Woods. Her goal was to uncover whether Tiger Woods had any effect −adverse or positive− on his competitors' performance. She compared performances in tournaments with and without Tiger Woods and unveiled that there was a sharp decline in performance in tournaments in which Tiger Woods competed in. This evidence points out that Tiger Woods, as a superstar, creates a psychological pressure on his competitors which has a discouraging effect, causing them to perform worse than their typical performance.

In this study, we analyze the superstar effect using observations from chess. Employing a rich move-level dataset from 1962 to 2019, we study the impact of six different superstars in different time periods on tournament performance: Magnus Carlsen, Garry Kasparov, Anatoly Karpov, Bobby Fischer, Hou Yifan, and Igors Rausis. Using computer evaluations with a state-of-the-art chess engine, we find that a superstar lowers the performance in a tournament if there is a very large skill gap between the superstar and the competitors. This effect seems to be driven by the players' belief that their chances to win the tournament are slim. There appears to be a slight positive effect with superstar presence when the players believe they indeed have a chance to win the tournament. In terms of head-to-head competition, the effect is clear. For all samples, the superstar players strongly dominate their opponents, and some superstars are more dominating than others.

Chess provides a clean setting to analyze the superstar effect for the following reasons. First, non-player related factors are minimal to non-existent in chess since every chess board is the same for all players. Second, both game-level and move-level performance indicators can be obtained with the use of computer algorithms that can evaluate the quality of each move. Third, multiple chess superstars exist who lived in different time periods and come from different backgrounds, improving the external validity of the study.

The literature following Brown (2011) use alternative settings ranging from professional track and field competitions to swimming. A study in a similar spirit to Brown (2011) that also analyzes a superstar from golf is Tanaka and Ishino (2012). Their superstar is Masashi Ozaki from Japan who competed in Japan golf tour and dominated the tournaments he participated in throughout the 1990s. Their results are in parallel with Brown (2011): the presence of a superstar affects adversely the scores of the other players. Guryan, Kroft and Notowidigdo (2009) is another study that focuses on the partners' performance. They measure how a golfer's performance is affected by their partner's performance and find that the partner's performance has very little impact on a player's own performance. This finding differs from previous studies focusing on peer effects in the workplace or in the classroom where typically positive peer effects exists. (Mas and Moretti 2009, Duflo, Dupas and Kremer 2011, Cornelissen, Dustmann and Schönberg 2017)

Further work done by Hill (2014*b*) focuses on a different superstar: Usain Bolt. He compares the performance of athletes in a run where Usain Bolt is competing and where Usain Bolt is not present. His results are the opposite of the results in Brown (2011). Athletes perform much better when Usain Bolt is competing. This can be attributed to non-superstar athletes being motivated by having Usain Bolt running just "within their reach", enabling them to push one step further and show extra effort. Findings in Hill (2014*a*), focusing on track and field events are similar to those in Hill (2014*b*): higher performing athletes are creating a positive impact on their competitors' performance.

Swimming is used in Yamane and Hayashi (2015) and Jane (2015). Yamane and Hayashi (2015) compare performance of swimmers who compete in adjacent lanes and find that the performance of a swimmer is positively affected by the performance of the swimmer in the adjacent lane. In addition, this effect is amplified by the observability of the competitor's performance. Specifically, in backstroke competitions where observability of the adjacent lane is minimal, there appears to be no effect; whereas the effect exists in free-style competitions with higher observability. Jane (2015) uses data on swimming competitions in Taiwan and finds that having faster swimmers in a competition increases the overall performance of all the competitors participating in the competition. This finding agrees with Yamane and Hayashi (2015) and Hill (2014*b*,*a*).

Connolly and Rendleman (2014) and Babington, Goerg and Kitchens (2020) re-assess the findings in Brown (2011). Their evidence points out that an adverse superstar effect may not be as strong as suggested by in Brown (2011), and that the results from Brown (2011) are not robust to alternative specifications. They suggest that the effect could work in the opposite direction – that the top competitors can perhaps bring forth the best in other players' performance. In addition, Babington, Goerg and Kitchens (2020) provide further evidence using observations from men's and women's FIS World Cup Alpine Skiing competitions and find little to no peer effects when skiing superstars Hermann Maier and Lindsey Vonn participate in a tournament.

A set of studies investigate the effect of superstars in tournaments from Topcoder competitions. Topcoder and Kaggle are the two largest crowdsourcing platforms where contest organizers can run online contests offering prizes to contestants who score the best in finding a solution to a difficult technical problem stated at the beginning of the contest. Archak (2010) finds players avoid competing against superstars in Topcoder competitions. Studying the effect of increased competition on responses from the competitors, Boudreau, Lakhani and Menietti (2016) find lower-ability competitors respond negatively to competition, while higher-ability players respond positively. Lastly, Zhang, Singh and Ghose (2019) suggests there may be potential future benefits of competing with a superstar via competitors learning from the superstar contestant.

There is ample empirical evidence showing that incentives matter in rank order tournaments. Earlier empirical work in Ehrenberg and Bognanno (1990*a*,*b*) −which also use observations from PGA golf tour as in Brown (2011)− find that offering higher prizes in tournaments improves performance.[1] Coffey and Maloney (2010) compare horse and dog races to separate out the selection of stronger competitors in tournaments when large monetary prizes are offered. They find stronger responses to prizes in horse races where handlers are with their horses during the races while in dog races they are not. Sunde (2009) documents incentive effects in tennis tournaments.

There is a growing literature studying a broad range of questions using data from chess competitions. Gerdes and Gränsmark (2010) test for gender differences in risk taking using evidence from chess games played between male and female players. They find that women choose more risk-averse strategies playing against men. In terms of performance differences, Backus et al. (2016) find that female players make more mistakes playing against male opponents with similar strength.[2] On the other hand, Stafford (2018) has an opposite finding in which women perform better against men with similar ELO ratings. Further set of research testing different questions using chess; Dreber, Gerdes and Gränsmark (2013) test the relationship between attractiveness and risk taking using chess games; Künn, Palacios and Pestel (2019) and Klingen and van Ommeren (2020) find indoor air quality effects on performance and risk taking behavior of chess players; Moul and Nye (2009) show evidence of Soviet collusion in top level chess tournaments; Levitt, List and Sadoff (2011) test whether chess masters are better at making backward induction; Kunn and D. (2020) show adverse effects in performance in online chess tournaments compared to offline tournaments.

Economic theory on contests suggests an adverse effect to exist when players with largely different abilities compete for a prize. Rosen (1981) makes the

[1] Orszag (1994) shows results in Ehrenberg and Bognanno (1990*a*,*b*) may not be robust using data from a different PGA golf tour season (1992) and the weather conditions.

[2] In a more recent work, Smerdon et al. (2020) agrees with findings in Backus et al. (2016) showing evidence from a different sample.

first contribution in understanding "superstars" by shedding light on how skill sets in certain markets become excessively valuable. Contributions in Lazear and Rosen (1981), Green and Stokey (1983), Nalebuff and Stiglitz (1983), and Moldovanu and Sela (2001) describe the incentive effects of heterogeneous players in rank-order tournaments with relative performance. Prendergast (1999) provides a review on incentives in workplaces. Baik (1994) and Nti (1999) analyze Tullock (1980) contests with two-players with heterogeneous abilities, and show a decrease in the equilibrium effort for the competitors as the relative ability difference increases. Brown (2011) provides a Tullock contest extended to n-players in which the players are adversely affected by the presence of a high ability superstar. Xiao (2020) shows the possibility of having a positive or a negative incentive effect when a superstar participates in a tournament. His work suggests the effect to depend on the prize structure, ability composition of the participants, and the degree of difference between the ability types.

The rest of the paper is organized as follows: First, a two-player tournament model with heterogeneous ability and multiple prizes is presented in section 2. Section 3 gives background information on chess and describes how chess data is collected and analyzed. Section 4 provides the empirical design. Section 5 presents the results, and section 6 concludes.

2. Theory

Consider a two-player contest in which player 1 competes against a superstar, player 2. Player 1 maximizes his expected payoff: expected benefits minus a costly effort, that is,[3]

$$\max_{e_1} \quad \frac{e_1}{(e_1+\theta e_2)} V_1 - e_1,$$

where e_i is the effort of player $i = 1, 2$, V_1 is a (monetary or rating/ranking) prize which player 1 can win, and θ is the ability of player 2. We normalize the ability of player 1 at one. Player 2, a superstar, has high ability $\theta \geq 1$ and maximizes her expected payoff:

$$\max_{e_2} \quad \frac{\theta e_2}{(e_1+\theta e_2)} V_2 - e_2,$$

where V_2 is the prize which player 2 can win. Note that θ is not only the ability of player 2, but also the difference in player's abilities.

The first order conditions for players 1 and 2 are

$$\frac{\theta e_2}{(e_1+\theta e_2)^2} V_1 - 1 = 0,$$

[3] We assume that costs are linear functions.

and

$$\frac{\theta e_1}{(e_1+\theta e_2)^2}V_2 - 1 = 0.$$

Therefore, in an equilibrium

$$\frac{e_2}{e_1} = \frac{V_2}{V_1}.$$

We can state our theoretical results now.

Proposition 1 *There exists a unique equilibrium in the two-player contest model, where player $i = 1,2$ exerts effort*

$$e_i^* = \frac{\theta V_1 V_2}{(V_1+\theta V_2)^2}V_i.$$

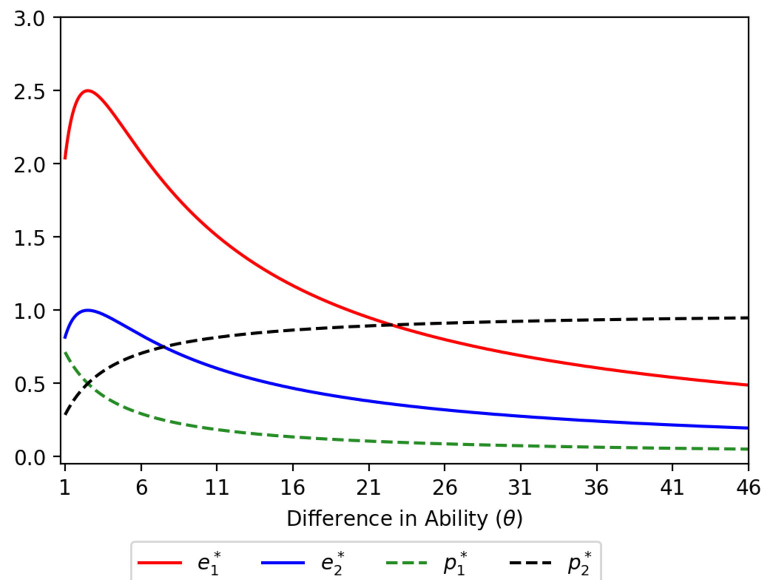
Individual equilibrium efforts are maximized if the superstar ability is $\theta^* = \frac{V_1}{V_2}$. In the equilibrium, player $i = 1,2$ wins the contest with the probability p_i^*, where

$$(p_1^*, p_2^*) = \left(\frac{V_1}{V_1+\theta V_2}, \frac{\theta V_2}{V_1+\theta V_2}\right).$$

Usually, the prize for the underdog is greater than the prize for the superstar in the two-player contest: everyone expects the superstar to win the competition and her victory is not a big deal. However, the underdog's victory makes him special, which is also evident from rating point calculations in chess: a lower rated player gains more rating points if he wins against a higher ranked player. Proposition 1 gives a unique value of the superstar ability which maximizes individual equilibrium efforts. This observation suggests the best "level" of a superstar for the contest designer. It also follows from proposition 1 that the underdog, player 1, always exerts higher effort than the superstar, player 2, in the equilibrium, if the prize for player 1 is greater than the prize for player 2, that is, $V_1 > V_2$.

Figure 1 shows how equilibrium efforts and winning probabilities change for different levels of superstar abilities. Initially, when the ability difference is small, effort levels for both players increase. As the difference in abilities increases, both players show less effort. In other words, if the gap between the superstar and the underdog is small, the superstar effect is positive as both players exert higher efforts. However, if the superstar is much better than the underdog, then the superstar effect is negative and both players shirk in their efforts.

Figure 1: Equilibrium effort and winning probabilities



Note: In the figure, prizes are $V_1 = 10$ and $V_2 = 4$ reflecting the fact that the prize for the underdog is greater than the prize for the superstar. By assuming $V_1 > V_2$, we emphasize that the underdog gets a higher payoff than the superstar, if he wins the contest. This is also evident in ELO rating calculations in chess: a lower rated player gains more rating points if he wins against a higher ranked player.

3. Data

3.1 Chess Background

Chess is a two-player game with origins dating back to 6th century AD. Chess is played over a 8x8 board with 16 pieces for each side (8 pawns, 2 knights, 2 bishops, 2 rooks, 1 queen, and 1 king). Figure 2 shows a chess board. Players make moves in turns, and the player with the white pieces moves first. The ultimate goal of the game is to capture the enemy king. A player can get close to this goal by threatening the king through a "check": if the king has no escape, the game ends with a "checkmate". A game can end in three ways: white player wins, black player wins, or the game ends in a draw.

The possible combinations of moves in a chess game is estimated to be more than the number of atoms in the universe.[4] However, some moves are better than others. With years of vigorous training, professional chess players learn how to find the best moves by employing backward-induction and calculating the consequences of each move to a certain complexity level. Failing to find the best

[4] A lower bound on the number of possible moves is 10^{120} moves, per Shannon (1950) while the number of atoms in the observable universe is estimated to be roughly 10^{80}.

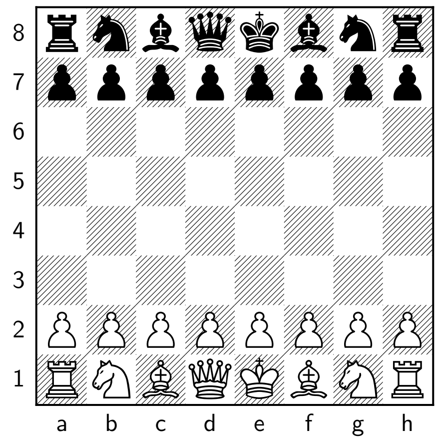


Figure 2: A chess board

move(s) in a position would result as a "blunder" or a "mistake" which typically leads to the player losing their game at the top level if a player commits multiple blunders or mistakes. The player who performs better in general is the player who manages to find the correct moves more often.

The standard measure of player strength in chess is the ELO rating system first adopted by FIDE in 1970. This system was created by the Hungarian physicist Arpad Elo (Elo 1978). Elo considers the performance of a player in a given game as a random distribution distributed normally centered at their unobservable true level of performance. Each player gets a starting ELO rating which is updated according to the outcome of each game via

$$ELO_{R,t+1} = ELO_{R,t} + K\left[S_i - E_t\left(S_i \mid R_i, R_j\right)\right] \tag{1}$$

where S_i is the outcome of a game where S_i=1 if player i wins their game, S_i=0 for a loss, and S_i=1/2 in case of a draw; $E_t\left(S_i \mid R_i, R_j\right)$ is the expected probability of player i winning their game given the ELO ratings of the two players R_i and R_j which equals $E(S_R \mid R_R, R_B) = \Phi\left(\frac{R_R - R_B}{400}\right)$ where $\Phi(.)$ is the c.d.f. for the normal distribution.[5] K is a parameter for rate of adjustment.

Having such rating system allows for making comparisons on player strengths. For instance, every month, FIDE publishes Top 100 players in the world according to their ELO ratings. Specifically, World's Top 10 players are considered the most elite players in the world who earn significant amount of prizes and sponsorships. Moreover, chess titles have specific ELO rating requirements. For

[5] The probability of player i wins in a given game played against player j is a function of true abilities of both players $P(p_i > p_j) = P(p_i - p_j > 0)$
$= \int_0^\infty \frac{1}{\sqrt{2\sigma^2}} \Phi\left(\frac{x - [\mu_i - \mu_j]}{\sqrt{2\sigma^2}}\right) dx = 1 - \Phi\left(\frac{0 - [\mu_i - \mu_j]}{\sqrt{2\sigma^2}}\right) = \Phi\left(\frac{[\mu_R - \mu_B]}{\sqrt{2\sigma^2}}\right)$ where p_i is the probability that fighter i with true ability μ_i wins his game.

instance, the highest title in chess, Grandmaster, requires the player to have an ELO rating 2500 or higher; for International Master title 2400 or higher; and FIDE Master title 2300 or higher.[6]

Over the past decades, computer scientists have developed algorithms, or "chess engines" that exploit the game-tree structure of chess. These engines analyze each possible tree branch to come up with the best moves. The early chess engines were inferior to humans. After a few decades however, one chess engine developed by IBM in the 1990s, Deep Blue, famously defeated the world chess champion at the time, Garry Kasparov in 1997. This was the first time a world chess champion lost to a chess engine under tournament conditions. Since then, chess engines have passed well beyond the human skill. As of 2020, Stockfish 11 is the strongest chess engine with an ELO rating of 3497.[7] In comparison, the current world chess champion, Magnus Carlsen, has an ELO rating of 2862.[8]

In addition to finding the best moves in a given position, a chess engine can be used to analyze the games played between human players.[9] Quality of a move can be measured numerically by evaluating the move chosen by a player and comparing it to the list of moves suggested by the chess engine. If the move played by a player is considered a bad move by the engine, then that move is assigned a negative value with its magnitude depending on the engine's evaluation.

3.2 Chess Superstars

The first official world chess champion is Wilhelm Steinitz who won the title in 1886. Since Steinitz, there have been fifteen world chess champions in total. Among these fifteen players, four of them have shown an extraordinary dominance over their peers: Magnus Carlsen, Garry Kasparov, Anatoly Karpov, and Bobby Fischer.[10]

Magnus Carlsen is the current world chess champion who first became champion in 2013 at age 22. He reached the highest ELO rating ever achieved in history. Garry Kasparov was the world champion from 1985-2000 and was the number one ranked chess player for 255 months, setting a record for maintaining the number one position the longest duration of time. Anatoly Karpov was

[6] Our sample consists of the very elite chess players, often called "Super GMs", with ELO ratings higher than 2700 in most cases.

[7] Modern chess engines, such as Stockfish, have much higher ELO ratings compared to humans. Most modern computers are strong enough to run Stockfish for analyzing chess positions and finding the best moves, which is the engine use in our analyses.

[8] The highest ELO rating ever achieved by a human was 2882 in May 2014 by Magnus Carlsen.

[9] Every chess game played at the top-level is recorded, including all the moves played by the players.

[10] In his classic series, "My Great Predecessors", Kasparov (2003) gives in depth explanations on his predecessors, outlining qualities of each world champion before him. In this paper, we consider the "greatest of the greatest" world champions as "superstars" with sufficient observations available on the tournaments of top players in their era. We present evidence why these players were so dominating and were considered "superstars" in each era.

the world champion before Kasparov in the years 1975-1985. He won over 160 tournaments, which is a record for the highest number of tournaments won by a chess player.[11] Lastly, Bobby Fischer was the world champion before Karpov between 1972-1975. He won all U.S. championships he played from 1957 (at age 14) to 1966, with a 11/11 score in the 1963 U.S. championship in which no other player in history has ever achieved a perfect score on a U.S. chess championship other than Fischer to this date.[12]

In addition to the four male superstar world chess champions, there exists a female chess superstar: Hou Yifan, a four time women's world chess champion between the years 2010-2017. She played three women's world chess championship matches in this period and did not lose a single game against her opponents.[13] She dominated the tournaments from 2014 until she decided to stop competing in women's tournaments and started to play solely in men's tournaments.

Figures 5–14 show how the four world chess champions, Carlsen, Kasparov, Karpov and Hou Yifan performed compared to their peers across years.[14] The ELO rating difference between each superstar and the average of world's top 10 players in each corresponding era is about 100 points. This is a very significant gap especially at the top-level competitive chess. For instance, expected win probabilities between two players with a gap of 100 ELO rating points are approximately 64%-36%.

Lastly, we consider a chess grandmaster, Igors Rausis, who competed against non-masters in the years between 2012-2019. He was one of the top 100 chess players in the world at the time he competed in tournaments against players who had ELO ratings 500 points less than him. The ELO rating difference between him and the average opponent in the tournaments he competed in between these years is similar to Magnus Carlsen, with an ELO rating of 2882

[11] Kasparov (2003) shares an observation on Karpov's effect on other players during a game in Moscow in 1974: *"Tal, who arrived in the auditorium at this moment, gives an interesting account: "The first thing that struck me (I had not yet seen the position) was this: with measured steps Karpov was calmly walking from one end of the stage to the other. His opponent was sitting with his head in his hands, and simply physically it was felt that he was in trouble. 'Everything would appear to be clear,' I thought to myself, 'things are difficult for Polugayevsky.' But the demonstration board showed just the opposite! White was a clear exchange to the good – about such positions it is customary to say that the rest is a matter of technique. Who knows, perhaps Karpov's confidence, his habit of retaining composure in the most desperate situations, was transmitted to his opponent and made Polugayevsky excessively nervous."* p. 239 "My Great Predecessors" Vol 5.

[12] Kasparov (2003) on Fischer's performance in 1963 U.S. championship: *"Bobby crushed everyone in turn, Reshevsky, Steinmeyer, Addison, Weinstein, Donald Byrne... Could no one really whitstand him?! In an interview Evans merely spread his hands: 'Fantastic, unbelievable...' Fischer created around himself such an energy field, such an atmosphere of tension, a colossal psychological intensity, that this affected everyone."* p. 310 "My Great Predecessors" Vol 4.

[13] Not losing a single game in world championship matches is a very rare phenomenon, since the world champion and the contestant are expected to be at similar levels.

[14] ELO rating information is not available for Fischer's era. FIDE adopted the ELO ratings system in 1970.

competing against Stockfish 11 with an ELO rating 3497. Figure 15 shows the ELO rating distribution of such tournament. Rausis' participation in such tournaments creates a unique setting in which a very strong chess grandmaster plays in tournaments against much lower rated non-master opponents.[15]

Table 1 presents further statistics on the dominance of the superstars in the sample showing their tournament win probabilities. Panels A-E includes the World's Top 10 chess players for the corresponding era and a summary of their tournament performances. Our contemporary superstar, Magnus Carlsen, participated in 35 tournaments with classical time controls between 2013 and 2019, and won 21 of them. This 60% tournament win rate is two times higher than World's #2 chess player, Fabiano Caruana, who has a tournament win rate of 30%. A more extreme case is with Anatoly Karpov who won 26 out of the total 32 tournaments he competed in scoring a 81% tournament win rate while the runner up Jan Timman had a tournament win rate of 22%.[16] The final panel, Panel F, shows the tournament performances for Rausis and his top performing opponents. Rausis showed an outstanding performance by winning all eight tournaments in the sample without facing a single loss.

Figures 10–14 show individual tournament performances across years for each superstar with the vertical axis showing whether the superstar gained or lost rating points at the end of a tournament. For instance, in 2001, Kasparov played in four tournaments and won all four of them. Despite winning all four tournaments, he lost rating points in one tournament. For the world's strongest player, winning tournaments alone is not sufficient to maintain their number one position: they also have to win tournaments decisively.

[15]Additionally, Igors Rausis was banned by FIDE, the International Chess Federation, in July 2019 due to cheating using a chess engine via his phone during tournaments.

[16]Restricting the runner ups' tournament wins to tournaments in which a superstar participated lowers their tournament win rate significantly. (tables available upon request)

Table 1: World's Top 10 chess players and their tournament performances

years: 2013-2019 *PANEL A*

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Carlsen, Magnus	21	35	60%	2855	0.352	0.576	0.072	14.413	16,104	303
Caruana, Fabiano	15	49	30%	2802	0.283	0.592	0.126	16.758	22,205	447
So, Wesley	6	27	22%	2777	0.226	0.666	0.108	14.928	11,622	263
Aronian, Levon	5	33	15%	2788	0.196	0.662	0.142	16.059	13,455	294
Giri, Anish	3	31	9%	2770	0.149	0.719	0.131	14.873	14,224	304
Karjakin, Sergey	3	28	10%	2768	0.168	0.689	0.143	15.947	12,764	281
Mamedyarov, Shakhriyar	3	22	13%	2777	0.172	0.674	0.154	15.050	9,405	216
Vachier Lagrave, Maxime	3	26	11%	2777	0.163	0.703	0.134	14.539	10,227	232
Ding, Liren	2	10	20%	2784	0.221	0.696	0.082	15.213	5,077	102
Grischuk, Alexander	0	15	0%	2777	0.183	0.633	0.184	18.081	6,852	146

years: 1995-2001 *PANEL B*

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Kasparov, Garry	17	22	77%	2816	0.439	0.510	0.051	17.595	18,082	488
Kramnik, Vladimir	12	30	40%	2760	0.322	0.621	0.058	16.743	22,782	610
Anand, Viswanathan	9	25	36%	2762	0.305	0.595	0.099	19.337	18,879	517
Topalov, Veselin	6	26	23%	2708	0.279	0.514	0.207	21.193	22,081	515
Ivanchuk, Vassily	4	17	23%	2727	0.255	0.582	0.164	19.626	13,673	362
Adams, Michael	3	22	13%	2693	0.255	0.575	0.169	19.096	17,472	421
Short, Nigel D	3	18	16%	2673	0.272	0.475	0.253	22.717	13,538	348
Svidler, Peter	3	13	23%	2684	0.234	0.599	0.167	19.340	9,458	260
Karpov, Anatoly	2	12	16%	2742	0.214	0.679	0.107	18.292	8,966	211
Shirov, Alexei	2	26	7%	2706	0.288	0.460	0.253	21.865	22,277	529

Table 1 (cont): World's Top 10 chess players and their tournament performances

years: 1976-1983 *PANEL C*

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Karpov, Anatoly	26	32	81%	2707	0.432	0.524	0.044	17.429	14,581	391
Timman, Jan H	8	36	22%	2606	0.338	0.515	0.146	21.614	19,061	261
Larsen, Bent	5	26	19%	2608	0.379	0.336	0.285	23.749	16,809	166
Kortschnoj, Viktor Lvovich	3	7	42%	2667	0.448	0.388	0.164	23.112	3,683	88
Tal, Mihail	3	11	27%	2632	0.296	0.604	0.100	20.782	5,456	104
Portisch, Lajos	2	18	11%	2635	0.315	0.534	0.151	20.456	9,390	160
Spassky, Boris Vasilievich	2	13	15%	2626	0.189	0.691	0.120	19.804	4,908	117
Beliavsky, Alexander G	1	4 25%	2591	0.265	0.514	0.221	24.018	2,176	45	
Petrosian, Tigran V	1	9	11%	2608	0.262	0.633	0.105	21.673	3,963	56
Kasparov, Garry	0	2	0%	2627	0.252	0.573	0.175	23.106	858	13

years: 1962-1970 *PANEL D*

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Fischer, Robert James	12	16	75%	.	0.641	0.286	0.073	18.405	10,706	252
Kortschnoj, Viktor Lvovich	7	12	58%	.	0.469	0.459	0.072	19.964	7,728	197
Keres, Paul	4	8	50%	.	0.420	0.547	0.032	19.080	4,830	139
Spassky, Boris Vasilievich	4	9	44%	.	0.410	0.570	0.020	18.240	4,365	138
Botvinnik, Mikhail	3	5	60%	.	0.529	0.414	0.056	18.769	2,251	63
Geller, Efim P	2	12	16%	.	0.425	0.506	0.069	18.519	8,432	220
Tal, Mihail	2	8	25%	.	0.466	0.402	0.133	21.894	4,615	123
Petrosian, Tigran V	1	13	7%	.	0.334	0.621	0.045	20.311	7,622	227
Reshevsky, Samuel H	1	11	9%	.	0.258	0.505	0.237	24.871	5,253	140
Bronstein, David Ionovich	0	6	0%	.	0.283	0.628	0.089	21.604	3,043	94

Table 1 (cont): World's Top 10 chess players and their tournament performances

years: 2014-2019 *PANEL E*

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Hou, Yifan	4	4	100%	2644	0.614	0.364	0.023	16.222	4,028	88
Ju, Wenjun	3	6	50%	2563	0.400	0.523	0.077	16.565	5,826	130
Koneru, Humpy	2	6	33%	2584	0.379	0.424	0.197	20.033	5,832	132
Dzagnidze, Nana	0	6	0%	2540	0.359	0.347	0.295	24.728	6,080	128
Goryachkina, Aleksandra	0	1	0%	2564	0.364	0.636	0.000	14.322	1,116	22
Kosteniuk, Alexandra	0	7	0%	2532	0.297	0.508	0.195	22.841	6,878	150
Lagno, Kateryna	0	2	0%	2544	0.227	0.682	0.091	16.283	1,666	44
Muzychuk, Anna	0	5	0%	2554	0.218	0.582	0.200	18.416	4,814	110
Muzychuk, Mariya	0	3	0%	2544	0.242	0.576	0.182	18.302	3,056	66
Zhao, Xue	0	6	0%	2519	0.288	0.424	0.288	24.058	5,990	132

years: 2012-2019 *PANEL F**

Name	# of tournament wins	# of tournaments played	% tournament wins	$\overline{ELO}$	proportion of games won	proportion of draws	proportion of games lost	$\overline{ACPL}$	# of moves	# of games
Rausis, Igors	8	8	100%	2578	0.783	0.217	0.000	18.319	3,864	105
Naumkin, Igor	1	4	25%	2444	0.667	0.228	0.106	24.891	1,746	48
Patuzzo, Fabrizio	1	3	33%	2318	0.600	0.133	0.267	28.208	1,322	25
Reinhardt, Bernd	1	4	25%	2207	0.423	0.215	0.362	32.870	1,299	27
Bardone, Lorenzo	0	3	0%	2095	0.433	0.267	0.300	27.199	890	24
Gascon del Nogal, Jose R	0	2	0%	2469	0.625	0.250	0.125	23.560	1,162	32
Lubbe, Melanie	0	4	0%	2316	0.401	0.263	0.336	25.243	1,730	40
Lubbe, Nikolas	0	4	0%	2467	0.527	0.442	0.031	24.480	1,676	48
Luciani, Valerio	0	4	0%	2158	0.485	0.083	0.432	35.437	1,352	35
Montilli, Vincenzo	0	3	0%	2117	0.311	0.422	0.267	32.871	1,278	26

Notes: Panels A-E show the tournament performance for the World's Top 10 chess players for the corresponding time period. ELO rating was first adopted by the International Chess Federation (FIDE) in 1970, hence this information is absent in Panel D for Fischer's sample.
*: Panel F shows the tournament performance for Rausis and his top performing opponents.

3.3 ChessBase Mega Database

Our data comes from the 2020 ChessBase Mega Database containing over 8 million chess games dating back to 1400s. Every chess game is contained in a pgn file with including information on the player names, player's side, ELO ratings, date and location of the game, tournament name, round, and the moves played. An example pgn file and a tournament table is provided in the appendix Table A.2 and Figure A.1, respectively. In a chess tournament, each move is recorded by the players, including the details about the players such as their names and their ELO ratings, as well as, game round, date, time and location. A copy of these records are then collected by the tournament organizers and stored for record-keeping. ChessBase collects these games from the organizers and makes them available for those would like to study and analyze the games for a fee.

Table A.1 in the appendix provides a summary of variables used and their definitions. Table 2 presents the summary statistics for each era with tournaments grouped according to superstar presence. In total, our study analyzes over 2 million moves from approximately 35,000 games played in over 300 tournaments between 1962 and 2019.[17]

3.4 Measuring Performance

3.4.1 Average Centipawn Loss

Our first metric comes from computer evaluations where we identify mistakes committed by each player in a given game.[18] A chess game g consists of $moves$ $m \in \{1,\ldots,M\}$ where player i makes an individual move m_{ig}. A chess engine can evaluate a given position by calculating layers with depth n at each decision node and make suggestion on the best moves to play. Given a best move is played, the engine provides the relative (dis)advantage in a given position $C_{igm}^{computer}$. This evaluation is then compared to the actual evaluation score C_{igm}^{player} once a player makes his or her move. The difference in scores reached via the engine's top suggested move(s) and the actual move a player makes can be captured by

$$error_{igm} = \left| C_{igm}^{computer} - C_{igm}^{player} \right| \tag{2}$$

If the player makes a top suggested move, the player has commited zero error, i.e., $C_{igm}^{computer} = C_{igm}^{player}$. Notice chess is a game of attrition where the player who is able to make less mistakes eventually wins the game. The evaluation stays constant if top moves are played; while the evaluation goes towards showing advantage to the opponent if a player commits a mistake via playing a bad move.

[17] A list of the tournaments is provided in the appendix.

[18] Guid and Bratko (2011) and Regan, Biswas and Zhou (2014) are two early examples of implementations of computer evaluations in chess. Regan has applied computer evaluations to detect cheating in chess games by investigating the proportion of "engine moves" a human player makes in a game.

We then take the average of all the mistakes commited by player i in game g via

$$\overline{error_{ig}} = \frac{\sum_{m=1}^{M} \left| C_{igm}^{computer} - C_{igm}^{player} \right|}{M} \tag{3}$$

which is a widely accepted metric named Average Centipawn Loss (ACPL). ACPL is the average of all the penalties a player is assigned to by the chess engine for the bad moves they made in a game. If the player plays the best moves in a game, his ACPL score will be small where a smaller number means the player performed better. On the other hand, if the player makes moves that are considered bad by the engine in the game, the player's ACPL score would be higher.

We use Stockfish 11 in our analyses with depth $n = 19$ moves. For each move, the engine was given half a second to analyze the position and assess $|C_{igm}^{computer} - C_{igm}^{player}|$. Figure 16 shows an example for how a game was analyzed. For instance, at move 30, the computer evaluation is +3.2, which means that the white player has the advantage by a score of 3.2: roughly the equivalent of being one piece (knight or bishop) up compared to his opponent. If the white player had come up with the best moves throughout the rest of the game, the evaluation can also stay 3.2 (if the black player also makes perfect moves) or would only go up leading to a possible win towards the end of the game. In the actual game, player with the white pieces starts to lose his advantage by making moves that are considered bad by the chess engine, and eventually loses the game. The engine analyzes all 162 moves played in the game, and evaluates the quality of each move. Dividing the sum of mistakes committed by player i to the total number of moves played by player i gives the player-specific ACPL score.

3.4.2 Board Complexity

Our second measure that reinforces our ACPL metric is "board complexity" which we obtain via an Artificial Neural Network (ANN) approach. The recent developments with AlphaGo and AlphaZero demonstrated the strength of using heuristic-based algorithms that perform at least as good as the traditional approaches, if not better.[19] Instead of learning from self-play, our neural-network algorithm "learns" from human players.[20] To train the network, we use an independent sample published as part of a Kaggle contest consisting of 50,000 games and more than 4 million moves. The average player in this sample have an ELO rating of 2280, which corresponds to the "National Master" level per the United States Chess Federation (USCF).[21]

The goal of the network is to predict the probability of a player making a mistake with its magnitude. This task would be trivial to solve for positions that

[19] https://en.chessbase.com/post/leela-chess-zero-alphazero-for-the-pc

[20] Sabatelli et al. (2018) and McIlroy-Young et al. (2020) are two recent implementations of such architecture.

[21] http://www.uschess.org/index.php/Learn-About-Chess/FAQ-Starting-Out.html

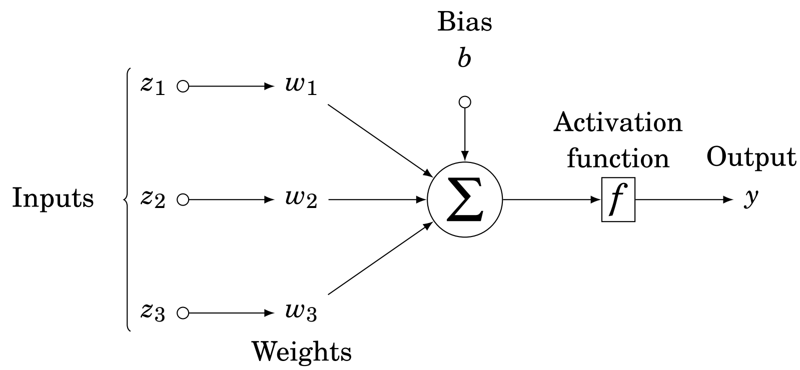


Figure 3: Example of a simple perceptron, with 3 input units (each with its unique weight) and 1 output unit.

were previously played. However, each chess game reaches to a unique position after the opening stage which requires accurate extrapolation of human play in order to predict the errors.[22] We represent a chess position through the use of its 12 binary features, corresponding to the 12 unique pieces on the board. (6 for White, 6 for Black) A chess board has $8 \times 8 = 64$ squares. We split the board into 12 separate 8×8 boards (one for each piece) where a square gets "1" if the piece is present on that particular square and gets "0" otherwise. In total, we represent a given position using $12 \times 8 \times 8 = 768$ inputs. We add one additional feature to represent the players' turn (white to move, or black to move) thus have $768 + 1 = 769$ inputs in total.[23]

The neural network "learns" from 50,000 games by observing each of the ≈4 million positions and estimates the optimal weights by minimizing the error rate that results from each possible set of weights with the Gradient Descent algorithm. The set of 1,356,612 optimal weights uniquely characterizes our network. The network can then be used to make prediction on two statistics for a given position: (i) probability that a player commits an error (ii) the amount of error measured in centipawns. For a full game, the two statistics multiplied (and averaged out across moves) gives us an estimate for the ACPL that each player is expected to get as the result of the complexity of the game

[22] This approach is vastly different than traditional analysis with an engine such as Stockfish. Engines are very strong, and can find the best moves. However, they cannot any give information on how a human would play in a given situation. They are designed to find the best moves without any human characteristics. Our neural-network algorithm is specifically designed to learn how and when humans make mistakes in given positions from analyzing mistakes committed by humans from a sample of 4 million moves.

[23] We use a network architecture with three layers. The layers have 1048, 500, and 50 neurons, each with its unique weight. In order to prevent overfitting, a 20% dropout regularization on each layer is used. Each hidden layer is connected with the Rectified Linear Unit (ReLU) activation function. The Adam optimizer was used with a learning rate of 0.001.

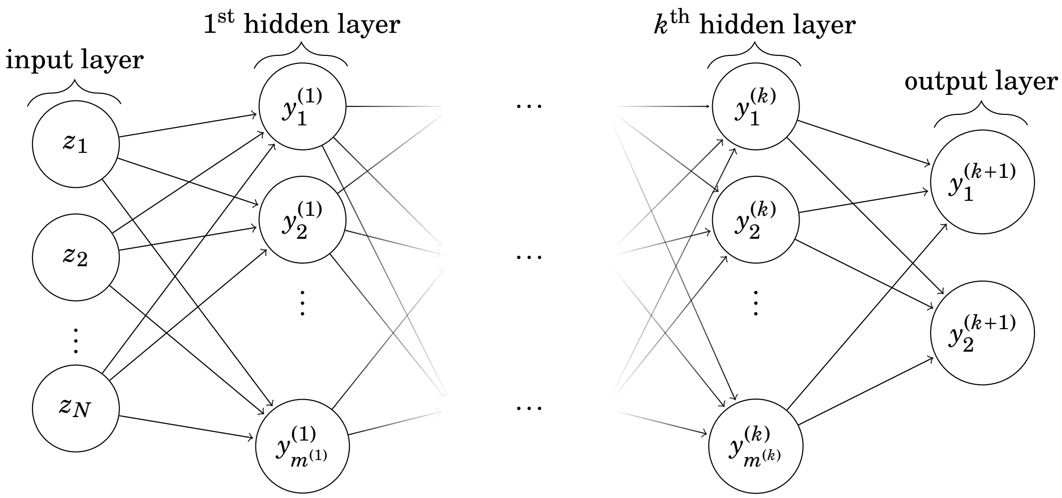


Figure 4: Network graph of a multilayer neural network with $(k+1)$ layers, N input units, and 2 output units. Each neuron collects unique weights from each previous unit. The k^{th} hidden layer contains $m^{(k)}$ neurons.

$$E(\overline{error_{ig}}) = \frac{\sum_{m=1}^{M} P\left(\left|C_{igm}^{computer} - C_{igm}^{network}\right| > 0\right) \left|C_{igm}^{computer} - C_{igm}^{network}\right|}{M} \quad (4)$$

where $\left|C_{igm}^{computer} - C_{igm}^{network}\right|$ is the expected centipawn loss in a given position predicted by the neural network. We test our network's performance on our main "superstars" sample.[24] The mean ACPL for the whole sample with 35,000 games is 25.87, and our board complexity measure, which is the expected ACPL that we obtained through our network is 26.56.[25] Figure 19 shows a scatterplot of ACPL and the expected ACPL. The slope coefficient is 1.14, which implies that a point increase in our complexity measure results in a 1.14 point increase in actual ACPL score.[26] Figure 20 shows the distributions of ACPL and the expected ACPL.

The board complexity measure addresses the main drawback of using only ACPL scores. The ACPL score of a player is a function of his or her opponent's strength, and their strategic choices. For instance, if both players find it optimal to not take any risks, they can have a simple game where players make little to

[24] Figures 17–18 show our network's prediction on a game played by Carlsen.

[25] The reason why our network −which was trained with games played at on average 2280 ELO level− makes a close estimate for the ACPL in the main sample is that the estimates come from not a single player with ELO rating 2280, but rather from a "committee" of players with ELO rating 2280 on average. Hence the network is slightly "stronger" compared to an actual 2280 player.

[26] The highest ACPL prediction of the network is 50.2 while about 8% of the sample has an actual ACPL>50.2. These extreme ACPL cases are under-predicted by the network due to the network's behavior as a "comittee" than a single player, where the idiosyncratic shocks are averaged out.

no mistakes, resulting in low ACPL scores. Yet this would not imply that players showed great performance compared to their other −potentially more complex− games. Being able to control for complexity of a game enables us to compare mistakes committed in similarly-complex games.

3.4.2 Game outcomes

The third measure we use are game-level outcomes. Every chess game ends in a win, a loss, or a draw. The player who wins a tournament is the one who accumulates more wins and fewer losses, as the winner of a game receives a full point towards his or her tournament score.[27] In other words, a player who has more wins in a tournament shows higher performance. In terms of losses, the opposite is true. If a player had many losses in a tournament, their chances to win the tournament would be slim. Lastly, a draw is considered better than a loss and worse than a win against opponents with similar ELO ratings.

4. Empirical Design

The baseline model compares a player's performance in a tournament where a superstar is present with a tournament where there is no superstar competing. This can be captured by the following,

$$\begin{aligned} Performance_{i,j} = \beta_0 + \beta_1 Superstar_j \times HighELO_{i,j} + \beta_2 Superstar_j \times MidELO_{i,j} \\ + \beta_3 Superstar_j \times LowELO_{i,j} + \beta_4 HighELO_{i,j} + \beta_5 MidELO_{i,j} \\ + \mathbf{\Theta X_{i,j}} + \eta_i + \epsilon_{i,j} \end{aligned} \quad (5)$$

where $Performance_{i,j}$ is the performance of player i in tournament j, measured by methods discussed in section 3.4. $Superstar_j$ is an indicator for superstar being present in tournament j. $\epsilon_{i,j}$ is an idiosyncratic shock. Having negative signs for β_1-β_3 would mean the presence of a superstar creates an adverse effect, creating a disincentive for players to show effort resulting in worse performance outcomes. $HighELO_{i,j}$ equals one if the player has an ELO rating on the first quartile in the ELO rating distribution of the tournament participants. $MidELO_{i,j}$ captures the second and third quartiles, and $LowELO_{i,j}$ captures the bottom quartile. $\mathbf{\Theta X_{i,j}}$ contains the game and tournament level controls. In addition to tournament level specifications, chess allows for a game level analysis which can be specified as the following,

$$Performance_{i,j,k} = \alpha_0 + \alpha_1 AgainstSuperstar_{i,j,k} + \mathbf{\Phi X_{i,j}} + \eta_i + \epsilon_{i,j,k} \quad (6)$$

where $AgainstSuperstar_{i,j,k}$ equals one if player i in tournament j plays against a superstar in round k. In this specification, α_1 captures the effect of head-to-head competition against a superstar.

[27] A draw brings half a point, a loss brings no points in a tournament.

In terms of which tournaments to join, chess superstars typically consider their schedule. They play in the strongest tournaments; however it is typically not possible for them to play in all top-level tournaments since it would be difficult for them to prepare for a large number of tournaments in a year.[28] Generally, if they play a world championship match in a given year, they tend to play in fewer tournaments in that particular year to be able to better prepare for the world championship match.[29] In years without a world championship match, they typically pick a certain number of tournaments to participate in and make preperations. They may play in fewer tournaments in a given year if they believe their schedule does not allow for adequate preparation for each tournament. We control for the average ELO rating in a tournament to account for any selection issues.[30]

5. Results

Table 3 shows the performance of non-superstar players playing against a superstar for each sample. There is a distinct pattern that is true for all superstars: playing against them is associated with a higher ACPL score, more blunders, more mistakes, lower chances to win, and higher chances to lose. What is more, games played against superstars are more complex. This higher complexity could be due to the superstar's willingness to reach to more complex positions in order to make the ability-gap more salient. It could also be linked to non-superstar player taking more risk.[31] Taken as a whole, these findings verify that the superstars considered in our study indeed show greater performance compared to their peers. For instance, a player who plays against Fischer shows 4.3 points higher ACPL compared to his games against other players. His likelihood of win is 10 percentage points less; for a draw, 18 percentage points less; and for a loss 29 percentage points higher compared to his typical games. A game against Fischer is This implies that in terms of direct competition, these superstars had a strong dominance over their peers. The strongest domination

[28]In our sample with elite tournaments, a tournament with a superstar on average has 50 points higher average ELO score compared to the tournaments without a superstar. This shows that chess superstars indeed play in the strongest tournaments.

[29]We indeed document a negative correlation between the number of tournaments a superstar plays and world championship years. (results available upon request)

[30]Linnemer and Visser (2016) document self-selection in chess tournaments with stronger players being more likely to play in tournaments with higher prizes. A central difference between their sample and ours is the level of tournaments. Their data comes from the World Open tournament, which is an open tournament with non-master participants with Elo ratings between 1400-2200. Our sample consists of players from a much restricted sample with only the most elite Grandmasters with Elo ratings often above 2700. Moreover, these high-level tournaments are invitation based, i.e., tournament organizers offer invitations to a select group of strong players. These restrictions work against any possible selection issues.

[31]It is not a trivial task to identify which player initiates complexity. Typically, complex games are reached with mutual agreement by players, avoiding exchanges and keeping the tension on the board.

appears to be with Rausis and Hou Yifan, followed by Fischer as the the magnitudes for ACPL, win, and loss probabilities are stronger for these players compared to the rest of the samples.

The following set of tables, Tables 4–12, show the effect of a superstar's presence on the performance of other competitors. It appears that the most dominant superstar according to Table 3, Rausis, had an adverse effect on the top players' performance. These players had 3.2 points higher ACPL score, 10 percentage points less winning chances and 6 percentage points higher loss rate. A similar adverse effect is true for the second most dominant superstar, Hou Yifan. Her presence is associated with a 4.5 points of higher ACPL, 11 percentage points less winning chances and a 17 percentage points higher loss rate for the top players in a tournament. For Fischer, the coefficient for ACPL is positive but imprecise. However the players indeed had more wins and less complex-games, which agrees with the findings in Moul and Nye (2009) on Soviet collusion.

Another situation with intense competition is when two superstars, Kasparov and Karpov both participated in a tournament. This means that for a given player, he or she will have to face both Kasparov and Karpov and perform better than both of them in order to win a tournament. This tough competition appears to lead to more decisive games and less draws. Players commit fewer blunders and mistakes. The next set of results shows that Kasparov and Karpov's presence separately does appear to create an positive effect on the top players' performance. Top players have smaller ACPL scores, and commit fewer blunders and mistakes.

Lastly, Carlsen had the least dominance compared to the rest of the superstars in our study according to Table 4. His presence appears to create a slight positive effect on performance. Players played more accurately and made fewer mistakes under higher challenges with more complex positions. For instance, top players had games with 0.75 higher board complexity but 0.80 points smaller ACPL scores. The positive effect appears to apply for all the tournament participants.[32]

Table 11 shows the impact of superstar presence for all samples aggregated. Table 12 and Figure 21 show the aggregate superstar effect broken down to each sub-sample for the top quartile players. Moving from Carlsen to Rausis, we observe an increase in the mistakes committed; a higher overall complexity; an increase in blunders and mistakes; a decrease in the win rates; a slight decrease in draw rates; and an increase in the loss rates. These results suggest that an increase in the intensity of the superstar is associated with stronger adverse responses from the top players. When the gap between the superstar and the rest of the group is not too wide, players perform better. As the gap widens, performance drops are anticipated.

[32]Additionally, draw rates are higher for all participants in tournaments with Carlsen. Many chess fans criticize modern chess to have more draws than ever before in the history of chess, which we document in our analyses.

6. Conclusion

Theory predicts an adverse effect to exist in tournaments where a highly skilled competitor is present. Considering their chances to win a tournament against a "superstar", the competitors are discouraged, thus their effort level goes down. On the other hand, if the superstar is only slightly better than the rest of the group, theory predicts that players will show higher effort, as they will have higher chances to win the tournament and win the prize.

Using evidence from chess, we empirically show an adverse effect to exist when a "super" superstar is present in a tournament. Players make more mistakes, win fewer games and lose more games when they compete in a tournament with an extremely highly skilled superstar. In terms of head-to-head competition, our findings are consistent with the theory. A superstar shows greater skill, has higher chances to win, and lower chances to lose against their opponents. However, when a superstar is not "super", there is suggestive evidence for a slight positive effect, despite the superstar still show better performance in head-to-head competition. In these tournaments, players "step-up" their game and collectively show greater performance.

The literature analyzing the superstar effect shows mixed empirical evidence. In golf, the effort level decreases with superstar presence; in 100-metres running or swimming contests, the effort level appears to increase. In this paper, we show that the effect depends on the intensity of the superstar against the rest of the competitors. An intense superstar creates an adverse effect in tournaments; while a superstar who is only slightly more skilled than the rest of the competitors may have a positive impact on the effort level in a tournament.

The takeaway for firms seeking to hire a superstar employee is that hiring a superstar employee may create a positive or an adverse effect on the cohort's performance depending on the skill level gap. If the gap is too large, there may be negative side effects of hiring a superstar employee. In these settings, a highly skilled team member would destroy competition and create an adverse effect on the rest of the team members.

References

Archak, Nikolay. 2010. "Money, Glory and Cheap Talk: Analyzing Strategic Behavior of Contestants in Simultaneous Crowdsourcing Contests on TopCoder.com." *Proceedings of the Nineteenth International World Wide Web Conference, April 26–30*.

Babington, Michael, Sebastian J. Goerg, and Carl Kitchens. 2020. "Do Tournaments With Superstars Encourage or Discourage Competition?" *Journal of Sports Economics*, 21(1): 44–63.

Backus, Peter, María Cubel, Matej Guid, Santiago Sánchez-Pages, and Enrique Lopez Manas. 2016. "Gender, Competition and Performance: Evidence from Real Tournaments." IEB Working Paper. https://ieb.ub.edu/wp-content/uploads/2018/04/2016-IEB-WorkingPaper-27.pdf.

Baik, Kyung Hwan. 1994. "Effort Levels in Contests with Two Asymmetric Players." *Southern Economic Journal*, 61(2): 367–378.

Boudreau, Kevin J., Karim R. Lakhani, and Michael Menietti. 2016. "Performance responses to competition across skill levels in rank-order tournaments: field evidence and implications for tournament design." *The RAND Journal of Economics*, 47(1): 140–165.

Brown, Jennifer. 2011. "Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars." *Journal of Political Economy*, 119(5): 982–1013.

Coffey, Bentley, and Michael Maloney. 2010. "The Thrill of Victory: Measuring the Incentive to Win." *Journal of Labor Economics*, 28(1): 87–112.

Connolly, Robert A., and Richard J. Rendleman. 2014. "The (Adverse) Incentive Effects of Competing with Superstars: A Reexamination of the Evidence." SSRN Working Paper. https://ssrn.com/abstract=2533537.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2017. "Peer Effects in the Workplace." *American Economic Review*, 107(2): 425–56.

Dreber, Anna, Christer Gerdes, and Patrik Gränsmark. 2013. "Beauty queens and battling knights: Risk taking and attractiveness in chess." *Journal of Economic Behavior & Organization*, 90(C): 1–18.

Duflo, Esther, Pascaline Dupas, and Michael Kremer. 2011. "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya." *American Economic Review*, 101(5): 1739–74.

Ehrenberg, Ronald G., and Michael L. Bognanno. 1990*a*. "Do Tournaments Have Incentive Effects?" *Journal of Political Economy*, 98(6): 1307–1324.

Ehrenberg, Ronald G., and Michael L. Bognanno. 1990*b*. "The Incentive Effects of Tournaments Revisited: Evidence from the European PGA Tour." *Industrial and Labor Relations Review*, 43(3): 74S–88S.

Elo, Arpad E. 1978. *The Rating of Chessplayers, Past and Present.* New York.

Gerdes, Christer, and Patrik Gränsmark. 2010. "Strategic behavior across gender: A comparison of female and male expert chess players." *Labour Economics*, 17(5): 766–775.

Green, Jerry, and Nancy Stokey. 1983. "A Comparison of Tournaments and Contracts." *Journal of Political Economy*, 91(3): 349–64.

Guid, Matej, and Ivan Bratko. 2011. "Using Heuristic-Search Based Engines for Estimating Human Skill at Chess." *J. Int. Comput. Games Assoc.*, 34: 71–81.

Guryan, Jonathan, Kory Kroft, and Matthew J. Notowidigdo. 2009. "Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments." *American Economic Journal: Applied Economics*, 1(4): 34–68.

Hill, Brian. 2014*a*. "The Heat Is On: Tournament Structure, Peer Effects, and Performance." *Journal of Sports Economics*, 15(4): 315–337.

Hill, Brian. 2014*b*. "The Superstar Effect in 100-Meter Tournaments." *International Journal of Sport Finance*, 9(2): 111–129.

Jane, Wen-Jhan. 2015. "Peer Effects and Individual Performance: Evidence From Swimming Competitions." *Journal of Sports Economics*, 16(5): 531–539.

Kasparov, Garry. 2003. *My Great Predecessors.* Everyman Chess.

Klingen, Joris, and Jos van Ommeren. 2020. "Risk Attitude and Air Pollution: Evidence from Chess." Tinbergen Institute Discussion Paper. https://papers.tinbergen.nl/20027.pdf.

Kunn, S., Seel C., and Zegners D. 2020. "Cognitive Performance in the Home Office - Evidence from Professional Chess." IZA Discussion Paper. http://ftp.iza.org/dp13491.pdf.

Künn, Steffen, Juan Palacios, and Nico Pestel. 2019. "Indoor Air Quality and Cognitive Performance." IZA Discussion Paper. http://ftp.iza.org/dp12632.pdf.

Lazear, Edward P., and Sherwin Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy*, 89(5): 841–864.

Levitt, Steven D., John A. List, and Sally E. Sadoff. 2011. "Checkmate: Exploring Backward Induction among Chess Players." *American Economic Review*, 101(2): 975–90.

Linnemer, Laurent, and Michael Visser. 2016. "Self-selection in tournaments: The case of chess players." *Journal of Economic Behavior & Organization*, 126(PA): 213–234.

Mas, Alexandre, and Enrico Moretti. 2009. "Peers at Work." *American Economic Review*, 99(1): 112–45.

McIlroy-Young, Reid, Siddhartha Sen, Jon Kleinberg, and Ashton Anderson. 2020. “Aligning Superhuman AI with Human Behavior.” *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery Data Mining*.

Moldovanu, Benny, and Aner Sela. 2001. “The Optimal Allocation of Prizes in Contests.” *American Economic Review*, 91(3): 542–558.

Moul, Charles C., and John V.C. Nye. 2009. “Did the Soviets collude? A statistical analysis of championship chess 1940-1978.” *Journal of Economic Behavior & Organization*, 70(1-2): 10–21.

Nalebuff, Barry J., and Joseph E. Stiglitz. 1983. “Prizes and Incentives: Towards a General Theory of Compensation and Competition.” *The Bell Journal of Economics*, 14(1): 21–43.

Nti, Kofi O. 1999. “Rent-Seeking with Asymmetric Valuations.” *Public Choice*, 98(3/4): 415–430.

Orszag, Jonathan M. 1994. “A new look at incentive effects and golf tournaments.” *Economics Letters*, 46(1): 77–88.

Prendergast, Canice. 1999. “The Provision of Incentives in Firms.” *Journal of Economic Literature*, 37(1): 7–63.

Regan, Kenneth Wingate, Tamal Biswas, and Jason Zhou. 2014. “Human and computer preferences at chess.” *Workshops at the Twenty-Eighth AAAI Conference on Artificial Intelligence*.

Rosen, Sherwin. 1981. “The Economics of Superstars.” *The American Economic Review*, 71(5): 845–858.

Sabatelli, Matthia, Francesco Bidoia, Valeriu Codreanu, and Marco Wiering. 2018. “Learning to Evaluate Chess Positions with Deep Neural Networks and Limited Lookahead.” *7th International Conference on Pattern Recognition Applications and Methods*.

Smerdon, David, Hairong Hu, Andrew McLennan, William von Hippel, and Sabina Albrecht. 2020. “Female Chess Players Show Typical Stereotype-Threat Effects: Commentary on Stafford (2018).” *Psychological Science*, 31(6): 756–759.

Stafford, Tom. 2018. “Female chess players outperform expectations when playing men.” *Psychological Science*, 29(3): 429–436.

Sunde, Uwe. 2009. “Heterogeneity and performance in tournaments: a test for incentive effects using professional tennis data.” *Applied Economics*, 41(25): 3199–3208.

Tanaka, Ryuichi, and Kazutoshi Ishino. 2012. "Testing the incentive effects in tournaments with a superstar." *Journal of the Japanese and International Economies*, 26(3): 393–404.

Tullock, Gordon. 1980. "Efficient rent seeking." In *Efficient Rent-Seeking*. J.M. Buchanan, R.D. Tollison, G. Tullock (Eds.), Toward a Theory of the Rent-seeking Society, Texas AM University Press, College Station, TX.

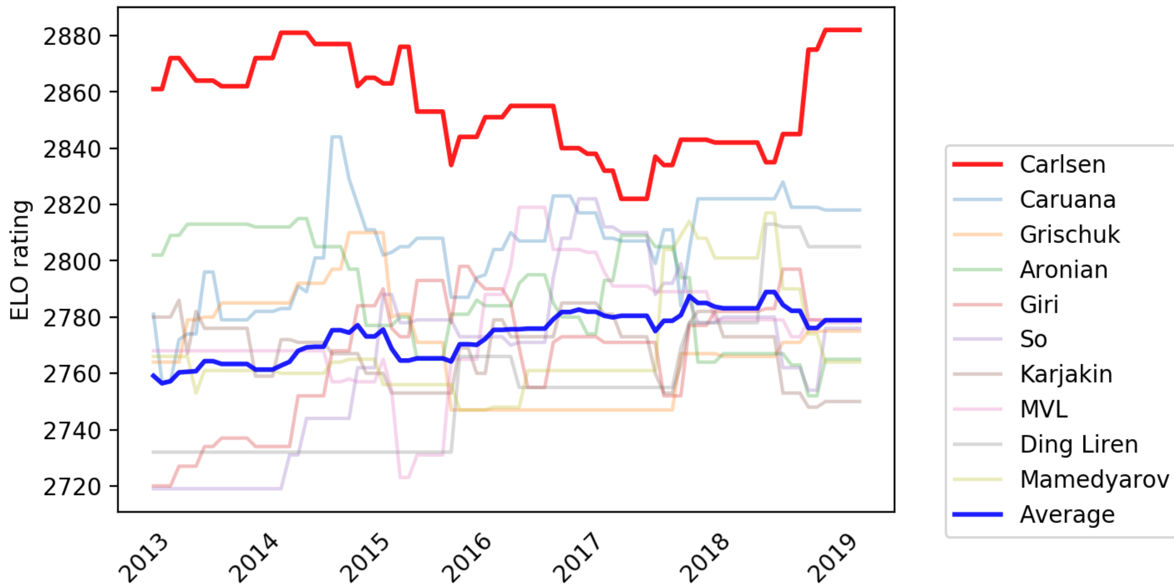
Xiao, Jun. 2020. "Whether to Hire A(nother) Superstar." Working Paper. http://www.junxiao1.com/Files/JunXiao%20WhetherHireSuperstar.pdf.

Yamane, Shoko, and Ryohei Hayashi. 2015. "Peer Effects among Swimmers." *The Scandinavian Journal of Economics*, 117(4): 1230–1255.

Zhang, Shunyuan, Param Vir Singh, and Anindya Ghose. 2019. "A Structural Analysis of the Role of Superstars in Crowdsourcing Contests." *Information Systems Research*, 30(1): 15–33.

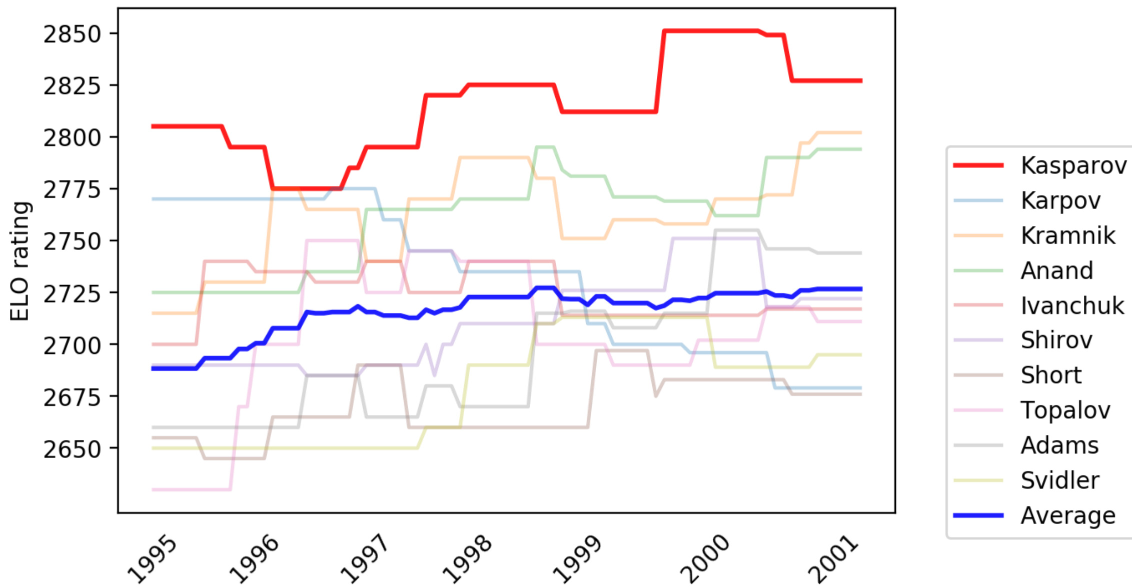
Tables & Figures

Figure 5: ELO ratings of top chess players between 2013-2019.



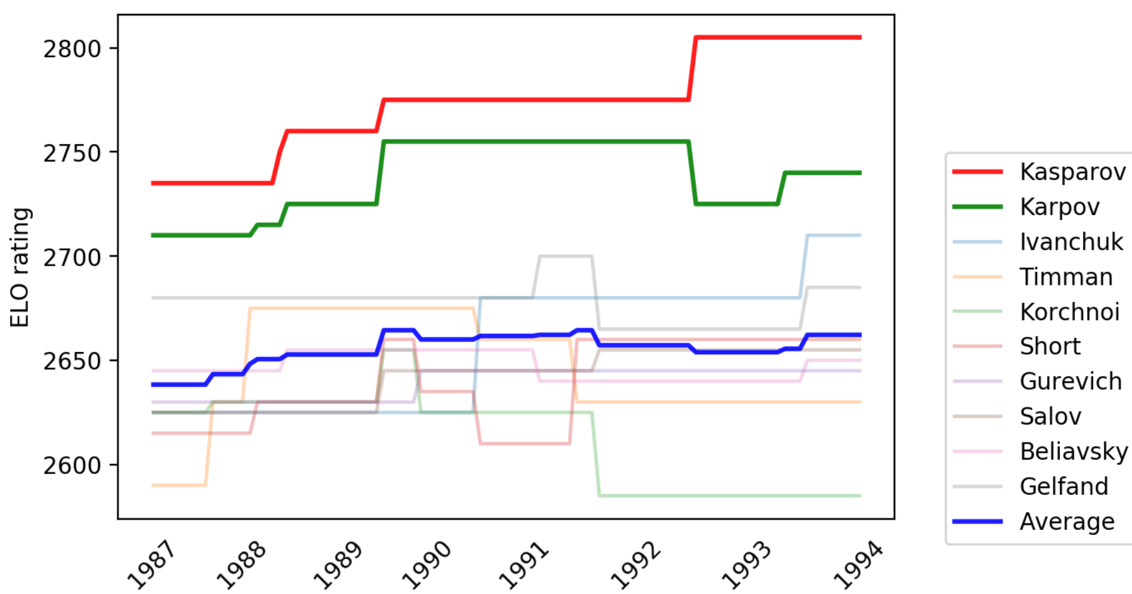
Note: The blue line shows the average ELO rating of top chess players other than Carlsen (World ranking 2−10). ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 6: ELO ratings of top chess players between 1995-2001.



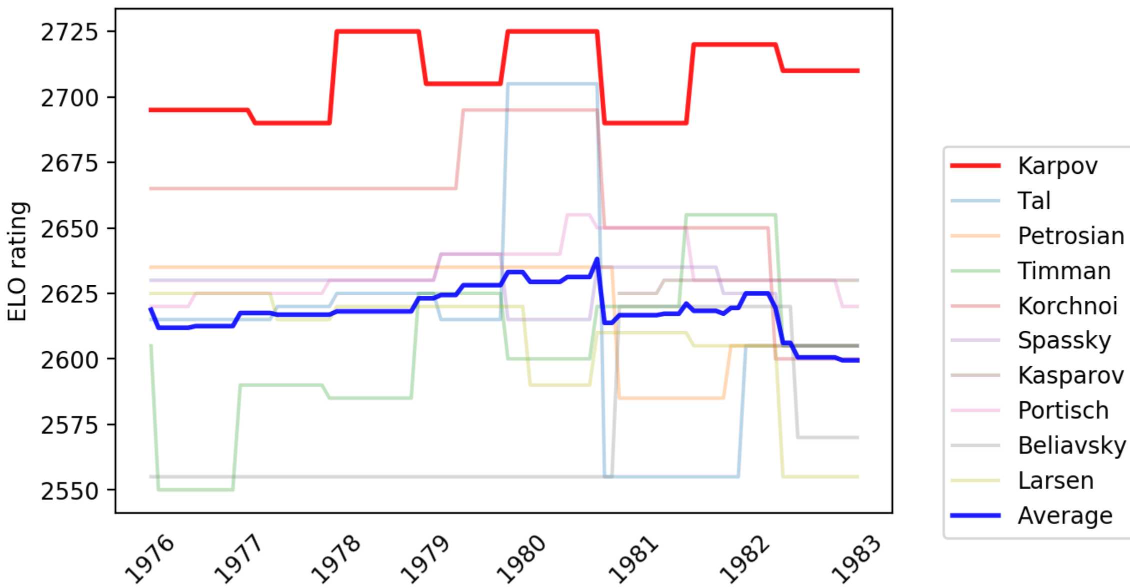
Note: ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 7: ELO ratings of top chess players between 1987-1994.



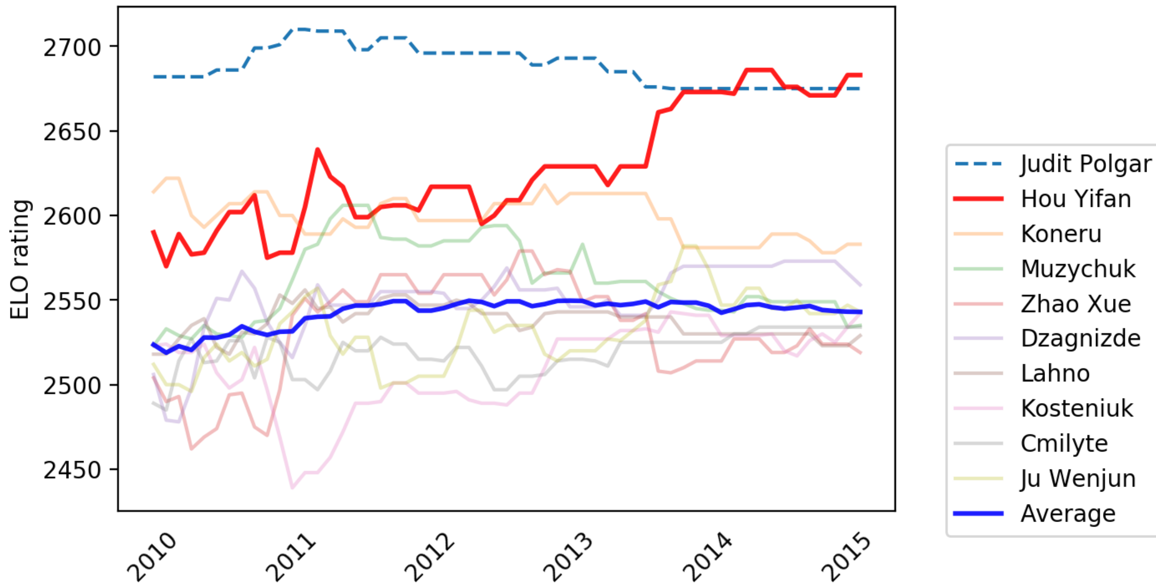
Note: ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 8: ELO ratings of top chess players between 1976-1983.



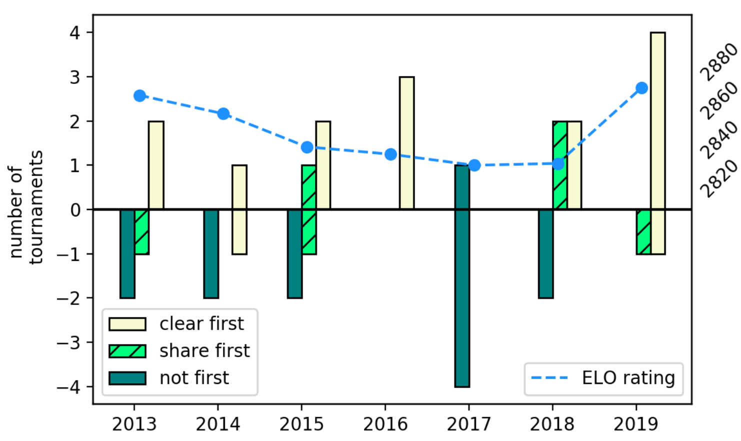
Note: ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 9: ELO ratings of top female chess players between 2010-2015.



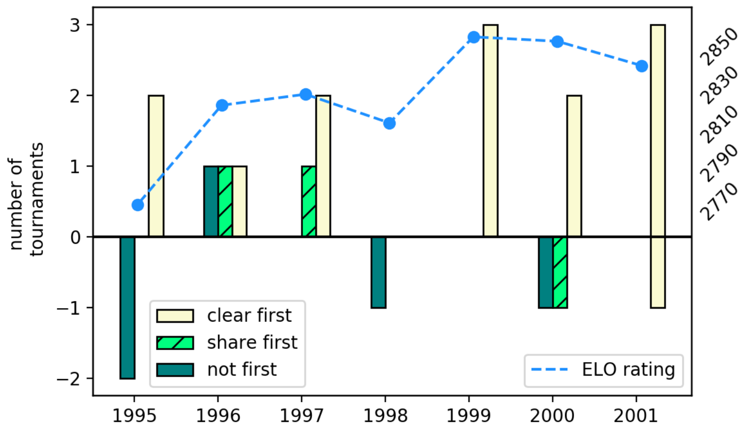
Note: Judit Polgar is considered the strongest female chess player of all time, however she stopped competing in female tournaments in 1990 when she was 14 years old. Hou Yifan stopped competing in female tournaments after 2015. ELO rating data is obtained from FIDE available online at https://ratings.fide.com

Figure 10: Carlsen's tournament performance (classical)



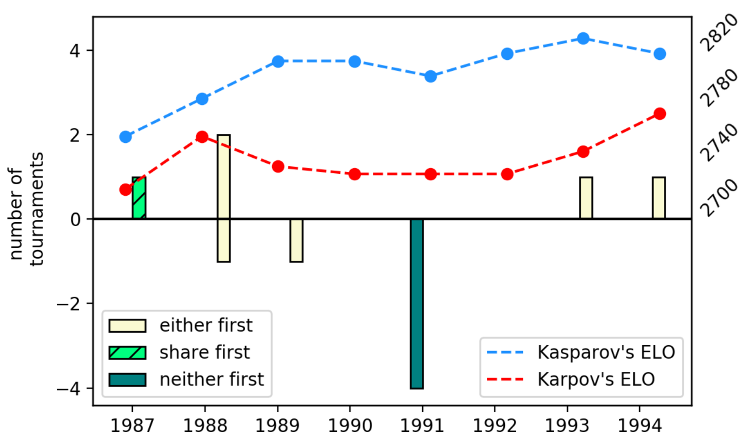
Note: Carlsen's ELO rating data is obtained from FIDE.

Figure 11: Kasparov's tournament performance (classical)



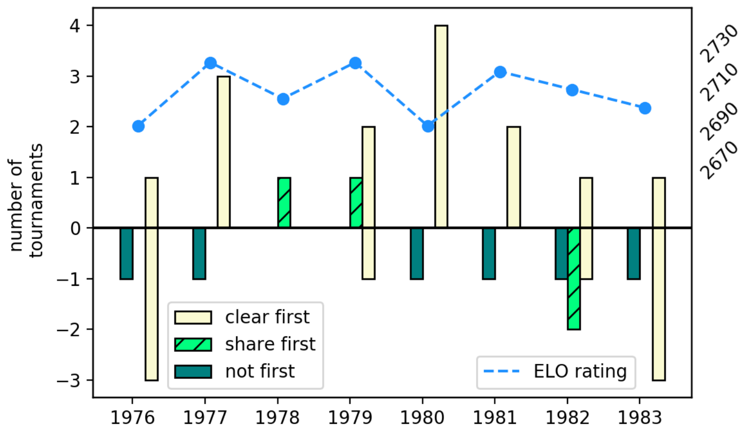
Note: Kasparov's ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 12: Kasparov and Karpov's tournament performance (classical)



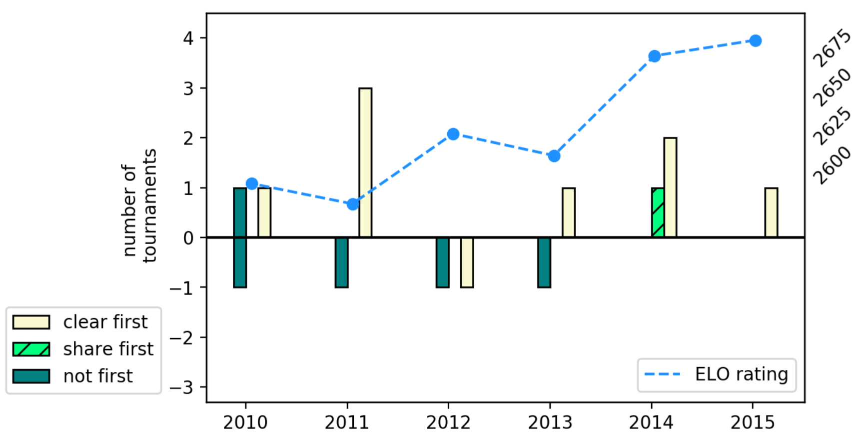
Note: Kasparov's and Karpov's ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 13: Karpov's tournament performance (classical)



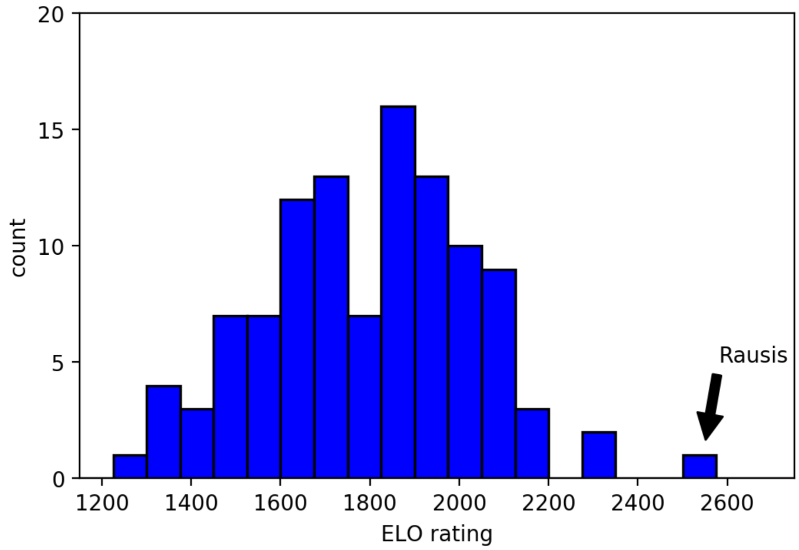
Note: Karpov's ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 14: Hou Yifan's tournament performance (classical)



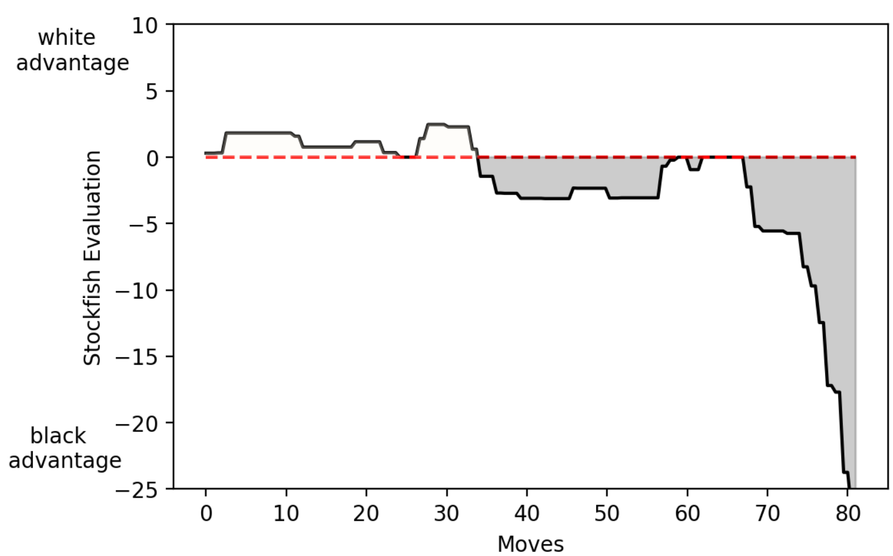
Note: Hou Yifan's ELO rating data is obtained from Chessbase Mega Database 2020.

Figure 15: Elo rating distribution of a tournament Rausis competed in 2012.



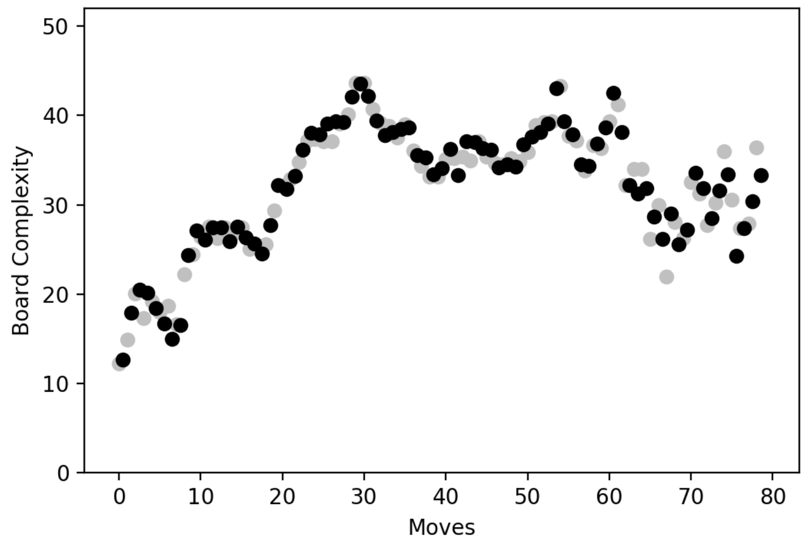
Note: The tournament is Tres Cantos Open played in June 2012 in Spain. Rausis had an ELO rating of 2514. His nine opponents had an average ELO rating of 2046. ELO rating information is obtained from Chessbase Mega Database 2020.

Figure 16: Computer evaluation of a game played by Carlsen in 2019.



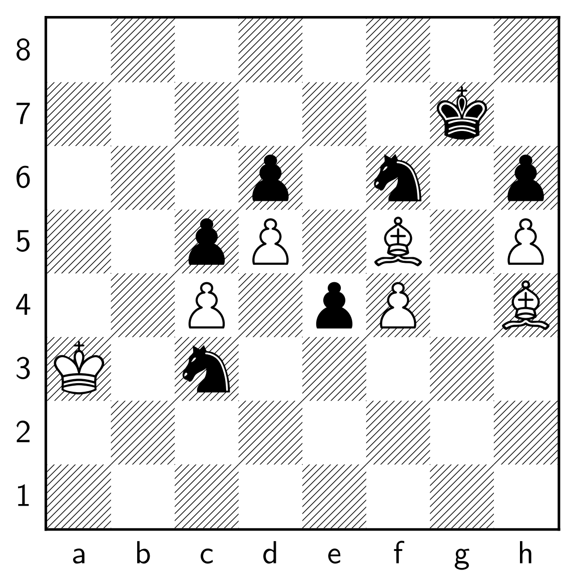
Note: The game was played between Vincent Keymer (White) and Magnus Carlsen (Black) on April 20, 2019 during the first round of Grenke Chess Classic 2019. Keymer's Average Centipawn Loss (ACPL) was 35.22 and Carlsen's 26.17 using our algorithm. A higher ACPL means the player made more mistakes according to the chess engine. The chess engine used for evaluations is Stockfish 11 with a depth of 19 moves.

Figure 17: Complexity evaluation of a game played by Carlsen in 2019 using an Artificial Neural Network (ANN) algorithm.



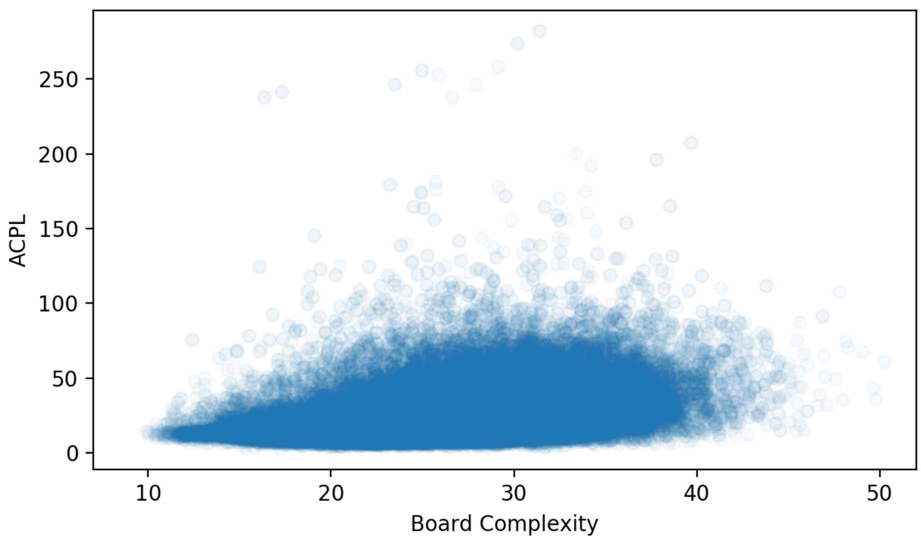
Note: The game was played between Vincent Keymer (White) and Magnus Carlsen (Black) on April 20, 2019 during the first round of Grenke Chess Classic 2019. Keymer's Average Centipawn Loss (ACPL) was 35.22 and Carlsen's 26.17 using our algorithm. Our neural-network board complexity estimate assigns an expected ACPL score of 34.87. This score is substantially higher than the sample average, 26.56. The game is within the top 10% of the sample in terms of complexity.

Figure 18: A position from Keymer vs. Carlsen (2019).



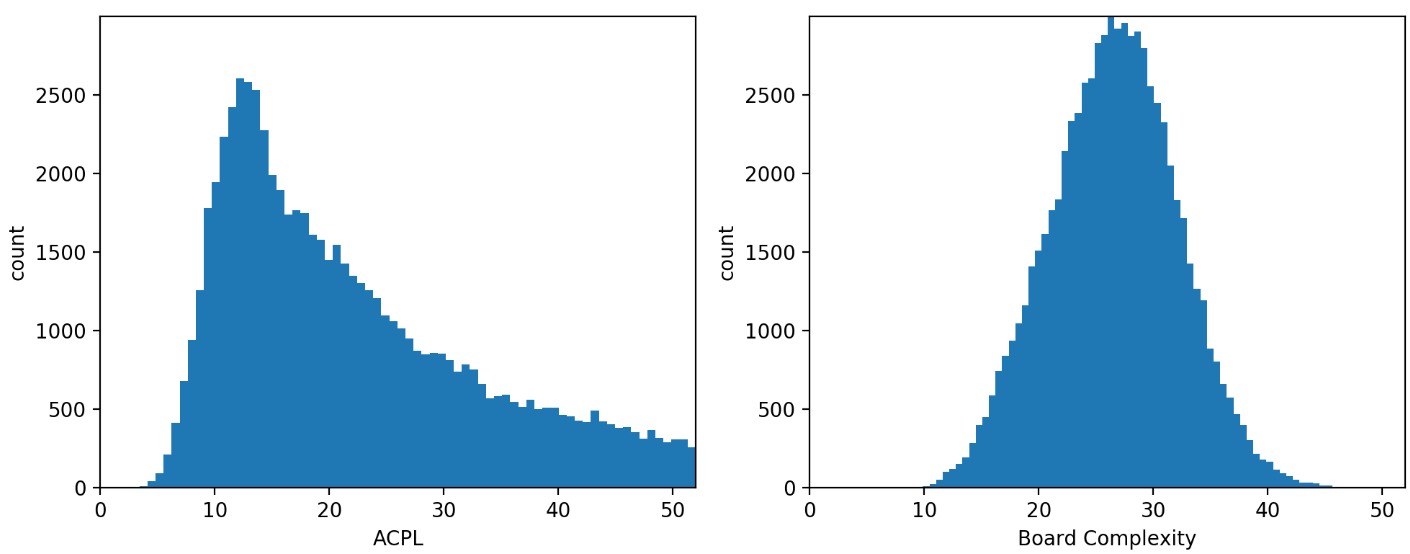
Note: The position is from Vincent Keymer (White) vs. Magnus Carlsen (Black), Grenke Chess Classic 2019 (white to play). Our neural-network algorithm calculates the probability of making an error as 0.52 (about twice as high as the sample average) in an amount of 65 centipawns. In the game, white blundered (by playing Bf2) in an amount of 180 centipawns, according to Stockfish. Before this blunder, this position was a forced draw.

Figure 19: Scatterplot of board complexity and ACPL scores.



Note: The board complexity measure is obtained via a neural-network algorithm. It is the "expected ACPL score" according to the AI, depending on the complexity of a game. The estimated slope is 1.12 for the overall sample of 36,000 games and 2.8 million moves.

Figure 20: Distribution of ACPL and board complexity scores.



Note: The board complexity measure is obtained via a neural-network algorithm. It is the "expected ACPL score" according to the AI which depends on the complexity of a game. The average ACPL score in the sample is 25.49 and the board complexity score is 26.57 for the overall sample with 36,000 games and 2.8 million moves. The neural-network was trained with an independent sample consisting of 50,000 games and 4 million moves with games played between players with "National Master" ranking on average.

Table 2: Summary statistics for all samples.

years: 2013-2019					*years: 1995-2001*			
	with Carlsen		*without Carlsen*		*with Kasparov*		*without Kasparov*	
variable	mean	sd	mean	sd	mean	sd	mean	sd
ACPL	17.810	11.766	16.681	10.836	21.316	12.992	20.759	12.782
Difficulty	27.048	5.419	26.796	5.278	27.298	5.525	27.867	5.501
TotalBlunder	.229	.576	.188	.515	.285	.677	.241	.561
TotalMistake	1.682	1.941	1.457	1.817	1.907	2.039	1.786	1.882
win	.205	.403	.166	.372	.227	.419	.208	.406
draw	.593	.491	.643	.479	.544	.498	.549	.498
loss	.203	.402	.191	.393	.229	.420	.243	.429
ELO	2714	80.37	2758	47.43	2644	65.33	2685	59.27
Moves	45.21	17.68	43.59	15.97	38.82	15.69	38.34	15.92
#of tournaments	=35		=40		=22		=44	
#of games	=1,336		=1,774		=1,727		=3,696	
#of moves	=114,898		=160,362		=133,184		=286,787	
years: 1987-1994					*years: 1976-1983*			
	with Kasparov & Karpov		*without Kasparov & Karpov*		*with Karpov*		*without Karpov*	
ACPL	21.578	13.226	20.949	12.335	25.694	14.907	21.805	13.495
Difficulty	26.838	5.820	27.040	5.501	26.010	5.755	25.403	5.928
TotalBlunder	.318	.685	.272	.610	.307	.697	.276	.642
TotalMistake	1.921	2.029	1.829	1.917	2.575	2.323	1.840	2.036
win	.233	.423	.195	.396	.254	.435	.207	.406
draw	.533	.499	.561	.496	.493	.500	.552	.497
loss	.235	.424	.243	.429	.253	.435	.241	.427
ELO	2590	56.02	2627	59.77	2529	76.13	2558	68.08
Moves	39.66	16.87	39.04	16.77	37.67	17.01	36.67	17.48
#of tournaments	=11		=37		=32		=34	
#of games	=874		=1,989		=2,036		=3,084	
#of moves	=68,012		=157,668		=149,122		=232,375	

Notes: Superstar player observations are exluded in each sample. Data comes from Chessbase Mega Database 2020.

Table 2: Summary statistics for all samples. (cont.)

years: 1962-1970					*years: 2014-2019*			
	with Fischer		*without Fischer*		*with Hou Yifan*		*without Hou Yifan*	
ACPL	25.284	15.663	24.196	15.649	34.717	22.405	23.022	14.525
Difficulty	26.078	5.750	26.024	5.600	26.750	5.217	26.863	5.198
TotalBlunder	.349	.746	.347	.764	.717	1.107	.377	.693
TotalMistake	2.311	2.254	2.206	2.134	3.400	2.687	2.482	2.475
win	.250	.433	.242	.428	.353	.478	.246	.431
draw	.500	.500	.479	.500	.290	.454	.462	.499
loss	.250	.433	.279	.449	.357	.479	.293	.455
ELO	.	.	.	.	2099	296.55	2493	68.85
Moves	36.10	15.63	38.43	16.42	39.30	16.13	45.28	18.69
#of tournaments	=16		=81		=4		=6	
#of games	=1,660		=7,832		=440		=748	
#of moves	=126,578		=565,611		=40,324		=69,084	
years: 2012-2019								
	with Rausis		*without Rausis*					
ACPL	34.642	22.113	39.216	23.904				
Difficulty	26.536	5.278	27.121	5.122				
TotalBlunder	.714	1.108	.818	1.162				
TotalMistake	3.395	2.688	3.773	2.750				
win	.352	.478	.386	.487				
draw	.294	.455	.209	.407				
loss	.354	.478	.405	.491				
ELO	2096	281.02	1984	276.78				
Moves	38.988	16.231	37.655	14.955				
#of tournaments	=8		=30					
#of games	=2,106		=6,357					
#of moves	=159,052		=495,482					

Notes: Superstar player observations are exluded in each sample. Data comes from Chessbase Mega Database 2020.
$*$: ELO rating system was first adopted by FIDE beginning 1970.

Table 3: Performance against a superstar.

	Panel A. Classical								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty	*# of games*	*# of moves*
Against Carlsen	1.868***	0.080***	0.174**	-0.069***	-0.100***	0.169***	0.172	3,316	294,876
2013-2019	(0.449)	(0.026)	(0.085)	(0.015)	(0.023)	(0.025)	(0.252)		
Against Kasparov	2.300***	0.093**	0.226**	-0.104***	-0.049	0.153***	1.485***	5,770	446,322
1995-2001	(0.634)	(0.046)	(0.095)	(0.012)	(0.035)	(0.037)	(0.346)		
Against Kasparov/Karpov	2.757***	0.174***	0.184*	-0.102***	-0.078***	0.180***	-0.427	2,768	219,607
1987-1994	(0.656)	(0.033)	(0.093)	(0.016)	(0.027)	(0.030)	(0.326)		
Against Karpov	3.171***	0.167***	0.150*	-0.106***	-0.089***	0.195***	0.522**	5,326	396,903
1976-1983	(0.579)	(0.036)	(0.083)	(0.012)	(0.024)	(0.024)	(0.253)		
Against Fischer	4.379***	0.150***	0.222	-0.106***	-0.186***	0.292***	2.255***	9,626	703,525
1962-1970	(0.949)	(0.040)	(0.149)	(0.022)	(0.032)	(0.040)	(0.361)		
Against Hou Yifan	4.415**	0.203***	0.502	-0.111***	-0.203***	0.314***	0.839**	1,232	113,436
2014-2019	(1.530)	(0.047)	(0.437)	(0.031)	(0.034)	(0.029)	(0.331)		
Against Rausis	9.275***	0.400***	0.635**	-0.295***	-0.135**	0.430***	0.457	7,924	603,694
2012-2019	(1.741)	(0.092)	(0.257)	(0.024)	(0.055)	(0.057)	(0.708)		
Against Superstar	2.721***	0.100***	0.018	-0.115***	-0.059***	0.174***	0.627***	36,266	2,801,958
1962-2019	(0.312)	(0.016)	(0.055)	(0.008)	(0.014)	(0.015)	(0.155)		

Notes: All regressions include player and year fixed effects, round fixed effects, event site fixed effects, average ELO rating in the tournament (except for pre-1970 games, as ELO rating was adopted in 1970 by FIDE), player's ELO rating, board complexity measured by our neural-network algorithm, opponent ACPL, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Performance in tournaments with and without Rausis.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
All players	-2.023*	-0.141**	0.074	0.030	0.048	-0.078***	0.346
	(1.017)	(0.061)	(0.099)	(0.024)	(0.031)	(0.028)	(0.325)
Top players^{+}	-1.227	-0.063	0.017	0.045	0.026	-0.071	0.395
	(1.246)	(0.058)	(0.085)	(0.047)	(0.030)	(0.051)	(0.521)
Round>5	3.019***	0.202**	-0.170	-0.109***	0.068***	0.041	0.258
	(1.025)	(0.077)	(0.147)	(0.038)	(0.024)	(0.028)	(0.643)
Number of moves	654,534	654,534	654,534	654,534	654,534	654,534	654,534
Number of games	8,463	8,463	8,463	8,463	8,463	8,463	8,463

Notes: Rausis' games are excluded. The sample consists of open tournaments in Swiss system as opposed to the previous tables in which the samples consist of invitation-based Round robin tournaments. Round >5 indicates the second half of the tournament where competition is more intense in a Swiss-format tournament, as winners in each round get paired with other winners. All regressions include player fixed effects, year fixed effects, month fixed effects, event site fixed effects, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
$^{+}$: These are the players with the top 2 highest ELO rating in a given tournament following Rausis' ELO rating.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Performance in tournaments with and without Hou Yifan.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
Top 25% players	4.344**	-0.012	0.807**	-0.104*	-0.048	0.152**	1.204
	(1.846)	(0.112)	(0.305)	(0.054)	(0.054)	(0.066)	(0.753)
Mid 50% players	1.143	0.015	0.076	-0.068	0.085*	-0.017	1.172**
	(1.039)	(0.083)	(0.207)	(0.042)	(0.047)	(0.056)	(0.447)
Bottom 25% players	1.511	-0.017	0.138	-0.050	-0.032	0.082	0.390
	(1.699)	(0.104)	(0.236)	(0.054)	(0.044)	(0.075)	(0.690)
Number of moves	109,408	109,408	109,408	109,408	109,408	109,408	109,408
Number of games	1,188	1,188	1,188	1,188	1,188	1,188	1,188

Notes: Hou Yifan's games are excluded. All regressions include player fixed effects, year fixed effects, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Performance in tournaments with and without Fischer.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
All players	0.435	0.022	0.016	-0.011	-0.013	0.024*	-0.736***
	(0.322)	(0.014)	(0.057)	(0.009)	(0.012)	(0.012)	(0.119)
Top players	0.594	0.016	0.153	-0.029	0.043*	-0.014	-0.819***
	(0.616)	(0.031)	(0.107)	(0.028)	(0.026)	(0.026)	(0.243)
Number of moves	692,072	692,072	692,072	692,072	692,072	692,072	692,072
Number of games	9,491	9,491	9,491	9,491	9,491	9,491	9,491

Notes: Fischer's games are excluded. Top 10 players are the top chess players in the world from 1962-1970 other than Fischer.[+] All regressions include player fixed effects, year fixed effects, round fixed effects, event site fixed effects, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
[+]: These players are Tigran Petrosian, Viktor Korchnoi, Boris Spassky, Vasily Smyslov, Mikhail Tal, Mikhail Botvinnik, Paul Keres, Efim Geller, David Bronstein, and Samuel Reshevsky.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Performance in tournaments with and without Kasparov & Karpov.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect *when both present*							
Top 25% players	-0.174	-0.057	-0.034	0.014	-0.072*	0.058	0.692
	(1.048)	(0.052)	(0.185)	(0.031)	(0.038)	(0.041)	(0.452)
Mid 50% players	0.088	-0.006	-0.093	0.021	-0.028	0.007	0.285
	(0.568)	(0.050)	(0.084)	(0.021)	(0.026)	(0.023)	(0.347)
Bottom 25% players	-2.137**	-0.099*	-0.174	0.063**	-0.006	-0.057*	0.316
	(0.935)	(0.049)	(0.146)	(0.025)	(0.036)	(0.031)	(0.418)
Number of moves	207,880	207,880	207,880	207,880	207,880	207,880	207,880
Number of games	2,624	2,624	2,624	2,624	2,624	2,624	2,624

Notes: Kasparov and Karpov's games are excluded. Top 25% is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. Bottom 25% is defined as having an ELO in the bottom quartile. All regressions include player fixed effects, year fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Performance in tournaments with and without Kasparov.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
Top 25% players	-1.253*	-0.061*	-0.111	0.025	0.045	-0.069***	0.496
	(0.696)	(0.034)	(0.103)	(0.025)	(0.030)	(0.023)	(0.407)
Mid 50% players	-0.229	-0.002	-0.054	0.028*	0.003	-0.031	-0.191
	(0.538)	(0.027)	(0.072)	(0.017)	(0.023)	(0.020)	(0.387)
Bottom 25% players	0.559	-0.005	0.049	-0.027	0.012	0.014	-0.097
	(0.688)	(0.041)	(0.096)	(0.020)	(0.024)	(0.029)	(0.490)
Number of moves	420,348	420,348	420,348	420,348	420,348	420,348	420,348
Number of games	5,427	5,427	5,427	5,427	5,427	5,427	5,427

Notes: Kasparov's games are excluded. Top 25% is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. Bottom 25% is defined as having an ELO in the bottom quartile. All regressions include player by year fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament, player's side (white or black), and number of moves played. Clustered standard errors (clustered by player-year) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Performance in tournaments with and without Karpov.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
Top 25% players	-2.811***	-0.080	-0.335**	0.088***	-0.091***	0.003	0.482
	(0.976)	(0.060)	(0.144)	(0.031)	(0.030)	(0.032)	(0.458)
Mid 50% players	-1.870***	-0.029	-0.242**	0.072***	-0.033*	-0.039*	0.255
	(0.633)	(0.037)	(0.108)	(0.019)	(0.020)	(0.023)	(0.331)
Bottom 25% players	-3.331***	-0.096	-0.293*	0.059*	-0.004	-0.054	-0.531
	(1.220)	(0.066)	(0.151)	(0.032)	(0.033)	(0.035)	(0.470)
Number of moves	381,460	381,460	381,460	381,460	381,460	381,460	381,460
Number of games	5,120	5,120	5,120	5,120	5,120	5,120	5,120

Notes: Karpov's games are excluded. Top 25% is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. Bottom 25% is defined as having an ELO in the bottom quartile. All regressions include player by year fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament, player's side (white or black), and number of moves played. Clustered standard errors (clustered by player-year) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Performance in tournaments with and without Carlsen.

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
Top 25% players	-0.080	0.040	-0.128	0.010	0.022	-0.032	0.756**
	(0.698)	(0.032)	(0.097)	(0.031)	(0.038)	(0.032)	(0.362)
Mid 50% players	-1.221*	0.008	-0.186*	-0.002	0.072**	-0.069**	0.241
	(0.680)	(0.033)	(0.097)	(0.029)	(0.030)	(0.030)	(0.314)
Bottom 25% players	-0.680	-0.004	-0.073	-0.013	0.059	-0.046	0.770*
	(0.993)	(0.044)	(0.128)	(0.035)	(0.041)	(0.039)	(0.423)
Number of moves	275,260	275,260	275,260	275,260	275,260	275,260	275,260
Number of games	3,110	3,110	3,110	3,110	3,110	3,110	3,110

Notes: Carlsen's games are excluded. Top 25% is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. Bottom 25% is defined as having an ELO in the bottom quartile. All regressions include player by year fixed effects, month fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament, player's side (white or black), and number of moves played. Clustered standard errors (clustered by player-year) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Performance in tournaments with and without a Superstar (overall effect).

	Panel A. Classical						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty
Superstar effect for							
Top 25% players	-0.383	-0.007	-0.036	0.003	-0.003	0.000	0.320**
	(0.329)	(0.018)	(0.054)	(0.012)	(0.015)	(0.013)	(0.156)
Mid 50% players	-0.258	0.009	-0.054	0.008	-0.005	-0.003	0.134
	(0.234)	(0.013)	(0.043)	(0.008)	(0.011)	(0.009)	(0.122)
Bottom 25% players	-0.224	-0.020	0.049	0.011	-0.010	-0.001	0.159
	(0.345)	(0.019)	(0.055)	(0.011)	(0.012)	(0.013)	(0.162)
Number of moves	2,708,766	2,708,766	2,708,766	2,708,766	2,708,766	2,708,766	2,708,766
Number of games	35,121	35,121	35,121	35,121	35,121	35,121	35,121

Notes: Superstars' games, and Rausis' and Fischer's samples are excluded. Top 25% is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. Bottom 25% is defined as having an ELO in the bottom quartile. All regressions include player and year fixed effects, month fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament, player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Performance in tournaments with and without a superstar for top players.

	Panel A. Classical								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
	ACPL	TotalBlunder	TotalMistake	win	draw	loss	Difficulty	*# of games*	*# of moves*
Carlsen present	-0.080	0.040	-0.128	0.010	0.022	-0.032	0.756**	3,110	275,260
2013-2019	(0.698)	(0.032)	(0.097)	(0.031)	(0.038)	(0.032)	(0.362)		
Kasparov present	-1.427**	-0.086**	-0.142	0.025	0.028	-0.053**	0.694	5,427	420,348
1995-2001	(0.696)	(0.035)	(0.102)	(0.025)	(0.033)	(0.025)	(0.466)		
Kasparov&Karpov present	-0.848	-0.062	-0.124	0.031	-0.082**	0.051	0.377	2,624	207,880
1987-1994	(1.030)	(0.059)	(0.168)	(0.033)	(0.036)	(0.039)	(0.436)		
Karpov present	-2.807***	-0.080	-0.334**	0.088***	-0.091***	0.003	0.478	5,120	381,460
1976-1983	(0.975)	(0.060)	(0.143)	(0.031)	(0.030)	(0.032)	(0.458)		
Fischer present++	0.431	0.007	0.138	-0.040	0.042*	-0.002	-0.768***	9,491	692,072
1962-1970	(0.655)	(0.031)	(0.103)	(0.031)	(0.025)	(0.028)	(0.267)		
Hou Yifan present	4.557**	-0.041	0.970***	-0.118**	-0.055	0.172**	0.734	1,188	109,408
2014-2019	(1.999)	(0.112)	(0.341)	(0.058)	(0.057)	(0.071)	(0.752)		
Rausis present+	3.234***	0.294***	-0.199	-0.097***	0.033	0.063***	0.096	8,463	654,534
2012-2019	(0.742)	(0.065)	(0.165)	(0.026)	(0.032)	(0.023)	(0.603)		
Aggregate effect+++	-0.403	-0.009	-0.031	0.012	-0.010	-0.002	0.384**	35,121	2,708,766
1962-2019	(0.324)	(0.018)	(0.052)	(0.011)	(0.016)	(0.013)	(0.170)		

Notes: Superstars' games are excluded. A top player is defined as having an ELO rating in the top 25% among the competitors at the time of the tournament. All regressions include player and year fixed effects, round fixed effects, event site fixed effects, average ELO in a tournament (except Fischer's sample), player's side (white or black), and number of moves played. Clustered standard errors (clustered by tournament) are shown in parentheses.

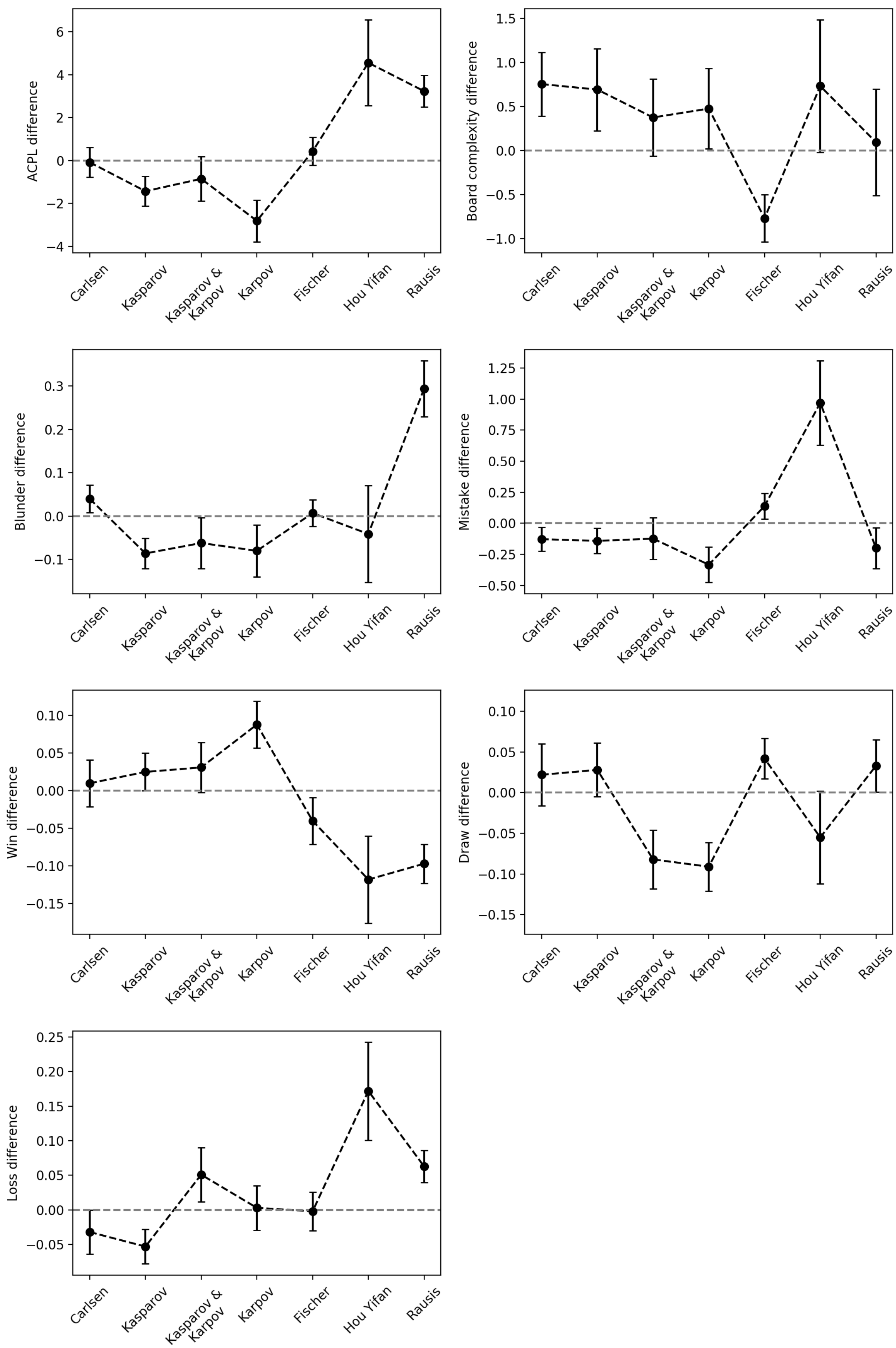
$^{+}$: The estimates are for the top 5% players with the highest ELO ratings in a given tournament following Rausis' ELO rating during the second half of the tournament. In a Swiss type open tournament, only the very top players have a chance to win the tournament, and the compeition gets more intense as winners in each round are paired with other winners.

$^{++}$: Since no ELO rating information was available in Fischer's era, we define the top players as the top chess players in the world from 1962-1970 other than Fischer. These players are Tigran Petrosian, Viktor Korchnoi, Boris Spassky, Vasily Smyslov, Mikhail Tal, Mikhail Botvinnik, Paul Keres, Efim Geller, David Bronstein, and Samuel Reshevsky. Kasparov (2003) provides a detailed overview on each of these players.

$^{+++}$: The sample restricted to Round-robin tournaments with average ELO information available.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 21: Superstar presence coefficients for top players over different superstar intensity levels.



Note: The figure presents the coefficients in Table 12 with confidence intervals over different superstar intensity levels.

Appendix

Table A.1: Variables list.

Variable Name	**Variable Meaning**
Superstar Present	=1 if a superstar is present in a tournament.
Against Superstar	=1 if a game is played against a superstar.
ELO	ELO rating of a player.
ACPL	Average Centipawn Loss of a player in a game.
TotalBlunder	Total number of blunders committed by a player in a game. A move is considered a blunder if the change in ACPL is more than 300 centipawns.
TotalMistake	Total number of mistakes committed by a player in a game. A move is considered a mistake if the change in ACPL is between 100-300 centipawns.
Difficulty	The board complexity metric estimated via an Artificial Neural Network algorithm.
win	=1 if a player wins his or her game.
draw	=1 if a games ends in a draw.
loss	=1 if a player loses his or her game.
white	=1 if a player's side is white.
moves	Total number of moves played by a player in a game.

Table A.2: An example pgn file.

[Event "GRENKE Chess Classic"]
[Site "Karlsruhe GER"]
[Date "2019.04.20"]
[EventDate "2019.04.20"]
[Round "1"]
[Result "0-1"]
[White "Vincent Keymer"]
[Black "Magnus Carlsen"]
[ECO "A56"]
[WhiteElo "2516"]
[BlackElo "2845"]
[PlyCount "162"]

1 d4 ♘f6 2 c4 c5 3 d5 g6 4 ♘c3 d6 5 e4 ♗g7 6 ♘f3 O-O 7 ♗e2 e5 8 O-O ♘e8 9 ♘e1 f5 10 e×f5 g×f5 11 f4 ♘d7 12 ♘d3 e4 13 ♘f2 ♗×c3 14 b×c3 ♘df6 15 ♗e3 ♘g7 16 ♕e1 ♗d7 17 ♘d1 ♗a4 18 h3 ♗×d1 19 ♕×d1 ♕e8 20 ♔f2 ♕g6 21 ♖g1 ♔h8 22 a4 ♖g8 23 ♕f1 ♘fh5 24 g3 ♖af8 25 ♕g2 ♕f6 26 ♖ac1 ♕d8 27 ♕h2 ♘f6 28 g4 ♘d7 29 g5 ♕a5 30 g6 h6 31 ♖b1 ♖b8 32 ♕g3 ♕d8 33 ♔e1 ♘e8 34 ♔d2 ♘f8 35 ♗f2 ♕e7 36 ♔e3 ♕f6 37 ♔d2 ♘×g6 38 h4 ♘e7 39 ♕h3 ♖×g1 40 ♖×g1 ♕f7 41 h5 ♘f6 42 ♗h4 b6 43 ♖b1 ♕f8 44 ♖g1 ♕f7 45 ♖b1 ♕g7 46 ♖g1 ♕f8 47 ♔c2 ♘fg8 48 ♔d2 ♕f7 49 ♔c2 ♖f8 50 ♔d2 ♕e8 51 ♖a1 ♖f7 52 a5 b×a5 53 ♖×a5 ♘c8 54 ♖a1 ♕f8 55 ♖b1 ♘b6 56 ♖g1 ♖g7 57 ♖×g7 ♔×g7 58 ♕g3+ ♔h8 59 ♕g6 a5 60 ♗f1 a4 61 ♔c2 a3 62 ♔b3 ♘a4 63 ♗h3 ♕g7 64 ♕×g7+ ♔×g7 65 ♗×f5 ♘f6 66 ♔×a3 ♘×c3 67 ♗f2 ♘e2 68 ♔a4 ♘×h5 69 ♔a5 ♘f6 70 ♔b6 ♔f7 71 ♔c7 ♔e7 72 ♗e3 ♘d4 73 ♗g6 h5 74 ♗f2 ♘f3 75 ♗f5 ♘d2 76 ♗h4 e3 77 ♗d3 ♘f3 78 ♗×f6+ ♔×f6 79 ♔×d6 h4 80 ♔c7 ♘d4 81 ♔c8 e2 0-1

Figure A.1: An example tournament table.

Grenke Chess Classic 6th 2019

				1	2	3	4	5	6	7	8	9	10		TB	Perf.	+/-
1		Carlsen,Magnus	2845	*	½	½	1	½	1	1	1	1	1	7.5 / 9		2990	+14
2		Caruana,Fabiano	2819	½	*	1	½	½	½	½	½	1	1	6.0 / 9		2833	+3
3		Naiditsch,Arkadij	2695	½	0	*	½	1	½	0	½	1	1	5.0 / 9	19.00	2766	+9
4		Vachier Lagrave,Maxime	2773	0	½	½	*	½	½	½	½	1	1	5.0 / 9	18.25	2758	-1
5		Anand,Viswanathan	2774	½	½	0	½	*	½	½	1	0	1	4.5 / 9	19.75	2719	-6
6		Aronian,Levon	2763	0	½	½	½	½	*	1	½	½	½	4.5 / 9	18.75	2720	-5
7		Svidler,Peter	2735	0	½	1	½	½	0	*	½	1	½	4.5 / 9	17.75	2723	-1
8		Vallejo Pons,Francisco	2693	0	½	½	½	0	½	½	*	½	1	4.0 / 9		2689	-1
9		Meier,Georg	2628	0	0	0	0	1	½	0	½	*	0	2.0 / 9	8.75	2518	-12
10		Keymer,Vincent	2516	0	0	0	0	0	½	½	0	1	*	2.0 / 9	6.50	2529	+1

Average Elo: 2724 <=> Cat: 19

gm = 3.24 m = 1.44

(45 Games)

Note: The tournament table is obtained from Chessbase Mega Database 2020.

Table A.3: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Carlsen Present
2019	GCT Croatia 2019, Grenke Chess Classic 2019, Gashimov Memorial 2019, Norway Chess 2019, Sinquefield 2019, Tata Steel 2019
2018	Gashimov Memorial 2018, Sinquefield 2018, Biel 2018, Norway Chess 2018, Grenke Chess Classic 2018, Tata Steel 2018
2017	London Classic 2017, Norway Chess 2017, Sinquefield 2017, Grenke Chess Classic 2017, Tata Steel 2017
2016	Norway Chess 2016, Tata Steel 2016, Bilbao Masters 2016
2015	London Classic 2015, Sinquefield 2015, Norway Chess 2015, Gashimov Memorial 2015, Grenke Chess Classic 2015, Tata Steel 2015
2014	Norway Chess 2014, Zuerich Chess Challange 2014, Sinquefield 2014, Gashimov Memorial 2014
2013	Moscow Tal Memorial 2013, Norway Chess 2013, Candidates Tournament 2013, Tata Steel 2013, Sinquefield 2013
	Panel B. Carlsen Not Present
2019	U.S. Championship 2019, Dortmund 2019
2018	Candidates Tournament 2018, U.S. Championship 2018, Dortmund 2018
2017	U.S. Championship 2017, Dortmund 2017, Gashimov Memorial 2017
2016	London Classic 2016, Sinquefield 2016, Gashimov Memorial 2016, Candidates Tournament 2016, Moscow Tal Memorial 2016, U.S. Championship 2016, Dortmund 2016
2015	Dortmund 2015, Zuerich Chess Challenge 2015, Tbilisi FIDE GP 2015, Khanty-Mansiysk FIDE GP 2015, Capablanca Memorial 2015, U.S. Championship 2015
2014	Beijing Sportaccord Basque 2014, London Classic 2014, Tashkent FIDE GP 2014, Dortmund 2014, Tata Steel 2014, U.S. Championship 2014, Candidates Tournament 2014, Baku FIDE GP 2014, Capablanca Memorial 2014, Bergomo ACP Golden Classic 2014
2013	Paris FIDE GP 2013, Dortmund 2013, Thessaloniki FIDE GP 2013, Zug FIDE GP 2013, Beijing FIDE GP 2013, Zuerich Chess Challenge 2013, Grenke Chess Classic 2013, Capablanca Memorial 2013, U.S. Championship 2013

Table A.4: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Kasparov Present
2001	Astana 2001, Zuerich 2001, Linares 2001, Corus Wijk aan Zee 2001
2000	Fujitsu Siemens Giants 2000, Sarajevo Bosnia 2000, Linares 2000, Corus Wijk aan Zee 2000
1999	Sarajevo Bosnia 1999, Linares 1999, Hoogovens Wijk aan Zee 1999
1998	Linares 1998
1997	Tilburg 1997, Novgorod 1997, Linares 1997
1996	Las Palmas 1996, Dos Hermanas 1996, Amsterdam Euwe Memorial 1996
1995	Horgen 1995, Amsterdam Euwe Memorial 1995, Novgorod 1995
	Riga Tal Memorial 1995
	Panel B. Kasparov Not Present
2001	Sigeman & Co 2001, Biel 2001, Dortmund 2001, Pamplona 2001, Dos Hermanas 2001
2000	Japfa Classic 2000, Dortmund 2000, Sigeman & Co 2000, Biel 2000
1999	Pamplona 1999, Lost Boys Amsterdam 1999, Dortmund 1999, Sigeman & Co 1999
	Dos Hermanas 1999, Biel 1999
1998	Hoogovens Wijk aan Zee 1998, Tilburg 1998, Dortmund 1998, Madrid 1998, Pamplona 1998
1997	Hoogovens Merrillville 1997, Sigeman & Co 1997, Ubeda 1997, Hoogovens Wijk aan Zee 1997
	Dos Hermanas 1997, Lost Boys 1997, Dortmund 1997, Madrid 1997, Belgrade Investbank 1997
1996	Koop Tjuchem 1996, Donner Memorial 1996, Hoogovens Wijk aan Zee 1996,
	Tilburg 1996, Dortmund 1996, Dos Hermanas 1996, Madrid 1996
1995	Belgrade Investbank 1995, Horgen 1995, Donner Memorial 1995, Biel 1995, Madrid 1995,
	Dos Hermanas 1995, Groningen 1995, Dortmund 1995

Table A.5: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Kasparov & Karpov Both Present
1994	Linares 1994
1993	Linares 1993
1992	
1991	Reggio Emilia 1991, Tilburg 1991, Amsterdam Euwe Memorial 1991, Linares 1991
1990	
1989	World Cup Skelleftea 1989
1988	USSR Championship 1988, World Cup Belfort 1988, Optiebeurs Amsterdam 1988
1987	Brussels 1987
	Panel A. Kasparov & Karpov Neither Present
1994	Donner Memorial 1994, Dortmund 1994, Hoogovens Wijk aan Zee 1994, Groningen 1994, Munich 1994
1993	Antwerp 1993, Amsterdam VSB 1993, Madrid 1993, Las Palmas 1993, Munich 1993
1992	Alekhine Memorial 1992, Amsterdam Euwe Memorial 1992, Hoogovens Wijk aan Zee 1992, Groningen 1992, Munich 1992
1991	World Cup Reykjavik 1991, Hoogovens Wijk aan Zee 1991, Groningen 1991, Munich 1991
1990	Tilburg 1990, Hoogovens Wijk aan Zee 1990, Prague 1990, Groningen 1990, Munich 1990
1989	Hoogovens Wijk aan Zee 1989, Groningen 1989, Munich 1989, Amsterdam Euwe Memorial 1989
1988	Amsterdam Euwe Memorial 1988, OHRA Amsterdam 1988, Linares 1988, Hastings 1988
1987	Belgrade Investbanka 1987, Hoogovens Wijk aan Zee 1987, Interpolis 1987, OHRA Amsterdam 1987, Reykjavik 1987

Table A.6: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Karpov Present
1983	Interpolis 1983, International DSB Mephisto GM 1983, USSR Final 1983, Bath 1983, Linares 1983
1982	Interpolis 1982, Turin 1982, Hamburg 1982, London Phillips 1982, Mar del Plata Clarin Masters 1982
1981	IBM Herinnerungs Toernooi 1981, Moscow 1981, Linares 1981
1980	Buenos Aires 1980, Interpolis 1980, IBM Kroongroep 1980, Bugojno 1980, Bad Kissingen 1980
1979	Interpolis 1979, Waddinxveen KATS 1979, Montreal International 1979, GER International 1979
1978	Bugojno 1978
1977	Interpolis 1977, October Revolution 1977, Las Palmas 1977, GER International 1977
1976	USSR Final 1976, Montilla 1976, Manila Marlboro 1976, Amsterdam 1976, Skopje Solidarnost 1976
	Panel B. Karpov Not Present
1983	Jakarta International 1983, Hoogovens Wijk aan Zee 1983
1982	Interzonal 1982, Hoogovens Wijk aan Zee 1982
1981	Las Palmas 1981, IBM Herinnerungs Toernooi 1981, Interpolis 1981, Hoogovens Wijk aan Zee 1981
1980	Buenos Aires 1980, London Phillips 1980, Hoogovens Wijk aan Zee 1980, Las Palmas 1980, Reykjavik International 1980
1979	Buenos Aires Clarin 1979, Interzonal 1979, Vidmar Memorial 1979, IBM 1979 Hoogovens Wijk aan Zee 1979, Buenos Aires Konex 1979
1978	Interpolis 1978, Reykjavik International 1978, Hoogovens Wijk aan Zee 1978, Las Palmas 1978 IBM 1978, Clarin 1978
1977	Geneve 1977, Vidmar Memorial 1977, Hoogovens Wijk aan Zee 1977, IBM 1977
1976	Interzonal 1976, Las Palmas 1976, Reykjavik International 1976, Hoogovens Wijk aan Zee 1976, IBM 1976

Table A.7: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Fischer Present
1970	Interzonal 1970, Buenos Aires 1970, Rovinj Zagreb 1970
1969	
1968	Vinkovci 1968, Nathanya 1968,
1967	Skopje 1967, Monaco Grand Prix 1967, Interzonal 1967
1966	Piatigorsky Cup 1966, U.S. Championship 1966
1965	U.S. Championship 1965, Capablanca Memorial 1965
1964	
1963	U.S. Championship 1963
1962	U.S. Championship 1962, Candidates Tournament 1962, Interzonal 1962
	Panel B. Fischer Not Present
1970	Vinkovci 1970, IBM Amsterdam 1970, Budapest 1970, Sarajevo 1970, Caracas 1970, Hoogovens Wijk an Zee 1970, Costa del Sol 1970, Skopje 1970, Rubinstein Memorial 1970, Christmas Congress 1970
1969	Monaco Grand Prix 1969, Hoogovens Wijk an Zee 1969, Venice 1969 U.S. Championship 1969, Palma de Mallorca 1969, IBM Amsterdam 1969, Sarajevo 1969, Christmas Congress 1969, Rubinstein Memorial 1969, Capablanca Memorial 1969
1968	Rubinstein Memorial 1968, Christmas Congress 1968, Palma de Mallorca 1968, U.S. Championship 1968, Bamberg 1968, IBM Amsterdam 1968, Sarajevo 1968 Hoogovens Wijk an Zee 1968, Monaco Grand Prix 1968, Skopje 1968
1967	Winnipeg 1967, October Revolution Leningrad 1967, October Revolution Moscow 1967, Capablanca Memorial 1967, Palma de Mallorca 1967, Sarajevo 1967, Hoogovens Beverwijk 1967, Christmas Congress 1967, Rubinstein Memorial 1967, Venice 1967, IBM Amsterdam 1967
1966	IBM Amsterdam 1966, Sarajevo 1966, Palma de Mallorca 1966 Hoogovens Beverwijk 1966, Venice 1966, Rubinstein Memorial 1966, Christmas Congress 1966
1965	ZSK International 1965, Zagreb 1965, Mer del Plata 1965, IBM Amsterdam 1965, Sarajevo 1965, Hoogovens Beverwijk 1965, Christmas Congress 1965, Rubinstein Memorial 1965
1964	Buenos Aires 1964, Capablanca Memorial 1964, Rubinstein Memorial 1964, Interzonal 1964, IBM Amsterdam 1964, Sarajevo 1964, Hoogovens Beverwijk 1964, Christmas Congress 1964, ZSK International 1964
1963	Piatigorsky Cup 1963, Alekhine Memorial 1963, IBM Amsterdam 1963, Sarajevo 1963, Hoogovens Beverwijk 1963, Rubinstein Memorial 1963, Christmas Congress 1963, Capablanca Memorial 1963
1962	Mer del Plata 1962, IBM Amsterdam 1962, Sarajevo 1962, Hoogovens Beverwijk 1962, Rubinstein Memorial 1962, Christmas Congress 1962, Capablanca Memorial 1962

Table A.8: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Hou Yifan Present
2015	Monte Carlo FIDE GP 2015
2014	Lopota FIDE GP 2014, Khanty-Mansiysk FIDE GP 2014,
	Sharjah FIDE GP 2014
	Panel B. Hou Yifan Not Present
2019	Skolkovo FIDE GP 2019, Saint Louis Cairns Cup 2019
2016	Khanty-Mansiysk FIDE GP 2016, Chengdu FIDE GP 2016,
	Batumi FIDE GP 2016, Tehran FIDE GP 2016

Table A.9: List of tournaments (classical)

Year	*Tournament Name*
	Panel A. Rausis Present
2019	Lugano op 2019
2018	Sautron op 2018
2017	
2016	Salon de Provence op 2016
2015	
2014	Chemnitz op 2014, Biella op 2014
2013	Charleroi op 2013, Lueneburg op 2013
2012	Tres Cantos op 2012
	Panel B. Rausis Not Present
2019	Locarno op 2019, Ascona op 2019, Porto San Giorgio op 2019
2018	Erfurt op 2018, Pfarrkirchen Rottal op 2018, Locarno op 2018,
	Paderborn op 2018, Forchheim op 2018
2017	Pfarrkirchen Rottal op 2017, Porto San Giorgio op 2017
	Lugano op 2017, Sautron op 2017
2016	Wasselonne op 2016, Heraklion op 2016
2015	Salon de Provence op 2015, Biella op 2015, Porto San Giorgio op 2015,
	Erfurt op 2015, Lugano op 2015, Ascona op 2015, Lugano op 2015, Forchheim op 2015
2014	Salon de Provence op 2014, Paderborn op 2014, Erfurt op 2014
	Arco op 2014, Ascona op 2014, Forchheim op 2014
2013	Biella op 2013, Forchheim op 2013