Influence of Experts' Domain-specific Knowledge on Risk Taking in Adversarial Situations

Journal of Expertise
2020. Vol. 3(2)

ISSN 2573-2773

Philippe Chassy[1] and Fernand Gobet[2]
[1] Mathematical Psychology lab, University of Liverpool, UK
[2] London School of Economics and Political Science, UK

Correspondence: Philippe Chassy, Philippe.Chassy@liverpool.ac.uk

Abstract
Experts play a considerable role in society, as they have to evaluate the risk of policies in many fields of social life and in adversarial situations (e.g., the military). Yet, the influence of expertise on risk taking in adversarial situations has received little attention. An examination of the strategies used by chess players ranging from amateurs to masters in competitive games (n = 73,341) revealed an unexpected pattern of results. First, the majority of players favored the riskier strategy. This result is in line with the literature on economic decision making that indicates a tendency to take risks in situations where the outcome can be either positive or negative. More surprising is our second finding: As skill increased, the majority of players still adopted a risk seeking attitude but the proportion of players taking a more conservative approach increased. This result would tend to indicate that experts making decisions with impact on their own life become increasingly risk averse. Overall, our findings indicate that knowledge moderates but does not eliminate risk taking behavior. They also highlight that risk taking in adversarial situations might result from a complex set of factors. Further research should establish which psychological processes drive players to adopt a risk taking or conservative strategy in their games.

Keywords
Risk, expertise, uncertainty, strategy, adversarial situations

Introduction
Evolutionary pressures drive individuals to compete for resources. Occasionally, people or groups decide to engage in high-risk operations to win over the competition. The confrontation, whether direct or indirect, will have significant consequences for all parties involved. At the group level, high-risk operations are common in institutionalized activities such as politics, business, and the military. Competition can be observed at the individual level in both direct confrontations such as in sports and indirect oppositions such as promotion at work. In these real-life situations, characterized by potential loss, people face uncertain environments where risks cannot be evaluated precisely. Due to this uncertainty, society relies on experts to inform and often establish strategies (Knighton, 2004; Vertzberger, 1995). Despite its importance, the actual influence of experts on risk taking in high-risk situations has not received much attention in the scientific literature (Gobet, 2016). Yet as experts inform key decisions in society, there is a need to understand how experts evaluate risk and set their attitude with respect to potential losses. In the present paper, we evaluate the influence of expert knowledge on strategic risk by examining

decisions at the individual level. To ensure that decisions are concrete, we selected a domain where deciders incur the consequences of their decisions.

Attitude to risk has been extensively explored in laboratory conditions with experiments involving economic decisions (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). In situations that can have either a positive or a negative outcome, the bulk of the evidence points to individuals being risk seeking (Birnbaum, 2008; Ert & Erev, 2013). Perceived risk has been shown to depend upon how the decider frames the situation (Birnbaum, 2008; Kahneman & Tversky, 1984). Crucially, it is during the phase of building a representation of the situation that experts' domain-specific knowledge provides them with a substantial advantage over non-experts. This representation, built nearly instantaneously (Chassy & Gobet, 2011a), enables experts to solve simple problems correctly within a few seconds (Van der Maas & Wagenmakers, 2005). Considering that recognition of strategic features is rapid and immediately offers potential solutions (Bilalić et al., 2009; Chassy, 2013), the influence of such domain-specific knowledge should be sizable on risks estimates. It is known that people tend to avoid situations that might involve potential loss even if there is the possibility of a gain (Ert & Erev 2008). But, once they face the prospect of a potential loss individuals become risk seeking (Scholer et al., 2010). The immediate prospect of the loss promotes risk seeking behavior—a mechanism that is served by specific brain regions (Tom et al., 2007). The evidence from various domains of expertise, on the other hand, indicates that experts tend to perceive less risk than laypeople when evaluating the level of risks in potentially damaging technologies (Slovic et al., 1995). A study from Savadori et al. (2004) has provided evidence that experts do not base their judgement on the same cues as laypeople. Taken together, these studies indicate that domain-specific knowledge modifies the construction of the problem situation, and by doing so impacts on the final estimate of risk.

These studies, however, do not put the expert in a situation wherein they would incur the consequences of their decisions. In addition, and crucially, they refer to hypothetical situations, where experts advise a policy on a fictitious experimental scenario. Testing risk taking in high-risk confrontations requires meeting several methodological criteria: a real-life situation to ensure ecological validity of the findings, a domain of expertise that puts the experts in a position wherein risk is quantifiable, a situation that is competitive, and, crucially, decisions that will impact on the decider.

Chess is one of the very few domains that meets all these methodological criteria. It is a zero-sum game where the gain of one player corresponds to the loss of the other player. Players' skill level is measured precisely and quantitatively by the Elo rating system (Elo, 1978). This feature, which is nearly unique in research into expertise, is particularly useful as, in adversarial situations, the opponent's actions might affect the course of events and with it the outcome. Knowing the opponent's level of expertise provides important information when framing the situation. Three additional features contribute to the use of chess as a fitting domain for studying risk. First, it is a visuospatial game played with the same rules worldwide, which avoids biases linked to language (Casasanto, 2008). Second, the presence of databases including games played all over the world ensures that the results will not be biased by cultural approaches to risk (e.g., Li et al., 2009). Last and most importantly, the Elo rating, initially developed as a measure of expertise, is regarded by chess players as a reward system. For most if not all players, Elo points are at the core of their chess life, as they not only indicate the level of expertise (a source of prestige) but also are the key factor upon which players are invited to play in tournaments, to participate in team competitions, and to deliver lectures.

In this context, the literature indicating dominance of loss aversion in mixed gambles (Ert & Erev, 2008; Scholer et al., 2010) implies that experts take the risky option to avoid high losses when they face weaker opponents. The attitude of the weaker players is subtler. The larger the rating difference with the better player, the higher the gain in case of a win but also the higher the probability of losing small. If the weaker player focuses on the potential gain (winning a large number of Elo points), then a risk-taking strategy might be undertaken; however, if the player focuses on the low probability of winning, then a more conservative strategy might be undertaken. To understand which factor is the most important to non-experts, Slezak and Sigman (2012) examined the speed-accuracy tradeoff of non-expert players (rating < 2000 Elo) in games where the thinking time was limited to three minutes for each player. The results indicated that weaker players tended to focus on accuracy by playing slower. Players are thus sensitive to risk, becoming more conservative when meeting better rated opponents.

Our study aimed at expanding on this initial finding by examining the decisions of experts. We examined the strategies chosen by chess players during competitive events that took place during one entire year all over the world. Our analysis is based on the first move played in the game, a move that is often chosen by players *before the game*. At the beginning of the game, there is a definite number of strategies to choose from (Matanović et al., 1971). Different strategies involve different levels of risk. The fact that players decide the strategy they are going to play beforehand is demonstrated by the fact that they know the first moves by rote memory (Chassy & Gobet, 2011b) and that they can identify the strategy upon mere recognition of the position (Chassy, 2013).

Based on the reviewed literature, we put forward three hypotheses. First, considering that chess players willingly engage in a game which in essence is a battle, we would expect the players to be predominantly risk takers in this context. Second, the theoretical considerations discussed above suggest that experts' domain-specific knowledge will enable them to generate a more accurate representation of the situation and thus to evaluate risk better; thus, based on the fact that all players are essentially sensation seekers (Joireman et al., 2002), we predicted that experts would be more risk taking than non-experts. Third, we would predict that players adapt to their opponent levels of skill so as to minimize loss.

Method

Materials

We used the games from a commercial chess database (Fritz Database, version 12; Morsch, 2009). We selected all the games played over a year, namely from April 1, 2008, to March 31, 2009, by players whose rating spanned the 1600-2399 Elo range. The final sample consisted of 73,341 games. Players were assigned to one of four groups: amateurs (1600-1799 Elo, M = 1719.18; SD = 56.57), club players (1800-1999 Elo, M = 1915.62; SD = 56.05), candidate masters (2000-2199 Elo, M = 2103.34; SD = 57.21), or masters (2200-2399 Elo, M = 2292.64; SD = 57.16). (To minimize ambiguity between the candidate-master and the master classes, we will refer to the candidate-master class as the candidate class.) The cutoff point at 2,000 Elo corresponds to the definition of chess expertise in the scientific literature (Elo, 1978). Hence, our sample was made of two non-expert and two expert groups. The four selected skill levels ensured that a sufficiently large number of games were used and had the advantage that the levels occupied adjacent positions in the rating scale, which made comparisons easier.

Measure of Risk

Although other measures exist, it is common in research on judgment and decision making to use standard deviation (σ) around the expected value (μ) to define risk (Rothschild & Stiglitz, 1970; Damodaran, 2007). The application of this definition to risk taking in chess has already proven useful to analyze attitude to risk in adversarial situations (Chassy & Gobet, 2015). After partitioning the data set as a function of the first move, we calculated the variance around the mean outcome for each skill to determine their level of risk (see Appendix 1). Based on an extensive chess literature (e.g., Matanović, et al., 1971), one can categorize the first moves of the game in two main groups: open games (1.e4) and closed games (1.d4, 1.c4, and 1.Nf3). Prior to our sample year, these four moves account for 96% of all openings on a period covering 5 years (2003-2007), for the same player range (1600-2399). To estimate risk directly from the empirical data, we used the games in the Fritz database (Big Database 2010). For all games where moves were traceable during the period of 2002-2007, we analyzed the pattern of wins, draws, and losses. The time window 2002-2007 was selected so as to be close to the period being analyzed and to be sufficiently large to enable accurate estimates. Games with only one move or incomplete games were removed from the database ($n < 1\%$). Risk, defined as variance around the mean outcome, was estimated by analyzing 1,474,378 games. For all skill levels pooled, σ was 42.69% for open games and 41.59% for closed games; the difference is statistically highly reliable given the large number of observations (see below). In line with the definition of risk, as compared to closed games open games increase the chances of both winning (39.58% vs 38.91%) and losing (33.66% vs 30.93%) while decreasing the chances of drawing (26.75% vs 30.16%). Our empirical definition of risk is in line with the subjective experience of chess authorities for over a century (e.g., Aagard, 2002; Gunsberg, 1901). Since open games involve more risks, they were labeled as “risky”, and closed games were labeled as “conservative”. The reader should bear in mind the fact that these labels refer to relative risk, since conservative openings still entail some degree of risk.

Payoffs

To shed light on the factors influencing the choice of risky or conservative strategies by chess players, we calculated the payoff for each game. We followed the mathematical procedures developed by Elo (1978). The first step consisted in computing the rating difference between the player initiating the game (henceforth, first player) and the player playing the second move (henceforth, second player), see equation 1 below. Then, we calculated the probability of winning of the first player in each game (see equation 2). The results were checked against the table of probabilities provided by the International Chess Federation (FIDE).

The second step consisted in calculating the potential change in rating (see equations 3 and 4 below). As indicated by FIDE, the k parameter is adjusted to various situation (e.g., age of the player, stage of career). To facilitate comparisons, we used $k = 20$ for the four skill levels. As a control for the correctness of our calculations of the payoffs and probabilities, we calculated the utility of each game (Von Neumann & Morgenstern, 2007). All games should have a zero value as chess is, by definition, a zero-sum game; this theoretical assumption was verified (see Appendix 2).

$$\text{Rating difference: } \Delta = \text{Elo}_{\text{second}} - \text{Elo}_{\text{first}} \quad (1)$$
$$\text{Probability of winning of the first player: } p = (1+10^{\Delta/400})^{-1} \quad (2)$$
$$\text{Payoff of the game (win): Payoff} = k(1 - p) \quad (3)$$
$$\text{Payoff of the game (loss): Payoff} = k(0 - p) \quad (4)$$

Results

The data show that the risky strategy was selected more often (54.40%) than the conservative strategy (45.60%); a difference that that is statistically significant as indicated by a chi-square analysis on frequencies, $\chi^2(1, n = 73{,}341) = 569.184$, $p < .05$, $\varphi = .09$. This result supports the hypothesis that chess players are predominantly risk seeking. To explore whether the level of expertise influences risk taking, we compared the frequencies of occurrence of risky and conservative systems as a function of skill level. Figure 1 shows that, at all risk levels, risky strategies dominate conservative strategies. A key finding is that, as their skill increases, players tend to be more conservative. The difference between levels of expertise is statistically significant, $\chi^2(3, n = 73{,}341) = 117.742$, $p < .05$, $\varphi = .04$.

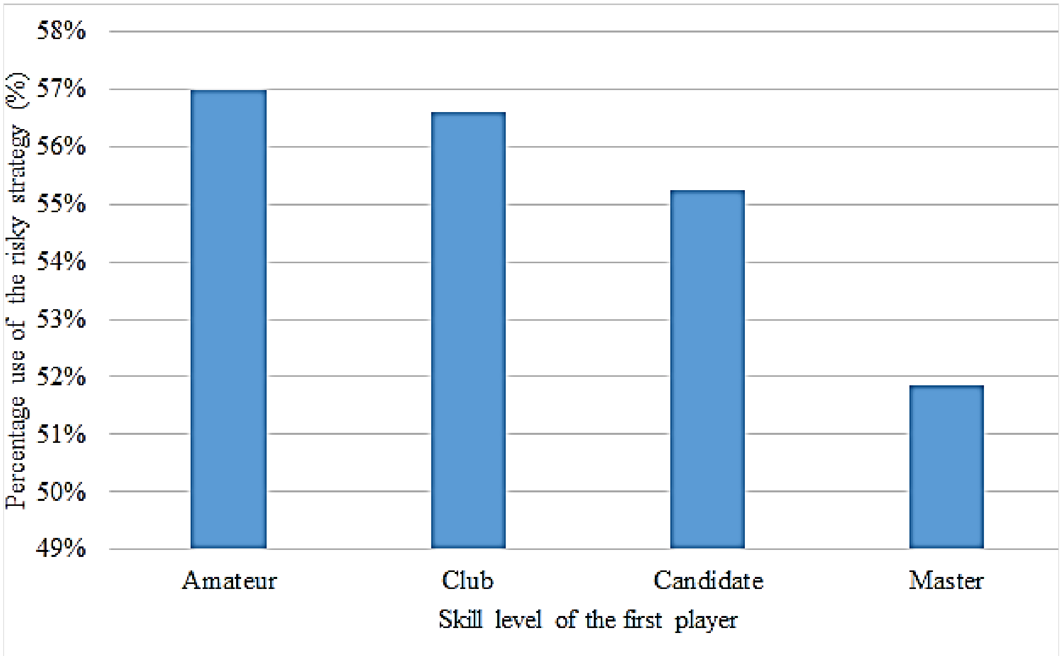

Figure 1. Percentage use of the risky strategy for each group of skill.

We then analyzed whether players are influenced by the level of the opponent in their attitude to risk. This is a crucial analysis since it shows whether players adapt to the opponent's level of skill. Figure 2 shows the percentage of first players who selected a risky strategy as a function of the level of skill of their opponents. While variations in the use of risky strategies can be noted within a class, Figure 2 confirms a global trend of decreasing risk as the skill level of a player increases. But Figure 2 also highlights two noticeable situations: *Amateurs meeting Masters* and vice-versa. Amateurs, like Masters, turn more cautious than against any other opposition when they meet the opposite end of the spectrum of skill.

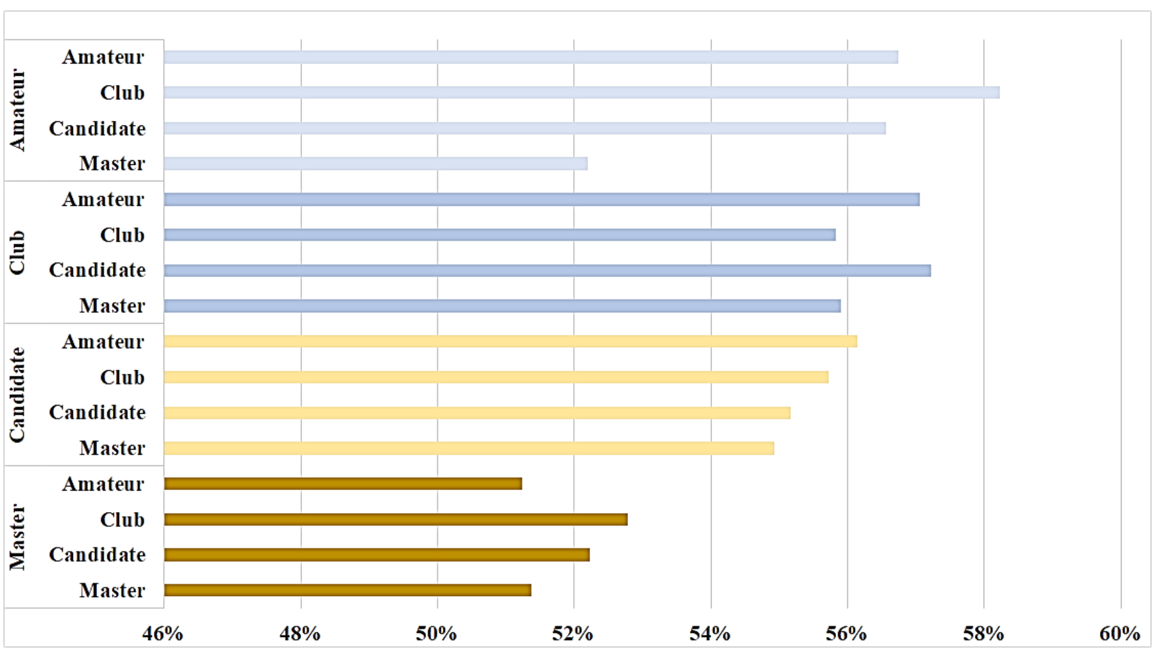

Figure 2. Risk taking of the first player as a function of the skill level of the first player and the opponent.

Table 1 reports, for each of the 16 conditions, the average payoff and probability, the percentage of risky strategy, and the χ^2 test of independence. Payoff and probability characterize the situation that players were facing. Their decision, which is whether to adopt a conservative or risky strategy, is reflected in the average percentage of risky strategies used. To illustrate with an example, we consider the case of first players at club level facing a second player at master level. In the case of a win, the club players could win 17.45 Elo points on average and in the case of a loss, they incurred an average loss of 2.55 Elo points; the low probability of winning (p = .13) and the high probability of losing (p = .87) defined the challenge these players were facing (see Appendix 2). In these conditions, club players decided to use the risky strategy in 55.90% of the games; a choice that departs significantly from an equal distribution of conservative and risky strategies, as indicated by the associated significant χ^2 value of 36.82.

Table 1. Mean values for the payoffs and probabilities in case of victory or defeat of the first player.

Player		Victory		Defeat		Mean risk	*n*	χ^2
First	Second	Payoff	*p*	Payoff	*p*			
Amateur	Amateur	9.84	0.51	-10.16	0.49	56.74%	994	18.06*
	Club	14.84	0.26	-5.16	0.74	58.23%	1937	52.54*
	Candidate	17.55	0.12	-2.45	0.88	56.57%	1386	23.90*
	Masters	19.13	0.04	-0.87	0.96	52.20%	341	0.66
Club	Amateur	5.10	0.75	-14.90	0.26	57.05%	2042	40.62*
	Club	9.97	0.50	-10.03	0.50	55.82%	3522	47.73*
	Candidate	14.66	0.27	-5.34	0.73	57.22%	6159	128.32*
	Masters	17.45	0.13	-2.55	0.87	55.90%	2644	36.82*
Candidate	Amateur	2.47	0.88	-17.53	0.12	56.14%	1466	22.10*
	Club	5.30	0.74	-14.70	0.27	55.72%	6455	84.60*
	Candidate	9.97	0.50	-10.03	0.50	55.16%	9561	101.89*
	Masters	14.57	0.27	-5.43	0.73	54.93%	10352	100.52*
Masters	Amateur	0.87	0.96	-19.13	0.04	51.24%	363	0.22
	Club	2.55	0.87	-17.45	0.13	52.78%	2702	8.33*
	Candidate	5.39	0.73	-14.61	0.27	52.23%	10737	21.37*
	Masters	10.00	0.50	-10.00	0.50	51.37%	12680	9.55*

Note: * Significant at $p < .05$, n: number of games

The independence tests reported in Table 1 indicate for each of the 16 conditions whether the distribution of games using risky or conservative strategy departs from chance or not. In fourteen conditions out of 16, chess players significantly favored the risky strategy over the conservative one. Only when amateurs and masters met did the players not show this preference. As indicated in Table 1, the significant differences are found in the two conditions that have the lower number of cases, casting a shadow on the validity of the finding.

Discussion

This paper has investigated risk taking in chess, a zero-sum confrontational situation. We have analyzed the strategic choices made by players of four different levels of skill (amateur, club, candidate, and master level). The analysis was conducted on 73,341 chess games that were played across the globe in an entire year. The results support the hypothesis that chess players, whether expert or not, tend in general to choose the riskier option at the beginning of the game.

The second result of interest is that risk levels are inversely proportional to skill. Finally, due to differences in statistical power across conditions, we cannot come to a definite conclusion as to whether our data support our third hypothesis; it remains unclear whether players adapt to the opponent. Our findings inform the current literature on risk taking and open new avenues for investigating decision making processes in adversarial situations.

As predicted by Tversky and Kahneman's (1992) theory of decision making, loss aversion drove a majority of players to use more risk-seeking strategies. Yet, a substantial 45.60% of the players favored conservative strategies, a figure highlighting the specificity of confrontational situations. The dynamics underlying the choice of a strategy, whether conservative or risky, emerge from interaction between numerous factors. One factor that might play a key role is players' personality. It is known that children who play chess score higher on the Big Five dimensions of Intellect/openness and Energy/extraversion than children who do not play chess (Bilalić et al., 2007), although this pattern of results was not found with adult chess players (Vollstädt-Klein et al., 2010). Another personality trait potentially playing a role in determining the level of risk undertaken by players is sensation seeking (Horvath & Zuckerman, 1993)—the keenness to engage in activities yielding intense experiences. Chess players have been shown to score higher than the general population on sensation seeking (Joireman et al., 2002), a trait that is unsurprisingly correlated with risk taking behaviors (Kern et al., 2014). We speculate that chess players' attitude to risk results from the balance between the natural tendency to avoid loss, on the one hand, and chess players' personalities, on the other hand. The net result of these opposing forces, which vary from player to player, determines whether a player will be driven primarily by loss aversion and choose the conservative option or by sensation seeking and thus be more risk taking.

Our results highlight that experts use more conservative strategies. This key result is unexpected since it stands in stark contrast with previous literature. In domains of expertise that do not include competition or confrontations, estimates of risk by experts have been lower than estimates of risk by laypeople (Slovic, et al., 1995). Since experts perceive less risk in a given situation, they usually are more risk taking than non-experts who are more conservative because of the higher level of perceived risk. Assuming that experts have on average the same level of risk tolerance would lead naturally to the conclusion that they might take more risks. Another factor that might increase risk taking in confrontational situations is self-confidence (Krueger & Dickson, 1994). Since experts in various domains demonstrate high levels of confidence (Shanteau, 1988), we could reasonably think that the level of risk would be higher than for laypeople. Our results suggest otherwise. It appears that, in confrontational situations, loss aversion outweighs self-confidence and risk seeking, and this is more the case with experts than with club players. We would attribute this counter-intuitive result to the fact that our study is strictly ecological. Most studies conducted in the field of risk and risk taking are laboratory manipulations of fictitious costs and gains. Although these studies are informative about the cognitive processes underpinning the evaluation of costs, the deciders do not incur any real penalty in case of losses. The chess players in our sample were putting their Elo rating at stake in each game. The reality of a potential loss has made chess players relatively conservative, thus showing sensitivity to potential loss. Paradoxically, chess players' conservatism might directly stem from their huge amount of domain-specific knowledge. The representation of the situation, which is richer for experts (Campitelli & Gobet, 2004), drives them to consider more potential outcomes and thus get a more accurate representation of uncertainty; this in turn might generate more loss aversion. A second factor potentially accounting for the conservative attitude of many players is the fact that the situation is confrontational. While most experiments conducted on risk-taking provide probabilities of losing, they are set as gambles where the loss of the decider is not necessarily beneficial to a competitor. In a chess game, there is a will of the opponent to win, and thus if nothing is done, the game will be lost. As it entails a threat, this confrontational situation might make players more prudent.

Our third hypothesis stating that players adapt risk to the opponent's skill level has found some supportive evidence in the statistical analysis of the distribution of risky and conservative strategies; however, as highlighted above, in the two cases where statistically significant differences were not observed, the number of players was drastically smaller than in the other fourteen conditions. Thus, there is an issue of statistical power. On the one hand, statistics do not disprove our views. There is some, even if fractional, evidence that amateurs and master players adapt to their opponent when the Elo rating difference is at its highest. However, the analysis relies on a relatively limited number of cases as compared to other conditions. In several of the other conditions, the same proportion of conservative strategies revealed a statistical difference between conservative and risky strategies favoring the latter ones. So, on the other hand, we have not reached the point where evidence is undisputable. As a consequence, it is not clear whether there is a definite trend or whether our data are an artefact reflecting random fluctuations in the use of conservative strategies. We have to conclude at this point that the debate remains open and must be investigated in future studies.

The present study has limitations that should be kept in mind for a correct interpretation of the results. An important aspect of the study was that damage was limited to chess rating. Even though Elo ratings impact on status and potential income, they are definitely different from physical damage and our results are not predictive, for example, of the levels of risk in combat situations. Second, the effects sizes are small; thus, while the results are theoretically important, their practical implications might be more limited. A third factor to bear in mind is that the culture of the domain plays a role in biasing non-experts' risk attitudes. In chess, many chess books value openings that lead to aggressive, high-risk situations for the first player (e.g., Levy & Keene, 1976). The first move 1.e4, which was found risk-seeking in our study, was even promoted by a world champion as the best move (Fischer, 1995). This type of advice and the social pressure that might accompany it could bias non-experts to take more risks. As noted by Pleskac and Hertwig (2014), social norms can influence risk taking, and chess is certainly a domain where the norm is to take risks. Fourth, though competitive, non-expert players might approach the game paying less attention to the potential outcome, as it would not impact them as much as it would impact professional players. Lastly, we would like to mention that our measure of risk based on the first move is somewhat arbitrary. Our use of the first move has the merit of measuring risk ecologically, but players' attitude to risk might be more subtle than a binary choice between risky and conservative options.

A new picture of risk taking in adversarial situations emerges. Whereas, in line with theoretical predictions, chess players are predominantly risk taking when playing chess, the results also brought to light the fact that a significant proportion of players chose the more conservative option. Such a finding calls for a revision of risk-taking theories that predict unconditional loss-averse behaviors. With respect to the influence of domain-specific knowledge, we have showed that experts in adversarial situations are more conservative, thus suggesting that domain-specific knowledge increases loss aversion. The extent to which this finding applies to other adversarial situations is left undetermined but opens an avenue for future investigations on the relationship between domain-specific knowledge and attitude to risk. In conclusion, experts' strategic thinking integrates two factors: domain-specific information which makes experts more conservative and the level of expertise of the opponent which can make experts more risk taking.

Author's Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the

research in this article.
The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

References

Aagard, J. (2002). *Excelling at chess*. London: Everyman Chess.
Bilalić, M., McLeod, P., & Gobet, F. (2007). Personality profiles of young chess players. *Personality and Individual Differences, 42*, 901-910.
Bilalić, M., McLeod, P., & Gobet , F. (2009). Specialization effect and its influence on memory and problem solving in expert chess players. *Cognitive Science, 33*, 1117-1143.
Birnbaum, M. H. (2008). New paradoxes of risky decision making. *Psychological Review, 115*, 463-501.
Campitelli, G., & Gobet, F. (2004). Adaptive expert decision making: Skilled chessplayers search more and deeper. *Journal of the International Computer Games Association, 27*, 209-216.
Casasanto, D. (2008). Who's afraid of the big bad Whorf? Crosslinguistic differences in temporal language and thought. *Language Learning, 58*, 63-79.
Chassy, P. (2013). The role of memory templates in experts' strategic thinking. *Psychology Research, 3*, 276-289.
Chassy, P., & Gobet, F. (2011a). A hypothesis about the biological basis of expert intuition. *Review of General Psychology, 15*, 198-212.
Chassy, P., & Gobet, F. (2011b). Measuring chess experts' single-use sequence knowledge: An archival study of departure from 'theoretical' openings. *PLoS ONE, 6*(11), e26692.
Chassy, P., & Gobet, F. (2015). Risk taking in adversarial situations: Civilization differences in chess experts. *Cognition, 141*, 36-40.
Damodaran, A. (2007). *Strategic risk taking: A framework for risk management*. Upper Saddle River, NJ: Wharton School Publishing.
Elo, A. (1978). *The rating of chessplayers, past and present*. New York: Arco.
Ert, E., & Erev, I. (2008). The rejection of attractive gambles, loss aversion, and the lemon avoidance heuristic. *Journal of Economic Psychology, 29*(5), 715-723.
Ert, E., & Erev, I. (2013). On the descriptive value of loss aversion in decisions under risk: Six clarifications. *Judgment and Decision Making, 8*, 214-235.
Fischer, R. J. (1995). *My 60 memorable games*. London: Batsford.
Gobet, F. (2016). *Understanding expertise*. London: Palgrave Macmillan.
Gunsberg, I. (1901). *The chess openings*. London: Bell and Sons.
Horvath, P., & Zuckerman, M. (1993). Sensation seeking, risk appraisal, and risky behavior. *Personality and Individual Differences, 14*, 41-52.
Joireman, J. A., Fick, C. S., & Anderson, J. T. I. (2002). Sensation seeking and involvement in chess. *Personality and Individual Differences, 32*, 509-515.
Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica, 47*, 263-291.
Kahneman, D., & Tversky, A. (1984). Choices, values and frames. *American Psychologist, 39*, 341-350.
Kern, L., Geneeau, A., Laforest, S., Dumas, A., Tremblay, B., Goulet, C., et al. (2014). Risk perception and risk-taking among skateboarders. *Safety Science, 62*, 370-375.
Knighton, R. J. (2004). The psychology of risk and its role in military decision-making. *Defence Studies, 4*, 309-334.
Krueger, N., & Dickson, P. R. (1994). How believing in ourselves increases risk taking: perceived self efficacy and opportunity recognition. *Decision Sciences, 25*, 385-400.
Levy, D., & Keene, R. (1976). *An opening repertoire for the attacking club player*. London: Batsford.
Li, S., Bi, Y.-L., & Zhang, Y. (2009). Asian risk seeking and overconfidence. *Journal of Applied Social Psychology, 39*, 2706-2736.

Matanović, A., Molorović, M., & Božić, A. (1971). *Classification of chess openings*. Belgrad: Chess Informant.
Morsch, F. (2009). Fritz (Version 12). Hamburg, Germany: Chessbase.
Pleskac, T. J., & Hertwig, R. (2014). Ecologically rational choice and the structure of the environment. *Journal of Experimental Psychology: General, 143*(5), 2000-2019.
Rothschild, M., & Stiglitz, J. E. (1970). Increasing risk: I. A definition. *Journal of Economic Theory*, *2*(3), 225-243.
Savadori, L., Savio, S., Nicotra, E., Ruminati, R., Finucane, M., & Slovic, P. (2004). Expert and public perception of risk from biotechnology. *Risk Analysis*, *24*, 1289-1299.
Scholer, A. A., Zou, X., Fujita, K., Stroessner, S. J., & Higgins, E. T. (2010). When risk seeking becomes a motivational necessity. *Journal of Personality and Social Psychology, 99*(2), 215.
Shanteau, J. (1988). Psychological characteristics and strategies of expert decision makers. *Acta Psychologica, 68,* 203-215.
Slezak, D. F., & Sigman, M. (2012). Do not fear your opponent: Suboptimal changes of a prevention strategy when facing stronger opponents. *Journal of Experimental Psychology: General, 141*(3), 527-538.
Slovic, P., Malmfors, T., Krewski, D., Mertz, C. K., Neil, N., & Bartlett, S. (1995). Intuitive toxicology II: Expert and lay judgments of chemical risks in Canada. *Risk Analysis, 15,* 661-675.
Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. *Science*, *315*(5811), 515-518.
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*, 297-323.
Van der Maas, H. L. J., & Wagenmakers, E. J. (2005). A psychometric analysis of chess expertise. *American Journal of Psychology, 118*, 29-60.
Vertzberger, Y. Y. L. (1995). Rethinking and reconceptualizing risk in foreign policy decision-making: a sociocognitive approach. *Political Psychology*, *16*, 347-380.
Vollstädt-Klein, S., Grimm, O., Kirsch, P., & Bilalić, M. (2010). Personality of elite male and female chess players and its relation to chess skill. *Learning and Individual Differences, 20*, 517-521.
Von Neumann, J., & Morgenstern, O. (2007). *Theory of games and economic behavior*. Princeton University Press.

Submission: 22 March 2018
Resubmission: 25 January 2020
Acceptance: 4 May 2020

Appendix 1. Calculation of risk

Risk is calculated as variation around the mean. For a sample of *n* observations of outcome, risk is calculated in three steps:

$$\overline{x} = \frac{\sum x}{n}$$

$$\sigma^2 = \sum(x-\overline{x})^2 / n$$

$$\text{Risk} = \sqrt{\sigma^2}$$

In full agreement with the regulations of the International Chess Federation (Section 11.1 of the FIDE Laws of Chess [see https://www.fide.com/FIDE/handbook/LawsOfChess.pdf]), a win is coded as 1, a loss as 0 and a draw as 0.5. Following the same regulations, the expected result is the win probability plus half the probability of drawing.

Hence an opening move that would lead to 40% wins, 30% draws and 30% losses on a sample of n = 1,000 games would have a mean expectancy of

$M = (.40 \times 1) + (.30 \times 1/2) = .55$ thus entailing a risk variance of

$\sigma^2_R = [(1 - .55)^2 \times 400 + (.5 - .55)^2 \times 300 + (0 - .55)^2 \times 300)] / 1000 = 0.1725$ and so,

$\text{risk} = \sqrt{0.1725} = 0.415331$.

Appendix 2: Zero-Sum Game and Distribution of Payoffs in the Sample

Chess is a zero-sum game, so the gain of one player is the loss of the other. For example, let us consider player A, rated 1800 Elo, playing against player B, rated 2200 Elo. By following the formulas provided by Elo (1978) and rounding numbers to the nearest integer, we obtain the following information: Player A has a 9% chance of winning 18 Elo and a 91% chance of losing 2 Elo. In case of a win, Player A wins 18 Elo and Player B loses 18 Elo. In case of loss, Player A loses 2 Elo and Player B wins 2 Elo. In both cases, the loss of a player equals the gain of the other, but the stakes differ according to the outcome of the game.

In our sample of 73,431 games, the combination of four levels of skill for the first player and four levels of skill of the second player generates 16 conditions. The probabilities of winning and losing for the first player are depicted in Figure A1. The probability distribution of winning as calculated from the data is in dark green and the probability distribution of losing in light green. Figure A1 shows that the probabilities for the win and loss prospects are mirror images of one another as they naturally sum to 1. Figure A2 depicts the distribution of payoff in Elo points in case of gains (dark blue) and loss (light blue). Density for payoffs exactly shows the distribution of potential gains and losses for all 73,341 games. Taken together, Figures A1 and A2 depict the prospects that the players were facing.

In all games, following the formulas provided by Elo (1978), we found that the added expected utilities for each outcome cancelled each other, confirming that chess is a zero-sum game.

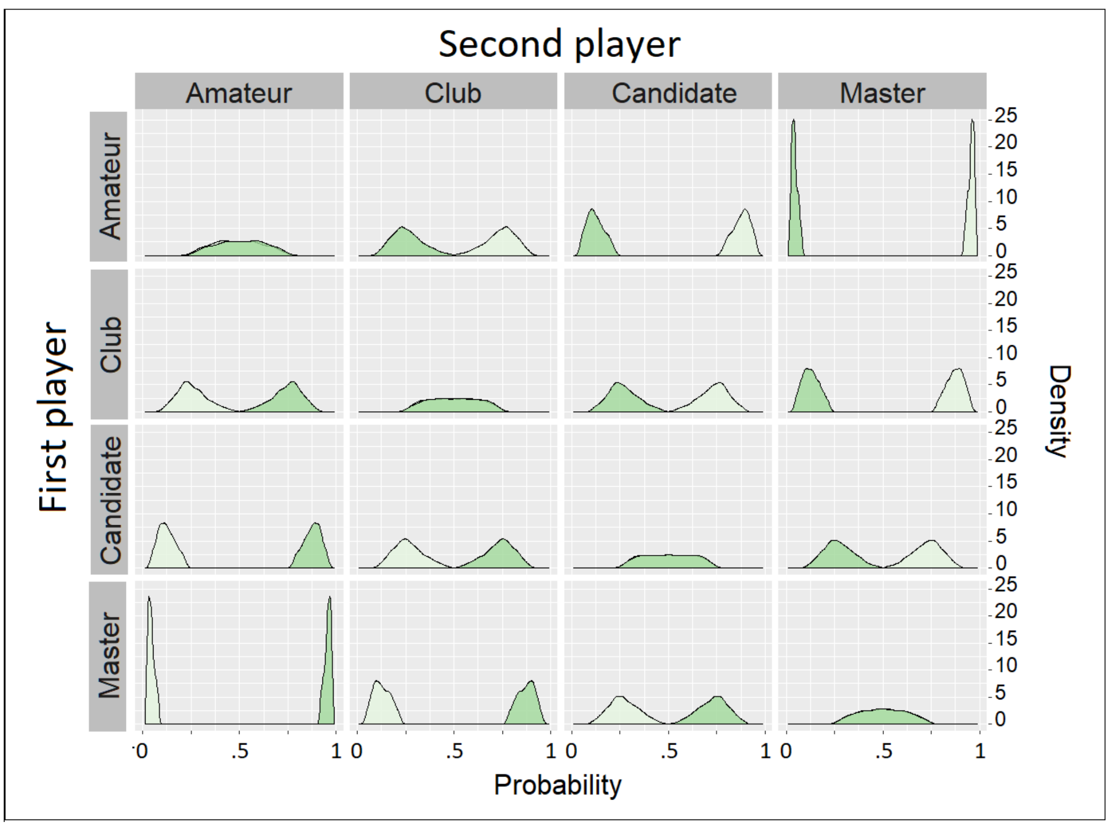

Figure A1. Probability distribution of winning (dark green) and losing (light green) for the first player.

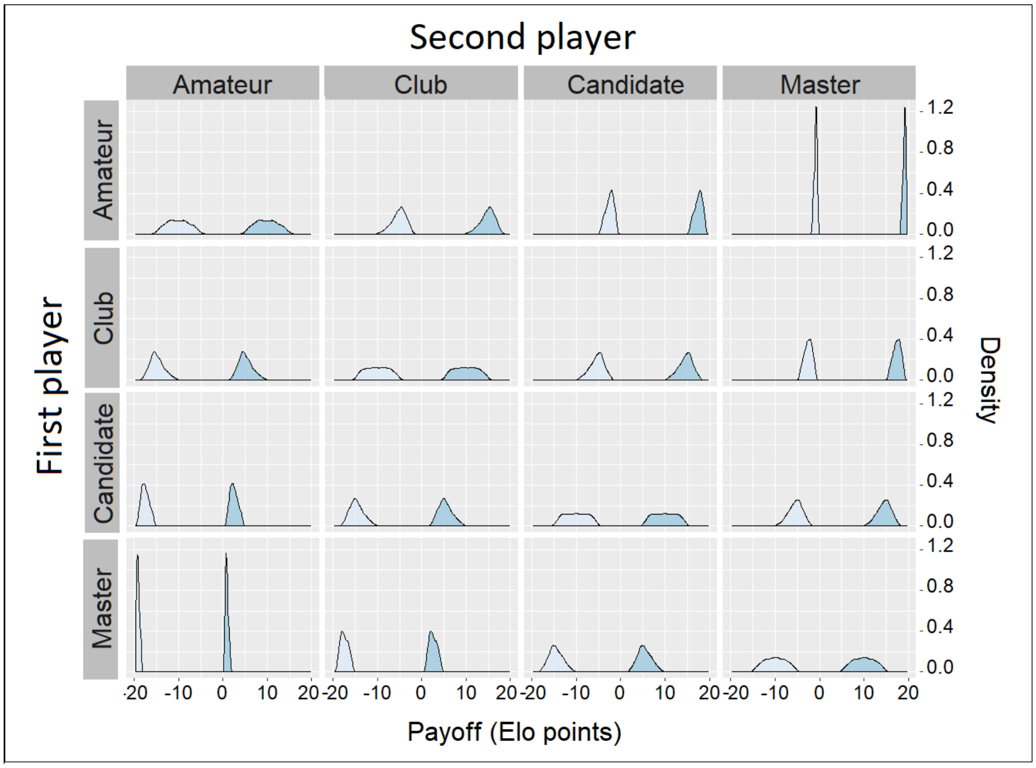

Figure A2. Distribution of payoffs as a function of the skill of the first and second players for both winning (dark blue) and losing (light blue), from the first player standpoint.