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Peer Competition:
Evidence from 5- to 95-Year-olds*

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Good peers may help you learn, but they may also steal your spotlight. We use the panel of chess players in the French club championship to document this trade-off. With an instrumental variable strategy based on club closures, we show that better clubmates help players improve, but only when they do not monopolize the (good) opportunities to play. For players at the bottom of the club distribution, positive externalities are offset by competition. Junior players, who enjoy a steep learning curve, suffer more from peer competition in the short-run, but they may also reap higher benefits in the long-run.

Keywords — Peer effects, Competition, Participation.

JEL Codes — J24, R23

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1 Introduction

The powerful intuition that peers matter, supported by a widespread conception of knowledge as a public good with spatial spillovers, comes in stark contrast with the lack of scientific consensus regarding the causal impact of the peer environment on the average student (Sacerdote, 2014; Angrist, 2014). In addition, evidence that positive peer effects, if any, are often concentrated on high-achieving students (see, e.g., Balestra et al., 2020) seems at odds with possibly diminishing returns in the learning process. One mechanism may explain these two apparent paradoxes: *peer competition*. In a context of limited resources, such as teacher's attention, good peers may also *capture the best opportunities* for improvement.[1] As long argued by tracking advocates, if pedagogical approaches are not tailored to the needs of low-achieving students, having good peers may end up hurting them by preventing them from participating in class (Betts, 2011). However, the case of peer competition is difficult to make, because participation is not readily observable in the classroom.[2]

In this paper, we provide evidence that competition effects exist and may mask positive peer effects on learning. The core of our argument is that learning takes place on a social scene that agents want or need to engage in. We explore this argument in a simple formal model where participation prospects may alter the impact of peer effects through agents' effort. Of particular interest is the case of moderate peer competition. Despite a concave learning curve, agents benefit from having good peers if and only if their level is sufficiently high to shield them against the negative impact of good peers on participation. The model suggests a straightforward partition criterion of the population of

[1] In a labor market context, for instance in law or consulting firms, those limited resources may take the form of better assignments, with more exposure, or more interesting content.

[2] Education specialists have long conducted observational studies based on small samples to measure the correlation between participation and performance. They document which characteristics make classroom more conducive to students' participation (see, e.g., Fassinger, 2000), but without causal inference.

interest and delivers testable implications for the absence of peer competition.

We take our predictions to a particular environment that is well-suited to the measurement of participation and performance: the panel of chess players who take part in the French club championship. Chess offers a unique opportunity to study the link between competition and peer effects for several reasons. First, the measurement of performance is truly individual and based on an accurate and transparent measure: the International Elo Rating,[3] which allows us to compare players over time and space. Second, players have well-identified clubs, where they train together and which they represent in team competitions. Third, the structure of the club championship allows us to document peer competition in a straightforward way, using the number of games per teammate and their position on the team. Finally, compared to workers within a firm, or to students over the course of their studies, chess players all and always perform the same task, which allows us to pay special attention to differences over the life cycle.

In order to measure the impact of peer quality on individual performance, we focus on the player's probability of improvement, defined by whether the player has gained Elo points throughout the season. We control for the player's level at the start of the season because the weaker the player, the higher the probability of improvement. We estimate peer effects at the club-season level based on a predetermined variable of peer quality, the mean Elo of clubmates at the beginning of the season. Our setting also makes it possible to include player-by-club fixed effects, which control for player-club match specific unobserved heterogeneity. Yet, despite these controls, it may still be the case that improving players would endogenously sort into clubs with good peers. In order to account for these issues, we focus our attention on players already present in their club the year before, the "stayers". Then, we instrument their peer quality by the characteristics

[3] A complete description of the Elo rating system can be found on the website of the World Chess Federation, FIDE (http://www.fide.com). See Appendix A.1 for details.

of "evicted" players in clubs that closed in the same metropolitan area the year before. The identifying assumption is that, conditional on controls, the closure shock is as good as random for the stayers. This assumption is based on the fact that club closings are non-rare events that are driven by local idiosyncrasies, such as the departure of a volunteer in charge of the club or the loss of local subsidies.

We document large positive average peer effects on improvement. Overall, our IV estimates show that a 1% increase in peer quality raises the probability of individual improvement by 3.6%, on average. This effect is robust to the control for several time-varying club characteristics and to the exclusion of the highest leagues. We then turn to our second interest: measuring the impact of peer competition. We show that having good peers makes players play fewer games, pushes them down the team hierarchy, and compels them to play losing games against opponents who are too good for them. These effects explain why, in line with the model's predictions, positive peer effects on improvement are concentrated among the best players in the club, who suffer less from these competition effects, compared to the players at the bottom of the club distribution.

Finally, we take advantage of players' wide age range (from 5 to 95 years old) to explore their learning curve and look into the impact of peers over different regimes of human capital accumulation. We show that performance is increasing with age for children and teenagers, before a slow, regular decrease from age 19 onward.[4] Conversely, peer effects are only positive for adult players, who suffer less from competition. This finding suggests that a good peer environment may slow down the cognitive decay associated with aging. Yet, as we show, such positive effect is restricted to performance over a single season. By contrast, junior players, who are initially hurt by having good peers, reap higher benefits over time if they persist in the game long enough.

[4]Using data from professional chess tournaments and only games played by world champions, Strittmatter et al. (2020) also document a hump-shaped performance profile over the life cycle. However, in their case, the learning phase extends to age 35 before declining.

Relationship to the literature — The size and nature of peer effects vary tremendously by outcome, age, location, and the precision with which the peer group is defined, as it possibly goes from one, a roommate, to several hundreds, a cohort in a school (Sacerdote, 2014). In our case, the relevant peer group comes out naturally from the purpose of a chess club as a learning and training center, where clubmates are therefore instrumental. Clubs' size (around 20 clubmates, on average) is similar to a (small) classroom. Our main contribution to this very mature field is to provide a case study where not only the *magnitude*, but also the *sign*, of peer effects may change with agents' characteristics.

Besides randomized controlled trials (Katz et al., 2001), most causal estimates on the effect of peers rely on exogenous variations in the peer group due to natural experiments.[5] A well-known example is the sudden dismissal of Jewish scientists in Germany in 1933, which impaired the local scientific fabric of German research departments (Waldinger, 2011). However, most studies focus on the reverse situation, where a preexisting group (the focus of the investigation) is faced with new population inflows. This type of setting has been used extensively in the economics of education. Notable examples include busing (Angrist and Lang, 2004), international migration (Gould et al., 2009) or regional migration following a natural disaster (Imberman et al., 2012). We follow the same methodology. However, in most cases, newcomers differ from preexisting students, which can bias the conclusions drawn from such experiments (Kramarz et al., 2015). In our case, movers and stayers are very comparable.

We use similar covariates as in Imberman et al. (2012), who study the impact of Katrina evacuees on school performance in Louisiana. They control for initial level of both evacuees and pre-existing students, and find little effect, in line with a large body of evidence on peer effects on test scores. This lack of conclusive findings may be related to

[5] Note that a smaller literature relies on partial-population experimental approaches, where different subgroups face different institutional constraints (Moffitt, 2001).

the shortcomings of test scores for evaluating knowledge acquisition (Heckman et al., 2014). For example, the information contained in test scores may be blurred by the fact that tests are stressful events that only occur a few times a year. One may want to use more permanent measures of performance to smooth out this problem. This is done by studies on academic productivity, who use a moving average of publication records (see, e.g., Waldinger, 2011 or Bosquet et al., 2021). However, these studies face the challenge to disentangle between research productivity and researchers' networks effects. In our case, performance is truly individual and the stock of past performances is regularly updated through the Elo rating system.

More specific to our purpose, peers may also affect performance beyond knowledge transmission channels.[6] Murphy and Weinhardt (2020) show that students' rank in a subject may have long-lasting effects, through increased motivation, possibly because of image concerns: this is the emulation component of the peer effect, which is akin to social pressure and has also been observed in labor market settings (Mas and Moretti, 2009). They test for various alternative mechanisms and do not observe that competition for the top of the class is driving their results. However, they mostly focus on a fixed individual trait: competitiveness, which is absorbed by student fixed effects. In contrast, we consider a collective definition of competition, whereby the peer environment directly impacts individual access to the opportunities for improvement, through participation (controlling for individual fixed effects). To the best of our knowledge, this type of mechanism, which is quite difficult to identify outside the lab, has never been studied in real-world settings.[7]

[6] A straightforward example on the impact of peers on the *measurement* of performance is grading on a curve (Calsamiglia and Loviglio, 2019).

[7] The notion of peers as competitors is present in Borjas and Doran's (2015) study of the exodus of Jewish Soviet mathematicians after 1992, where they distinguish between the impact of "collaborators, colleagues and competitors" and show that nonémigré mathematicians benefit from the departure of competitors in the "idea space". However, their definition of peers, based on research networks, is very extensive. In our case, peers are defined by geographical proximity, which corresponds to what they label as "colleagues".

Lastly, a puzzle of the peer effects literature is the discrepancy between studies on education, which often find little impact, and studies on the labor market, which find bigger effects. Besides possible publication bias, this discrepancy may be related to the fact that the learning process at young age is fundamentally different from mechanisms that spur individual productivity in the workplace. For example, Jarosch et al. (2021) show that complementarities between coworkers of different levels of skills are crucial to generating knowledge spillovers within the firm. In our setting, we abstract from production complementarities because all chess players perform the same individual task. We still document larger positive effects for adult players, and we offer suggestive evidence that some of the differences between junior and adult players may be due to the fact that the former are more subject to peer competition.

The advantages offered by chess explain why this environment is quite pervasive in the economics literature. The game is well measured and codified, which allows to study performance and compare strategies in a straightforward manner. Chess is used to explore game theoretical concepts (Palacios-Huerta and Volij 2009; Levitt et al. 2011; Matros 2018), the determinants of cognitive performance (González-Díaz and Palacios-Huerta 2016; Strittmatter et al. 2020; Künn et al. 2020), the mechanisms of self-selection (Linnemer and Visser 2016) and gender differences in competitive environments (Gerdes and Gränsmark 2010; Dreber et al. 2013; De Sousa and Hollard 2021; De Sousa and Niederle 2021). We contribute to this literature by being closer to labor and education economics. In particular, we borrow our instrumentation strategy from studies on labor flows and the impact of plant closures on local labor market outcomes.

The remainder of the article is organized as follows: Section 2 describes the setting and the data; Section 3 illustrates the possible role of peer competition with a simple model; Section 4 details the empirical strategy; Section 5 describes the empirical results, and Section 6 concludes.

2 Data and Context

2.1 Clubs and Players

The Chess Club Championship — In spite of chess being an individual game, club championships involving teams of players have long existed in many countries across the world. The French national club championship was created in 1980 and progressively expanded to include five leagues in 2002, when our dataset starts. While players must register with a club to be affiliated with the French federation and participate in official tournaments, not all players play in the club championship.[8] Before each championship meet, clubs seek to select a team made of their best players in order to maximize their probability to win.

From 2004 onward, participation to the championship has remained quite stable, with about 440 clubs and between 7,700 and 8,700 players involved each year, in spite of a regular increase in online playing over the period.[9] Overall, 28,942 players, belonging to 775 clubs located in 673 municipalities and 342 metropolitan areas, participated in the club championship between 2002 and 2015. As shown in Appendix Figure S1, there are more clubs and players close to the German border, reflecting a longstanding chess tradition in the region.[10] Yet, the geography of the club championship now covers a large fraction of the French territory, even if large cities are still over-represented.

[8] Affiliation to a national federation is also required to have a FIDE number and rating. Unofficial or online tournaments do not require such an affiliation.

[9] A reform of the lowest league in the championship reduced the number of clubs allowed in championship from 573 in 2003 to 438 in 2004. In 2015, 8,722 players were involved in the championship, accounting for 28% of the affiliated members. The corresponding numbers were 8,108 and 32% in 2004.

[10] The championship was initiated, and long dominated, by a club in Strasbourg, which benefited from its proximity to Germany, where the level was noticeably higher at the time, to attract good German players.

Descriptive Statistics — We arrange the data in a panel format at the player-season level, which records players' age, gender, origin and Elo rating.[11] Players are 37 years old on average, but the age range extends from 5 to 96. Overall, women are a small minority.[12] A small yet substantial fraction of players are registered in a foreign federation, which we call "foreigners" for the sake of brevity. Players are of all levels, from beginners, with a minimum Elo rating of 1001 points, to a former world champion, Vladimir Kramnik, with an Elo of 2807.

Summary statistics for players are displayed in Col. 1 to 4 of Table 1 for the first and last years of our dataset. Elo level, share of female players and share of foreign players are remarkably stable in the two dates. Conversely, players are older and more seasoned at the end of the period. The seniority variable is constructed as the number of years from first registration in the federation.[13] OLS regressions of the Elo level on these individual characteristics show that they explain more than 40% of the variance on both dates (Col. 2 and 4). Female players have lower ratings, contrary to foreigners. When we control for seniority, older players have a lower Elo, but a year spent since first registration is almost nine times more impactful than a year of age in 2002 (Col. 2) and still four times more impactful in 2015 (Col. 4).

Players' mobility between clubs at the end of the season, a crucial feature for separately identifying club and individual fixed effects, is quite high. Even though players are only observed for three years on average, more than 20% of them play in at least two

[11] The dataset is extensively described in De Sousa and Niederle (2021). Seasons start on September 1st and end on August 31th. Unfortunately, we do not observe players' place of residence.

[12] This unbalance, which chess authorities are seeking to remedy (De Sousa and Niederle, 2021), precludes any statistical analysis of potential differences between peers' gender and players' gender, as in Bosquet et al. (2021).

[13] This variable is right-censored because we only observe registrations to the French federation since 1984, except for a few older internationally rated players, who are observed in the international rating list prior to 1984. However, note that this variable is not identified separately from the combination of a player fixed effect with time dummies. Therefore, in our empirical analysis, we will use instead a variable of experience in the championship, measured as the number of years during which the player has participated in the championship since first accessible records.

Table 1: Individual and Club Characteristics

Level	Player				Club			
Year	2002		2015		2002		2015	
	Mean (1)	OLS (2)	Mean (3)	OLS (4)	Mean (5)	OLS (6)	Mean (7)	OLS (8)
Elo	1,725	–	1,731	–	1,685	–	1,700	–
	(316)		(313)		(149)		(148)	
Woman	0.07	-147[a]	0.07	-147[a]	0.06	-13.8	0.06	-22.20
	(0.26)	(8.87)	(0.26)	(9.91)	(0.07)	(64.1)	(0.07)	(70.71)
Foreigner	0.04	454[a]	0.05	443[a]	0.03	591.0[a]	0.05	599.3[a]
	(0.20)	(11.42)	(0.22)	(11.27)	(0.06)	(67.45)	(0.08)	(50.68)
Age	34	-3.74[a]	40.2	-5.42[a]	35	-4.69[a]	41.5	-6.82[a]
	(16)	(0.16)	(18)	(0.17)	(6.93)	(0.67)	(7.8)	(0.68)
Seniority	9.6	31.0[a]	16.8	20.8[a]	9.4	37.1[a]	16.8	26.0[a]
	(6.4)	(5.78)	(10.2)	(6.54)	(6.4)	(1.57)	(3.94)	(1.25)
Nb. of players	–		–		19.6	1.89[a]	19.2	2.68[a]
					(13.5)	(0.33)	(11.51)	(0.39)
R-Squared	–	0.45	–	0.43	–	0.62	–	0.65
Observations	10,451		8,722		533		455	

Notes: The table presents the mean and standard deviation in parentheses of individual (Col. 1 and 3) and average club characteristics (Col. 5 and 7) as well as the results from an OLS regression of the individual (Col. 2 and 4) and average (Col. 6 and 8) Elo on these characteristics for the first (2002) and last (2015) years of our sample. Nb. stands for number.

different clubs over the period. Better players and female players tend to move more, while foreign players and older players move less. Mobility is driven by many factors, both observable (such as past performance and age) and unobservable (such as motivation and job changes). Professional players may elaborate spatial strategies to build their career, and clubs may compete to attract very good players. However, as we argue in Section 4, some moves may also be triggered by random shocks such as club closures, and facilitated by geographical proximity.

Club characteristics are displayed in Col. 5 to 8 of Table 1 for the first and last years of the period. We document substantial cross-sectional differences in club-level characteristics. On average over the period, clubs that participate in the championship comprise 19

Table 2: Within-Club Variation in Club Characteristics

	Unexplained Variation					
	Elo	Size	Female	Foreign	Age	Seniority
All Clubs	0.31	0.23	0.52	0.31	0.24	0.22
Persistent Clubs	0.42	0.24	0.62	0.32	0.25	0.26

Notes: Club-year characteristics are mean Elo, size (number of players), share of female players, share of foreign players, mean age and mean seniority. Share of the variation not explained by club fixed effects and time dummies. In the row "All Clubs", the sample is all club-year observations for clubs observed at least twice (698 clubs and 6,316 observations). In the row "Persistent Clubs", the sample is restricted to club-year observations for clubs observed every year between 2003 and 2015 (218 clubs and 3,043 observations).

players, but with a lot of dispersion.[14] The patterns of descriptive statistics for clubs are quite similar as for individual players. For example, in 2002, 7% of players were women (Col. 1) and clubs averaged 6% of female players (Col. 5). This similarity suggests that larger clubs do not stand out in terms of observable characteristics, even if club size, measured by the number of players, is positively correlated with mean Elo rating. An OLS regression of the mean Elo of the club shows that standard mean club characteristics explain more than 60% of the variance on both dates (Col. 6 and 8).

On top of cross-sectional variation, there is a lot of within-club variability over the period. This variability is due to players' mobility and clubs' internal dynamics, for example, if their members are improving over time. Table 2 shows that between 20% and 50% of the variation in club-year-level characteristics, and in particular, 30% of the variation in the mean Elo level, is not explained by time dummies and club fixed effects. This unexplained component is even larger if we focus on clubs that are observed across the full period. As detailed in Section 4, we exploit this within-club variation in our empirical framework.

[14] Each club may register more than one team in different leagues of the championship. On average, clubs have 1.5 teams over the period.

2.2 Performance and Participation

Performance — Table 3 describes the variables that we use as our measures of performance and participation. As the Elo rating is regularly updated, we can precisely compare the level of players at the start (initial Elo, hereafter, IE) and at the end of the season (final Elo). These two ratings are highly correlated (97%), because one season is a relatively short time span and the Elo is a stock of past performances. However, there is substantial dispersion in the seasonal gains, with an average of 9 points, a standard deviation of 68, and very high maximum losses or gains. Higher-rated players at the beginning of the season are less likely to earn points, because they will need to draw against better players or to win to do so. They also face stronger opposition. Indeed, there is a 82% correlation between a player's IE and the mean Elo of her opponents throughout the year.

Given this pattern and the high level of correlation between IE and final Elo, we opt to measure seasonal achievement with the probability of strict Elo increase throughout the season, that is only weakly correlated with IE (-9%). This variable is a proxy of the goal of any player, regardless of their initial level, the level of their opponents or the tournaments played. On average, players have a 47% probability of improvement over the season. As detailed in Section 5, an alternative measure of performance is the number of Elo points earned in championship. This variable is also uncorrelated with IE but its value depends on the expected score of the player and her adjustment factor (see Appendix A.1). Finally, performance may also be measured using an index of seasonal record (score), which is a weighted sum of all games played in championship, with weights equal to 0, 0.5 and 1 for lost, drawn and won games, respectively. Better players are more likely to end up with a high score, but, as detailed below, this feature is driven by the fact that they play more games, and it does not translate into higher gains in terms of Elo points.

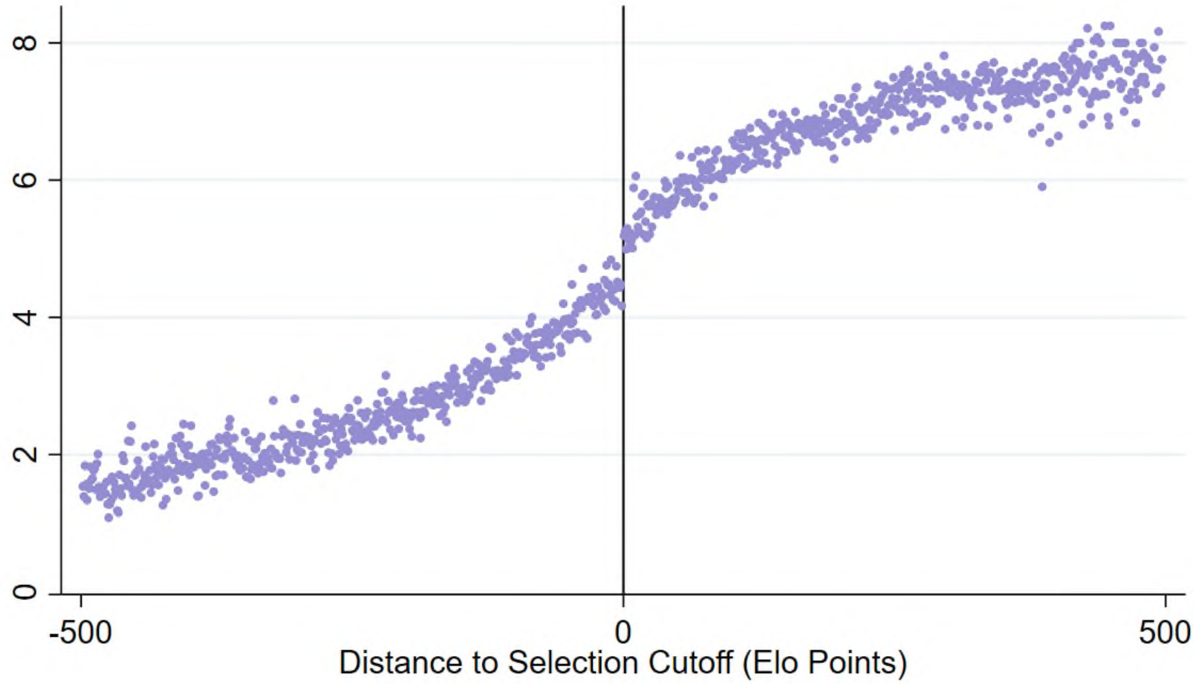
Table 3: Measures of Performance and Competition

	Mean (1)	SD (2)	Min (3)	Max (4)	Corr./IE (5)
Initial Elo (IE)	1,807	291	1,002	2,807	1
Final Elo	1,816	284	1,001	2,798	0.97
Total Elo change (points)	8.9	68.8	-510	750	-0.22
Total Elo change (%)	0.7	4.5	-32.6	74.3	-0.25
Probability of improvement	0.47	0.50	0	1	-0.09
Elo points earned in championship	0.05	15.3	-164	130	- 0.03
Seasonal score in championship	2.62	1.94	0	11	0.49
Number of games in championship	5.3	2.8	1	12	0.45
Mean board in championship	4.7	2.2	1	9	-0.61
Mean Elo of opponents in championship	1,809	263	1,000	2,764	0.82
Participation in individual tournaments	0.52	0.50	0	1	-0.03
Elo points earned in tournaments	0.24	40.8	-434	625	-0.15
Seasonal score in tournaments	12.2	13.0	0	194.5	0.12

Notes: Main variables of level, performance and participation. The unit of observation is the player-season, for all players with documented initial and final Elo. Col. 1: Mean; Col. 2: Standard deviation; Col. 3: Minimum; Col. 4: Maximum; Col. 5: Correlation with initial Elo. There are 24,679 players and 112,582 observations in the full sample. The sample of players who participate in individual tournaments contains 15,095 players and 53,349 observations.

Participation — We also gather information on the level of competition among club-mates. Competition stems from the fact that the club championship is based on matches between teams of 8 players (or 9 before 2006). Teams line up their best available players in an order that is mostly determined by Elo rating. The top players of each team compete in the "first board," the next best in the "second board," and so on. The competition can therefore be fierce to be selected into the team. However, the best players may not always be available for championship games, which generates a high turnover, as reflected in the number of championship games played during the season. Depending on the league and the year, teams usually play between 9 and 11 matches. However, on average, players only play a little over 5 games, with a high level of dispersion, with 30% of players play-

Figure 1: Initial Position in the Club and Mean Rank in the Team during the Season



Notes: Regression discontinuity design (RDD) plot of the mean rank in the team as a function of the position in the club based on initial Elo, compared to the initial Elo of the player ranked eighth (or ninth before 2005) in the club. We include as covariates player's age, experience, and initial Elo, but the picture is quite similar without covariates. Sample: all observations in clubs with a single team during the season. Each bin corresponds to 1 Elo point. For visual clarity, only observations with a difference lower than 500 Elo points are reported (94% of the sample). The sharp RDD estimate with optimal bandwidth selection of being rated higher than the selection cufoff is equal to 0.43 (0.03) on the full sample (N=110,781) and to 0.56 (0.04) on players in clubs with a single team (N=46,091).

ing 3 games or less.[15] Better players are more likely to play (correlation with IE of 45%), which represents the *extensive margin* of peer competition.

The *intensive margin* of peer competition relates to the ranking of players within the team, which will determine the "board number". Higher board numbers correspond to less prestigious games and they are assigned to the lower-rated teammates (correlation with IE of -61%). For ease of interpretation, we reverse the measure and call it rank, so that the higher the rank, the lower the board and the better the position in the team. Once again, the rate of turnover is high within teams and most players end up playing

[15]We exclude games forfeited by the player herself or her opponent.

for different ranks throughout the season. However, the distance between players' initial rating and the initial rating of the eighth (or ninth) best player in the club at the beginning of the season remains a very important driver of participation. Figure 1 shows that the relationship between this distance to the selection cutoff and the average mean board in the team during the season displays a logistic shape, whereby participation is almost independent of marginal improvements for players who are far away from the selection cutoff, but quite sensitive to marginal changes around this cutoff.

Tournaments — Finally, we match our player-season level data with all available information on individual tournaments played between 2002 and 2015.[16] Tournaments are mostly of two kinds: rapid games (43% of tournaments) and regular games. Even if rapid games are associated with a separate Elo rating, we consider both types of tournaments indifferently, as a proxy of player's eagerness to play outside the club championship. Players in club championship have a 52% probability of taking part in a tournament throughout the season, and this probability is not correlated with IE. Some players participate in a very large number of tournaments, and the dispersion of seasonal gains is larger than in the championship. Conversely, the correlation between seasonal score in tournament and IE is much weaker than in the championship.

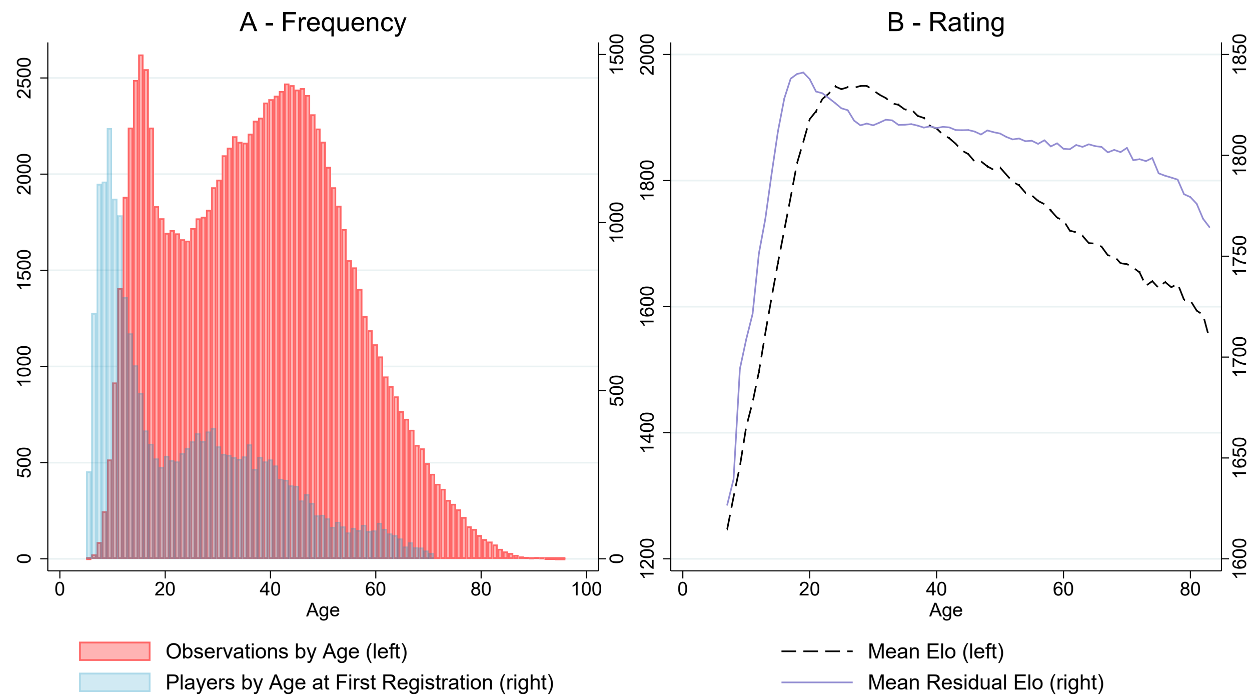
2.3 The Chess Learning Curve

Chess is part of the school curriculum in many countries across the world and, as almost any leisure activity, it is disproportionately practiced by children.[17] However, a substan-

[16] The website of the French Chess organization (http://www.echecs.asso.fr/) provides information on 10,075 tournaments. It describes a tournament in terms of its participants (including player's ratings, age category and clubs), the number of rounds, the points scored by each participant, the final ranking of the players and their performance. Note, however, that information on tournaments is not exhaustive prior to 2012.

[17] Countries with widespread optional chess programs include Hungary or Iceland. In 2012, chess was even made compulsory in Armenian public schools.

Figure 2: Age Distribution



Notes: **Panel A:** There are 24,679 players and 112,582 observations in the full sample used to compute the number of observations. The distribution of players according to age at first registration in the French Chess federation is computed for a subsample composed of 20,767 non-foreign players who first registered after 1984. The difference in the number of observations between the two samples is explained by missing information on age at first registration. **Panel B:** The mean Elo is computed for the full sample. The mean residual Elo is obtained as the residual of a linear regression of the Elo as a function of experience, player fixed effects and time dummies, averaged over each age. It is computed for 17,879 players observed at least twice (105,782 observations). Elo measures are not reported for ages 5 and beyond 83 for statistical accuracy concerns (small sample size).

tial number of players also engage in the game once they become adults, even if their chance of reaching a very high level is extremely low. Figure 2 provides a graphical summary of these various features for the French club championship. Panel A shows that the age distribution is bimodal, with peaks at age 15 and 43. Many players register in the federation as kids or teenagers, but drop out after a few years, contrary to adults for whom entry rates increase almost monotonically from age 19 to age 29 and remain sizable until beyond age 40.

In Panel B, we graph the mean Elo rating by age, without any controls and controlling for year dummies, years of experience, and player fixed effects. Both measures display a very steep learning curve for young players, even if adding controls reduces the magnitude of Elo gains threefold. If we focus on the conditional measure, we can see that the mean Elo monotonically increases from 1610 to 1840 between age 6 and age 18/19. This gap of over 200 Elo points is sizable and corresponds to the difference between the world champion and a top-100 player.[18] Beyond age 19, a slow downward trend of a little over one Elo point a year is observed until oldest age.

The combination of these two sets of observations, displayed in Panels A and B, highlights two distinct phases of human capital accumulation in chess: a *learning phase*, followed by a *playing phase*. This lifecycle pattern is reflected in the differences in the probability of seasonal improvement during the learning phase (66%) and during the playing phase (44%). Similarly, the negative correlation between initial Elo and the probability of seasonal improvement is twice lower for young players than for older players, thus suggesting a less concave learning profile.

3 Theoretical Background

3.1 Model

Set-up — We lay out a simple model of the determinants of players' performance. A player j is characterized by her own initial rating $\underline{R}_j \in [\underline{R}^{\min}, \underline{R}^{\max}]$ and her club. The club is defined as the set of all clubmates $\mathcal{J}$, and its quality only depends on the peer environment $\Pi = \sum_{k \in \mathcal{J}} \underline{R}_k / n(\mathcal{J})$. Player j seeks to maximize utility $U(R_j, P_j)$. The first argument of utility, R_j, is player j's final rating, which depends on initial level $\underline{R}_j$, on

[18]Note also that, as explained in Appendix A.1, a player ranked 100 points below her opponent has a 36% expected probability of winning the game.

the peer environment Π and on her chosen level of effort ε_j, which entails a cost $c(\varepsilon_j)$.[19] The second argument of utility, P_j, measures the participation of the player in the club's (only) team, both in terms of quantity (number of games) and quality (mean position in the team).

Participation in the club's team may be constrained, because the club maximizes the probability of success of its team by simply selecting the best players who are available at the time of the game. Drawing from the correlational evidence discussed in Section 2, we assume that a player's participation is determined *ex ante* according to her initial level, compared to the initial level of all the other clubmates.[20]

A possible representation of the learning process of player j is:

$$R_j := R(\underline{R}_j, \Pi) = \underline{R}_j + k(\underline{R}_j) \times f(\varepsilon_j, \Pi), \tag{1}$$

where the function $f(\cdot)$ represents knowledge exchange between peers, with decreasing returns and positive cross derivatives, since training and discussing with peers more often is more valuable when those peers are better. The function $k(\cdot)$, with $k(\cdot) > 0$ and $k'(\cdot) < 0$ summarizes decreasing returns in the learning process, because high-rated players are less likely to learn new material by meeting with a random player.[21] We posit, for simplicity, that $f(\varepsilon, \Pi) = \varepsilon^{\alpha}\Pi^{1-\alpha}$, with $\alpha \in (0, 1)$, and $c(\varepsilon) = \varepsilon^2/2$.

Selection into the team is represented by a minimal initial rating that may depend on the average level of clubmates, $S(\Pi)$, where $S'(\cdot) \geq 0$ measures the intensity of peer

[19] Effort may be interpreted as the frequency at which the player attends the club to train.

[20] In effect, we model club behavior with a lag: the selection process into the team is based on past performance, embedded in $\underline{R}_j$. This approximation is due to the fact that ratings produce anchoring effects and the club's beliefs regarding players' level may not update in real time. We believe that this is a reasonable first-order approximation, which bears some relevance in the school context. For example, teachers are aware of their students' past performance at the beginning of the year and may take time to adjust their priors.

[21] In all generality, $k(\cdot)$ could depend on other individual characteristics, such as age. As shown in Figure 2, it may be the case that $R_{\underline{R}}(\cdot) < 0$ for older players.

competition. This cutoff is fuzzy, because the best players may not always be available at the time of the game. Drawing from Figure 1, we consider that a plausible representation of the relationship between peer competition and player j's participation prospects is given by equation 2:

$$P_j := P(\underline{R}_j, \Pi) = \frac{1}{1 + \exp[S(\Pi) - \underline{R}_j]}. \tag{2}$$

Learning from Peers — Let us assume for the moment that participation in the team is not constrained, so that player j's utility depends solely on her final rating. We further posit that $U(R_j, P_j) = R_j$. Under these assumptions, we can write the following proposition:

Proposition 1. THE PEER PARADOX — *If the learning process features decreasing returns and complementarity between effort and the peer environment,*

1. *a player's rating unambiguously improves with better peers;*

2. *the positive impact of better peers on a player's rating is lower for initially better players.*

Proof. Utility maximization yields an optimal level of effort $\varepsilon_j^* := \varepsilon^*(\underline{R}_j, \Pi) = [\alpha \Pi^{1-\alpha} k(\underline{R}_j)]^{1/(2-\alpha)}$. Plugging ε_j^* back into $R(\cdot)$ yields $R_\Pi(\underline{R}_j, \Pi) = 2k(\underline{R}_j) \times \frac{1-\alpha}{2-\alpha} \times (\varepsilon_j^*/\Pi)^\alpha > 0$ and $R_{\Pi\underline{R}}(\underline{R}_j, \Pi) = \frac{2}{2-\alpha} \times \frac{R_\Pi(\underline{R}_j, \Pi)}{k(\underline{R}_j)} \times k'(\underline{R}_j) < 0$. □

As explained in the Introduction, both results of Proposition 1 are at odds with many empirical studies that find that good peers have no positive effect on the learning of the average student and that positive effects, if any, are concentrated on the best students.

Peer Competition — Now consider that players value final rating, but only to the extent that they participate in official games, so that player j's utility is now given by $U(R_j, P_j) = P_j \times R_j$. Under this assumption on utility, and using the same parametrization as before, we can write the following proposition:

Proposition 2. PARTICIPATION PROSPECTS MATTER — *If players' valuation of final rating is weighted by participation prospects,*

1. *under high (resp., low) peer competition, peer effects are unambiguously negative (resp., positive);*

2. *under moderate peer competition, peer effects are negative for low-level players and positive for high-level players.*

Proof. Utility maximization yields an optimal level of effort $\tilde{\varepsilon}_j := \tilde{\varepsilon}(\underline{R}_j, \Pi) = \varepsilon_j^* \times (\alpha P_j)^{1/(2-\alpha)}$. Plugging $\tilde{\varepsilon}_j$ back into $R(\cdot)$ yields $R_\Pi(\underline{R}_j, \Pi) = \frac{P_j k(\underline{R}_j)}{(2-\alpha)e^{\underline{R}_j}} \times (\tilde{\varepsilon}_j/\Pi)^\alpha \times \tilde{A}(\underline{R}_j, \Pi)$ with $\tilde{A}(\underline{R}_j, \Pi) = 2(1-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)}) - \alpha\Pi S'(\Pi)e^{S(\Pi)}$. Therefore, if $\tilde{A}(\underline{R}^{min}, \Pi) > 0$ (resp., $\tilde{A}(\underline{R}^{max}, \Pi) < 0$), peer effects are unambiguously positive (resp., negative). Under intermediate values of $S'(\Pi)$, peer effects will be positive for player j if and only if $P_j > \tilde{P} = 1 - \frac{2(1-\alpha)}{\alpha\Pi S'(\Pi)}$. □

In contrast to Proposition 1, Proposition 2 states that participation prospects can alter the impact of peer effects. Of particular interest is the intermediate case of moderate peer competition where the impact of good peers depends on the level of the players: positive for high-level players and negative for low-level players.

Juniors and Adults — The framework may be extended by looking at the difference between junior and adult players. There are two potential differences: first, since juniors are less experienced, they need to play to actually learn; second, they learn faster. Therefore, from equation 1, if player j is a junior player, her learning process is represented by equation 3 instead:

$$\widehat{R}_j := \widehat{R}(\underline{R}_j, \Pi) = \underline{R}_j + \widehat{k}(\underline{R}_j) \times \widehat{f}(\varepsilon_j, \underline{R}_j, \Pi) \tag{3}$$

where $\widehat{f}(\varepsilon_j, \underline{R}_j, \Pi) := P(\underline{R}_j, \Pi) \times f(\varepsilon_j, \Pi)$ and $\widehat{k}(\underline{R}_j) > k(\underline{R}_j)/P(\underline{R}^{\min}, \Pi)$, so that any junior player, regardless of her level, learns faster than an adult player of the same level.

Under this parameterization, and assuming that junior player j seeks to maximize $P_j \times \widehat{R}_j$, we can write the following proposition:

Proposition 3. PLAYING TO LEARN — *If juniors' final rating depends directly on participation prospects,*

1. *fewer juniors enjoy positive peer effects than adults;*

2. *better peers have a more detrimental impact on the effort of low-level juniors than on the effort of comparable adults.*

Proof. Utility maximization yields an optimal level of effort $\widehat{\varepsilon}_j := \widehat{\varepsilon}(\underline{R}_j, \Pi) = \tilde{\varepsilon}_j \times [K(\underline{R}_j)P_j/k(\underline{R})]^{1/(2-\alpha)} > \tilde{\varepsilon}_j$. Plugging $\widehat{\varepsilon}_j$ back into $\widehat{R}(\cdot)$ yields $\widehat{R}_\Pi(\underline{R}_j, \Pi) = \frac{P_j^2 K(\underline{R}_j)}{(2-\alpha)e^{\underline{R}_j}} \left(\frac{\widehat{\varepsilon}_j}{\Pi}\right)^\alpha \times \widehat{A}(\underline{R}_j, \Pi)$ with $\widehat{A}(\underline{R}_j, \Pi) = 2(1-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)}) - (2+\alpha)\Pi S'(\Pi)e^{S(\Pi)} < \tilde{A}(\underline{R}_j, \Pi)$. Under intermediate values of $S'(\Pi)$, peer effects are positive for junior player j if and only if $P_j > \widehat{P} = 1 - \frac{2(1-\alpha)}{(2+\alpha)\Pi S'(\Pi)} > \tilde{P}$. Therefore, player j such that $P_j \in [\tilde{P}, \widehat{P}]$ benefits from positive peer effects if he is an adult and suffers from negative peer effects if he is a junior. In addition, we have $\widehat{e}_\Pi(\underline{R}_j, \Pi) = \frac{\widehat{e}(\underline{R}_j, \Pi)}{(2-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)})\Pi} \times [(1-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)}) - 2e^{S(\Pi)}\Pi S'(\Pi)]$ and $\tilde{e}_\Pi(\underline{R}_j, \Pi) = \frac{\tilde{e}(\underline{R}_j, \Pi)}{(2-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)})\Pi} \times [(1-\alpha)(e^{\underline{R}_j} + e^{S(\Pi)}) - e^{S(\Pi)}\Pi S'(\Pi)]$. Therefore, if we define low-level players as players j such that $P_j < 1 - \frac{1-\alpha}{\Pi S'(\Pi)}$, we have indeed $\widehat{e}_\Pi(\underline{R}_j, \Pi) < \tilde{e}_\Pi(\underline{R}_j, \Pi) < 0$. $\square$

3.2 From the Model to the Data

Clubs select the best players according to their initial level. We can proxy the selection cutoff $S(\Pi)$ as the rating of the 8th (or 9th until 2005) best player in the club, according to their rating at the beginning of the season. Appendix Table A shows that there is a close to 1 to 1 relationship between our proxy for $S(\Pi)$ and the peer quality Π, which suggests that $S'(\Pi)$ is not zero. Therefore, taking Proposition 2 at face value, the model suggests a natural partition of the sample, based on the selection cutoff into the team, leading to the following proposition:

Proposition 4. TESTABLE IMPLICATIONS — *Provided we observe an approximation of the selection cutoff into the team, we can test the following hypotheses:*

H0.1 "There is no (moderate) peer competition";

H0.2 "The performance of junior and adult players are equally impacted by peer competition".

Proof. Hypothesis H0.1 will be rejected if peer effects on improvement are larger for high-level players than for low-level players. Hypothesis H0.2 will be rejected if peer effects are lower for junior players than for adult players and if peer effects have a higher detrimental impact on the effort of low-level junior players than on the effort of similar adult players. □

This stylized model is meant to illustrate our intuition for the connection between peer effects and peer competition. We now take our predictions to the data.

4 Empirical Strategy

4.1 Framework and Correlational Evidence

In order to measure the impact of peers, we estimate equation 4 at the player-season level, with peer quality defined at the club-pre-season level.

$$Y_{it} = \eta(\text{Peer})_{c(it)t_0} + X_{it}\beta + \Gamma_{c(it)i} + \tau_t + \varepsilon_{it}, \tag{4}$$

where Y_{it} represents measures of individual i's performance or participation during season t. Our parameter of interest is η which aims at assessing the impact of $\text{Peer}_{c(it)t_0}$ measured as the log mean Elo rating in club c at the beginning of season t. The vector X_{it} includes the player's own initial Elo rating, because of concavity in the Elo-gaining process, as discussed in Section 2. Additional time-varying individual controls are traditional Mincerian characteristics: age and experience. These three controls are in logs. We also include club-by-player fixed effects Γ_{ci} in order to control for unobserved heterogeneity in individual ability and motivation, club endowments and potential differences in the congruence between club and player characteristics. We control for seasonal dummies τ_t to account for aggregate time-varying changes such as the rise of online playing. Finally, we allow for an error term ε_{it}, clustered at the club level.

Table 4 displays the OLS estimation results for our three main dependent variables (Y_{it}) of interest: "Improve", the probability of Elo increase throughout the season, "Number of Games", the log number of games played in club championship throughout the season, and "Mean Rank", the mean position in the team throughout the season. Results confirm the importance of controlling for the initial level of the player, because high-Elo players are much less likely to improve, even though they play more games, on better boards. As shown in Col. 1, peer quality is positively correlated with improvement. This correlation disappears once we control forclub-by-player fixed effects (Col. 2) and it reappears if we take into account the correlation between improvement and concomitant measures of participation (Col. 3). These correlational patterns suggest that the influence of the peer environment on individual performance may be masked by the influence of the peer environment on participation.[22] Conversely, the correlation between peer quality and the participation variables is quite stable, regardless of the specification, with an

[22] As shown in Appendix Table S1, the correlational patterns described in Table 4 are similar if we focus on the main estimation sample used in our IV approach, although the coefficients are less precisely estimated.

Table 4: Peer Competition: Correlational Evidence

	Improve			Number of Games			Mean Rank		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	0.164[a]	0.023	0.226[a]	-1.018[a]	-1.330[a]	-1.048[a]	-10.758[a]	-10.393[a]	-10.191[a]
	(0.026)	(0.045)	(0.046)	(0.071)	(0.074)	(0.077)	(0.252)	(0.219)	(0.212)
Initial Elo	-0.274[a]	-4.455[a]	-4.640[a]	1.926[a]	1.673[a]	1.745[a]	10.754[a]	7.716[a]	7.875[a]
	(0.014)	(0.057)	(0.059)	(0.034)	(0.063)	(0.072)	(0.202)	(0.216)	(0.225)
Age	-0.189[a]	2.192[a]	2.167[a]	-0.026[a]	0.344[a]	0.188[b]	0.029	0.624[a]	0.366[c]
	(0.004)	(0.051)	(0.050)	(0.008)	(0.079)	(0.080)	(0.021)	(0.187)	(0.191)
Experience	-0.036[a]	0.146[a]	0.143[a]	0.153[a]	0.069[a]	0.059[a]	-0.168[a]	0.011	-0.014
	(0.004)	(0.013)	(0.013)	(0.010)	(0.018)	(0.018)	(0.021)	(0.048)	(0.048)
Number Games			0.050[a]						0.154[a]
			(0.003)						(0.013)
Mean Rank			0.013[a]			0.027[a]			
			(0.001)			(0.002)			
Improve						0.063[a]			0.093[a]
						(0.004)			(0.010)
Fixed effects	**t**	**c×i, t**	**c×i, t**	**t**	**c×i, t**	**c×i, t**	**t**	**c×i, t**	**c×i, t**
Observations	100,927	100,927	100,927	100,927	100,927	100,927	100,927	100,927	100,927
R-Squared	0.057	0.338	0.341	0.181	0.556	0.559	0.503	0.752	0.753
Within R-Squared	0.049	0.125	0.129	0.180	0.034	0.041	0.481	0.147	0.152

Notes: OLS estimates of the correlation between peer quality and the probability of Elo increase throughout the season (Col. 1 to 3), the log number of games player (Col. 4 to 6) and the mean rank (Col. 7 to 9). All controls are in log except Mean Rank. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

estimated elasticity below -1 for the number of games (Col. 4 to 6) and a coefficient of -10 for the mean rank (Col. 6 to 9). Col. 6 and 9 also show that both margins are correlated with each other: players who play more games also play for higher ranks.

4.2 Constructing the Instrument

There are several reasons why the correlations displayed above may not be interpreted as causal. In particular, there may be non-random sorting of players in clubs with characteristics best suited to their time-varying needs and goals. If there are positive spillovers from having good clubmates, players with the highest motivation or the fastest learning curve may self-select into the clubs with the best players. In this case, OLS estimates will be biased upwards. However, it may also be the case that players self-select negatively, because of competition effects. For example, if players who seek to improve anticipate that good clubmates will reduce their game time in the championship, they may opt for another club. In this case, the OLS estimates will be biased downwards. Which direction dominates depends on whether players mostly use clubs as daily training centers, or as springboards to the the club championship.

In addition, despite the accuracy of the Elo rating system, there may be measurement error in the peer quality variable. For example, we do not observe organization inside the clubs. Usually, teammates train and practice together. They may participate to joint training sessions supervised by a coach that most of the clubs hire. However, we cannot infer who players usually train with. Some players may not often be physically present at the club, so that their influence on clubmates remains limited. Depending on whether attendance is positively or negatively correlated with players' Elo rating, the measure of peer quality as the unweighted mean of Elo ratings will either underestimate or overestimate the spillover potential of clubmates. Finally, there may be an amplification bias due to reflection among clubmates (Manski, 1993). This last problem is however mitigated here because we only consider year-specific events as outcomes and control for the player's Elo rating at the beginning of the season.

In order to tackle these issues, we instrument our measure of peer quality with the size and the level of clubs that closed nearby the year before. Club closure is not rare: 12% of clubs closed between 2002 and 2015 (93 out of 775). To identify closures, we use information from the French Chess Organization website. Each club has a unique identifier and the federation dedicates a web page to each club, including those that have closed.[23] On

[23]See, e.g., http://www.echecs.asso.fr/FicheClub.aspx?Ref=899 for an active club near our respective institutions, and http://www.echecs.asso.fr/ListeEquipes.aspx?ClubRef=1686 for a closed club in southern France. The closing date is identified the year the club disappears from any club championship, either national or regional. Note that closures only make up a small subset of clubs' dropping from the club championship from one year to another, since less than one club out of three participate in the championship

average, closing clubs have 14 players, with a mean Elo of 1,800. As shown in Appendix Table B, their average level is not lower than other clubs. They are somewhat smaller, but they are not bleeding players. Overall, both observable club characteristics and unobservable fixed club heterogeneity are weak predictors of the probability of closure.

Our assumption is that closures are mostly dependent on local idiosyncrasies, such as the departure of one single volunteer who decides to retire or moves away, for reasons unrelated to chess.[24] Moreover, chess clubs are nonprofits that rely a lot on public subsidies such as free rent in a public-owned space. Extensive anecdotal evidence suggest that local authorities may decide to promote chess, before changing their mind because of a switch in their youth and culture policy (see Appendix A.2 for details). A potential concern for our instrument is that two clubs in the same *municipality*, the French local jurisdiction in charge of such subsidies, might compete for the same source of funding. They might even merge so that one of them effectively closes. For this reason, we only use closures that took place in the same *city* (metropolitan area) but in different municipalities.[25]

4.3 Sample Selection

We adopt a stayer strategy, whereby we only focus on players who were already registered in the same club the year before the observation, which corresponds to two-thirds of the initial sample. We instrument their mean initial Elo by two variables: the size and the mean Elo of the clubs that closed in the same city the year before. Out of 1,322 "evict-

every year over the period.

[24]Studying the geography of chess practice in France, Borzakian (2007) points outs that many clubs "rely on the motivation of a passionate club manager, usually a volunteer. However, this type of situation is particularly precarious. A move, family difficulties or sometimes a death generally lead to the rapid disappearance of the association, for lack of a successor."

[25]We cannot rule out the possibility that some of the closures are actually mergers of clubs, but those that we are aware of are occurring within municipalities and are not included in the instrument. In addition, these mergers have the same origin as more traditional closures: departure of a key volunteer or change in local public policy.

ed" players, 395 play in another club the next year. Our assumption is that most evicted players, if they want to keep playing, will in priority seek to register in the same city. The rationale is that attending a chess club is a frequent activity, which should not involve too much commuting, and it is a leisure activity, which will not trigger residential mobility decisions.[26] The arrival of some of the evicted players impacts the peer environment of their new club, but is as good as random to the pre-existing players (the "stayers"), conditional on club and individual fixed effects.

However, the choice of a new club may not be random for the evicted players if there are several alternative clubs nearby where they can register. In addition, in a large city with many clubs, the effect of a single closure will be too diluted. For this reason, we restrict the analysis to cities where there is only one club left. We end up with a sample of 19,308 observations involving 3,985 players in 232 clubs. As shown in Appendix Figure B, the distribution of the main variables of interest is not dramatically affected by this drastic selection, although the remaining clubs are somewhat smaller.

4.4 First Stage Results

Appendix Table C reports the first-stage results and shows that the sample selection only affects the predictive power of the instruments: the coefficients on the individual controls remain almost constant across samples, suggesting that individual-level correlations between players' and clubs' characteristics are similar in small and large cities. Conversely, the coefficients associated with the two instruments increase a lot when we focus on players who play for the only remaining club in the city, with an elasticity of -0.38 for the number of evicted players and 0.12 for their mean Elo. The corresponding F-statistic

[26] In their study of peer effects among France-based research economists, Bosquet et al. (2021) refer to a similar argument. They use as an instrument the outcome of a competitive promotion process that allocates new researchers to departments, and they observe that distance to their previous department is the only factor that seems to influence candidates' choice.

is above 60. Appendix Figure S2 provides a graphical summary of the relevance of the instruments on the final sample with bin scatter plots. With this IV setting in hand, we now explore the impact of clubmates on performance and competition.

5 The Ambiguous Impact of Clubmates

5.1 Peer Effects and Improvement

In Table 5, we display our results on the impact of peer quality on the probability of Elo increase throughout the season. Our preferred specification is displayed in Col. 1, which corresponds to the 2SLS estimation of Equation 4. The 2SLS estimation dramatically alters the magnitude of the coefficient associated with peer quality, which is virtually zero in OLS (see Col. 2 in Appendix Table S1). We interpret this discrepancy as suggestive evidence of the existence of negative selection related to peer competition for improving players. Taking the estimate at face value, a 1% increase in peer quality increases the probability of improvement by 1.6 percentage points (hereafter, p.p.). Given the mean probability is equal to 47%, this corresponds to a 3.4% increase in the baseline probability.

In Col. 2, we control for separate individual and club fixed effects, instead of the individual-club match. The estimates are virtually unchanged compared to Col. 1, but they are less precisely estimated, and the instrument is a little weaker. Therefore, the individual-by-club fixed effects improve the precision of the results. In Col. 3, we control for other time-varying club characteristics: mean age, mean experience and number of players as well as the share of female players and the share of foreign players and the number of teams in the club. The peer estimate increases by 50%, but the difference with Col. 1 is not statistically significant. In Col. 4, we control for whether the player has improved during her previous season, in order to account for the possibility of serial depen-

Table 5: The Impact of Clubmates on Seasonal Improvement

Dep. Var.	Probability to Improve						
	Current Year						*Previous* Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Peer Quality	1.636[b]	1.631[c]	2.565[b]	1.621[b]	1.565[b]	1.679[b]	-0.032
	(0.787)	(0.883)	(1.203)	(0.736)	(0.763)	(0.765)	(0.243)
Initial Elo	-5.507[a]	-5.486[a]	-5.600[a]	-5.464[a]	-5.472[a]	-5.866[a]	-4.886[a]
	(0.174)	(0.193)	(0.200)	(0.174)	(0.176)	(0.173)	(0.134)
Age	2.325[a]	2.331[a]	2.335[a]	2.194[a]	2.325[a]	2.365[a]	2.616[a]
	(0.133)	(0.147)	(0.138)	(0.131)	(0.130)	(0.132)	(0.130)
Experience	0.246[a]	0.242[a]	0.282[a]	0.160[a]	0.238[a]	0.184[a]	0.204[a]
	(0.051)	(0.057)	(0.054)	(0.057)	(0.055)	(0.055)	(0.033)
Fixed effects	**c×i, t**	**c,i,t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	19,308	19,308	18,827	17,035	18,827	18,827
F-stat	62.964	50.009	43.049	59.998	66.304	60.027	59.744
p-value Hansen	0.930	0.932	0.909	0.883	0.919	0.897	0.364

Notes: 2SLS estimates of the impact of peer quality on the probability of Elo increase throughout the season, except in Col. 7 where the outcome is lagged one year (and individual controls are lagged one year as well, except Peer). Col. 2 controls for separate individual and club fixed effects, instead of the individual-club match. Col. 3 adds control (in logs) for number of players, mean age, mean experience, as well as the share of women and foreigners in the club and the number of teams in the club; Col. 4 controls for whether the player has improved or not during previous season. Col. 5 discards players who at some point participate in either of the first two leagues. Col. 6 uses the same sample as Col. 4 and 7, excluding players for whom information on the lagged value of the IE is missing. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

dence in performance. The peer estimate is barely affected. In Col. 5, we check whether the effect is not driven by the players who aim at playing for the highest leagues, who may have more sophisticated strategies regarding their choice of club or their decision to participate in the championship. To that end, we discard all players who, at some point, are observed playing in either of the two highest leagues. This concerns approximately 10% of the players in our sample. All estimates are remarkably stable when focusing on the subsample of players who never played for the highest leagues.

Robustness — To give further support to our results, we run a placebo test: we regress the probability of Elo increase throughout the *previous* season on the quality of the current year's peers. If the exclusion restriction is valid, the IV estimate of the placebo test should be equal to zero. Col. 7 in Table 5 confirms that it is indeed the case, with a coefficient of 0.32, no different from zero and statistically different from that estimated in Col. 6, where we restrict the sample to all observations for which we can estimate the placebo effect shown in Col. 7.

These results are also robust to alternative definitions of peer quality. First, as shown in Appendix Table S2, the results are qualitatively similar if we define peer quality in level instead of log. A one-standard-deviation increase in peer quality increases the probability of improvement by 13 p.p. Second, we define peer quality as the leave-out mean of Elo level among clubmates. As shown in Appendix Table S3, the peer effect estimates are very similar to Table 5.[27] Another threat to the exogeneity of our instrument would be that some clubs may decide not to participate on a given year because of too strong competition with nearby clubs; or, conversely, that some clubs may be created to take advantage of a less competitive environment induced by nearby closures. To address this issue, we show in Appendix Table S4 that the results are very stable if we focus the analysis on players located in clubs that participate in the championship every year between 2003 and 2015.

5.2 Peer Effects and Participation

Having shown that a higher peer quality improves individual performance, we now turn to its impact on the key variables that proxy peer competition: the number of games played in championship and the mean rank played in the team. As shown in Table 4, the

[27] The instruments are still valid, with F-statistics around 20, but weaker because peer quality now varies within club-year, while instruments do not.

correlation between these variables and peer quality is likely to mask potentially positive correlation between peer quality and improvement. Table 6 confirms that better peers do decrease the number of games played in championship, with a -1.7 elasticity (Col. 4) and make players play for lower-quality boards (coefficient of -11.6 in Col. 7). These 2SLS estimates are of the same magnitude as the OLS estimates (see Col. 4 and 7 of Table 4) and suggest that a 10% increase in peer quality makes players play 17% fewer games and pushes them down one board in the team hierarchy.

According to our theoretical predictions (see Section 3), if we are to interpret these results in terms of competition among peers for access to the best playing opportunities, players among the eight (nine before 2006) best of their clubs should not be as negatively impacted by peer competition as others. These players are natural candidates for selection into championship, where teams are made of eight (or nine) players. We verify this assumption by separately estimating the impact of peer quality on improvement and competition for two subsamples of players defined by their initial position in the Elo distribution of their club. We define "Bottom" players, who are ranked ninth or higher in their club at the beginning of the season, and "Top" players, who are ranked between first and eighth. Results displayed in the remaining columns of Table 6 are fully in line with our theoretical predictions. Bottom players end up playing fewer games (elasticity of -6.9 in Col. 5), and for worse ranks (coefficient of -24.6 in Col. 9), when they are surrounded by better peers. Conversely, the participation of top players is much less affected. Strikingly, the impact of peer quality on the probability of improvement is low (0.5) and statistically insignificant for Bottom players (Col. 3), while it is higher than 2 and quite precisely estimated for Top players (Col. 2). Taking the estimates at face value, we can reject H0.1 of Proposition prop4 with a 87% confidence level.

Table 6: Peer Effects and Competition

Dep. Var.	Improve			Number of Games			Mean Rank		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	1.636[b]	2.277[a]	0.530	-1.725[a]	-1.075[b]	-6.889[a]	-11.582[a]	-8.603	-24.564[a]
	(0.787)	(0.689)	(0.843)	(0.484)	(0.509)	(1.255)	(2.168)	(5.593)	(3.869)
Initial Elo	-5.507[a]	-6.734[a]	-5.051[a]	1.788[a]	1.559[a]	2.658[a]	9.859[a]	12.364[a]	8.641[a]
	(0.174)	(0.241)	(0.229)	(0.163)	(0.220)	(0.301)	(0.523)	(0.919)	(0.916)
Age	2.325[a]	2.344[a]	2.483[a]	-0.168	-0.342	-0.171	0.308	0.401	0.494
	(0.133)	(0.191)	(0.184)	(0.179)	(0.271)	(0.266)	(0.439)	(0.691)	(0.752)
Experience	0.246[a]	0.237[a]	0.182	-0.128[c]	-0.156[c]	-0.096	0.002	-0.002	0.500
	(0.051)	(0.061)	(0.114)	(0.068)	(0.082)	(0.141)	(0.149)	(0.176)	(0.352)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	13,393	5,252	19,308	13,393	5,252	19,308	13,393	5,252
F-stat	62.969	32.108	34.003	62.969	32.108	34.003	62.969	32.108	34.003
p-value Hansen	0.930	0.860	0.755	0.796	0.376	0.337	0.345	0.457	0.949

Notes: The dependent variable changes across the 2SLS specifications: Col. 1 to 3: Probability of Elo increase; Col. 4 to 6: Log number of games played in championship; Col. 7 to 9: Mean rank in the team. "Top" players are among the 8 (9 before 2006) best clubmates at the start of the season and "Bottom" players are other players. Controls are in log. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Rank Effect within Clubs or Level Effect across Clubs? — There remains the possibility that the heterogeneous results described above only reflect some specificity in the learning process of high-Elo players in general. To examine this possibility, we consider another partition of the sample. For each season, we order all players in the championship based on their initial Elo level. We then keep the number of players needed to fill each team with eight (or nine) players. This counterfactual reshuffling of players is only based on level, independently of club membership. Specifically, in a given year, the number of teams we construct is equal to the number of first teams in our sample in that year. We call this new partition "global" in contrast to the partition based on the position in the club. Approximately 30% of observations switch from bottom to top or from top to bottom between the two partitions.

Results depicted in Appendix Table S5 show that this global partition delivers quite different results as the local partition based on the position in the club. In particular, “Bottom (global)” players neither play fewer games, nor for lower ranks, when they have better peers. Finally, we focus on the subsample of “Top (global)” players and we look at the differential impact of peers between top global players who are also top (local) players or not. Results depicted in Appendix Table S6 show that this partition delivers strikingly similar results as the one in Table 6: only the locally top players improve with better clubmates, and only the locally bottom players end up playing fewer games, for lower ranks, with better clubmates.

5.3 Mechanisms

We have shown that better peers do not only affect performance but also competition. To better understand the mechanisms that link peer quality, performance and competition, we now focus on a new dependent variable: the Elo points gained or lost in the championship. First, we verify, as shown in Appendix Table D, that the impact of peer quality on Elo changes is qualitatively similar to that on the probability of improvement. Quantitatively, 2SLS estimates show that a 10% increase in peer quality increases the number of Elo points earned in championship by over 0.2 standard deviation.[28] Second, similar to what is observed for the probability of improvement, Panel A of Table 7 shows that only top players gain Elo points in the championship thanks to better peers, with an effect of 0.4 standard deviation (Col. 2), while for bottom players, the effect is very small, negative, and statistically insignificant (Col. 3). Focusing on the Elo points gained or lost in the championship allows us to study two mechanisms: the roles of opposition (A) and motivation (B).

[28]This relatively small effect compared to the effect on the probability of improvement documented in Section 5 suggests that peers make many marginal players switch from Elo decrease to Elo increase. In the sample, 25% of players gain or lose less than 4 points in the championship.

Table 7: Peer Effects, Competition and Performance: Mechanisms

Panel A - Performance in Championship

Dep. Var.	Elo Points			Elo Points per Game			Score per Game		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	2.102[b]	3.782[a]	-0.172	1.696[c]	3.058[a]	-2.286	-0.066	-0.012	-1.408[b]
	(0.823)	(1.059)	(1.929)	(1.002)	(0.927)	(1.642)	(0.624)	(0.676)	(0.553)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	19,308	13,393	5,252	19,308	13,393	5,252	19,308	13,393	5,252
F-stat	62.969	32.108	34.003	53.743	30.327	33.645	62.969	32.108	34.003
p-value Hansen	0.274	0.398	0.543	0.437	0.521	0.561	0.713	0.535	0.543

Panel B - Opposition in Championship

Dep. Var.	Lowest League			Stronger Opponent			Teammate Quality		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	-2.698[a]	-1.804	-6.224[a]	1.677[b]	1.401	2.386[a]	0.303[c]	0.084	0.965[a]
	(0.889)	(1.570)	(1.048)	(0.805)	(1.296)	(0.792)	(0.171)	(0.246)	(0.188)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	19,308	13,393	5,252	19,300	13,393	5,245	19,308	13,393	5,252
F-stat	62.969	32.108	34.003	62.994	32.108	34.169	62.969	32.108	34.003
p-value Hansen	0.617	0.277	0.448	0.319	0.319	0.398	0.728	0.395	0.551

Panel C - Participation and Performance in Tournaments

Dep. Var.	Play			Elo Points			Score per Game		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	0.406	0.633	0.511	-1.555	-2.377	2.054	0.251	-0.114	0.237
	(0.708)	(1.055)	(0.903)	(1.850)	(2.676)	(2.483)	(0.152)	(0.147)	(0.299)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	19,308	13,393	5,252	8,709	5,671	2,627	8,709	5,671	2,627
F-stat	62.969	32.108	34.003	72.091	32.459	21.053	72.091	32.459	21.053
p-value Hansen	0.710	0.445	0.405	0.123	0.063	0.093	0.454	0.955	0.467

Notes: All specifications include club-by-individual and year fixed effects as well as our typical controls in log: Initial Elo, Age and Experience (see Appendix Table S7 for full results). The dependent variable changes across the 2SLS specifications. **Panel A:** Col. 1 to 3: standardized total of Elo points gained or lost in championship; Col 4 to 6: standardized mean Elo points earned in championship per game; Col. 7 to 9: Mean score by game played in championship. **Panel B:** Col. 1 to 3: Probability to play mainly for the lower league; Col. 4 to 6: Probability that the average opponent is rated higher than the player's initial Elo; Col. 7 to 9: Log mean initial Elo of teammates. **Panel C:** Col. 1 to 3: Probability to participate in a tournament; Col. 4 to 6: standardized total number of Elo points gained or lost in tournaments; Col. 7 to 9: Mean score by game played in tournaments. "Top" players are ranked among the 8 (9 before 2006) best clubmates at the start of the season and "Bottom" players are ranked beyond. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Peer Effects and Opposition — The variation in Elo points in championship depends on the number of games played, as well as the difficulty and outcome of each game. As already documented, better peers negatively impact the number of games played in championship, even for top players. As a consequence, better peers should make players gain more points per game if their overall effect is positive. Col. 4 of Panel A in Table 7 confirms that, on average, a 10% increase in peer quality increases the number of Elo points gained per game by 0.2 standard deviation. However, this effect is small and hardly statistically significant. Once again, this average result hides a large heterogeneity between top and bottom players. For top players, the peer effect is about twice as large (Col. 5), while for bottom players, the estimate is negative and statistically insignificant (Col. 6). As shown in Col. 7 to 9 of Panel A, the difference between top and bottom players is partly due to the differential effect of peers on the mean outcome of each game played: while better peers do not affect top players' score (Col. 8), they have a large negative impact on the score of bottom players (Col. 9): a 10% increase in peer quality decreases their score per game by 0.14 point, which corresponds to a 28-p.p. increase in the probability of drawing instead of winning or losing instead of drawing.

This last result may strike as a surprise: in theory, bottom players who do not have access to the best boards could also be shielded against too good opponents. However, as shown in Panel B of Table 7, this is not the case: peer competition results in stronger opposition. First, Col. 1 to 3 show that bottom players with good peers are much less likely to play for the lowest league, whereas this is not the case for top players, whose coefficient is not statistically significant. Then, this translates into more difficult games for bottom players: a 10% increase in peer quality makes them 23 p.p. more likely to meet with higher-rated opponents (Col. 6), which corresponds to a 43% increase in their baseline probability.[29] Conversely, the peer estimate is smaller and statistically insignificant

[29]We lose a few observations because of missing information on the Elo of some opponents.

for top players (Col. 5). This result suggests that when bottom players are given the opportunity to play in championship by their peers, they are somewhat sacrificed and play games that they cannot possibly win.

One could think that being assigned to these good teams in a higher league is a good thing for bottom players, even if that makes them lose more games.[30] In particular, players could benefit from feedback from their teammates and stronger opponents. Col. 7 to 9 show that, indeed, there is a 1-to-1 relationship between the level of clubmates and the level of teammates for bottom players, while there is no such relationship for top players. Therefore, even if bottom players could indirectly benefit from peer competition through post-game feedback sessions among teammates, which are common practice in chess, our estimates show that this channel does not translate into Elo improvement for them in the short-run.

Effects Outside Championship: the Role of Motivation — Our preferred interpretation of the detrimental effect of good peers on participation in the club championship relates to within-club competition for access to the best opportunities to gain points in championship. However, it may also be the case that being exposed to better peers lowers motivation and self-confidence, which would translate into lower effort.[31] In order to explore the impact of clubmates on participation and performance outside the club championship, we use information on individual tournaments. Results are displayed in Panel C of Table 7.

First, we study whether the peer environment influences the decision to participate in

[30] Note that the teaching potential of lost games is a trope of chess players' discourse. For example, world chess champion and influential chess writer Jose Raul Capablanca wrote: "You may learn much more from a game you lose than from a game you win. You will have to lose hundreds of games before becoming a good player" (Capablanca, 1935).

[31] For example, De Sousa and Hollard (2021) show that lower effort may account for the large gender gap observed in chess across the world.

tournaments. The decision to participate in these tournaments only belongs to the player herself and it can be quite costly, both in terms of money and time. Since we control for club fixed effects, supply factors, such as geographical accessibility, are unlikely to play a large role if players live close to their club, so we assume that participation in tournaments is an indication of players' motivation. Results displayed in Col. 1 to 3 show that clubmates have no impact on the probability to participate in a tournament during the season, regardless of whether players are subject to peer competition or not.

Then, we study whether better peers impact performance in tournament, conditional on the decision to participate. Results shown in Col. 4 to 9 show that the results are very different from what is observed in club championship: the impact of peers on the number of Elo points gained or lost in tournaments or on player's expected score by game is imprecisely estimated, but, if anything, point estimates tend to be higher for top players than for bottom players, in line with what the theoretical framework would suggest in the absence of peer competition (Proposition 1).

5.4 Playing to Play or Playing to Learn?

We have shown that good peers increase the probability of seasonal improvement but with high heterogeneity, with positive effects concentrated among the best players in the club, who suffer less from within-club competition. However, those short-term effects may not be very consequential relative to the overall building of players' human capital. Therefore, we now turn to the longer-term consequences of the peer environment. To that end, we draw from the age-related patterns documented in Section 2 and explore an alternative partition of our sample, between *juniors* (until age 18) and *adults* (after age 18).

Table 8: Peer Effects and Attrition

Dep. Var.	Probability to Drop from Championship the Following Year								
Sample	All	Top	Bottom	Junior	Adult	Junior		Adult	
						Top	Bottom	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	0.113	-1.129	5.101[a]	1.179	-0.017	-0.651	31.408[a]	-1.390	4.431[a]
	(0.722)	(0.933)	(1.892)	(2.729)	(0.929)	(0.702)	(8.779)	(1.073)	(1.149)
Initial Elo	-0.380[a]	-0.210	-1.056[a]	-0.444	-0.506[a]	-0.533	-1.546	-0.261	-1.262[a]
	(0.144)	(0.215)	(0.330)	(0.308)	(0.180)	(0.428)	(1.022)	(0.245)	(0.322)
Age	1.275[a]	1.246[a]	1.678[a]	-3.644[a]	1.175[a]	-8.155[a]	-3.416	1.209[a]	1.371[b]
	(0.159)	(0.229)	(0.300)	(1.015)	(0.242)	(2.398)	(2.741)	(0.294)	(0.594)
Experience	0.682[a]	0.704[a]	0.599[a]	0.824[a]	0.657[a]	0.852[a]	0.287	0.707[a]	0.529[a]
	(0.058)	(0.066)	(0.127)	(0.227)	(0.060)	(0.294)	(0.930)	(0.067)	(0.119)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	17,760	12,269	4,854	2,029	15,528	852	1,023	11,283	3,743
F-stat	38.640	21.145	30.932	274.318	21.293	147.719	32.999	12.185	37.604
p-value Hansen	0.816	0.563	0.314	0.284	0.888	0.335	0.441	0.710	0.296

Notes: The dependent variable (Dep. Var.) is the probability that the player will not participate in the club championship the following season. Samples include all observations, except for the final year (2015). All controls are in log. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Peer Effects and Persistence in the Game — The long-term effect of the peer environment on performance depends on two intertwined mechanisms: persistence in the game and knowledge accumulation over time. Results displayed in Table 8 show that on average, the peer environment does not impact the probability to drop from the championship the following season (Col. 1). However, once again, the average effect of good peers on dropping out hides substantial heterogeneity between top players, for whom the effect is negative, albeit statistically insignificant (Col. 2), and bottom players, for whom it is positive and very high (Col. 3). This difference is all the more striking that both type of players have almost the same average probability of dropping out the following year (22% and 24%, respectively). It may be due to the fact that peer competition takes the fun out of participation in the championship for bottom players, who are eventually discouraged.

A focus on the age-based partition reveals new patterns. First, as shown in Col. 4 and 5, the peer environment has no impact on juniors' or adults' persistence. However, this average result depends on the composition of the two groups in terms of exposure to peer competition. Indeed, about half of junior players are bottom players, while this is only the case of a quarter of adult players. Therefore, in Col. 6 to 9, we study the impact of peers on the four subgroups separately. While top players in both groups are unaffected (Col. 6 and 8), in line with results of Col. 2, a striking difference appears between juniors and adults in the group of bottom players: the negative effect of the peer environment on persistence is seven times higher for juniors than for adults (Col 7 and 9). For bottom juniors, a 1% increase in peer quality more than doubles their probability to quit the championship. This extremely high effect suggests that the peer environment acts as a powerful screening device for junior players. If we interpret persistence in the game as a proxy for player's effort, this result is in line with the second part of Proposition 3, whereby better peers have a more detrimental impact on the effort of low-level junior players than on the effort of similar adults.

As shown in Appendix Table S8, junior players are more subject to peer competition than adult players, even top junior players. This feature may be due to the fact that junior players cannot impose themselves within the team as much as older or more senior players do. As a consequence, the peer environment negatively impacts top junior players' probability to improve over the season. Col. 1 of Panel A in Table 9 shows that a 1% increase in peer quality decreases their probability of improvement by 2.8 p.p., while for top adult players, the same increase translates into a 3.2 p.p. increase in their probability of improvement (Col. 4). This result is in line with the first part of Proposition 3, whereby fewer junior players benefit from positive peer effects than adults. Combined with the previous result on differential effort for juniors and adults, it shows that we can reject H0.2 of Proposition 4 with any conventional confidence level.

Table 9: Short and Long-run Effects

Sample	Juniors - Top				Adults - Top			
Subsample	All	Observed after 3 years			All	Observed after 3 years		
	Panel A: Probability of Improvement over a Given Number of Years							
Number of Years	One	One	Two	Three	One	One	Two	Three
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Quality	-2.809[a]	-3.888[a]	1.827[b]	4.366[a]	3.227[b]	2.523[b]	1.710	1.188
	(0.551)	(0.839)	(0.759)	(0.926)	(1.314)	(1.135)	(1.345)	(1.505)
	Panel B: Probability of Playing for the Lowest League							
Season of Observation	First	First	Second	Third	First	First	Second	Third
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Quality	-3.160	1.244	-4.003[a]	-10.026[a]	-1.084	-0.610	-0.631	-1.382
	(2.456)	(0.846)	(0.923)	(1.300)	(1.235)	(0.634)	(0.883)	(1.663)
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	905	349	349	349	12,352	5,755	5,755	5,755
F-stat	22.286	67.939	67.939	67.939	21.113	23.655	23.655	23.655

Notes: All specifications include club-by-individual and year fixed effects as well as our typical controls in log: Initial Elo, Age and Experience (see Appendix Table S9 for the full results). The dependent variable changes across the 2SLS specifications. **Panel A:** Probability of strict Elo increase over different years: one (Col. 1-2 and 5-6), two (Col. 3 and 7) and three (Col. 4 and 8). **Panel B:** Probability of mainly playing for the lowest league during the season considered. Samples in Col. 2 to 4 and 6 to 8 are restricted to continuing players over at least three seasons. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Differed Benefits for Juniors — Given the learning curve of junior players (see Figure 2), one may however wonder whether such a negative impact may only be temporary, and whether there can be differed benefits from suffering from peer competition for junior players. To answer this question, we define as "improvement" over x seasons an event whereby a player's Elo observed at the end of the x-th season is higher than her Elo at the beginning of the first season. Results are displayed in Col. 2 to 4 and 6 to 8 of Panel A in Table 9, on a balanced sample. The pattern for the effects of peers over the longer run is in line with the hypothesis of differential capital accumulation of juniors and adults: the effect increases over time for top juniors, with a peer estimate equal to -3.9 over a single season, to 1.8 over two seasons and to 4.4 over three seasons. On the contrary, for adults, the peer estimate drops from 2.5 over a single season to statistically insignificant estimates of 1.7 over two seasons and to 1.2 over three seasons.

These long-term effects of being exposed to good clubmates on the probability of improvement are quite high for top junior players. An alternative way of measuring them is to look at the probability that players end up moving to higher leagues in the championship. Therefore, we turn in Panel B of Table 9 to the probability that players mainly play for the lowest league (League 5) throughout the season, either during the current season, the next season or the next-but-one season. Depending on the sample and the timing considered, this probability spans between 47% and 58%. In line with the results displayed in Panel C of Table 7, short-run results confirm that the peer environment has no statistically significant impact on the current probability of playing for the lowest league, even for juniors (Col. 1-2 and 5-6). However, during the next seasons, top juniors who once benefited from good peers are much less likely to play for the lowest league: a 1% increase in peer quality decreases their baseline probability by 7% over two seasons (Col. 3) and by 21% over three seasons (Col. 4). Conversely, for top adult players, the effect is lower, and statistically insignificant.

These results suggest that good peers have extremely contrasted results for junior players. If their initial position in the club makes their participation in the championship more difficult, they will most likely quit the game. However, if their initial position is good enough to partly shield them against peer competition, juniors who enjoy better peers will be launched on a stark upward trajectory.

6 Conclusion

In this paper, we use the population of chess players in the French club championship between 2002 and 2015 to provide evidence that having good peers is a mixed blessing. Good peers help players improve, but if they capture the best opportunities to participate in the championship, they will have no positive externalities on low-level clubmates. Players who face peer competition are pushed down the team hierarchy, play fewer games, against better players, and they are much more likely to lose. However, there may be differed benefits from playing these losing games for good junior players, who are endowed with a steep learning curve, if they persist in the game long enough.

Since players' online profile cannot easily be matched with the official championship data, a limitation of this case study is that we cannot assess to what extent having access to online chess platforms, which have boomed since the late XX$^{\text{th}}$ century, may mitigate the negative consequences of peer competition. However, recent evidence from an online tournament played by elite players during the COVID-19 lockdowns shows a decrease in performance when competing online, thus suggesting that both activities are imperfect substitutes (Künn et al., 2020). Another limitation is that, contrary to recent studies (Balestra et al., 2020; Bosquet et al., 2021), we cannot decompose the average peer effect between different kinds of "senders", because instruments based on specific subgroups of players are too weak in our setting.[32] Therefore, we are unable to assess the role of peer competition on the interplay between senders and receivers in the peer network structure.

Overall, peer competition may contribute to explaining the vast heterogeneity in the results found by studies on peer effects. It may also inform the debate on the impact of tracking in education (Guyon et al., 2012). For example, lowering the threshold for accessing the elite sector in a tracked school system will lower the level of peer compe-

[32] For the same reason, we abstract from the impact of higher moments of the peer quality distribution and focus on a linear-in-means model, despite its limitations (Kline and Tamer, 2020).

tition faced by incumbent students in both elite and non-elite schools. Conversely, new entrants to elite schools will enjoy better classmates but face more competition. The aggregate and redistributive effects of such policy change are likely to depend on teaching practices, such as the role of group work or questioning strategies, which may be a large component of teachers' or schools' fixed effects.

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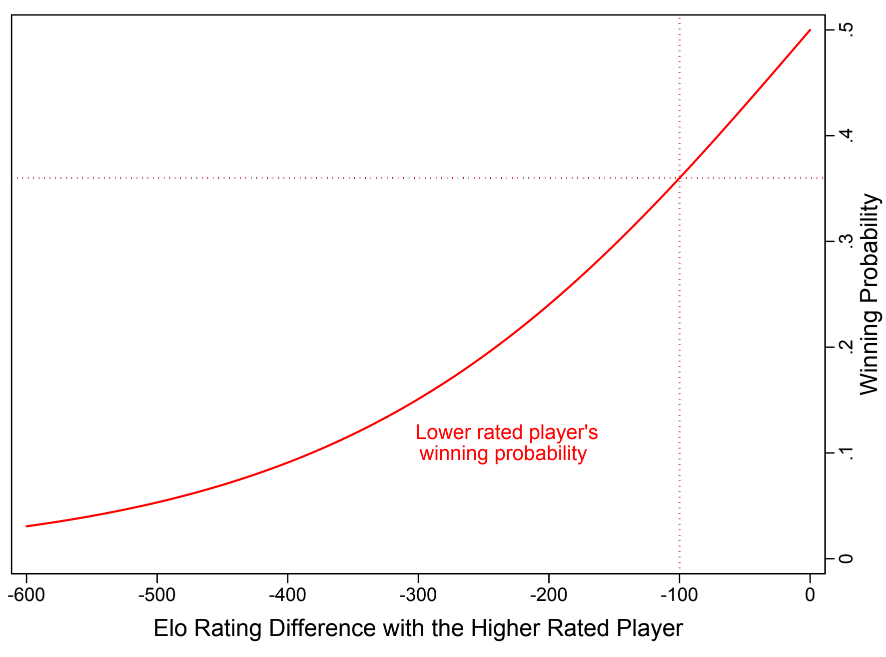
A Institutional Details

A.1 More details on the Elo rating system

The Elo rating is a numerical grading that indicates the history of a player's performance. The World Chess Federation (FIDE) updates it, at regular intervals. Beginners start at 1,000 points. Players reach 3rd-category level between 1,600 and 1,800, and 1st-category between 2,000 and 2,200. They become Grandmasters above 2,500, World top-rated above 2,650, and World Champion above 2,800.

The expected score of i winning against j (using the logistic curve) is defined as: $E_{ij} = (1 + 10^{-\Delta_{ij}/400})^{-1}$, with $\Delta_{ij} = Elo_i - Elo_j$. Player i's rating $Elo_{i,t-1}$ is updated to $Elo_{i,t}$ as $Elo_{i,t} = Elo_{i,t-1} + K_i(S_{ij} - E_{ij})$, with S_{ij} Player i's actual score (loss=0, draw=0.5, win=1) and K some adjustment factor.[33] As shown in Figure A, the Elo rating can be viewed as a statistical prediction of performance.

Figure A: Expected Probability of Victory Against a Higher-rated Player



Notes: If the lower rated player has 100 points less, her expected probability of winning the game is 0.36.

[33] K is called the "development coefficient" and takes into account the player's rating and playing history. The value grid has changed over the years. For current rules, see https://handbook.fide.com/chapter/B022017.

A.2 Examples of Relationship between Clubs and Municipal Power

The most emblematic example of the link between clubs and municipal power is offered by Lyon, France's third-largest city.[34] Michel Noir, Lyon's mayor between 1989 and 1995, was a chess enthusiast. Under his term, Lyon's chess club won the French club championship six times in a row from 1990 to 1995, and the European Club Championship twice in 1993 and 1994, thanks to the heavy support from the city council. However, in June 1995, a new mayor was elected and public subsidies to chess were greatly reduced. The professional team was cut and some employees were laid off, such as the coach and a receptionist. The International Chess Open of Lyon was suspended and the main team forfeited in the European Championship.

Most of the time, municipal support is less significant but quite crucial. In particular, "cities have always been the first partners of the clubs by providing facilities".[35] As a consequence, some clubs disappear because of the lack of municipality-provided venue.[36] Conversely, clubs flourish with rooms lent by the municipality .[37] Apart from members' contributions and rare sponsors, chess clubs also survive thanks to public subsidies (Borzakian, 2007). The history of the municipality of Hyères offers another interesting example.[38] In the 1980's, the local chess club initiated a project which brought chess to all local schools with the creation of two municipal positions as chess instructors. The chess schools developed until more than 1000 children were playing every week. In 2002, the club faced serious financial difficulties and relocated in the canteen room of a primary school. Chess in Corsica offers a similar example.[39] In 2016, the drastic fall of public subsidies from the Departmental Council and the Municipality of Ajaccio resulted in the suppression of at least a full post of teacher on the Department, and the disappearance of chess lessons for more than 500 schoolchildren.

[34] See website on "the history of Chess in Lyon from 1842 to 2021" – https://lyon-olympique-echecs.com/historique-historique-2-suite/.

[35] Eric Verlhac, chairman of the association of French mayors, quoted in a newspaper article in *La Gazette des Communes* – https://www.lagazettedescommunes.com/728262/les-maires-appeles-a-promouvoir-le-jeu-dechecs/.

[36] See, e.g., the club of Bruay-la-Buissière, as described by newspaper article in *La voix du Nord* – https://www.lavoixdunord.fr/438151/article/2018-08-27/le-club-d-echecs-menace-d-arreter-ses-activites-faute-de-salle.

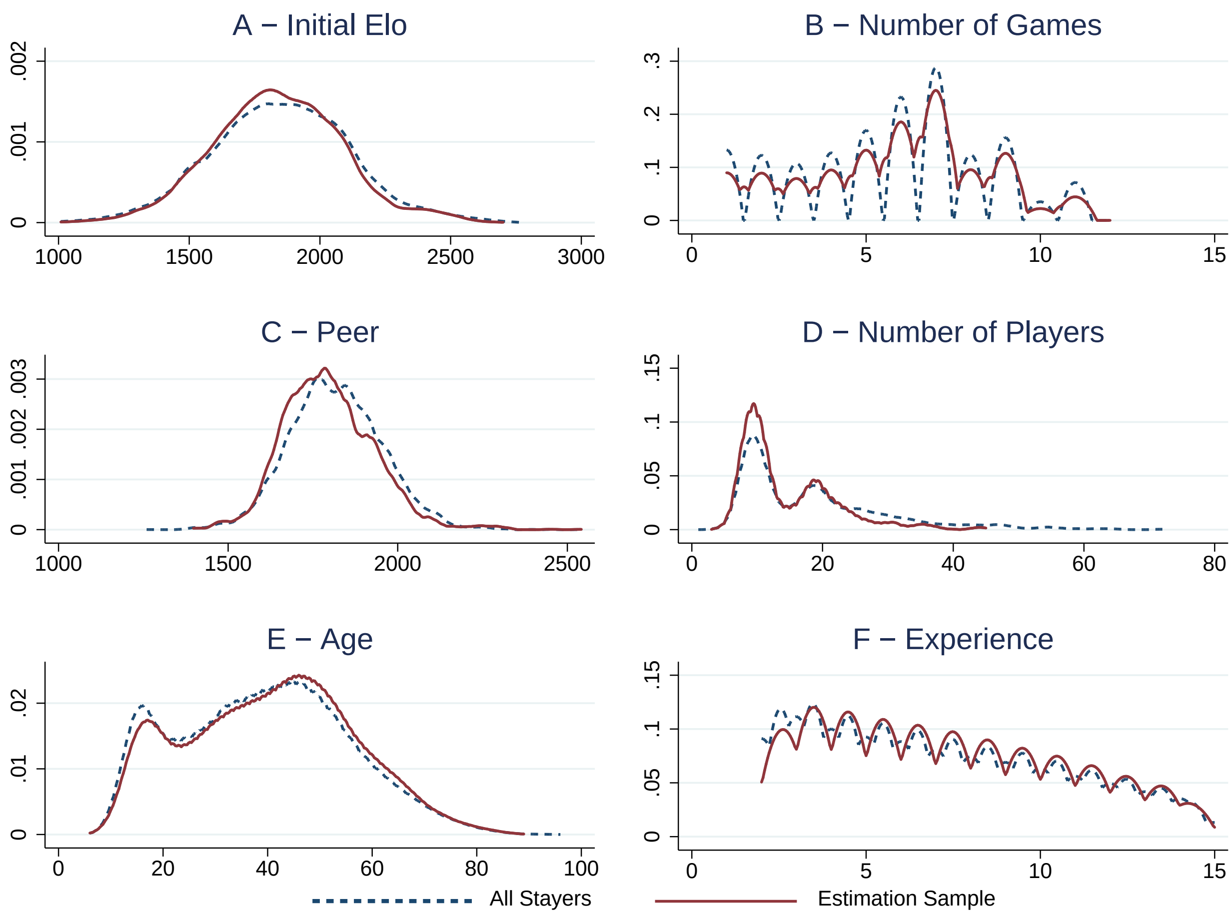
[37] See, e.g., the club of Les Tours du Berry, as described by newspaper article in *La Nouvelle Republique* – https://www.lanouvellerepublique.fr/indre/commune/sainte-severe-sur-indre/les-tours-du-berry-ont-pris-une-nouvelle-dimension.

[38] See website on "the history of Chess in Hyères" – http://latourhyeroise.free.fr/histoire/histo.pdf.

[39] See newspaper article on "chess subsidies in Corsica" (https://www.corsenetinfos.corsica/Coupe-de-subventions-pour-les-echecs-Le-coup-de-gueule-de-Leo-Battesti_a24038.html).

B Figures

Figure B: Sample Selection



Notes: Distribution (Epanechnikov kernel) of the described variables in the sample of all stayers (dashed, N=72,190) and in the estimation sample of stayers in one-club cities (solid, N=19,308).

C Tables

Table A: Correlation Between Elo Cutoff and mean Elo Rating

Dependent Variable	Elo Rating of the Last Admissible Player			
	(1)	(2)	(3)	(4)
Mean Peer Quality	1.608[a]	0.847[a]	1.005[a]	0.968[a]
	(0.018)	(0.022)	(0.019)	(0.020)
Number of Teams			✓	✓
Other Controls				✓
Fixed Effects		c, t	c, t	c, t
Observations	6392	6316	6316	6316
R-Squared	0.565	0.818	0.868	0.889
Within R-Squared		0.208	0.428	0.518

Notes: OLS regressions of the Elo rating of the last admissible player as a function of the mean Elo rating. The sample is at the club-year level. Col. 2-4 control for club fixed effects and time dummies; Col. 3-4 control for the number of teams in the club; Col. 4 controls for club size, mean age, mean experience, share of females and share of foreigners.

Table B: Characteristics of Closing Clubs

Dependent Variable	Probability of Closing Next Year								
Sample	All Club-Years					Club-Years in Estimation Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Elo	0.038[c]	0.067[b]	0.052[c]	0.056[c]	0.076	0.017	0.001	-0.007	0.050
	(0.019)	(0.026)	(0.031)	(0.030)	(0.055)	(0.037)	(0.047)	(0.070)	(0.078)
Number Players	-0.020[a]	-0.022[a]	-0.027[a]	-0.027[a]	-0.019[b]	-0.016[a]	-0.016[a]	-0.021[c]	-0.026[c]
	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)	(0.011)	(0.014)
Mean Age	-0.008	-0.009	-0.010	-0.013	-0.007	-0.001	-0.002	0.020	-0.001
	(0.012)	(0.013)	(0.019)	(0.019)	(0.019)	(0.014)	(0.014)	(0.029)	(0.027)
Mean Experience	-0.017[a]	-0.022[b]	-0.020[c]	-0.014	-0.015	-0.008[b]	0.012	0.001	0.010
	(0.003)	(0.010)	(0.011)	(0.012)	(0.021)	(0.004)	(0.014)	(0.024)	(0.027)
Share Female	0.075[a]	0.075[a]	0.102[a]	0.132[a]	0.129[a]	0.073[c]	0.079[c]	0.081	0.098[c]
	(0.028)	(0.029)	(0.032)	(0.036)	(0.037)	(0.044)	(0.045)	(0.052)	(0.055)
Share Foreign	0.031	0.024	0.061	0.063	0.008	-0.009	-0.000	0.012	-0.023
	(0.032)	(0.033)	(0.048)	(0.059)	(0.083)	(0.020)	(0.022)	(0.057)	(0.063)
Evolution Number of Players				-0.000	-0.004				-0.016[c]
				(0.008)	(0.007)				(0.009)
Fixed Effects		**t**	**t, C(c)**	**t, C(c)**	**t, c**		**t**	**t, c**	**t, c**
Observations	6,393	6,393	6,363	5,581	5,533	2,200	2,200	2,200	1,953
R-Squared	0.014	0.025	0.088	0.069	0.228	0.007	0.024	0.209	0.184
Within R-Squared		0.007	0.010	0.013	0.008		0.006	0.005	0.009

Notes: OLS regression of the probability of closing next year at the club-year level. Mean Elo, Number of Players, Mean Age, Mean Experience are in log and Evolution of Number of Players is the difference between previous and current log size. Fixed effects are t for time dummies, c for clubs, and $C(c)$ stands for city (metropolitan area) in which the club c is located. By construction of the regression sample, city dummies and club dummies are equivalent in this sample. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Table C: First-stage Results: Predicting Peer Quality

Dep. Var.: Log/Level	Log	Log	Log	Log	Log	Log	Level
All/Leave-out (L.-o.)	All	All	All	All	All	L.-o.	All
Sample: Nb. of clubs	Any	≤ 10	≤ 2	1	1	1	1
All/Persistent (Pers.)	All				Pers.	All	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument= Nb of players	0.001	0.017[b]	0.008	-0.381[a]	-0.374[a]	-0.425[a]	-4.281[a]
	(0.002)	(0.008)	(0.058)	(0.057)	(0.058)	(0.095)	(0.677)
Instrument= Elo of players	0.000	-0.006[c]	-0.006	0.117[a]	0.114[a]	0.131[a]	0.815[a]
	(0.001)	(0.003)	(0.019)	(0.019)	(0.020)	(0.032)	(0.166)
Initial Elo	0.093[a]	0.100[a]	0.116[a]	0.112[a]	0.109[a]	0.053[a]	1.139[a]
	(0.007)	(0.009)	(0.011)	(0.013)	(0.018)	(0.014)	(0.131)
Age	0.012	0.007	0.016	0.030	0.031	0.035[c]	0.306
	(0.012)	(0.014)	(0.018)	(0.020)	(0.025)	(0.021)	(0.205)
Experience	0.002	0.004	0.002	-0.000	0.009	-0.005	0.009
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)	(0.007)	(0.073)
Fixed Effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	64,842	44,214	26,682	19,308	11,532	19,308	19,308
R-Squared	0.800	0.795	0.771	0.792	0.749	0.760	0.793
Within R-Squared	0.011	0.014	0.017	0.029	0.037	0.016	0.028
F-stat	1.796	2.504	3.001	62.969	57.682	24.518	36.932
p-value Hansen	0.193	0.417	0.400	0.930	0.955	0.967	0.743

Notes: The dependent variable (Dep. Var.) changes across the OLS specifications: log mean initial Elo (IE) in the club (Col. 1 to 5), log leave-out mean IE in the club (Col. 6) and standardized mean IE in the club (Col. 7). The sample is made of all stayers (Col. 1), stayers in cities with ten remaining clubs or less (Col. 2), two remaining clubs or less (Col. 3) and one remaining club (Col. 4 to 7). In Col. 5, the sample is restricted to clubs observed every season in championship. All controls are in log, except instruments that are in levels and standardized in Col. 7. Nb. stands for number. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Table D: The Impact of Clubmates on Elo Points Gained in Championship

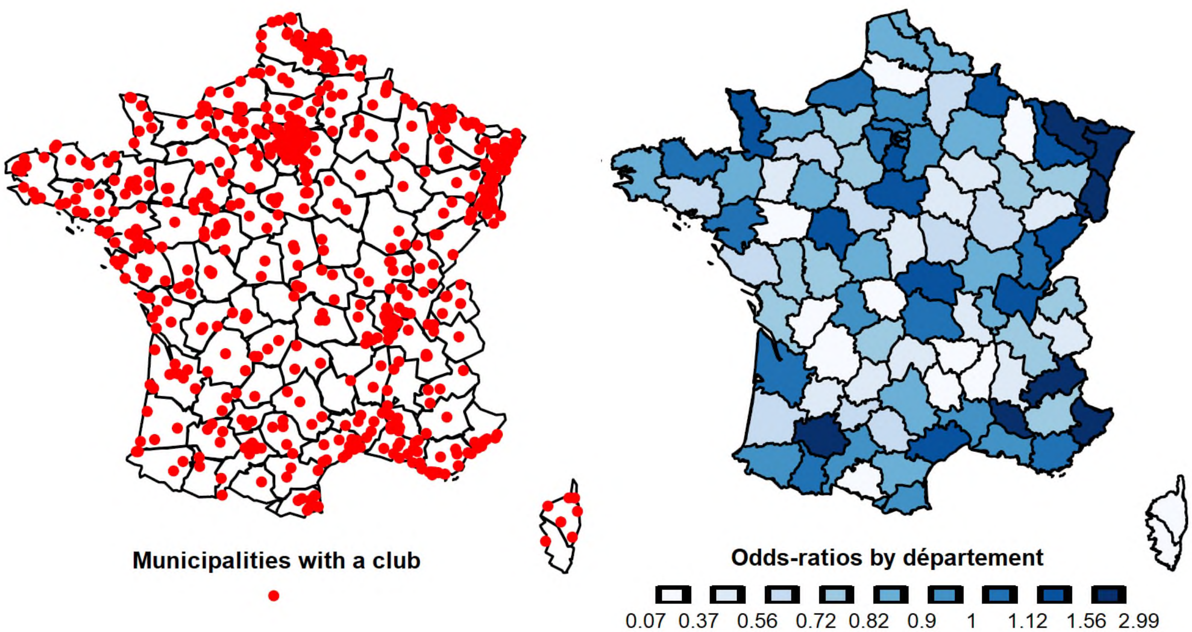
Dependent Variable	Elo Points Gained or Lost in Championship						
	Current Year						*Previous* Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer	2.067^{b}	2.045^{b}	3.283^{b}	2.041^{b}	1.933^{b}	2.100^{a}	0.285
	(0.810)	(0.897)	(1.335)	(0.797)	(0.765)	(0.784)	(0.713)
Initial Elo	-8.310^{a}	-8.252^{a}	-8.433^{a}	-7.737^{a}	-8.261^{a}	-8.767^{a}	-6.851^{a}
	(0.312)	(0.344)	(0.330)	(0.311)	(0.311)	(0.320)	(0.281)
Age	4.121^{a}	4.162^{a}	4.157^{a}	4.030^{a}	4.218^{a}	4.100^{a}	4.894^{a}
	(0.292)	(0.323)	(0.294)	(0.308)	(0.277)	(0.299)	(0.290)
Experience	0.462^{a}	0.441^{a}	0.508^{a}	0.398^{a}	0.417^{a}	0.414^{a}	0.227^{a}
	(0.097)	(0.108)	(0.099)	(0.103)	(0.099)	(0.107)	(0.065)
Fixed effects	**c×i, t**	**c,i,t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	19,308	19,308	19,308	17,035	18,827	18,827
F-stat	62.964	50.009	43.049	63.372	66.304	60.027	59.744
p-value Hansen	0.274	0.273	0.241	0.285	0.257	0.394	0.826

Notes: 2SLS estimates of the impact of peer quality on the standardized Elo points gained or lost in championship throughout the season, except in Col. 7 where the outcome is lagged one year (and individual controls are lagged one year as well, except Peer). Col. 2 controls for separate individual and club fixed effects, instead of the individual-club match. Col. 3 adds control (in logs) for number of players, mean age, mean experience, as well as the share of women and foreigners in the club and the number of teams in the club; Col. 4 controls for the Elo points gained or lost by the player during previous season. Col. 5 discards players who at some point participate in either of the first two leagues. Col. 6 uses the same sample as Col. 7. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

— Supplementary Appendix —

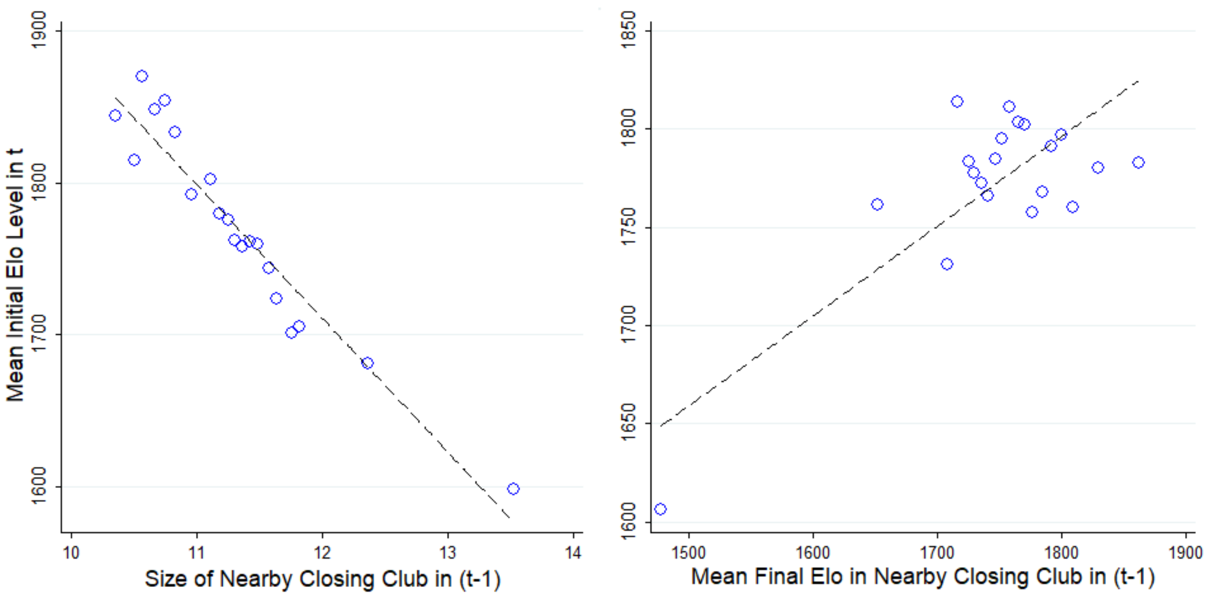
Figures

Figure S1: Spatial Distribution of Clubs and Players



Notes: Left: location of the 673 municipalities with at least one club in the club championship between 2002 and 2015. Right: share of players in club championship in the département (on average over the period) relative to the population share of the département in 2005.

Figure S2: Instrument Strength: Bin Scatter Plots



Notes: All players in the estimation sample exposed to a club closure nearby. Controls for initial Elo, age, experience and year dummies. The number of bins is set to 20.

Tables

Table S1: Peer Competition: Correlational Evidence on the Estimation Sample

Dependent Variable	Improve			Number Games			Mean Rank		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	0.031	-0.035	0.191[c]	-0.826[a]	-0.894[a]	-0.647[a]	-13.070[a]	-11.029[a]	-10.923[a]
	(0.054)	(0.095)	(0.102)	(0.106)	(0.140)	(0.148)	(0.397)	(0.418)	(0.413)
Initial Elo	-0.231[a]	-5.317[a]	-5.562[a]	1.685[a]	1.693[a]	1.773[a]	12.888[a]	9.796[a]	10.106[a]
	(0.032)	(0.147)	(0.155)	(0.071)	(0.154)	(0.174)	(0.346)	(0.474)	(0.495)
Age	-0.203[a]	2.377[a]	2.382[a]	-0.060[a]	-0.194	-0.333[c]	0.072	0.291	0.088
	(0.009)	(0.121)	(0.121)	(0.016)	(0.176)	(0.181)	(0.049)	(0.434)	(0.451)
Experience	-0.061[a]	0.246[a]	0.252[a]	0.155[a]	-0.128[c]	-0.141[b]	-0.240[a]	0.002	-0.007
	(0.010)	(0.052)	(0.052)	(0.025)	(0.068)	(0.069)	(0.055)	(0.149)	(0.151)
Number Games			0.050[a]						0.115[a]
			(0.008)						(0.024)
Mean Rank			0.016[a]			0.022[a]			
			(0.004)			(0.005)			
Improve						0.056[a]			0.095[a]
						(0.009)			(0.021)
Fixed effects	**t**	**c×i, t**	**c×i, t**	**t**	**c×i, t**	**c×i, t**	**t**	**c×i, t**	**c×i, t**
Observations	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308	19,308
R-Squared	0.050	0.343	0.346	0.130	0.534	0.537	0.561	0.791	0.792
Within R-Squared	0.043	0.129	0.133	0.129	0.018	0.023	0.548	0.187	0.191

Notes: OLS estimates of the correlation between peer quality and the probability of Elo increase throughout the season (Col. 1 to 3), the log number of games player (Col. 4 to 6) and the log mean board (Col. 7 to 9). Sample corresponds to the main estimation sample. All controls are in log. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S2: The Impact of Clubmates on Improvement: Peer Quality in Level instead of Log

Dependent Variable	Probability to Improve						
	Current Year						*Previous* Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Peer Quality	0.134^{b}	0.134^{c}	0.213^{b}	0.130^{b}	0.128^{b}	0.135^{b}	-0.003
	(0.064)	(0.072)	(0.101)	(0.059)	(0.062)	(0.061)	(0.020)
Initial Elo	-5.523^{a}	-5.501^{a}	-5.625^{a}	-5.476^{a}	-5.488^{a}	-5.879^{a}	-4.885^{a}
	(0.178)	(0.197)	(0.210)	(0.177)	(0.180)	(0.176)	(0.135)
Age	2.319^{a}	2.325^{a}	2.331^{a}	2.189^{a}	2.323^{a}	2.360^{a}	2.616^{a}
	(0.135)	(0.150)	(0.141)	(0.133)	(0.131)	(0.134)	(0.130)
Experience	0.244^{a}	0.240^{a}	0.283^{a}	0.158^{a}	0.238^{a}	0.182^{a}	0.204^{a}
	(0.051)	(0.057)	(0.055)	(0.057)	(0.055)	(0.055)	(0.033)
Fixed effects	**c×i, t**	**c,i,t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	19,308	19,308	18,827	17,035	18,827	18,827
F-stat	36.928	29.319	22.889	38.877	38.885	39.205	37.870
p-value Hansen	0.743	0.745	0.698	0.977	0.739	0.949	0.340

Notes: 2SLS estimates of the impact of peer quality (computed in level and standardized) on the probability of Elo increase throughout the season, except in Col. 7 where the outcome is lagged one year (and individual controls are lagged one year as well, except Peer). The instruments are also in level. Col. 2 controls for separate individual and club fixed effects, instead of the individual-club match. Col. 3 adds control (in logs) for number of players, mean age, mean experience, as well as the share of women and foreigners in the club and the number of teams in the club; Col. 4 controls for whether the player has improved or not during previous season. Col. 5 discards players who at some point participate in either of the first two leagues. Col. 6 uses the same sample as Col. 4 and 7, excluding players for whom information on lagged IE is missing. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S3: The Impact of Clubmates on Improvement: Peer Quality as Leave-out Mean

Dependent Variable	Probability to Improve						
	Current Year						*Previous* Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Peer Quality	1.514^b	1.510^b	2.667^a	1.525^b	1.446^b	1.580^b	-0.048
	(0.601)	(0.675)	(0.919)	(0.606)	(0.584)	(0.624)	(0.219)
Initial Elo	-5.403^a	-5.382^a	-5.454^a	-5.365^a	-5.371^a	-5.760^a	-4.885^a
	(0.151)	(0.168)	(0.155)	(0.153)	(0.152)	(0.151)	(0.133)
Age	2.320^a	2.325^a	2.318^a	2.191^a	2.321^a	2.361^a	2.616^a
	(0.131)	(0.146)	(0.137)	(0.130)	(0.130)	(0.130)	(0.130)
Experience	0.253^a	0.248^a	0.312^a	0.168^a	0.246^a	0.192^a	0.204^a
	(0.051)	(0.057)	(0.057)	(0.057)	(0.055)	(0.055)	(0.033)
Fixed effects	**c×i, t**	**c,i,t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	19,308	19,308	18,827	17,035	18,827	18,827
F-stat	24.514	19.439	16.329	24.915	24.559	24.720	25.460
p-value Hansen	0.967	0.968	0.980	0.862	0.943	0.874	0.368

Notes: 2SLS estimates of the impact of peer quality (computed as the leave-out mean) on the probability of Elo increase throughout the season, except in Col. 7 where the outcome is lagged one year (and individual controls are lagged one year as well, except Peer). Col. 2 controls for separate individual and club fixed effects, instead of the individual-club match. Col. 3 adds control (in logs) for number of players, mean age, mean experience, as well as the share of women and foreigners in the club and the number of teams in the club; Col. 4 controls for whether the player has improved or not during previous season. Col. 5 discards players who at some point participate in either of the first two leagues. Col. 6 uses the same sample as Col. 4 and 7, excluding players for whom information on lagged IE is missing. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S4: The Impact of Clubmates on Seasonal Performance in Persistent Clubs

Dependent Variable	Probability to Improve						
	Current Year						*Previous* Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Peer Quality	1.715^{b}	1.671^{c}	2.632^{b}	1.715^{b}	1.589^{c}	1.773^{b}	0.066
	(0.858)	(0.942)	(1.318)	(0.810)	(0.818)	(0.845)	(0.271)
Initial Elo	-5.526^{a}	-5.500^{a}	-5.585^{a}	-5.497^{a}	-5.480^{a}	-5.874^{a}	-4.890^{a}
	(0.219)	(0.239)	(0.232)	(0.209)	(0.216)	(0.210)	(0.192)
Age	2.219^{a}	2.213^{a}	2.198^{a}	2.110^{a}	2.216^{a}	2.265^{a}	2.578^{a}
	(0.175)	(0.191)	(0.180)	(0.175)	(0.171)	(0.175)	(0.169)
Experience	0.356^{a}	0.347^{a}	0.400^{a}	0.285^{a}	0.347^{a}	0.299^{a}	0.222^{a}
	(0.064)	(0.071)	(0.068)	(0.070)	(0.071)	(0.068)	(0.043)
Fixed effects	**c×i, t**	**c,i,t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	11,532	11,602	11,532	11,315	8,976	11,315	11,315
F-stat	57.682	47.208	35.154	54.656	62.504	54.700	54.577
p-value Hansen	0.955	0.997	0.967	0.768	0.979	0.768	0.375

Notes: Sample of players registered in clubs that are active in club championship every year between 2003 and 2015. 2SLS estimates of the impact of peer quality on the probability of Elo increase throughout the season, except in Col. 7 where the outcome is lagged one year (and individual controls are lagged one year as well, except Peer). Col. 2 controls for separate individual and club fixed effects, instead of the individual-club match. Col. 3 adds control (in logs) for number of players, mean age, mean experience, as well as the share of women and foreigners in the club and the number of teams in the club; Col. 4 controls for whether the player has improved or not during previous season. Col. 5 discards players who at some point participate in either of the first two leagues. Col. 6 uses the same sample as Col. 4 and 7, excluding players for whom information on lagged IE is missing. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S5: Heterogeneity by Global Elo Ranking

Dependent Variable	Improve		Number of Games		Mean Rank	
Sample	Top Glob.	Bot. Glob.	Top Glob.	Bot. Glob.	Top Glob.	Bot. Glob.
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Quality	1.132[a]	3.528[c]	-1.184[a]	-3.263	-9.654[a]	-10.277[a]
	(0.326)	(1.912)	(0.444)	(2.834)	(2.748)	(2.826)
Initial Elo	-7.897[a]	-5.229[a]	1.240[a]	2.109[a]	11.254[a]	6.807[a]
	(0.234)	(0.327)	(0.218)	(0.407)	(0.884)	(0.672)
Age	2.492[a]	2.269[a]	-0.566[b]	1.050[a]	0.138	0.346
	(0.203)	(0.264)	(0.264)	(0.298)	(0.612)	(0.605)
Experience	0.212[a]	0.262[a]	-0.197[b]	-0.122	-0.246	0.232
	(0.060)	(0.098)	(0.090)	(0.127)	(0.193)	(0.231)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	13,342	5,289	13,342	5,289	13,342	5,289
F-stat	64.167	28.491	64.167	28.491	64.167	28.491
p-value Hansen	0.899	0.849	0.986	0.127	0.201	0.617

Notes: The dependent variable changes across the 2SLS specifications: Col. 1 and 2: Probability of Elo increase; Col. 3 and 4: Log number of games played in championship; Col. 5 and 6: Mean rank in the team. "Top (global)" players are the best rated players in the championship at the start of the season so as to match the number of "Top (local)" players in Table 6 and "Bottom (global)" players are other players. Controls are in log. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S6: Heterogeneity by Local Elo ranking Among High-Elo Players

Sample	Top (Global) Players					
Dep. Var.	Improve		Number of Games		Mean Rank	
Subsample	Bottom	Top	Bottom	Top	Bottom	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Quality	0.186	1.800^a	-6.022^a	-0.663	-25.291^a	-6.245
	(1.073)	(0.469)	(1.131)	(0.450)	(1.713)	(4.148)
Initial Elo	-7.790^a	-8.722^a	1.903^a	1.123^a	7.927^a	13.007^a
	(0.498)	(0.286)	(0.513)	(0.241)	(1.993)	(0.905)
Age	2.445^a	2.461^a	-0.603	-0.665^b	1.300	-0.359
	(0.423)	(0.234)	(0.486)	(0.321)	(1.520)	(0.764)
Experience	0.076	0.241^a	-0.234	-0.205^b	0.083	-0.085
	(0.191)	(0.064)	(0.167)	(0.099)	(0.663)	(0.220)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	2,551	10,495	2,551	10,495	2,551	10,495
F-stat	166.465	60.050	166.465	60.050	166.465	60.050
p-value Hansen	0.278	0.399	0.287	0.409	0.786	0.307

Notes: The dependent variable changes across the 2SLS specifications: Col. 1 and 2: Probability of Elo increase; Col. 3 and 4: Log number of games played in championship; Col. 5 and 6: Mean board in the team. "Top (global)" players are the best rated players in the championship at the start of the season so as to match the number of "Top" local players in Table 6; "Top" local players are among the 8 (9 before 2006) best clubmates at the start of the season and "Bottom" local players are other players. Controls are in log. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S7: Peer Effects, Competition and Performance in Championship: Mechanisms - Full Results

Panel A - Performance in Championship

Dependent Variable	Elo Points			Elo Points by Game			Score by Game		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	2.102^{b}	3.782^{a}	-0.172	1.696^{c}	3.058^{a}	-2.286	-0.066	-0.012	-1.408^{b}
	(0.823)	(1.059)	(1.929)	(1.002)	(0.927)	(1.642)	(0.624)	(0.676)	(0.553)
Initial Elo	-8.452^{a}	-10.981^{a}	-6.292^{a}	-7.462^{a}	-9.102^{a}	-5.704^{a}	-0.907^{a}	-1.342^{a}	-0.321^{b}
	(0.317)	(0.496)	(0.468)	(0.316)	(0.442)	(0.495)	(0.099)	(0.145)	(0.131)
Age	4.191^{a}	4.027^{a}	3.596^{a}	3.869^{a}	3.423^{a}	3.422^{a}	0.617^{a}	0.633^{a}	0.478^{a}
	(0.297)	(0.434)	(0.435)	(0.279)	(0.432)	(0.468)	(0.070)	(0.111)	(0.131)
Experience	0.469^{a}	0.414^{a}	0.476^{b}	0.299^{a}	0.186	0.474^{c}	0.064^{b}	0.050^{c}	0.108^{c}
	(0.098)	(0.116)	(0.199)	(0.113)	(0.125)	(0.277)	(0.026)	(0.029)	(0.057)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	13,393	5,252	19,308	13,393	5,252	19,308	13,393	5,252
F-stat	62.969	32.108	34.003	62.969	32.108	34.003	62.969	32.108	34.003
p-value Hansen	0.274	0.398	0.543	0.392	0.512	0.560	0.713	0.535	0.543

Panel B - Opposition in Championship

Dependent Variable	Lowest League			Stronger Opponent			Teammate Quality		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	-2.698^{a}	-1.804	-6.224^{a}	1.677^{b}	1.401	2.386^{a}	0.303^{c}	0.084	0.965^{a}
	(0.889)	(1.570)	(1.048)	(0.805)	(1.296)	(0.792)	(0.171)	(0.246)	(0.188)
Initial Elo	-0.103	-0.104	0.289	-2.475^{a}	-2.736^{a}	-2.278^{a}	0.222^{a}	0.204^{a}	0.161^{a}
	(0.155)	(0.261)	(0.254)	(0.182)	(0.274)	(0.236)	(0.026)	(0.039)	(0.039)
Age	-0.886^{a}	-0.784^{a}	-1.124^{a}	0.730^{a}	0.586^{b}	0.626^{b}	0.085^{a}	0.065^{b}	0.112^{a}
	(0.154)	(0.204)	(0.253)	(0.181)	(0.258)	(0.263)	(0.021)	(0.026)	(0.033)
Experience	-0.018	-0.024	0.116	0.062	0.024	0.051	0.009	0.004	0.001
	(0.045)	(0.056)	(0.105)	(0.045)	(0.058)	(0.114)	(0.006)	(0.008)	(0.014)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	13,393	5,252	19,300	13,393	5,245	19,308	13,393	5,252
F-stat	62.969	32.108	34.003	62.994	32.108	34.169	62.969	32.108	34.003
p-value Hansen	0.617	0.277	0.448	0.319	0.319	0.398	0.728	0.395	0.551

Panel C - Participation and Performance in Tournaments

Dependent Variable	Play			Elo Points			Score by Game		
Sample	All	Top	Bottom	All	Top	Bottom	All	Top	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Quality	0.406	0.633	0.511	-1.555	-2.377	2.054	0.251	-0.114	0.237
	(0.708)	(1.055)	(0.903)	(1.850)	(2.676)	(2.483)	(0.152)	(0.147)	(0.299)
Initial Elo	0.099	-0.093	0.426^{b}	-7.220^{a}	-7.228^{a}	-8.077^{a}	-0.084^{c}	-0.056	-0.100
	(0.146)	(0.231)	(0.169)	(0.548)	(0.642)	(0.843)	(0.049)	(0.068)	(0.086)
Age	-1.088^{a}	-0.864^{a}	-1.409^{a}	2.516^{a}	2.484^{a}	3.219^{a}	0.266^{a}	0.286^{a}	0.251^{a}
	(0.143)	(0.213)	(0.181)	(0.450)	(0.565)	(0.845)	(0.050)	(0.062)	(0.085)
Experience	0.098^{b}	0.120^{b}	0.023	0.550^{a}	0.397^{b}	0.672^{b}	0.054^{a}	0.045	0.034
	(0.046)	(0.055)	(0.109)	(0.178)	(0.199)	(0.322)	(0.019)	(0.028)	(0.035)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	19,308	13,393	5,252	8,709	5,671	2,627	8,709	5,671	2,627
F-stat	62.969	32.108	34.003	72.091	32.459	21.053	72.091	32.459	21.053
p-value Hansen	0.710	0.445	0.405	0.123	0.063	0.093	0.454	0.955	0.467

Notes: The dependent variable changes across the 2SLS specifications. **Panel A:** Col. 1 to 3: standardized total number of Elo points gained or lost in championship; Col 4 to 6: standardized mean Elo points earned in championship by game; Col. 7 to 9: Score. **Panel B:** Col. 1 to 3: Probability to play mainly for the last league (sample restricted to clubs with a team in a higher league than league 5); Col. 4 to 6: Probability that the average opponent is rated higher than the player's initial Elo; Col. 7 to 9: Log mean initial Elo of teammates. **Panel C:** Col. 1 to 3: Probability to participate in a tournament; Col. 4 to 6: standardized total number of Elo points gained or lost in tournaments; Col. 7 to 9: Mean score by game played in tournaments. "Top" players are ranked among the 8 (9 before 2006) best clubmates at the start of the season and "Bottom" players are ranked beyond. Controls are in log. Standard errors are in parentheses and clustered at the club level with ^{a}, ^{b}, and ^{c}, respectively, denoting significance at the 1, 5, and 10 percent levels.

Table S8: Competition for Juniors and Adults

Dependent Variable	Number of Games				Mean Rank			
Sample	Juniors		Adults		Juniors		Adults	
Subsample	Top (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)	Bottom (8)
Peer Quality	-3.517^{a}	-7.465^{b}	-0.687	-7.212^{a}	-28.148^{a}	-52.332^{a}	-4.086	-24.910^{a}
	(1.085)	(3.535)	(0.454)	(0.984)	(8.993)	(14.292)	(2.607)	(4.037)
Initial Elo	2.556^{a}	2.052^{a}	1.243^{a}	2.826^{a}	10.244^{a}	5.615^{a}	12.474^{a}	10.827^{a}
	(0.674)	(0.424)	(0.224)	(0.335)	(1.595)	(1.499)	(0.675)	(1.220)
Age	7.338^{b}	4.286^{b}	-0.364	-0.320	5.553	-2.056	0.216	0.937
	(3.143)	(1.758)	(0.351)	(0.670)	(6.414)	(5.246)	(0.991)	(1.791)
Experience	-0.066	0.034	-0.166^{c}	-0.080	-0.743	2.242^{c}	-0.007	0.485
	(0.410)	(0.441)	(0.086)	(0.174)	(1.061)	(1.209)	(0.196)	(0.359)
Fixed effects	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**	**c×i, t**
Observations	905	1,088	12,352	4,079	905	1,088	12,352	4,079
F-stat	22.286	31.564	21.113	41.638	22.286	31.564	21.113	41.638
p-value Hansen	0.156	0.354	0.365	0.473	0.640	0.402	0.288	0.923

Notes: Col. 1 to 4: Log number of games played in championship; Col. 5 to 8: mean rank in the team. Junior vs Adult players and Bottom vs Top players are two partition of observations defined in the text. Standard errors are in parentheses and clustered at the club level with ^{a}, and ^{b}, respectively, denoting significance at the 1, and 5 percent levels.

Table S9: Short and Long-run Effects – Full Results

Sample	Juniors - Top				Adults - Top			
Subsample	All	Observed after 3 years			All	Observed after 3 years		
	Panel A: Probability of Improvement over a Given Number of Years							
Number of Years	One	One	Two	Three	One	One	Two	Three
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Quality	-2.809[a]	-3.888[a]	1.827[b]	4.366[a]	3.227[b]	2.523[b]	1.710	1.188
	(0.551)	(0.839)	(0.759)	(0.926)	(1.314)	(1.135)	(1.345)	(1.505)
Initial Elo	-4.324[a]	-4.963[a]	-4.706[a]	-3.390[a]	-7.516[a]	-8.535[a]	-9.579[a]	-9.263[a]
	(0.430)	(0.628)	(0.631)	(0.678)	(0.325)	(0.436)	(0.441)	(0.426)
Age	5.331[b]	7.547[b]	10.412[a]	11.269[a]	1.904[a]	1.785[a]	2.120[a]	1.711[a]
	(2.191)	(3.472)	(3.453)	(3.800)	(0.316)	(0.533)	(0.511)	(0.477)
Experience	0.399	0.669	0.388	0.438	0.194[a]	0.192	0.163	0.259[b]
	(0.318)	(0.488)	(0.498)	(0.491)	(0.068)	(0.138)	(0.116)	(0.109)
	Panel B: Probability of Playing for the Lowest League							
Season of Observation	First	First	Second	Third	First	First	Second	Third
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Quality	-3.160	1.244	-4.003[a]	-10.026[a]	-1.084	-0.610	-0.631	-1.382
	(2.456)	(0.846)	(0.923)	(1.300)	(1.235)	(0.634)	(0.883)	(1.663)
Initial Elo	-0.142	-0.118	-0.145	0.205	0.192	0.246	-0.111	0.112
	(0.417)	(0.520)	(0.620)	(0.710)	(0.240)	(0.254)	(0.252)	(0.305)
Age	-2.234	-3.800	-3.197	0.135	0.757[a]	1.112[a]	0.496	0.486
	(1.776)	(3.147)	(2.858)	(4.368)	(0.260)	(0.344)	(0.414)	(0.487)
Experience	0.207	0.424	0.733[b]	-0.753	0.017	0.119	-0.069	0.054
	(0.282)	(0.552)	(0.313)	(0.749)	(0.060)	(0.127)	(0.114)	(0.102)
Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	905	349	349	349	12,352	5,755	5,755	5,755
F-stat	22.286	67.939	67.939	67.939	21.113	23.655	23.655	23.655

Notes: The dependent variable changes across the 2SLS specifications. **Panel A:** Probability of strict Elo increase over different years: one (Col. 1-2 and 5-6), two (Col. 3 and 7) and three (Col. 4 and 8). **Panel B:** Probability of playing mainly for any league but the lowest during the season considered. Samples in Col. 2 to 4 and 6 to 8 are restricted to observations consistent with the measure of improvement over three seasons. Controls are in log. Fixed effects are defined at the player-club and at the season level. Standard errors are in parentheses and clustered at the club level with [a], [b], and [c], respectively, denoting significance at the 1, 5, and 10 percent levels.

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