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# Are Competitors Forward Looking in Strategic Interactions? Field Evidence from Multistage Tournaments*

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**Abstract**

This paper investigates whether decision makers are forward looking in dynamic strategic interactions and incorporate variations of continuation values in their choices. Using data from professional and semi-professional basketball tournaments, we find that the expected relative strength of a team in future interactions indeed affects behavior in the present. The results also show that the response to changes in the continuation value is stronger if the structure of prizes is convex across stages, if the players are in a decisive game and if the prevalence of free riding within a team is low.

*JEL Classification:* M51; J33

*Keywords*: Promotion tournament; multistage contest; elimination; forward-looking behavior; heterogeneity

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*We're going into it to win the series. But you've got to take it game by game, one game at a time.*

Tyronn Lue[1]

# 1 Introduction

Most situations of economic decision making, in particular in the context of internal labor markets, involve dynamic and strategic aspects. For instance, in the context of promotion tournaments, workers interact with their employer as well as with their co-workers repeatedly and face incentives that involve strategic and dynamic components related to higher pay, better promotion chances, or attractive outside offers in the future. Hence, the power and usefulness of such tournament schemes for incentive provision and promotion decisions in organizations depends crucially on an inherently dynamic trade-off, which requires forward-looking behavior of agents in order to be effective. Several influential contributions explicitly consider the dynamic incentive effects of promotion tournaments. For instance, Rosen (1986) argues that the continuation value of future promotion possibilities is an important determinant of current effort choices. Likewise, Ghosh and Waldman (2010) assume that competing workers anticipate the signal value of a promotion for future wage negotiations. The key assumption underlying these views is that the next promotion is not the ultimate goal, but rather a means to an end to forward-looking agents, namely either the prerequisite for future promotions to even more attractive positions within the same organization, or a signal observable by competing organizations that allows workers to demand higher wages. This should be reflected in the influence of expected future payoffs on behavior.

While in theory the influence of dynamic incentives is rather straightforward and intuitive, in reality it is not clear whether and to what extent decision makers incorporate dynamic incentives in their behavior. On the contrary, advice to take only 'one step at a time' and disregard complex future consequences of current actions is quite common.

[1] Tyronn Lue, head coach of the Cleveland Cavaliers on ESPN. Retrieved August 11, 2016. http://www.espn.com/nba/playoffs/2016/story/_/id/16243732/nba-finals-2016-tyronn-lue-finds-voice-cleveland.

As indicated by the introductory quote from basketball, professional athletes often focus entirely on the current game and claim to avoid thinking about the future consequences of winning or losing, i.e., the continuation value beyond success in the current game.[2] Despite the ubiquity of dynamic incentives in the theoretical literature, whether and to what extent individuals act in a forward looking way when faced with dynamic incentives such as promotion incentives in tournament settings has not been tested systematically. There is currently little to no empirical evidence whether decision makers are indeed forward looking in dynamic strategic interactions as often assumed in theory, even though the existence and extent of forward-looking behavior is essential for many practical purposes.

This paper investigates empirically whether agents are forward looking in multistage tournaments, testing one of the central theoretical predictions of the tournament literature, namely that agents are not only competing for the immediate prize for winning in any non-final round of multistage tournaments, but also for the continuation value of remaining in the tournament that entails the chance to win additional prizes in future rounds, see, e.g., Rosen (1986). We address the question by investigating how the expected relative strength in future interactions affect behavior in dynamic tournament situations, based on the predictions of a canonical multistage pairwise elimination tournament model, extended to a team setting. Since continuation values are typically unobservable in field data, the analysis exploits the fact that the continuation value is decreasing in the strength of future opponents, ceteris paribus: reaching the next round in a multistage tournament is more attractive if the future opponent is weak and chances to win a prize in the next round are high, than if the future opponent is strong and chances to win a prize in the next round are low. Consequently, everything else equal, current effort is expected to decrease in the strength of the future opponent if, and only if, agents are forward looking and take the continuation value into account. Alternatively, if agents focus entirely on the immediate consequences of their actions and omit the continuation value, current effort should be independent of the strength of the future opponent.

[2] Similar quotes can be found from other sports. For instance, the famous NFL coach Charles Henry "Chuck" Noll once said "The key to a winning season is focusing on one opponent at a time. Winning one week at a time. Never look back and never look ahead." (BrainyQuote.com. Retrieved August 11, 2016. http://www.brainyquote.com/quotes/quotes/c/chucknoll392799.html).

Considering teams rather than individuals in this context has several advantages. First, team work is the rule rather than the exception in most occupations, and performance is often measured at the team level. The most recent European Working Conditions Survey (EWCS 2010) indicates, for example, that close to 60% of all employees in member states of the European Union work in teams, and available numbers for the U.S. are comparable. Second, the competition between individuals is a special case of competition between teams. In particular, extending the Rosen (1986) multistage tournament model to a team setting indicates that aggregate team effort equals effort provision by individual contestants in the absence of free-riding, and that free-riding works against finding evidence for forward-looking behavior at the team level. Providing evidence in favor of forward looking behavior in teams thus provides a strong indication that decision makers indeed incorporate dynamic incentives in their choices. Moreover, we can explicitly test the theoretical prediction that free-riding within a team affects forward looking behavior, since the data allow for the construction of an appropriate empirical measure of free riding.

We use data from the playoffs of the National Basketball Association (NBA) championship tournament to test the empirical hypothesis. The NBA playoffs provide an ideal setting for this purpose. The structure of the competition implies that information on the strength of potential future opponents is publicly available, and the data provide precise information about all required elements, such as ability, effort and outcomes. Moreover, the tournament involves considerably large stakes and professional athletes are arguably familiar with the decision environment they are exposed to. Finally, the data allow us to study forward-looking behavior in the team context.

Our findings support the view that decision makers are indeed forward looking, even when being members of a team. In particular, the results show that, everything else equal, the expectation of a weaker future opponent team increases aggregate team effort in the current match. We also find that team effort is negatively affected by the ability of the current opponent, consistent with the theoretical prediction and previous evidence based on static interactions. When using the degree of competition for starting positions to measure free riding within teams, we also find that the degree to which teams incorporate their relative strength in future competitions is decreasing in the prevalence of free-riding within the team. In addition, the empirical results show that the effect of continuation values on current effort is more important the more convex is the structure of prizes across stages, as predicted by the theoretical model.

These findings have several implications for promotion tournaments. In particular, our findings show that even professional athletes who typically claim to focus entirely on the current game take account of continuation values in multistage tournaments. Employees are thus even more likely to account for continuation values in corporate tournaments where human resources management departments try to make career ladders salient for their employees. This implies that convex wage structures across hierarchy levels are likely to provide strong dynamic incentives for performance on internal labor markets in organizations. In addition, our findings indicate that team-based performance evaluations, which are common in many occupations, are unlikely to reduce dynamic incentives to provide effort in promotion tournaments if and only if the prevalence of free-riding within teams is low.

This paper adds to different strands of the empirical literature on tournaments. The results contribute to the empirical literature on multistage tournaments and contests. Even though several recent contributions provide evidence for incentive effects of continuation values when implementing multistage tournaments in the lab – see, e.g., Sheremeta (2010), Altmann, Falk, and Wibral (2012), or Stracke, Höchtl, Kerschbamer, and Sunde (2014) – we are not aware of any study that has investigated this issue using field data. The few existing studies that analyze behavior in multistage tournaments with field data focus on different aspects. Delfgaauw, Dur, Non, and Verbeke (2015) implement a two-stage elimination tournament in a field experiment, but they investigate the effect of variations in the structure of prizes and in the importance of noise *within* a given stage, not on the effect of continuation values *across* stages as done here. Brown and Minor (2014) account for dynamic incentive effects in multistage tournaments using tennis data, but they focus on implications for the selection properties using match outcomes. Our study, instead, opens the black box of how observed outcomes are achieved and investigates whether continuation values affect incentives to provide effort. Thereby, the paper also contributes to the empirical literature on the implications of tournament design for behavior, see, e.g., List et al. (2014).

The results also complement related work on basketball and soccer data that analyzes different aspects of forward looking behavior in tournaments. Taylor and Trogden (2002) use data from the NBA as we do and investigate whether teams who are unlikely to qualify for the playoffs respond to the incentive to lose that is present at the end of regular seasons. In particular, they test whether teams are forward looking and anticipate the delayed reward for bad performance in a season, namely the advantageous position in the draft order that facilitates hiring of strong players for the next season. The crucial difference to our study is that Taylor and Trogden (2002) analyze whether teams take account of a delayed reward in a static setting using regular season data, while we consider multistage tournaments in the playoffs and investigate whether changes in the value of future strategic interactions affect current behavior. The study by Bartling, Brandes, and Schunk (2015) tests whether teams behave differently in a loss-frame when their performance falls behind expectations, thus focusing on expectations and non-expected utility. In terms of using data from professional basketball to study team production, our paper also complements the recent study by Arcidiacono, Kinsler, and Price (2017). While their focus is on investigating productivity spillovers in teams, our findings complement theirs by investigating the extent to which teams respond to dynamic incentives, and exploring the role of heterogeneity and free riding.[3] Finally, Miklos-Thal and Ulrich (2016) show for soccer how the prospect of being selected into a national team might influence effort levels of individual players.

This paper is also related to existing work that investigates the effects of heterogeneity on behavior in tournaments. Several papers have investigated empirically whether incentives to provide effort decrease in the degree of heterogeneity as predicted by Baik (1994); see Bull, Schotter, and Weigelt (1987) and Chen, Ham, and Lim (2011) for evidence from lab experiments, for example, or Sunde (2009), Brown (2011), and Berger and Nieken (2014) for evidence from the field. These papers focus on the effect of current heterogeneity on current effort in a static one-shot interaction, while we investigate whether (expected) relative ability in the next stage of a multistage tournament affects current effort choices. We control for current heterogeneity in our analysis, however, and find

[3]Data from professional basketball have also been previously used to study risk taking in tournaments (Grund, Höcker, and Zimmermann 2013), or the determination of wages (Deutscher, Gürtler, Prinz, and Weimar 2014).

that current effort is lower if current heterogeneity is high, in line with results reported in the aforementioned contributions. Therefore, our work complements this literature by showing that static incentive effects of heterogeneity continue to matter in each stage of a multistage tournament structure. Finally, the results provide a rationalization of the convex wage structures across hierarchy levels that are predicted by theory, see Rosen (1986), and that are typically observed in reality, see, e.g., Lambert, Larcker, and Weigelt (1993), Eriksson (1999), or Bognanno (2001).

The remainder of the paper is structured as follows. Section 2 presents a simple prototype model to derive testable hypotheses. Section 3 describes the data, the measures of heterogeneity and effort, and the empirical strategy. Section 4 presents the main results and several robustness checks. Section 5 investigates whether the reaction to changes of continuation values depends on the prevalence of free riding and the convexity of rewards across stages, respectively, and Section 6 concludes.

# 2 Theoretical Predictions

## 2.1 The Model

**A Simple Tournament with Two Teams.** Consider a tournament with two teams $i = \{\mathtt{F};\mathtt{U}\}$ who compete for a prize $R_{\mathtt{now}}$, where $\mathtt{F}$ is the 'favorite' and $\mathtt{U}$ the 'underdog'. Both teams consist of $N \geq 1$ symmetric agents. Each agent $k$ within team $i$ chooses costly effort $e_{ik}$ and faces cost of effort $c(e_{ik}) = \frac{e_{ik}}{a_i}$, where $a_i$ is the average ability of team $i$. Assuming that winning the prize $R_{\mathtt{now}}$ as a team has value $\frac{R_{\mathtt{now}}}{M_i}$ for each member of team $i$ delivers the objective function

$$\hat{\Pi}_{ik} \quad = \quad p_i[(\hat{e}_{i1}, ..., \hat{e}_{iN}); (\hat{e}_{-i1}, ..., \hat{e}_{-iN})] \cdot \frac{R_{\mathtt{now}}}{M_i} - \frac{\hat{e}_{ik}}{a_i} \quad . \tag{1}$$

The parameter $M_i$ measures the extent of free-riding within team $i$.[4] Intuitively, low values of $M_i$ imply that team members internalize the positive externality of their effort on the payoff of their team members, while high values of $M_i$ imply that team members

[4]We abstract from heterogeneity within teams, such that individual ability of each agent within team $i$ is assumed to be homogeneous. Heterogeneity is subsumed by its influence on free riding.

focus on the private benefit of their effort instead.[5] Ability parameters $a_i$ and cost of effort functions, as well as free-riding parameters $M_i$ are common knowledge.

Let winning probabilities $p_i[(\hat{e}_{i1}, ..., \hat{e}_{iN}); (\hat{e}_{-i1}, ..., \hat{e}_{-iN})]$ be determined by the ratio of team efforts. In particular, winning probabilities are given by the Tullock (1980) lottery contest technology according to which

$$p_i[(\hat{e}_{i1}, ..., \hat{e}_{iN}); (\hat{e}_{-i1}, ..., \hat{e}_{-iN})] = \frac{\sum_{k=1}^{N} \hat{e}_{ik}}{\sum_{k=1}^{N} \hat{e}_{ik} + \sum_{k=1}^{N} \hat{e}_{-ik}} \quad . \tag{2}$$

This technology implies that the performance of teams is determined by aggregate effort $\sum_{k=1}^{N} \hat{e}_{ik}$ and a multiplicative error term $\epsilon_i$ – see Konrad (2009) for details.[6]

Under the assumption that members of team $i$ take the aggregate effort $\sum_{k=1}^{N} \hat{e}_{jk}$ by all members of the opponent team $-i$ as given, it must hold for each member of team $i$ that the marginal value of increasing the probability of winning through a change in the aggregate effort of team $i$ is equal to the constant marginal cost of effort, i.e.,

$$\frac{\partial p_i[\sum_{k=1}^{N} \hat{e}_{ik}; \sum_{k=1}^{N} \hat{e}_{-ik}]}{\partial \sum_{k=1}^{N} \hat{e}_{ik}} \cdot \frac{R_{\texttt{now}}}{M_i} = \frac{1}{a_i} \quad .$$

Even though individual effort choices are not uniquely identified in equilibrium due to the linearity of the cost of effort function, the aggregate equilibrium effort of team $i$ is uniquely determined by mutually best responses as

$$\sum_{k=1}^{N} \hat{e}_{ik} = \alpha_i \cdot \frac{\theta_i}{(1+\theta_i)^2} \cdot R_{\texttt{now}} \quad , \tag{3}$$

where $\alpha_i = \frac{a_i}{M_i}$ is the absolute strength of team $i$ and $\theta_i = \left(\frac{\alpha_i}{\alpha_{-i}}\right)$ represents the *relative* strength of team $i$ vis-a-vis the opponent team. Intuitively, $\alpha_i = \frac{a_i}{M_i}$ is the absolute strength of team $i$, since the strength of a team increases in the individual ability of each

[5] The optimal effort choice of each member of team $i$ corresponds to the classical $1/N$ free-riding problem for $M_i = N$.

[6] In particular, the winning probability of team $i$ can also be defined as

$$p_i[(\hat{e}_{i1}, ..., \hat{e}_{iN}); (\hat{e}_{-i1}, ..., \hat{e}_{-iN})] = \Pr([\sum_{k=1}^{N} \hat{e}_{ik}] \cdot \epsilon_i > [\sum_{k=1}^{N} \hat{e}_{-ik}] \cdot \epsilon_{-i}) \quad ,$$

where $\epsilon_i$ and $\epsilon_{-i}$ are independent draws from the exponential distribution with mean one. For details on how to prove this equivalence, see Konrad (2009), p.52f.

team member, while it is decreasing in the prevalence of free-riding behavior within a given team. Inserting aggregate equilibrium efforts by both teams in equation (2) reveals that $\theta_i$ is a sufficient statistic for the winning probabilities of teams $\mathtt{F}$ and $\mathtt{U}$, which is intuitive given that $\theta_i$ measures the relative strength of competing teams. To ensure that the winning odds of the favorite team are at least as large as the winning odds of the underdog team, we subsequently assume that $\alpha_{\mathtt{F}} \geq \alpha_{\mathtt{U}}$, i.e., we assume that the 'favorite' is stronger than the 'underdog' team.

Aggregate equilibrium effort by both teams determines the expected equilibrium team payoffs. In particular, we obtain the expected equilibrium team payoffs by inserting aggregate equilibrium efforts by both teams in equation (1):

$$\sum_{k=1}^{N} \hat{\Pi}_{ik} = \frac{N\theta_i^2 + (N-1)\theta_i}{(1+\theta_i)^2} \cdot \frac{R_{\mathtt{now}}}{M_i} \,. \tag{4}$$

Equation (4) reveals that the expected equilibrium team payoff is strictly increasing in $\theta_i$, i.e., in the relative ability of team $i$. Intuitively, a higher relative ability does not only increase equilibrium winning odds, but also the expected value of participating in the tournament, the expected equilibrium team payoff.

**Accounting for Future Opponents and Multiple Stages.** Consider the same setting as before. Suppose, however, that the two teams $i = \{\mathtt{F};\mathtt{U}\}$ not only compete for the prize $R_{\mathtt{now}}$, but also for the right to participate in the next stage of the tournament where the winner of the current interaction competes with a team $j$ for a prize $R_{\mathtt{fut}}$. In such a setting, current aggregate team effort does not only depend on the absolute and relative strength of competing teams as suggested in equation (3), but also on characteristics of the (expected) future opponent team $j$.[7] Intuitively, participating in future interactions of the tournament becomes more attractive the weaker the future opponent $j$, since this implies that the chance to win against this opponent on the next stage of the tournament – and thus the chance to receive the prize $R_{\mathtt{fut}}$ – are higher. At the same time, it is comparably unattractive to participate in future stages of the tournament if the future

[7]We assume that both the relative strength of current opponent teams and future opponent teams are common knowledge.

opponent team $j$ is strong, since a team is less likely to win on the next stage of the tournament in this case, and thus unlikely to receive the prize $R_{\texttt{fut}}$.

Formally, the value of participation in the next stage of the tournament depends on the relative strength of team $i$ vis-a-vis team $j$. Defining the relative strength of team $i$ in the competition with the future opponent team $j$ as $\kappa_i = \left(\frac{\alpha_i}{\alpha_j}\right)$, it follows from equation (4) that the continuation value $\text{CV}_i$ for team $i$ in terms of the expected value of participating in the next stage of the tournament is formally defined as

$$\text{CV}_i^*(\kappa_i, R_{\texttt{fut}}, M_i) = \frac{N[\kappa_i]^2 + (N-1)\kappa_i}{(1+\kappa_i)^2} \cdot \frac{R_{\texttt{fut}}}{M_i} \quad . \tag{5}$$

The aggregate value of participation in the next stage of the tournament for team $i$, $\text{CV}_i^*(\kappa_i, R_{\texttt{fut}}, M_i)$, is increasing in future relative strength $\kappa_i$, since the chances of team $i$ to win against the future opponent team $j$ and thus to receive the prize are strictly increasing in future relative strength of team $i$. Moreover, the continuation value is increasing in the prize $R_{\texttt{fut}}$ awarded to the winner of the future interaction, and decreasing in the prevalence of free-riding $M_i$ within team $i$. The intuitive explanation for this last effect is that teams who manage to avoid free-riding behavior are stronger in any competition, ceteris paribus.

When considering individual optimization problems in the multistage tournament, each member of team $i$ has the objective function

$$\Pi_{ik} \quad = \quad p_i[(e_{i1}, ..., e_{iN}); (e_{-i1}, ..., e_{-iN})] \cdot \frac{R_{\texttt{now}} + \text{CV}_i^*(\kappa_i, R_{\texttt{fut}}, M_i)}{M_i} - \frac{e_{ik}}{a_i} \quad . \tag{6}$$

The only difference to the setting discussed in the previous section is that individuals now also incorporate the value of participation in future stages of the tournament in their current effort choice. This implies that the prize at stake is different as it includes also the continuation value. When accounting for these differences in the prize, aggregate equilibrium effort by all members of team $i$ in a non-final stage of a multistage elimination tournament is formally given by

$$\sum_{k=1}^{N} e_{ik}^* \quad = \quad \alpha_i \cdot f(\theta_i) \cdot g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}}) \tag{7}$$

where $f(\theta_i) = \frac{\theta_i}{(1+\theta_i)^2}$ and $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}}) = [R_{\texttt{now}} + \text{CV}_i^*(\kappa_i, M_i, R_{\texttt{fut}})]$. Consequently, $f(\cdot)$ is increasing in $\theta_i$ if $0 < \theta_i < 1$, and decreasing in $\theta_i$ if $\theta_i > 1$, and $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$ is increasing in $\kappa_i$ and $R_{fut}$, and decreasing in the prevalence of free riding $M_i$.[8]

## 2.2 Testable Hypothesis

Condition (7) delivers several comparative static predictions. In the following, we derive predictions that will then be tested in the empirical part below. Consider first the prediction that aggregate effort by team $i$ in a non-final stage of a multistage pairwise elimination tournament depends on the team's absolute strength $\alpha_i$. Intuitively, stronger teams provide ceteris paribus more effort than weaker ones, as being stronger means that effort costs of all team members are lower ($a_i$) and/or free-riding is less prevalent ($M_i$). Together, this implies that aggregate effort is increasing in the absolute strength of team $i$. Second, condition (7) predicts that aggregate effort depends on the relative strength of team $i$ in the current interaction, $\theta_i$. More precisely, the relative strength affects aggregate team effort through the concave function $f(\theta_i)$ that has its maximum value when competitors are equally strong, i.e., at $\theta_i = 1$. The greater is the heterogeneity among the competing teams in terms of their absolute strength, the lower is $f(\theta_i)$ and thus the aggregate effort by team $i$, regardless of whether team $i$ is the stronger or weaker team. In this sense, $f(\theta_i)$ reflects the well-known adverse incentive effect of heterogeneity in tournaments according to which both favorites and underdogs compete less intensively as the heterogeneity among them increases (Baik 1994).[9]

Finally, consider the last part of condition (7), which predicts that aggregate team effort increases in the prize for the winner of the current stage, $R_{now}$, and in the team-specific continuation value $\text{CV}_i^*(\kappa_i, M_i, R_{\texttt{fut}})$. Note that the strength of a future opponent

[8] See Appendix C for formal proofs. For simplicity, we abstract from the impact of differences between $\text{CV}_{\texttt{F}}^*(\kappa_{\texttt{F}}, M_{\texttt{F}}, R_{\texttt{fut}})$ and $\text{CV}_{\texttt{U}}^*(\kappa_{\texttt{U}}, M_{\texttt{U}}, R_{\texttt{fut}})$ on the relative strength of both teams in the current interaction. Accounting for the fact that the continuation value is higher for the favorite team 'F' than for the underdog team 'U' increases the relative strength disadvantage of the underdog. In particular, the relative strength of team $i$ would then be given by $\theta_i = \left(\frac{\alpha_i(R_{\texttt{now}}+\text{CV}_i^*)}{\alpha_{-i}(R_{\texttt{now}}+\text{CV}_{-i}^*)}\right)$. This simplifying assumption is uncritical for the results (proofs are available upon request).

[9] By definition of $\theta_i$, it must hold that $\theta_{\texttt{F}} = \frac{1}{\theta_{\texttt{U}}}$. Since $f(\theta_i) = f\left(\frac{1}{\theta_i}\right)$ holds, it follows that $f(\theta_{\texttt{F}}) = f(\theta_{\texttt{U}})$, which proves the argument that $f(\theta_i)$ controls for the effect of heterogeneity in the absolute strength of competitors on aggregate equilibrium team effort.

team affects current team effort only through this continuation value. At the same time, aggregate team effort in the current interaction of team $i$ will react only to variation in the future relative ability $\kappa_i$ if members of team $i$ are forward looking and incorporate the continuation value in their current decisions. Even though the theoretical model does not provide any reason why members of a team should not be forward looking, behavior in real life competitions might be different, as indicated by the introductory quote by Chuck Noll. Intuitively, thinking about future stages of the tournament for which competitors are not yet qualified might distract attention from the current interaction, so that reaching these stages might become less likely. The model provides a straightforward hypothesis to test if members of a team are forward-looking by investigating whether or not aggregate team effort in the current interaction is related to the relative future strength of a team:

**Hypothesis 1** (Forward Looking Behavior)**.** *Aggregate team effort in the* ***current*** *interaction is increasing in the relative* ***future*** *strength $\kappa_i$ of team $i$ in the next stage of the tournament if and only if members of team $i$ are forward looking; otherwise team effort in the current interaction is independent of $\kappa_i$.*

# 3 Empirical Implementation

## 3.1 Data

Data from professional basketball provide a unique possibility to test the hypothesis that teams incorporate future stages of the tournament in their behavior. The empirical analysis is based on data from playoff tournaments in the National Basketball Association (NBA).[10] During the regular season, a round-robin tournament is conducted in two separate conferences. After the regular season, the best teams participate in a pairwise elimination tournament (the "playoffs"). Every game of basketball in the NBA is a tournament covering 48 minutes of net playing time, split up in 4 quarters. In the regular season as well as during the playoff tournament every single game must have a winner. In case there is a tie at the end of regular time, a potentially infinite number of overtime periods of five minutes follows until a winner is determined. The empirical analysis is

[10] All data were collected online from www.basketball-reference.com using historical boxscores and team statistics.

based on information about the full time outcome of a game. Dummy variables are used to control for games that are decided in one or multiple overtime periods.

For organizational reasons, two separate elimination tournaments take place (the Eastern and Western conference), and the winners of each tournament only meet in a best-of-7 series of games, the "Finals", to determine the champion.[11] The empirical analysis focuses on the pairwise elimination tournaments that take place at the level of the conferences. Each tournament is structured into four stages; on each stage, two teams compete in best-of-5 (in stage 1 before the 2003/2004 NBA season) and otherwise best-of-7 match-ups; i.e., the winner is determined as the team that wins three or four games against the respective opponent team. The data contain information for 2,199 individual playoff games from the 1983/84 through 2013/14 seasons. While we restrict attention to data from the playoff phase of the season to capture the tournament structure, performance data from the regular season is used as background information to control for ability and other team-specific characteristics.

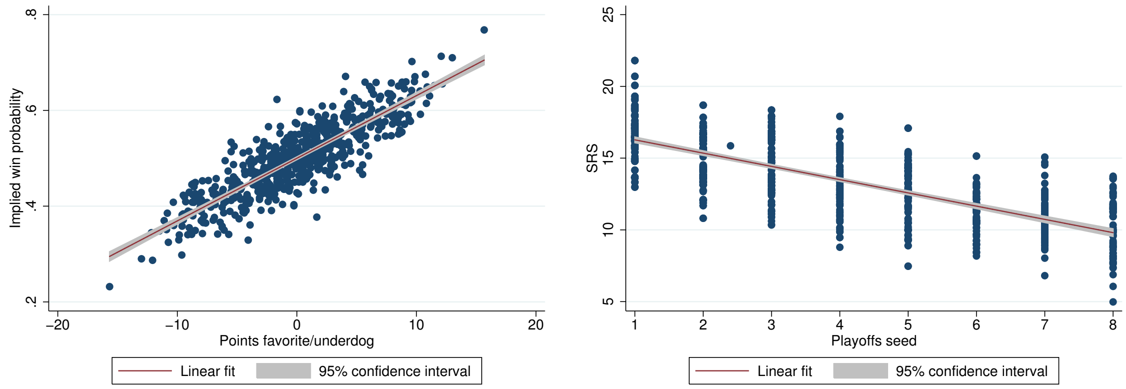
## 3.2 Measuring the Absolute and Relative Strength of Teams

**Absolute Strength.** The data cover detailed information on final outcomes of games, final scores, and various statistics of team performance. One of the key variables for the purpose of this paper is an empirical counterpart for the measure $\alpha_i$ of absolute strength employed in the theoretical analysis. The absolute strength of a team $\alpha_i$ does not only directly influence the level of effort – see equation (7) for details – but is also necessary to determine the current and the future relative strength measure. A naive statistic of the number of scores or the share of games won in the regular season is readily available, but might be misleading. Due to regional separation of the league into two conferences, different teams face different schedules and different pools of competitors, raising problems of comparability of scores during the regular season. We therefore employ the Simple Rating System (SRS) as calculated by the web-site www.basketball-reference.com.[12] This rating system is based on the regular season point differential for each team, weighted by

[11]The structure is illustrated by the playoffs of the 2013 season, see Figure 7 in Appendix A.

[12]This website provides free sports data and calculates advanced statistics for multiple professional sports leagues. The site is run by Sports Reference LLC, http://www.sports-reference.com.

Figure 1: Validation of the Measure of Absolute Strength Using the SRS




*Left panel:* Implied win probabilities (calculated using the SRS in a Tullock-type probability function) against mean point differentials per matchup, prediction by betting markets for rounds 1-3 in NBA seasons 1991 through 2013. $N = 644$
*Right panel:* SRS against tournament seed for rounds 1-3 in NBA seasons 1984 through 2014. $N = 868$

the team's strength of schedule.[13] The resulting measure of absolute strength corresponds to $\alpha_i$ in the theoretical model. This measure reflects both innate ability $a_i$ of members of team $i$ and the prevalence of free-riding $M_i$ within team $i$, since both factors are likely to matter for regular season performance. Importantly, the SRS-based measure of absolute strength employed in the subsequent analysis is exclusively based on information from the regular season preceding the respective elimination tournament. This measure is thus not influenced by the performance during the playoffs.

To validate the SRS-based measure of absolute strength, we compare it to betting odds and the seeds in the playoffs. Reassuringly, the winning probabilities calculated from using this measure of absolute strength are highly correlated with betting odds as is illustrated in the left panel of Figure 1.[14] The SRS-based measure of absolute strength is also highly correlated with the performance-based tournament seeds in the playoffs as shown in the right panel of Figure 1.

**Relative Strength in Current Interaction.** With $\alpha_{it}$ being measured by the SRS score of a favorite and an underdog team ($i = \{\texttt{F},\texttt{U}\}$), respectively, who compete on stage $t$, it is straightforward to compute empirical counterparts for the measure of relative

[13] As the SRS is negative for some team-years, we re-scale it as $SRS_{rescaled} = SRS + 10$ to restrict the measure to positive values and thus allow for a straightforward calculation of Tullock win probabilities.
[14] We obtained betting odds data from www.covers.com.

strength $\theta_{it}$ employed in the theoretical model. Close inspection of condition (7) reveals, however, that aggregate equilibrium team effort is affected by the heterogeneity in absolute strength between teams rather than by the relative strength of each team. Given that relative strength $\theta_i$ affects aggregate equilibrium team effort through the function $f(\theta_i)$, variation in relative strength has opposite effects on the effort provision of favorite and underdog teams. Intuitively, heterogeneity increases if the relative strength of the favorite increases, while heterogeneity decreases if the relative strength of the underdog improves, which implies that improvements in the relative strength of the underdog team increase aggregate equilibrium team effort, while the opposite holds for improvements of the relative strength of the favorite teams.

To avoid this complication in the empirical analysis, we use the relative strength of the favorite $\theta_{\texttt{F}}$ as a measure of heterogeneity for both the underdog and the favorite team. Current heterogeneity in stage $t$ is computed as

$$heterogeneity_t = \frac{\alpha_{\texttt{F}t}}{\alpha_{\texttt{U}t}} \ , \tag{8}$$

where $heterogeneity_t \geq 1$ holds due to the definition of favorite and underdog teams (since $\alpha_{\texttt{F}} \geq \alpha_{\texttt{U}}$). The advantage of this measure is that the effects of variation in $heterogeneity_t$ on aggregate team equilibrium effort work in the same direction for both teams. Intuitively, a higher relative strength of the favorite implies that heterogeneity in the current interaction increases, such that aggregate team equilibrium effort decreases.

Figure 2 Panel (a) plots the empirical kernel density of the respective heterogeneity measure and shows that games with comparatively low degrees of heterogeneity are most frequently observed in the data. High degrees of heterogeneity where $\theta_{\texttt{F}} > 1.5$ are rather the exception than the rule.

**Relative Strength in Future Interaction.** The empirical measure for the future relative strength of team $i \in \{\texttt{F},\texttt{U}\}$ in stage $t+1$ of the tournament against the opponent team $j$ with absolute strength $\alpha_{\texttt{j,t+1}}$ – which is labelled $E_t[rel.\ strength_{t+1}]$ in the following and corresponds to $\kappa_i$ in the theoretical analysis – is based on information available at stage $t$ and constructed as follows:

$$\mathrm{E}_t\ [rel.\ strength_{i,t+1}] = \frac{\alpha_i}{\mathrm{E}_t\ [\alpha_{j,\mathtt{t+1}}]}\ . \tag{9}$$

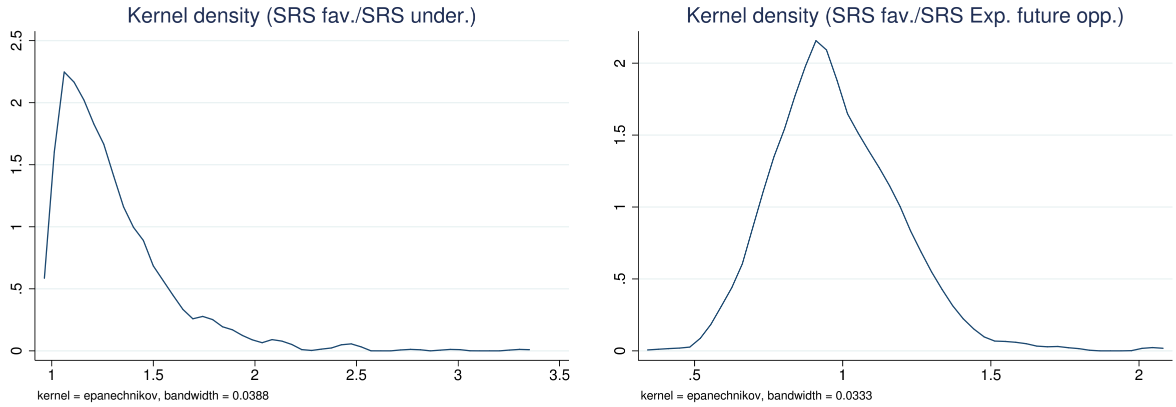
The only difference between this empirical measure and its counterpart $\kappa_i$ in the theoretical analysis is that the absolute strength of the future opponent team is not known with certainty and thus reflects an expected rather than a predetermined value. The reason for this difference is that, in many instances, the identity of the future opponent team is not known yet when decisions are made on the current stage. The structure of the competition implies, however, that teams competing in stage $t$ know that they will compete against the winner of the parallel stage-$t$ match on the next stage. Given that the absolute strength of those teams competing in this parallel match are observable, teams can form expectations about the probabilities with which they face any one of the two potential opponent teams in the next stage. Therefore, we compute the expected strength of the opponent $i$ in stage $t+1$ as follows in the empirical analysis: Assume that there are two potential future opponent teams $s$ and $l$ with absolute strength $\alpha_{s,\mathtt{t}}$ and $\alpha_{l,\mathtt{t}}$. The expected relative strength of the opponent team $j$ that team $i$ faces in stage $t+1$ upon winning the current stage is then defined as

$$\mathrm{E}_t\ [\alpha_{j,\mathtt{t+1}}] = p_s \cdot \alpha_{s,\mathtt{t}} + (1-p_s) \cdot \alpha_{l,\mathtt{t}}\ , \tag{10}$$

where $p_s = \frac{\alpha_{s,\mathtt{t}}}{\alpha_{s,\mathtt{t}}+\alpha_{l,\mathtt{t}}}$ is the probability that team $s$ wins against team $l$ in the parallel match on stage $t$. Whenever the identity of the future opponent team is already known at the time of a game in the parallel series, we replace the convex combination by the absolute strength of the actual next competitor.

Arguably, there are several alternative ways to construct the expected strength of the opponent on stage $t+1$, $\alpha_{j,\mathtt{t+1}}$, depending on the assumptions made on the expectation formation process. For simplicity and transparency, we restrict attention to competitors on the immediately next stage in the construction of the empirical measures. To account for potential concerns regarding the construction of this measure, we present results from several additional robustness checks that are derived under different assumptions regard-

Figure 2: Distribution of Heterogeneity and Relative Future Strength




(a) Heterogeneity (b) Relative Future Strength

*Notes*: The figures plot kernel densities of the heterogeneity measure and the measure of expected relative strength in the next round, respectively, using the raw data used in the estimation exercises. $N = 434$

ing the expected relative strength on the next stage. In particular, we consider measures that are based exclusively on the relative strength of the favorite in the parallel match-up, or adjusted measures that incorporate for each game if the future competitor is already known at the time of the game and accordingly replace the convex combination by the ability of the actual next competitor. Panel (b) of Figure 2 plots the empirical kernel density of future relative strength for current favorites.

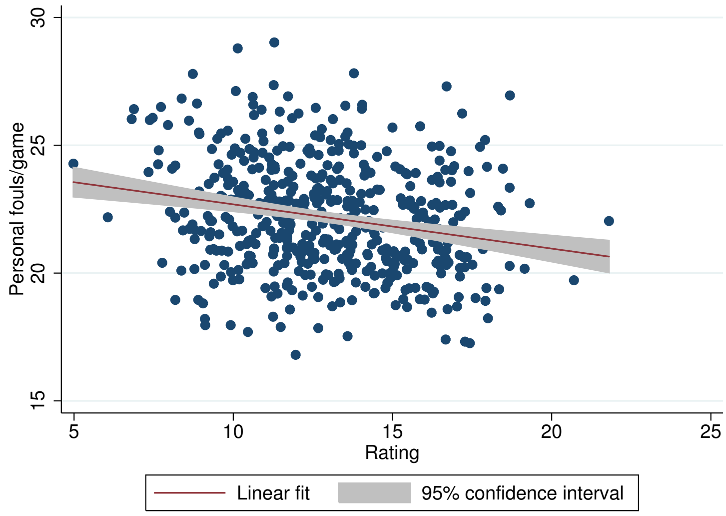
## 3.3 Measuring Effort

**Personal Fouls and the Intensity of Competition.** Whereas one can think of many indicators for final outcomes or performance, constructing a measure of effort of a team or of total effort per game by two teams is not entirely straightforward. In the empirical analysis of this paper, we use the number of personal fouls that a team is called for as a proxy for aggregate team effort. A personal foul in basketball is defined as a breach of the rules that regulate the legal or illegal form of personal contact between players. This mostly involves attempts to prevent the opposing team from scoring. These fouls are thus called defensive fouls. Much less frequent are offensive fouls that occur during an offensive phase when an illegal scoring attempt is observed. Hence, both types of fouls measure an attempt to change the course of a game in order to win. Consequently, the number of fouls in a game is a direct indicator for the intensity of the competition and, thus, for the effort of the respective team. In principle, fouls measure how intense the defender attacks his opponent, or how physically close he is in coverage, which may sometimes result in a personal foul. Notice that for this to hold it is not necessary to assume that teams explicitly decide to foul their opponent. Rather, it is presumably more likely that players try to avoid fouls in most instances, but are still more likely to foul the opponent when defending intensively. In that sense, personal fouls are an almost natural outcome of an intense game with close physical contact. The higher the intensity, the higher the probability that a foul is inadvertently committed and called. The intensity of play by a particular team should thus be closely correlated with the effort provided. In addition, the total number of fouls committed by a team in the course of a game corresponds closely to aggregate equilibrium team effort and thus to the theoretical counterpart, since personal fouls can be committed by all players of a team. The number of personal fouls is mostly influenced by a team's own effort, and a good proxy for how much effort members of a team provide in defense on average. More personal fouls correspond to a more physical, thus more tiring, style of play.[15]

One potential concern with this measure of effort is the possibility that fouls are committed for different reasons than an intensive defense, such as intentional fouls for tactical reasons. One situation where intentionally committing a foul might be an optimal strategy for a team is when the members of the team get tired and are not able anymore to defend without committing a foul. However, even if fouls are committed by mistake, or tactically, because players are worn out, this provides a useful indicator of the physical intensity of the match for a given team as fatigue is a clear indicator that the intensity – and therefore effort – has been on a high level during the game. Committing a foul may also be an optimal strategy to stop the clock at the end of a very close game when a team is behind. While it is neither direct offensive or defensive effort, it is still an attempt to try all available means to win the game. The number of personal fouls thus appears to be a suitable effort measure for the purposes of this paper.

[15] One could make the argument that fouls resemble 'sabotage behavior' as discussed in Lazear (1989) rather than 'effort'. This distinction does not matter for the subsequent analysis, however, since both measures account for the intensity of competition and move into the same direction when incentives change.

Figure 3: Personal Fouls per Game in Regular Season and Absolute Strength (SRS)




*Notes*: Average number of personal fouls per game in regular season against SRS. $N = 496$

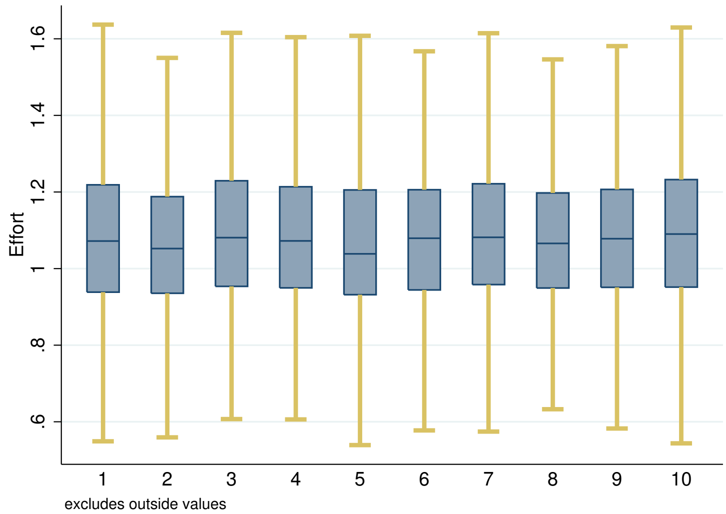
Another potential concern with this measure is that the number of personal fouls a team is called for might be affected by the absolute strength of a team in a counterintuitive manner when thinking about effort. In particular, the theoretical model predicts that aggregate team effort is increasing in the absolute strength $\alpha_i$, while it seems more reasonable to expect that stronger teams are more able to avoid fouls even when defending intensively.

Figure 3 depicts the relation between personal fouls and the strength of a team during the regular season. The data indeed suggest that stronger teams commit fewer fouls over the regular season. The corresponding pairwise correlation coefficient is -0.22 and highly significant. To control for a team's ability to avoid fouls as well as for the style of play of a particular team – the defense of some teams might explicitly decide to foul more often independent of the opponent team – our preferred proxy for team effort is therefore the number of fouls per game relative to the average per-game number of fouls the team has committed in the regular season preceding the playoffs.[16]

Figure 4 presents a box plot of the effort distribution during the playoffs by ability decile and shows that effort in the playoffs is, in general, larger than in the regular season.

[16]Relating the number of fouls per game relative to the average number of fouls during the regular season plays a similar role as season-team fixed effects by accounting for different styles of play, team compositions, coaching styles, etc., in a given season.

Figure 4: Effort Measure vs. Deciles of Absolute Strength (SRS)




*Notes*: Effort, as defined in (11) for deciles of ability measured by the SRS for rounds 1–3 for NBA seasons 1984–2014. Outliers are excluded. $N = 4398$

Moreover, the resulting proxy for aggregate team effort reveals no systematic relationship with the absolute strength of a team once we account for behavior in the regular season. Our empirical counterpart for aggregate equilibrium team effort is thus formally defined as

$$effort_{i,k,t} = \frac{\text{number of fouls in playoff game}_{i,k,t}}{\left(\frac{\sum \text{fouls regular season}_{i,k}}{\text{number of games}_k}\right)} \tag{11}$$

for team $i$ in year $k$ in stage $t$ of the tournament. Teams tend to commit more fouls in the playoffs than in the regular season on average – which is what one would expect given that stakes are typically higher in the playoffs than in the regular season.

**Additional Controls.** A potential concern with the proposed proxy for aggregate team effort is that teams might adjust their behavior to the style of play of their opponents. It is therefore necessary to control for various indicators that describe how opponents usually play the game. The nature of the data allows us to use regular season statistics in order to control for team-specific style of play. One crucial measure for the likelihood that a foul is called is the style of offense the opponent plays in terms of the distance from which they make their shot attempts. An increased number of shot attempts from behind the three-point line by the opponent could reduce the number of fouls, independent of effort provided.[17] In order to account for this, we control for the opponent team's number of three-point attempts in the regular season. In addition, we control for the speed of the opponent's play, as it seems quite possible that a team will commit fewer fouls if the opposing team slows down the game for tactical reasons or in order to reduce certain disadvantages. A good proxy for how fast an opponent plays is the regular season average of the number of field goal attempts per minute, which is therefore added to the set of control variables. Moreover, we control for the opponent team's free-throw success rate. Given that the penalty for a personal foul is a free-throw for the opponent team, free throws for the opponent are clearly more costly for a team if the opponent team's free-throw success rate is high.

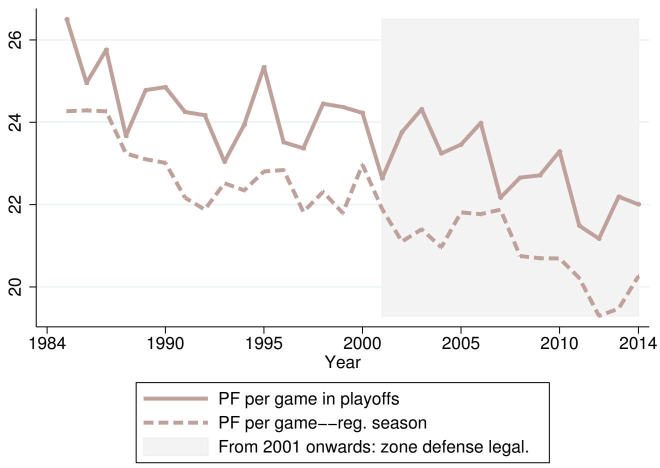
Another concern for the effort measure could be the presence of a so-called zone defense. Zone-defense is a style of defense that is less physical and relies more on optimal positioning in space and, thus, might produce fewer fouls independent of the effort provided.[18] One practical way of operating against an opposing zone defense is to concentrate more on distance shooting. Consequently, the number of attempted three-point shots should be higher in the presence of a zone defense, as the defense can be attacked more effectively from the distance. Figure 5 plots the evolution of fouls over time. The change in background shade indicates the rule change in the 2000/01 NBA season, which made zone defense legal. The figure suggests that the rule change had no effect on the average number of fouls, and the long time trend remained unaffected. In the empirical analysis we will control for season fixed effects to account flexibly for the time trend in the average number of personal fouls.

**Effort and Outcomes.** The discussion so far has provided several arguments why the relative deviation from the average number of personal fouls in the regular season is a valid proxy for aggregate team effort in the context of this paper. In what follows, we provide more direct evidence on these arguments. Recall that we use fouls as a measure

[17] The three-point line is a mark on the floor which separates the area where a successful basket counts two points from the rest of a field where it is worth 3 points. The distance between the three-point line and the basket has been the subject of multiple changes since the founding of the NBA. See www.nba.com/analysis/rules_history.html.

[18] A zone defense is a form of defense where a player defends a certain area rather than defending against an opposing player man-to-man. A detailed overview on the evolution of rules regarding illegal defense is to be found at www.nba.com/analysis/rules_history.html.

Figure 5: Personal Fouls During the Regular Season and During Playoff Tournaments




of aggregate team effort, since fouls measure how intense the defender attacks his opponent and how physically close he is in coverage. This type of defensive effort may then sometimes – but not always – result in a personal foul. One would therefore expect that higher defensive effort increases turnovers of the opponent team (i.e. stealing the ball) and thereby helps to prevent the opponent from scoring. This implies that teams that defend intensively have a higher share of ball possession. Since gaining possession of the ball is a necessary prerequisite for subsequent scoring attempts, we would also expect that intensively defending teams score more often.

Table 1 presents the corresponding regression results and documents that higher effort, indeed, increases turnovers of the opponent team, both for underdogs and favorites. Moreover, effort reduces the points scored by the opponent team out of the field (net of free throws), suggesting that one additional foul (relative to the regular season average) reduces points of the opponent team by 0.50. The effect is slightly larger when considering only the sample of underdogs, and slightly lower when considering favorites, but the differences are not significant. Finally, more fouls are apparently successful in increasing the number of own points scored, maybe because higher turnover rates make quick advances in the offense more profitable. Again, the effect appears to be slightly larger for underdogs than for favorites. The downside of more effort in terms of personal fouls, however, is a higher number of free throws for the opponent team. According to the point estimates, one

Table 1: The Effect of Effort on Outcomes

| *Sample:* | | Opponent's Points[a] | Opponent's Turnovers | Opponent's Free throws[b] | Own Points |
|---|---|---|---|---|---|
| *Pooled* | | | | | |
| | *effort* | -0.505*** | 0.053*** | 1.068*** | 0.349*** |
| | | (0.042) | (0.015) | (0.019) | (0.042) |
| | *N* | 4398 | 4266 | 4398 | 4398 |
| | $R^2$ | 0.259 | 0.109 | 0.532 | 0.350 |
| *Underdogs* | | | | | |
| | *effort* | -0.571*** | 0.055** | 1.057*** | 0.385*** |
| | | (0.060) | (0.021) | (0.025) | (0.057) |
| | *N* | 2199 | 2133 | 2199 | 2199 |
| | $R^2$ | 0.270 | 0.137 | 0.549 | 0.351 |
| *Favorites* | | | | | |
| | *effort* | -0.436*** | 0.047** | 1.103*** | 0.326*** |
| | | (0.056) | (0.021) | (0.028) | (0.064) |
| | *N* | 2199 | 2133 | 2199 | 2199 |
| | $R^2$ | 0.262 | 0.114 | 0.533 | 0.346 |

Robust standard errors (clustered for individual playoff-series) in round parentheses. All specifications include a dummy equal to 1 if team plays at home, a a dummy equal to 1 if series is decided in best-of-7 mode with best-of-5 as the base category, playoff-stage dummies, and overtime dummies. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively.

[a] Total number of points scored by opponent team from the field (without points from free throws).

[b] Total number of points scored by opponent through free throws.

additional foul leads to one additional point from free throws scored by the opponent team.

## 3.4 Empirical Framework

In order to test whether competitors are forward looking, we start by considering the following log-linearized version of equation (7):

$$\ln\left[\sum_{k=1}^{N} e^*_{ik}\right] \quad = \quad \ln\alpha_i + \ln f(\theta_i) + \ln g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}}) \quad .$$

According to the theoretical model, the log of current aggregate team effort thus depends additively on the log of own absolute strength, on the log of a function $f(\theta_i)$ that accounts for the impact of heterogeneity, and on the log of a function $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$ that determines the value of winning the current interaction. Based on the log-linearized version of equation (7), we estimate the empirical model

$$\ln(\mathit{effort}_{it}) = \beta_0 + \beta_1 \ln(\mathit{heterogeneity}_{it}) + \beta_2 \ln(\mathrm{E}_t[\mathit{rel.\ strength}_{i,t+1}]) + \Omega' X_{it} + \epsilon_{it} \quad (12)$$

where $\mathit{heterogeneity}_{it}$ is the empirical counterpart to $\theta_{\texttt{F}}$ and $\mathrm{E}_t$ $[\mathit{rel.\ strength}_{i,t+1}]$ is the empirical counterpart to $\kappa_i$. Intuitively, we use linear approximations for the two functions $f(\cdot)$ and $g(\cdot)$. Recall that $f(\cdot)$ is strictly concave with a maximum value for homogeneous teams ($\theta_i = 1$). Hence, $f(\cdot)$ is strictly decreasing in $\theta_{\texttt{F}}$ (since $\theta_{\texttt{F}} > 1$) and thus in $\mathit{heterogeneity}_{it}$. Also recall that $g(\cdot)$ is strictly increasing in $\kappa_i$ and thus in $\mathrm{E}_t[\mathit{rel.\ strength}_{i,t+1}]$, ceteris paribus. Consequently, the theoretical model predicts that $\beta_2$ – the effect of future relative strength $\kappa_{t+1}$ on stage-t effort – is positive if members of a team are forward looking. Alternatively, the coefficient estimate for $\beta_2$ is zero if members of a team focus entirely on the immediate consequences of their actions.[19]

Apart from the linear approximation of $f(\cdot)$ and $g(\cdot)$, there are two additional differences between the estimation equation and the log-linearized version of equation (7). First, the estimation framework does not explicitly control for the absolute strength of a team, since the effort measure is normalized with respect to the regular season average, which already accounts for strength. In particular, the regular season average of personal fouls is strongly correlated with the SRS-based measure of absolute strength.[20] Second, the empirical specification includes additional control variables. Specifically, the vector $X$ controls for team-specific playing styles such as the opponent's free throw percentage in the regular season, the opponent's three-point percentage, the absolute number of own shot attempts, the opponent's absolute number of shot attempts, the number of three-

[19]Unreported estimation results obtained with quadratic specifications for the influence of $\theta_{\texttt{F}}$ and $\kappa_i$ deliver no evidence for non-linear effects, suggesting that the linear approximation of the two functions $f(\cdot)$ and $g(\cdot)$ is justified.

[20]The pairwise correlation coefficient is -0.14 and highly significant. Unreported results show that adding ability as an additional control variable delivers coefficient estimates for this variable that are always insignificant, as one would expect if ability is already controlled for by the normalization of the effort measure. Details are available from the authors upon request.

point shot attempts allowed and the percentage of successful three-point shots allowed – everything measured for the regular season preceding the playoffs. Moreover, $X$ includes a variable counting the number of previous meetings in the preceding regular season, season fixed-effects, a dummy variable equal to 1 if the team $i$ plays at home, a dummy equal to 1 if the series are decided in best-of-7 mode with best-of-5 as the base category, playoff-stage dummies[21], standings dummies[22] and overtime dummies.[23] Standard errors are computed allowing for clustering at the level of individual playoff-series (thus comprising dependencies in observations of two teams that play each other in a given play-off round).

Note that the unit of observation in the empirical analysis is a single game. The main hypothesis underlying the analysis concerns the impact of the expected strength of the future opponent on current effort: variations in the strength of the future opponent change the incentives of a team from the outset of the game, but not within the game. Hence, we are not interested in (minute-by-minute) dynamics within a game. The dynamics within a game depends on the effort – and success – of the two teams as the game proceeds and can be considered to be noise with respect to our main hypothesis.

# 4 Main Results

## 4.1 Are Competitors Forward Looking?

Table 2 presents the main results from estimating model (12). Consider first column (1), the pooled sample that includes favorite and underdog teams on the current stage. The results show that aggregate team effort in the current round reacts to variation in the expected relative strength on the next stage of the tournament. In particular, teams exert significantly *more* effort in response to standing a better chance of prevailing in the *next* stage of the tournament, consistent with predictions of the theoretical model

[21] Playoff-stage dummies control for the structure of prizes and ensure that estimates across different stages are comparable.

[22] All standings are defined from the perspective of the observed team. A standing of, e.g., '1-0' indicates that the current observation is in the second game with the observed team leading the playoff series by one game.

[23] We also estimate a specification including the number of rest days and the travel distances between team locations. The results do change neither qualitatively nor quantitatively.

under the assumption that team members are forward looking. The negative sign of the interaction of future relative strength and the underdog dummy indicates that underdogs are less responsive to variation in their future relative strength, even though the coefficient estimate is not significantly different from zero.

Given that favorites and underdogs in a game may have different incentives and possibilities to react to variations in future relative strength, we estimate this effect separately for favorite and underdog teams in columns (2) and (3) of Table 2. The results show that both favorite and underdog teams compete more intensively if their (expected) future opponent becomes weaker, even though the point estimate is slightly larger for favorite than for underdog teams.

Regarding the set of additional control variables, we find that three factors are particularly important. First, we find evidence for the predicted negative influence of heterogeneity between current opponents on the intensity of the competition – the respective coefficient in column (1) is negative and highly significant. It appears, however, that it is mainly the favorite team that reduces its current effort in response to weaker (underdog) opponents, since the respective coefficient estimate is close to zero and insignificant for underdog teams in column (3). Second, we find some evidence that teams take the free-throw success rate of their opponents into account when choosing their defense intensity. In particular, ceteris paribus, teams commit fewer fouls if the free-throw success rate of their opponents is high. Finally, we find that the number of matches against the same opponent in the regular season affects behavior in the playoffs. The positive impact of this control variable on the intensity of play might be explained by local rivalries, for example, since teams play more often against nearby opponents from the same (eastern or western) conference in the regular season.

The log-log specification delivers a straightforward quantitative interpretation for the estimated coefficients for future relative strength that are of primary interest: if the strength relative to the expected future opponent increases by one percent, underdog and favorite teams respond by increasing the empirical proxy for current aggregate team effort by approximately 6 percent and 8 percent, respectively. It is not possible to directly link the size of the estimated coefficients for future relative strength to the theoretical model, however, since the value of winning the current interaction, $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$, is only

Table 2: Future Relative Strength and Current Effort

| | Dependent Variable: $\ln[effort_t]$ | | |
|---|---|---|---|
| | Pooled sample[a] | Favorites | Underdogs |
| | (1) | (2) | (3) |
| $\ln(\mathrm{E}_t[rel.\ strength_{i,t+1}])$ | 0.060** | 0.081*** | 0.056* |
| | (0.028) | (0.030) | (0.031) |
| $\ln(\mathrm{E}_t[rel.\ strength_{i,t+1}])$ | -0.048 | - | - |
| $\times$ *underdog* | (0.041) | - | - |
| *Additional control variables* | | | |
| $\ln(heterogeneity_t)$ | -0.039** | -0.076*** | 0.015 |
| | (0.020) | (0.029) | (0.028) |
| Underdog | 0.005 | - | - |
| | (0.008) | - | - |
| No. of field goal | 0.001 | 0.004* | -0.002 |
| attempts reg. season[b] | (0.001) | (0.002) | (0.002) |
| No. of opponent's field goal | -0.001 | -0.003 | 0.001 |
| attempts reg. season[b] | (0.001) | (0.002) | (0.002) |
| Three-point attempts | -0.001 | -0.002 | -0.002 |
| allowed in reg. season[b] | (0.003) | (0.004) | (0.005) |
| Three-point percentage | 0.204 | -0.092 | 0.530* |
| allowed in reg. season | (0.182) | (0.246) | (0.270) |
| Opponent's three-point % | -0.000 | -0.000 | 0.000 |
| regular season | (0.000) | (0.000) | (0.000) |
| Opponents free throw % | -0.004*** | -0.002 | -0.005*** |
| reg. season | (0.001) | (0.002) | (0.002) |
| No. of matches against | 0.018** | 0.017 | 0.020** |
| opponent in reg. season | (0.008) | (0.011) | (0.010) |
| *Additional binary controls* | | | |
| Season FE | YES | YES | YES |
| Home-game dummy | YES | YES | YES |
| Best-of-7 series dummy | YES | YES | YES |
| Playoff-Stage dummy | YES | YES | YES |
| Standing-in-Series dummy | YES | YES | YES |
| Overtime dummies | YES | YES | YES |
| Observations | 4398 | 2199 | 2199 |
| $R^2$ | 0.125 | 0.147 | 0.142 |

Note: Coefficients for additional variables controlling for team specific characteristics are not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in parentheses.

[a] Pooled sample with interaction term, binary variable indicating underdog is included.

[b] Absolute number re-scaled (divided) by 100.

approximated linearly by the empirical counterpart of $\kappa_i$ in the empirical implementation. In this sense, our empirical approach relies on the prediction that the *average* reaction to variation in $\kappa_i$ does not depend on the level of free-riding within a team $M_i$, on the immediate prize $R_{\mathtt{now}}$, and on the future prize $R_{\mathtt{fut}}$. Obviously, the effect might be heterogeneous, in particular along these dimensions. In fact, theory predicts that the *intensity* of the reaction to variation in $\kappa_i$ might depend on all these factors. Hence, the results so far constitute an estimate of the average effect of expected future strength on current effort, holding fixed all other potential determinants. In sections 5.1 and 5.2 below, we will investigate the heterogeneity in the intensity of the reaction of effort to variation in $\kappa_i$ exploiting (a) team-specific information from performance in the regular season preceding the payoffs, which allows us to construct a measure of free-riding within teams and (b) the convex prize structure across stages of the tournament, respectively.

## 4.2 Robustness Checks

In this subsection, we investigate the robustness of the results in two dimensions. In particular, we investigate whether the results depend on the log-log specification of our empirical model, or on the way the expected strength of the opponent in the next stage of the tournament is constructed.

Table 3 presents two alternative specifications for current aggregate team effort, current heterogeneity and the expected relative strength on the next stage of the tournament, using the same set of control variables as in Table 2. Specifications (1) and (2) estimate a reduced form version of equation (7). The estimates indicate that our findings do not depend on the log linearization of the estimation equation. When using the ratio (rather than the log of the ratio) of current heterogeneity and expected relative future strength, as well as the ratio of fouls in the playoffs over the average number of fouls in a regular season game (rather than the log ratio), the estimation results also reveal that teams compete more intensively if their expected future opponent becomes weaker – even though the effect is not statistically significant for underdog teams. Columns (3) and (4) report results for a specification where differences of absolute strength rather than ratios are used to construct heterogeneity in the current interaction and relative strength in the

Table 3: Future Relative Strength and Current Effort – Alternative Specifications

| *Dependent Variable:* | $effort_t$ | | *PF playoff - avg. PF season* | |
|---|---|---|---|---|
| | Favorites (1) | Underdogs (2) | Favorites (3) | Underdogs (4) |
| $\mathrm{E}_t[rel.\ strength_{i,t+1}]$ | 0.072** (0.029) | 0.063 (0.039) | - | - |
| $\mathrm{E}_t[\alpha_{it} - \alpha_{t+1}]$ | - | - | 0.133*** (0.049) | 0.102* (0.053) |
| *Additional control variables* | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes |
| Observations | 2199 | 2199 | 2199 | 2199 |
| $R^2$ | 0.157 | 0.156 | 0.153 | 0.151 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

next stage of the tournament.[24] Results are very similar to results obtained using either a ratio specification as in Table 3, or a log-log ratio specification as in Table 2, suggesting that the results are robust to variations in the specification of key variables.

The second robustness check concerns the construction of the measure for expected future relative strength. Recall that the expected strength of a future opponent was defined as the absolute strength of the actual next competitor whenever the opponent is known, and otherwise equal to the probability-weighted convex combination of the absolute strength of potential future opponents, $\mathrm{E}_t\left[\alpha_{j,\mathtt{t+1}}\right] = p_s \cdot \alpha_{s,\mathtt{t}} + (1 - p_s) \cdot \alpha_{l,\mathtt{t}}$.

Table 4 presents results for alternative specifications, while using the same set of additional control variables as in Table 2. The results in Columns (1) and (2) are based on the assumption that the expected strength of a future opponent is always equal to the probability-weighted convex combination of the absolute strength of potential future opponents, and thus not updated in case the future opponent is already known at the time of a game. In Columns (3) and (4), we discard the underdog in the respective parallel game and instead use the strength of the favorite team in the parallel interaction to construct the expected strength of the future opponent. Finally, columns (5) and (6) represent

[24]This difference specification would result from a Lazear and Rosen (1981) type contest model that determines winning probabilities based on effort differences rather than effort ratios as the Tullock (1980) model employed in our theoretical analysis.

Table 4: Future Relative Strength and Current Effort – Defining the Relative Strength of Future Opponents

| | *Dependent Variable:* $\ln[effort_t]$ | | | | | |
|---|---|---|---|---|---|---|
| | *probability weighted*[a] | | *favorite only*[b] | | *baseline + updating*[c] | |
| | Fav. (1) | Under. (2) | Fav. (3) | Under. (4) | Fav. (5) | Under. (6) |
| $\ln(\mathrm{E}_t[rel.\ str._{\cdot i,t+1}])$ | 0.079** (0.032) | 0.055* (0.033) | 0.091*** (0.029) | 0.058** (0.030) | 0.090*** (0.028) | 0.055* (0.029) |
| *Additional control variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2199 | 2199 | 2199 | 2199 | 2199 | 2199 |
| $R^2$ | 0.147 | 0.142 | 0.149 | 0.143 | 0.149 | 0.142 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

[a] The expected future opponent's strength is defined by the probability-weighted average of the absolute strength of both potential future opponents.

[b] Only the favorite in the parallel interaction is considered as the expected future opponent.

[c] For these specifications we use the same measure for future heterogeneity as in the preferred specification with an additional probabilistic updating of the win percentages of the potential future opponents.

an improved version of the baseline measure with an additional probabilistic updating of the win percentages of the future opponents.[25] The results are very robust across all specifications. In particular, both for favorites as well as underdogs, the coefficient for future heterogeneity is positive and significant in all specifications, but somewhat larger for the favorite teams than for the underdog teams.

# 5 Additional Results

This section reports the results of empirical analyses that explore additional aspects and implications of the model regarding free riding, the role of the prize structure, and the influence of pivotal games.

[25] Probabilistic updating takes into account the updated win probabilities according to the current standings in the best-of-5 or best-of-7 series using binomial updating.

### 5.1 Forward Looking Behavior and Prevalence of Free Riding

The properties of the continuation value deliver an additional prediction regarding the effect of relative *future* strength on *current* aggregate team effort. In particular, the continuation value is decreasing in the prevalence of free-riding within a team, $M_i$ – see condition (5). Consequently, variation in the relative future strength $\kappa_i$ of team $i$ is more important the lower the prevalence of free-riding within a given team.[26] Intuitively, a high prevalence of free riding reduces the aggregate expected equilibrium team payoff in any stage of the tournament and thus the value of participation in future stages of the tournament – see condition (4). Consequently, the continuation value decreases in the prevalence of free riding and it becomes ceteris paribus less attractive to reach future stages of the tournament if the prevalence of free-riding within a given team is high.

**Hypothesis 2** (Free Riding). *If members of team $i$ are forward looking, the effect of the relative strength of team $i$ in the* ***future*** *interaction on aggregate team effort in the* ***current*** *interaction is decreasing in the prevalence of free-riding $M_i$ within team $i$.*

Measuring the prevalence of free-riding within a given team empirically is difficult, even though the NBA data offer information on a rich set of team characteristics. We can exploit the fact that the number of players within any team is much larger than the maximum number of players who compete on the field in a game. In particular, only 5 players of each team are active at any point in time, even though NBA teams typically carry a stock of 13 players on their active roster.[27] Consequently, players typically compete for starting positions in a team. At the same time, the intensity of this competition is likely to differ across teams. In particular, the ability of different players for a given position within the team might be very similar in some and very different in other teams. This implies that a player for a given position is unlikely to be replaced if the ability difference to other team member is high – even if its current performance is bad – while the opposite holds if the ability difference is low. Consequently, players in a team without

[26] This prediction follows immediately from the fact that the derivative $\frac{\partial \mathrm{CV}_i^*(\kappa_i, M_i, R_{\mathrm{fut}})}{\partial \kappa_i}$ is strictly decreasing in $M_i$.

[27] Due to injuries, trades or suspensions, the number can even go up to 20 players or more who participate during the regular season.

competition for starting positions may slack off in some games and are nevertheless likely to play in future games since they are hard to replace.

It is an immediate consequence of intense competition for starting positions that players of a team cannot free ride on the effort of their team members, since they are then likely to be replaced by other players in future games. If competition for starting positions is essentially absent, however, there is no credible sanction for free riding behavior, as these players are likely to play in future games (almost) independent of their past performance.

Based on the idea that competition for starting positions increases personal costs of free riding, we use the distribution of individual playing times in the regular season preceding the playoffs to construct a proxy for the prevalence of free-riding within a given team. Intuitively, the more evenly total playing time in the regular season is distributed across the stock of players in the active roster, the lower is the ability difference between players. This implies that the competition for starting positions is high, such that the prevalence of free riding is low.

As measure of the prevalence of free-riding within team $i$, $M_i$, we therefore calculate the ratio of all minutes played by the five most-used players in the regular season over the average of minutes played by all other player's. Formally, we first order the $N$ players of team $i$ by their playing time in the regular season. Let $\text{time}_k$ be the respective playing time of the $k^{\text{th}}$ most active player (in minutes). The empirical counterpart for the parameter $M_i$ employed in the theoretical model is then given by

$$\text{FR}_i = \frac{\sum_{k=1}^{n} \text{time}_k}{\sum_{k=n+1}^{N} \text{time}_k} \tag{13}$$

for $n = 5$. As a robustness check, we also calculate the share of the team's most active player $k = 1$ in the regular season over the total playing time of all other players $k = 2, .., N$ who contributed during the regular season, i.e., we consider the case where $n = 1$.

Table 5 displays the empirically observed reaction to variation in the expected future strength separately for teams with a low and high prevalence of free riding, respectively. In particular, the coefficient of interest is estimated separately for teams above and below the median of the distribution of the aforementioned measures of free riding. Using the same set of control variables as in Table 2, the estimates show that the expected strength of

Table 5: Future Relative Strength, Current Effort, and Free Riding within Teams

| | *Dependent Variable:* $\ln[\textit{effort}_t]$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | FR Measure 1: *Share playing time* ($n = 5$) | | | | FR Measure 2: *Most used player* ($n = 1$) | | | |
| | Favorites | | Underdogs | | Favorites | | Underdogs | |
| | $\text{FR}_i$ low[a] | $\text{FR}_i$ high[b] | $\text{FR}_i$ low[a] | $M_i$ high[b] | $\text{FR}_i$ low[a] | $\text{FR}_i$ high[b] | $\text{FR}_i$ low[a] | $M_i$ high[b] |
| $\ln(\text{E}_t[\textit{rel. strength}_{i,t+1}])$ | 0.109** | 0.032 | 0.086* | 0.044 | 0.112*** | 0.039 | 0.108** | 0.010 |
| | (0.045) | (0.035) | (0.044) | (0.042) | (0.038) | (0.044) | (0.051) | (0.040) |
| *Additional control variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1048 | 1151 | 1152 | 1047 | 1082 | 1117 | 1114 | 1085 |
| $R^2$ | 0.152 | 0.192 | 0.164 | 0.196 | 0.197 | 0.163 | 0.159 | 0.177 |

Free riding measures as reported in the text. Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

[a] Below the median of overall free-riding parameter distribution.

[b] Above the median of overall free-riding parameter distribution.

the opponent on the next stage of the tournament has a much stronger impact on current aggregate team effort both for favorite and underdog teams if the prevalence of free riding is low, compared to the alternative case where the prevalence of free riding is high. In particular, even though the estimated coefficient is always positive, the estimate is small and not significantly different from zero if free riding is high, and instead much larger and significant if free riding is high. This pattern holds for both of the aforementioned free riding measures, i.e. both for $n = 1$ and $n = 5$. Taken together, the empirical evidence is thus consistent with Hypothesis 2.

## 5.2 Forward Looking Behavior and the Structure of Prizes

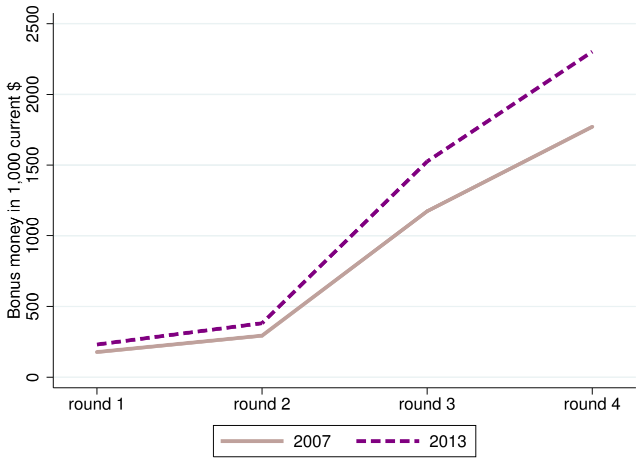
Another prediction regarding the effect of relative *future* strength on *current* aggregate team effort refers to the structure of prizes. In particular, recall that the continuation value is increasing in the prize $R_{\texttt{fut}}$ awarded to the winner of the interaction in the next stage of the tournament – see equation (5) for details. Consequently, provided that the members of a team are indeed forward looking, variation in the relative future strength $\kappa_i$ of team $i$ is more important the higher the prize $R_{\texttt{fut}}$.[28]

**Hypothesis 3** (Prize Structure)**.** *If members of team $i$ are forward looking, the effect of the relative strength of team $i$ in the **future** interaction on aggregate team effort in the **current** interaction is increasing in the prize $R_{fut}$ awarded to the winner of the **future** interaction.*

To investigate whether the response to the relative future strength depends on the reward for the winner of the future interaction, we exploit the well known fact that the reward structure in the playoffs is strictly convex across stages. Figure 6 displays the pattern of official bonus payments from the NBA to teams in 2007 and 2013, respectively, across different stages of the tournament. The figure nicely illustrates that rewards for winning round 3 and for winning the final (round 4) are substantially higher than bonus payments for teams that win round 1 or round 2. Given that team managers are likely to distribute these rewards among members of their team, these official rewards should also affect the

[28]This prediction follows immediately from the fact that the derivative $\frac{\partial \mathrm{CV}_i^*(\kappa_i, M_i, R_{\texttt{fut}})}{\partial \kappa_i}$ is strictly increasing in $R_{\texttt{fut}}$.

Figure 6: The Structure of Prizes in the NBA




behavior of players. Importantly, however, there are additional bonus payments to individual players that are part of confidential labor contracts. Anecdotal evidence suggests that these bonuses have a convex structure across stages as well.

Taken together, this implies that aggregate team effort is expected to be higher in round 3 than in earlier rounds of the tournament, since the prize for winning round 3 is substantially higher than in previous rounds of the tournament. The empirical counterpart for aggregate team effort indeed reflects this pattern. Effort as defined in equation (11) is roughly 5.5% higher in rounds 1 and 2 of the playoffs than in the regular season (where the value of winning a single game is arguably lower than in the playoffs), and increases by another 2% in round 3 as compared to rounds 1 and 2 of the playoffs. The convex structure of prizes across stages is also expected to affect the reaction to variation in the expected relative future strength, however. In particular, the reaction to variation in the expected relative future strength is expected to be more pronounced in later than in initial stages of the tournament.

Table 6 reports the results about the reaction of effort to variation in the expected future strength separately for rounds 1, 2 and 3, using the same set of additional control variables as in Table 2. The coefficient estimates for the effect of variation in the expected future strength are uniformly increasing from round 1 to round 3 both for favorite and underdog teams. In addition, the effects are significantly different from zero only in later rounds of the tournament, event though the number of observations is highest in the initial

Table 6: Future Relative Strength and Current Effort by Tournament Round

| | *Dependent Variable:* ln[$effort_t$] | | | | | |
|---|---|---|---|---|---|---|
| | Favorites | | | Underdogs | | |
| | round 1 | round 2 | round 3 | round 1 | round 2 | round 3 |
| $\ln(\mathrm{E}_t[rel.\ strength_{i,t+1}])$ | 0.060<br>(0.038) | 0.090*<br>(0.054) | 0.156**<br>(0.065) | 0.043<br>(0.039) | 0.058<br>(0.055) | 0.192***<br>(0.059) |
| *Additional control variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1145 | 699 | 355 | 1145 | 699 | 355 |
| $R^2$ | 0.133 | 0.276 | 0.318 | 0.162 | 0.181 | 0.319 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

round of the tournament. In this sense, the empirical evidence is in line with Hypothesis 3.

## 5.3 Extent of Forward-Looking Behavior

While the analysis so far has shown that teams are forward looking and account for the option value of participation in the next stage of the tournament, a related question refers to the extent to which the continuation value depends on the relative strength in even later stages. As a next step, we therefore investigate whether observed effort choices are only influenced by the next interaction, or whether they also react to variation in the continuation value taking the full tournament structure into account. The structure of the NBA playoff tournament allows us to compute continuation values that reach up to three stages into the future when restricting attention to round 1 games, and option values that reach two stages into the future when restricting attention to round 1 and round 2 games, respectively. To avoid making assumptions about the structure of prizes across stages, which are difficult to evaluate in terms of the actual rewards $R_{\texttt{fut}}$ as perceived by the teams, we assume that prizes are identical across stages for simplicity.[29] Extending

[29] As discussed previously in Section 5.2, prizes are likely to increase across stages. In this sense, the assumption employed in the subsequent analysis is conservative, since option values in future stages are likely to be even more important for current behavior when accounting for the convex structure of rewards.

our previous definition of option values, we define the option value of teams who account for up to two future stages of the tournament as

$$\mathrm{E}_t[rel.\ str._{i,t+1} + p_{i,t+1} \times rel.\ str._{i,t+2}], \tag{14}$$

where $p_{i,t+1}$ is the probability that team $i$ beats the expected future opponent team in stage $t+1$ of the tournament. Analogously, the option value of teams who account for all future stages of the tournament in round 1 is defined as

$$\mathrm{E}_t[rel.\ str._{i,t+1} + p_{i,t+1} \times (rel.\ str._{i,t+2} + p_{i,t+2} \times rel.\ str._{i,t+3})], \tag{15}$$

where $p_{i,t+2}$ is the probability that team $i$ beats the expected future opponent team in stage $t+2$ of the tournament.[30]

Table 7 displays the estimated coefficients for the expected relative strength when restricting attention to the immediate next stage of the tournament as in the baseline specification, or instead incorporating the next two stages of the tournament, respectively. For direct comparability, both sets of estimates are obtained on the same estimation sample, which comprises a lower number of independent observations than the baseline specifications as the observations for round 3 of the playoffs are not used. The coefficient estimates indicate that variation affects effort even when accounting not only for the expected relative strength during the next stage of the tournament, but also for the expected relative strength two stages into the future. In particular, the coefficient is significant and positive both for favorites and for underdogs, and more precisely estimated in statistical terms. The size of the coefficient is similar or even slightly larger when variation in expected strength further in the future is incorporated. This is an indication that the baseline specification, which focused on the relative strength on the next stage of the tournament, delivers rather conservative results as it systematically underestimates the continuation value.

[30] We refrain from estimating a model with separate variables for relative strength in $t+1$, $t+2$ and $t+3$ because of the high correlation between these variables. The correlation coefficients between $t+1$ and $t+2$ and between $t+1$ and $t+3$ are 0.92 and 0.86, respectively.

Table 7: Future Relative Strength Beyond $t+1$ and Current Effort

| | *Dependent Variable:* $\ln[effort_t]$ | | | |
|---|---|---|---|---|
| | Favorites | | Underdogs | |
| $\ln(\mathrm{E}_t[rel.\ strength_{i,t+1}])$ | 0.070** | | 0.057* | |
| | (0.031) | | (0.032) | |
| $\ln(\mathrm{E}_t[rel.\ str._{i,t+1} + p_{i,t+1} \times rel.\ str._{i,t+2}])$ | | 0.101*** | | 0.060** |
| | | (0.031) | | (0.032) |
| *Additional control variables* | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes |
| Observations | 1844 | 1844 | 1844 | 1844 |
| $R^2$ | 0.151 | 0.154 | 0.145 | 0.145 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

An alternative way of investigating the extent to which relative strength in future stages of the tournament influences current effort choices is to restrict attention to round 1 of the tournament. This allows computing the expected relative ability in up to three future stages of the tournament. Table 8 presents the corresponding results. The pattern is remarkably similar. In particular, both for favorite and underdog teams the coefficient estimates for the expected relative strength are comparable or even slightly larger once additional future stages are incorporated in the computation. Taken together, these results are consistent with the view that teams account not only for the immediate next step, but more generally for the continuation value of potential participation in all future stages of the tournament. At the same time, it appears that the effect of variation in relative strength, not only in the immediately following stage of the tournament but up to three stages in the future, seem to affect current effort provision of teams. This also suggests that the results of the baseline specification, which only incorporates variation in expected relative strength in the immediately next stage, is appropriate as it allows making the most efficient use of the available data. At the same time, this empirical strategy is conservative in the sense that testing the influence of the continuation value when restricting attention to the immediate next stage only constitutes a necessary condition for the purpose of the research question.

Table 8: Variation in the Computation of Future Relative Strength and Current Effort

| | *Dependent Variable:* $\ln[effort_t]$ | | | | | |
|---|---|---|---|---|---|---|
| | Favorites | | | Underdogs | | |
| $\ln(\mathrm{E}_t[rel.\ strength_{i,t+1}])$ | 0.060<br>(0.038) | | | 0.043<br>(0.039) | | |
| $\ln(\mathrm{E}_t[rel.\ str._{\cdot i,t+1} + p_{i,t+1}$<br>$\times rel.\ str._{\cdot i,t+2}])$ | | 0.076*<br>(0.039) | | | 0.050<br>(0.088) | |
| $\ln(\mathrm{E}_t[rel.\ str._{\cdot i,t+1} + p_{i,t+1}$<br>$\times(rel.\ str._{\cdot i,t+2} + p_{i,t+2} \times rel.\ str._{\cdot i,t+3})])$ | | | 0.064*<br>(0.036) | | | 0.055*<br>(0.035) |
| *Additional control variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1145 | 1145 | 1145 | 1145 | 1145 | 1145 |
| $R^2$ | 0.133 | 0.162 | 0.134 | 0.162 | 0.133 | 0.163 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

## 5.4 Forward Looking Behavior and Pivotal Games

A more subtle aspect of forward looking behavior relates to the extent to which the continuation value is salient in the decision making process. For instance, effort provision in a particular game might be more or less decisive for actually attaining the continuation value due to the specificities of the tournament. The NBA employs a best-of-seven (and sometimes best-of-five) winning rule in all stages of the tournament. The preceding analysis accounts for this feature by the inclusion of standing dummies. In addition, standard errors are clustered on the level of individual playoff-series. However, potentially team behavior might be influenced more or less by the continuation value in the course of a series depending on the particular standing in the series. In particular, in decisive games effort might be influenced more strongly by the continuation value as compared to games that are not decisive and thus sensed as less important for obtaining the continuation value. The theoretical model implicitly assumes a best of one winning rule in which each game on each stage is decisive to keep the theoretical analysis tractable. However, intuitively the continuation value appears in the objective function (6) with full weight only in decisive games, whereas its weight is reduced (e.g., in terms of a factor $0 < \rho < 1$)

in non-decisive games.[31] Consequently, the observed impact of relative future opponent strength might be more or less present in some games of a series, and the effect might be heterogeneous depending on the current standing within the series or across games within a series.

In the following, we address the question about heterogeneity of the effect depending on the salience of the continuation value by using an explorative approach and investigate whether it makes a difference if a game can potentially decide the series in the current stage of the tournament or not. In particular, we split the sample by distinguishing between pivotal and non-pivotal games. When considering pivotal games, we further distinguish between situations in which the favorite team can decide the series in its favor, and situations in which the underdog team can win the entire series.

Table 9 reports the estimated coefficients for the effect of variation in future relative strength on current behavior for the respective sub-samples. The qualitative pattern is the same for favorite and for underdog team and suggests that the effect of relative future strength on current aggregate team effort is most pronounced in pivotal games where a team can decide the series in its favor, intermediate in non-pivotal games, and least pronounced in pivotal games where a team faces the risk of losing the series. It appears that teams are forward looking whenever the opportunity costs of doing so – reflected by the risk of losing focus in the current interaction that goes hand-in-hand with the consideration of future games – are low, but not if these opportunity costs are high. In other words, teams seem not to react to the strength of their prospective future opponent if chances that they lose their current series are high, while they appear to take the strength of future opponent teams into account when they are close to winning the current series.

## 5.5 Evidence from the NCAA

To further investigate whether the teams behave differently in pivotal games, we use information from a complementary data set. In particular, we consider the championship

[31] Extending the model to explicitly account for a best-of-seven winning rule would be possible, but it while this extension would provide limited insights on the question at hand, it would still be deficient regarding the actual tournament structure of the NBA play-offs, since each series follows a predefined schedule of home and away games, and both winning odds and the style of play in basketball presumably depend on the location of a game. In the empirical analysis we control for this issue by adding a home dummy variable.

Table 9: Future Relative Strength and Current Effort – Stratified by Standings

| | *Dependent Variable:* $\ln[\mathit{effort}_t]$ | | | | | |
|---|---|---|---|---|---|---|
| | *non-pivotal* | | *favorite can win* | | *underdog can win* | |
| | Fav. (1) | Under. (2) | Fav. (3) | Under. (4) | Fav. (5) | Under. (6) |
| $\ln(\mathrm{E}_t[\mathit{rel.\ strength}_{i,t+1}])$ | 0.068* | 0.044 | 0.140** | 0.038 | 0.027 | 0.076 |
| | (0.037) | (0.036) | (0.055) | (0.062) | (0.094) | (0.090) |
| *Additional control variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Additional binary controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1578 | 1578 | 406 | 406 | 215 | 215 |
| $R^2$ | 0.154 | 0.149 | 0.222 | 0.207 | 0.293 | 0.263 |

Coefficients for the set of additional control variables – see Table 2 for a complete list – not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

tournament of the National Collegiate Athletic Association (NCAA). The most important differences between the NBA and the NCAA regulation in this context concern the organisation of playoffs. While in the NBA each round is decided by a best-of-seven or best-of-five series, each NCAA tournament round is decided in a single game, which is held on neutral ground to avoid home bias. We have access to data for 10 seasons from 2003 through 2013, covering a total of 682 games. Empirical counterparts for aggregate team effort as well as for current and future relative strength are constructed in the same way as for the NBA data. Unfortunately, the SRS measure of absolute team strength is only available for the entire season including all games in the playoffs. It is thus not only based on regular season performance preceding the playoffs as for the NBA. Consequently, the empirical counterparts for current heterogeneity and relative future strength that are based on the SRS measure of absolute team strength are likely to be less accurate in the initial stages of the playoffs. At the same time, the measure of absolute strength should be even more accurate than in the NBA in later stages of the tournament, since the measure of absolute strength accounts for the performance in initial stages of the tournament.

Table 10 presents the respective results for the NCAA using the same estimation equation previously employed for the NBA. The only difference is that the specifications no longer include controls for current standing in the series, as each tournament round in

Table 10: Future Relative Strength and Current Effort – NCAA Data

| | *Dependent Variable:* ln[$effort_t$] | | | | | |
|---|---|---|---|---|---|---|
| | Favorites | | | Underdogs | | |
| | all | rounds 1-2 | rounds 3-5 | all | rounds 1-2 | rounds 3-5 |
| $\ln(\mathrm{E}_t[rel.\ str._{\cdot i,t+1}])$ | -0.006 | -0.039 | 0.109* | 0.053* | 0.025 | 0.136* |
| | (0.032) | (0.037) | (0.063) | (0.031) | (0.034) | (0.072) |
| *Add. control variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Add. binary controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 682 | 528 | 154 | 682 | 528 | 154 |
| $R^2$ | 0.190 | 0.208 | 0.269 | 0.108 | 0.129 | 0.240 |

Coefficients for the set of additional control variables not reported due to space limitations. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively. Robust standard errors (clustered for individual playoff-series) in round parentheses.

the NCAA is decided in a single game. For favorite teams, we find no evidence for forward looking behavior when considering either the average across all rounds or only the initial two rounds of the tournament. However, favorite teams incorporate the strength of future opponents in their decisions in later rounds of the tournament – the coefficient estimate is similar in size to the respective coefficients in later rounds for the NBA and significant at the 10% level. Similarly, we find that underdog teams react strongly to variation in their future relative strength in later rounds, but not in the initial two rounds. Due to the construction of the SRS-based absolute strength measure in the NCAA, it is not entirely clear, however, whether observed differences in the degree of forward looking in different rounds of the tournament depend on convex rewards or on increased precision of the measure of (relative) strength.

# 6 Concluding Remarks

This paper provided an empirical test for whether decision makers are forward looking in dynamic strategic interactions. In particular, the evidence provides support for the central prediction that the continuation value of promotions in firms with multiple hierarchy levels is an important determinant of incentives in promotion tournaments. The empirical analysis is based on field data from professional basketball tournaments, and the results suggest that tournament participants exert more effort on the current stage of a tournament if it becomes more attractive to reach the next stage of the tournament because of a weaker expected opponent. The estimated reaction to changes in the continuation value is consistently found to be statistically and quantitatively significant.

Changes in the expected relative strength in future interactions may also cause selection effects, as previously noted by Brown and Minor (2014). Even though this paper focuses on the incentive effects of forward looking behavior, we can test whether differences in the reaction to changes of the continuation value across subgroups affects winning probabilities. Favorite teams should ceteris paribus be less likely to win if future opponents are stronger, for example, since the estimated response to variation in the continuation value is more pronounced for favorite than for underdog teams in all specifications. Reassuringly, we find that both the winning probability and the point margin of favorite teams are indeed decreasing in the expected strength of the future opponent.[32]

The finding that changes in the expected relative strength in future interactions affect current effort cannot be explained by dynamic or tactical interactions during the course of a game, since the expected strength of the future opponent team is fixed *before* the respective game and does not change during a game. In addition, it is worth mentioning that this paper gathers evidence in a setting where participants often negate that they think about future stages of the tournament and instead claim that they focus entirely on the current game, as indicated in the introductory quote. Moreover, the team setting implies that factors like the well-known free-riding problem work against finding evidence for forward looking behavior. In this sense, forward looking behavior is likely to be even more prevalent in corporate tournaments where human resources management departments try to make career ladders as transparent as possible for their employees. Consequently, continuation values should be more salient in the corporate context than in sports tournaments.

While this paper shows that current effort depends on chances to win the subsequent stage of the tournament, promotion tournaments often involve more than two stages in large organizations. Belzil and Bognanno (2008) show, for example, that there are up

[32]This finding, which is documented in Table 11 in the Appendix, corroborates analogous results by Brown and Minor (2014) who discard the effect of continuation values on effort and instead focus entirely on outcomes and selection.

to ten hierarchical levels between CEO and entry-level management in U.S. firms. The findings suggest heterogeneity in the degree to which the future is incorporated in current performance. In particular, forward looking behavior seems more prevalent if the future interactions are foreseeable with greater certainty or salience, or if they are associated with greater rewards. In that sense, players take the full future prospects in the tournament into account, but react more strongly to the immediate future. On the other hand, future interactions affect performance less if the future is less likely to play a role, as indicated by the results on decisive versus non-decisive games. Thus, a more explicit investigation of the formation of expectations about future events is a logical next step and a promising avenue for future research.

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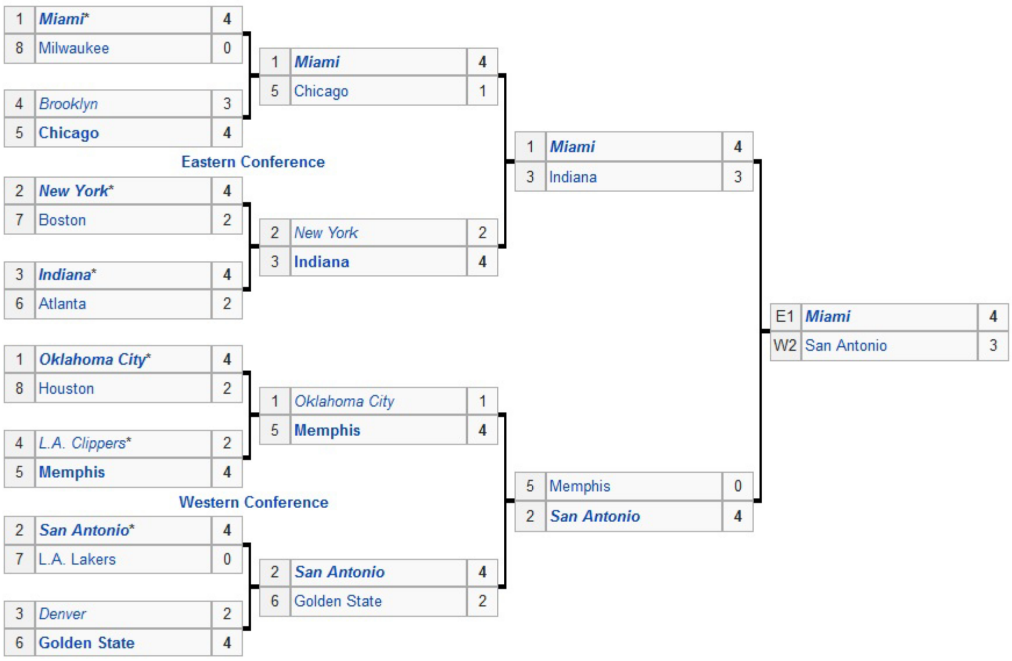
# A Additional Figures

Figure 7: Illustration of the NBA Tournament Structure - Example: 2013 NBA Playoffs




*Source: Wikipedia.*

# B Additional Tables

Table 11: Effect on Probability of the Favorite Winning and Favorite's Point Margins (NBA)

| | *game* | | *series* | |
|---|---|---|---|---|
| | win[a] | share of total points[b] | win[a] | share of total games[b] |
| | (1) | (2) | (3) | (4) |
| $heterogeneity_t$ | 0.442*** | 0.034*** | 0.417*** | 0.283*** |
| | (0.060) | (0.004) | (0.076) | (0.041) |
| $\mathrm{E}_t$ $[abs.\ strength_{t+1}]^c$ | -0.096 | -0.012** | -0.109 | -0.193* |
| | (0.088) | (0.006) | (0.163) | (0.100) |
| Observations | 2199 | 2199 | 434 | 434 |
| $R^2$ | 0.150 | 0.189 | 0.145 | 0.199 |

All specifications include a dummy equal to 1 if the team plays at home, a dummy equal to 1 if the series is decided in best-of-7 mode with best-of-5 as the base category, playoff-stage dummies, standings dummies. Robust standard errors (clustered for individual playoff-series for columns 1 and 2 - clustered on team-year level for columns 5 and 6) in parentheses. *, ** and *** indicate statistical significance at the 10-percent level, 5-percent level, and 1-percent level, respectively.

[a] Dependent variable is equal to 1 if favorite wins, 0 else.

[b] Dependent variable is equal to the favorite's share of total points (games) in game (series).

[c] Strength of expected future opponent in log.

# C Properties of $f(\theta_i)$ and $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$

**Properties of $f(\theta_i)$.** The function $f(\theta_i)$ is defined as follows:

$$f(\theta_i) = \frac{\theta_i}{(1+\theta_i)^2}$$

The first derivative of $f(\cdot)$ with respect to $\theta_i$ reads

$$\frac{\partial f(\theta_i)}{\partial \theta_i} = \frac{1-\theta_i}{(1+\theta_i)^3} \quad . \tag{C.1}$$

Consequently, $f(\cdot)$ is increasing in $\theta_i$ if $0 < \theta_i < 1$, and decreasing in $\theta_i$ if $\theta_i > 1$.

**Properties of $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$.** The function $g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})$ is defined as follows:

$$g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}}) = [R_{\texttt{now}} + \mathrm{CV}_i^*(\kappa_i, M_i, R_{\texttt{fut}})] = R_{\texttt{now}} + \frac{N[\kappa_i]^2 + (N-1)\kappa_i}{(1+\kappa_i)^2} \cdot \frac{R_{\texttt{fut}}}{M_i}$$

The first derivative of $g(\cdot)$ with respect to $\kappa_i$ reads

$$\frac{\partial g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})}{\partial \kappa_i} = \frac{N(\kappa_i+1) + \kappa_i - 1}{(1+\kappa_i)^3} \cdot \frac{R_{\texttt{fut}}}{M_i} \quad . \tag{C.2}$$

Since $N \geq 1$, it thus holds that $\frac{\partial g(\kappa_i, M_i, R_{\texttt{now}}, R_{\texttt{fut}})}{\partial \kappa_i} > 0$. Moreover, equation (C.2) is increasing in the future prize $R_{\texttt{fut}}$ and decreasing in the prevalence of free riding $M_i$.