Journal of Economic Behavior & Organization 107 (2014) 51–63

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Conflicts of interest distort public evaluations: Evidence from NCAA football coaches☆

Matthew J. Kotchen[a,*], Matthew Potoski[b]

[a] Yale University and National Bureau of Economic Research (NBER), 195 Prospect Street, New Haven, CT 06511, United States
[b] University of California, Santa Barbara, 2400 Bren Hall, Santa Barbara, CA 93106, United States

ARTICLE INFO

Article history:
Received 24 March 2014
Received in revised form 28 July 2014
Accepted 31 July 2014
Available online 2 September 2014

Keywords:
Conflicts of interest
Financial incentives
NCAA football

ABSTRACT

This paper investigates how private incentives distort public evaluations. Exploiting a unique empirical setting, we study the influence of conflicts of interest among NCAA football coaches participating in the USA Today Coaches Poll of the top 25 teams from 2005 to 2010. The research design takes advantage of a situation where many agents are evaluating the same thing, private incentives are clearly defined and measurable, and there exists an alternative source of computer rankings that is bias free. We find evidence that coaches distort their rankings to reflect their own financial and reputational interests. Most importantly, we find that coaches show more favoritism toward their own team when they stand to gain more financially and toward other teams when it generates higher direct financial payoffs for their own university. Additionally, coaches boost the ranking of their own team and teams from their same athletic conference, even after accounting for direct financial incentives. Coaches also rank teams they defeated more favorably, thereby making their own team look better.

1. Introduction

Many spheres of economic and political activity rely on expert ratings to guide choices when the quality of alternatives is otherwise difficult to assess. Credit rating agencies, including Moody's, Standard & Poor's, and Fitch, rate debt obligations and instruments to facilitate informed transactions in financial markets. Individuals concerned with things like corporate social responsibility, health, and the environment have a proliferation of ratings in these dimensions as well. Politicians in a representative democracy also provide a form of ratings for the public good: because citizens are rarely informed about the pros and cons of different policy alternatives, elected and appointed officials are tasked, in principle, with rating alternatives in order to implement the best public policies. An obvious concern arises when evaluators have incentives to distort ratings for their own private gain at the expense of those who rely upon them. Research exists on how conflicts of interest play out in credit rating agencies and from political campaign contributions.[1] Yet there are research challenges associated with the study of conflicts of interest in all areas that stem not only from the need to persuasively identify causality, but also

☆ We are grateful to Jesse Burkhardt, Nathan Chan, and John D'Agostino for valuable research assistance, in addition to two anonymous reviewers and Scott Adams for helpful comments on an earlier draft of the paper.
* Corresponding author. Tel.: +1 203 432 9533.
E-mail addresses: matthew.kotchen@yale.edu (M.J. Kotchen), mpotoski@bren.ucsb.edu (M. Potoski).
[1] For examples, see Ashcraft et al. (2010), Griffin and Tang (2010, 2011), Mehrana and Stulz (2007) and Ansolabehere et al. (2003).

http://dx.doi.org/10.1016/j.jebo.2014.07.018
0167-2681/

from the fact that incentives are frequently difficult to define and measure, as are deviations from otherwise unbiased behavior.

In this paper, we study the influence of private incentives on public evaluations in a way that seeks to overcome many of these challenges. In particular, we investigate whether distorting incentives are present among football coaches in the National Collegiate Athletic Association (NCAA) when participating in the USA Today Coaches Poll of the top 25 teams. Every season approximately 60 coaches are selected to provide weekly rankings of the top 25 college football teams, and the USA Today publishes aggregated results of the Poll as a weekly ranking of the top 25 teams. These rankings are closely followed by millions of football fans, television networks seeking to market and broadcast the games of highly ranked teams, and other observers interested in university reputations. Moreover, the final regular season poll, conducted in early December after all the pre-bowl games, carried additional importance during the BCS era (2004 through 2013) because it was used to determine the eligibility of teams for the five high-profile Bowl Championship Series (BCS) bowl games, including the national championship. Selection into a BCS bowl game was not only prestigious, it came with substantial financial rewards for participating teams and conferences, as indicated by the $182 million of revenue that was disbursed to universities after the 2010–2011 season.

The primary question motivating our research is whether coaches can be relied upon to overcome private incentives and provide unbiased team rankings, the credibility of which is a public good. The overall conclusion, based on more than 9000 ranking observations from 363 coach ballots between 2005 and 2010, is that private incentives—reputational and financial—have a significant and distorting influence on the way coaches rank teams. The direct economic result is that financial incentives influence coaches' rankings. Coaches rank their own teams more favorably when they have a greater financial incentive to do so, based on bonuses for having their team achieve a top 25 ranking. When it comes to ranking teams in contention for receiving an invitation to one of the BCS bowl games, coaches show favoritism to conferences and teams that generate higher financial payoffs to their own university. Above and beyond the direct financial results, coaches rank more favorably their own team and teams from their same athletic conference for apparent reputational and/or familiarity reasons. Moreover, playing a team during the season does not influence coach rankings, but coaches rank teams they defeated more favorably, thereby making their own team look better.

While we recognize that the rankings of NCAA football teams may not be of obvious scholarly concern, we believe our study has methodological advantages and results that make it of more general interest. Studies on conflicts of interest are often challenging because data are difficult to collect, incentives are not easy to define, and what constitutes a biased or distorted evaluation is hard to measure. Our study, in contrast, provides a unique setting in which many agents are evaluating the same thing, private incentives to distort evaluations are clearly defined and measurable, and, as we will describe, there exists an alternative source of computer evaluations that is bias free. Identifying the extent to which coaches are able to manage conflicts of interest is also useful because, as discussed above, their task of ranking teams closely mirrors that in more immediately relevant domains, such as credit rating agencies, college rankings, and even politicians voting on legislation. The finding that coaches are not immune to the lure of private interest, even when their rankings are so highly publicized and scrutinized, should cast further doubt on, for example, the reasonableness of assuming that elected politicians behave any differently, especially when their full set of decisions is typically more diffuse and less transparent. It is also the case that NCAA football has significant economic impacts: one quarter of the U.S. population, or between 75 and 80 million people, follow college football regularly (The Economist/YouGov Poll, 2010), resulting in television contracts worth several billions of dollars. Our study thus follows in the growing tradition of research that exploits the wealth of data and clearly defined incentives often found in sports to investigate more general economic phenomena.[2]

Finally, our findings have direct implications for the importance of information disclosure requirements. It was only after a wave of controversy about the integrity of the Coaches Poll that individual ballots for the final regular season poll were made publicly available starting in 2005. Moreover, the American Football Coaches Association (AFCA) attempted to revoke the disclosure rule for the 2010 final regular season ballots, until a public backlash caused officials to reconsider. Not surprisingly, the question of whether individual ballots of the Coaches Poll should be have been made public was controversial (Rittenberg, 2012), and knowing whether bias exists and in what form is useful for understanding the influence of conflicts of interest. The results of our analysis will also help understand the potential implications of recent reforms in NCAA football (discussed in Section 6) that replaced the BCS system to address concerns of the type identified here.

2. Background

We begin with background information that helps motivate our research questions and empirical strategy. Specifically, we provide information on the USA Today Coaches Poll for NCAA football, along with the BCS bowl game selection process and corresponding financial payoffs.

[2] See Munasinghe et al. (2001), Duggan et al. (2002), Romer (2006), Price and Wolfers (2010), Parsons et al. (2011) and Levitt et al. (2011). Several of these studies, including ours, are examples within the new meta-field of "forensic economics" that seeks to uncover hidden behavior through a clear understanding of incentives and detailed empirical data (Zitzewitz, 2012).

2.1. The USA Today Coaches Poll

The USA Today Coaches Poll is a weekly ranking of NCAA Division IA football teams based on the votes of approximately 60 members of the AFCA Division IA Board of Coaches. The Poll is sponsored by the USA Today and administered by the AFCA. Each season opens with a preseason poll that is updated every week during the regular season. The results are released as the USA Today Coaches Poll ranking of the top 25 teams, showing the number of points each team received, where points are allocated as 25 for a first-place rank, 24 for a second-place rank, etc., summed across the ballots of all participating coaches. The coaches top 25 rankings are important for the publicity they receive each week through television advertisements for upcoming games. While the Coaches Poll results are listed and promoted on their own, prior to 2014 they were also combined with other polls (described below) to produce an official BCS ranking.

During the BCS bowl era, the final regular season poll had added importance because it was part of the BCS formula for selecting teams to play in the national championship and to establish eligibility of teams for invitations to other BCS bowl games. Beginning in 2005, the AFCA began making public each coach's ballot for this poll, though ballots are not publicly available for other polls during the season. Public disclosure of these ballots was a requirement for keeping the Coaches Poll a part of the BCS rankings formula in the wake of controversy following the 2004 Poll and BCS rankings.

The 2004 controversy is interesting and relevant to the aim of our research. In the week leading up to the Poll in December 2004, California was ranked ahead of Texas in both the Coaches Poll and the overall BCS rankings. California thus appeared poised to become the lowest ranked team invited to play in a BCS game. But Texas head coach Mack Brown, whose team was ranked just below California, aggressively touted his team for the final BCS invitation over California. The effect was that in the next Coaches Poll, California's lead over Texas dropped 43 points, and Texas received the last BCS bowl invitation. In the fallout from this controversy came an important reform: in order for the Coaches Poll to be included in the BCS ranking formula, the AFCA was required to release the individual ballots for the final regular season poll. The disclosure was controversial, however, with the AFCA having preferred not to make ballots public at all, and critics claiming that the limited disclosure did not go far enough.

2.2. The BCS bowl games

College football bowl games are played in December and January as rewards for regular season performance. Selection into bowl games is by invitation, with most bowls having agreed in advance to select teams based on their conference ranking. In some cases, however, better performing teams can receive invitations to more prestigious and lucrative bowls. The BCS was a selection system that from 2004 through 2013 created match-ups for the most prestigious and high-paying bowls, including an arrangement for the two most highly rated teams to play in a national championship game. Over the period that we study, 2005 through 2010, there were four BCS bowl games (the Rose, Sugar, Fiesta, and Orange Bowls) with a fifth National Championship Game added beginning in 2006.[3] The BCS method for selecting teams into these games changed several times since its inception in 1990, as did its formula for distributing revenue to conferences and teams.[4]

From the 2005 through the 2013 seasons, the BCS regular season rankings were based on an equally weighted average of the Coaches Poll, the Harris Interactive College Football Poll, and a composite of computer rankings. The Harris Poll operates much like the Coaches Poll, but it is composed of ballots from former players, coaches, administrators, and current and former members of the media. The composite of computer rankings consisted of the average among six different algorithms produced and updated weekly by Jeff Sagarin, Anderson & Hester, Richard Billingsley, Wesley Colley, Kenneth Massey, and Peter Wolfe. The method for averaging the six computer programs was to drop the highest and lowest ranking and average the remaining four, before combining it with the other polls to produce the overall BCS ranking.

The BCS ranking at the end of the regular season was used to determine the two teams that receive invitations to play in the National Championship Game. The rankings were also important because they influence the eligibility of teams for invitations to the other four BCS bowl games. The champions of the BCS conferences—i.e., the Atlantic Coast, Big 12, Big East, Big Ten, Pacific-12, and Southeastern Conferences—received automatic invitations to one of the four bowl games. The remaining at large BCS bowl invitations were selected by the administrators of the Bowl games themselves, with each game selecting two teams and the order of selection rotating each year.[5] While the BCS rankings were used for determining the eligibility of teams for at large BCS bowl invitations, the individual bowls on occasion selected teams ranked in worse positions.

Over the period that we study, selection into one of the BCS bowl games had significant financial rewards for teams and conferences. Net revenues from the BCS games were substantial and continue to grow, reaching approximately $182 million

---

[3] BCS bowl games are played in January following the season of the previous calendar year. For simplicity we use the year of the fall football season to refer to all games, including bowls played in January after the regular season's end.

[4] Economics research has shown that some of these reforms have resulted in greater efficiencies within college football. For example, the BCS allows the matching of teams in bowl games to occur later in the season, and this results in more highly ranked teams playing in bowls, which increases viewership (Fréchette et al., 2007).

[5] At large invitations also were subject to some eligibility restrictions, such as a limit of two BCS invitations per conference, that Notre Dame automatically qualified if ranked in the top eight, and that a non-BCS conference team automatically qualified if ranked in the top 12 or if ranked in the top 16 and better than the champion of a BCS conference.

for the 2010 season bowls and up from $126 million in 2005. The BCS allocated this money to each of the BCS conferences and to the non-BCS Division 1A conferences, who then divided the money amongst themselves based on an agreed upon formula. Universities then received payments from their conference, with some conferences allocating funds more or less equally and others allocating them relatively unequally. The BCS revenue allocation heavily favored the major BCS conferences with rules that were set out in advance of each season. We discuss the specific rules in the Appendix, as they play a central role in the creation of payoff variables used in our analysis.

3. Criticism and hypotheses

The Coaches Poll has a significant impact on the reputation and visibility of college football teams throughout the season, and on whether contending teams received one of the highly sought after BCS bowl invitations. The Coaches Poll has nevertheless been the subject of continuing controversy and criticism.[6] Although the AFCA's decision to begin partial disclosure in 2005 was intended to reduce such criticism, it has been largely unsuccessful. Even upon the initial announcement, the ESPN network, citing concerns about conflicts of interest and lack of transparency, discontinued sponsorship of the Poll after the AFCA decided not to release the complete set of ballots each week (Carey, 2005).

The results in our paper are consistent with previous studies that find that the Coaches Poll voters are biased to favor their team's recent opponents and teams in their conference (Paul et al., 2007; Mirabile and Witte, 2010; Sanders, 2011).[7] While we consider the same potential sources of bias, our paper extends this research in two important ways. First, we adopt innovative identification strategies using both fixed effects and computer rankings. Second, our analyses reveal that even after controlling for these previously identified biases, coaches show additional voting biases in favor of their own personal and university's financial payoffs when ranking teams contending for BCS at large invitations.

We test for bias in several dimensions, the first of which is whether coaches rank their own teams more favorably, where hereafter ranking a team more favorably means giving it a "higher" rank. Higher-ranked teams enjoy reputation benefits, as they generate greater interest among fans, which increases demand for tickets and merchandize. More talented high school football players likewise favor higher-ranked teams when deciding where to play college football (Dumond et al., 2008), and having better recruits makes for stronger teams (Langelet, 2003). Also, some coaches have contracts that provide them with large financial bonuses for having their team achieve a top 25 ranking in the final poll. We thus predict that coaches are likely to have biased rankings in favor of their own teams, and even more so when their contracts provide bonuses for achieving a top 25 ranking. The mechanism may be either direct reputation benefits or overconfidence in one's own team, just as CEOs have been found to overconfidently rate the investment prospects of their own firm (Malmendier and Tate, 2005).

The quality of a team's opponents also affects its reputation. In particular, having played and defeated higher-ranked teams improves a team's own reputation in the eyes of fans, the media, and potential recruits. Because of this transitivity, we predict that coaches will tend to assign better rankings to teams they have played and defeated during the season. Alternatively, it is easy to envision how coaches might have the same incentive when ranking teams that defeated them, as a loss to a higher-ranked team does not look so bad. We think this effect is plausible, though perhaps less direct, and our empirical strategy tests for either possibility.

We have already referenced research on how high school football recruits favor higher-ranked teams, and that successful recruiting makes for stronger teams. Knowing that coaches compete rigorously for leading recruits, it follows that coaches may benefit from less favorable rankings of teams with whom they compete for recruits. We thus evaluate whether recruiting competition affects rankings. That is, we test whether coaches assign less favorable rankings to teams that offer scholarships to more of the same high school players.

The assertion that coaches show favoritism to teams in their own conference resonates with many because coaches have several reasons to do so.[8] At least two reasons are based on the collective benefits of making one's own conference look better. Higher-ranked teams attract more television appearances and better viewership ratings. More successful teams are therefore in a better position to negotiate television contracts, but these negotiations take place at the conference level, with earnings split among conference teams.[9] It follows that coaches seeking to increase their own benefits from television contracts have an incentive to promote the collective reputation of their conference by ranking member teams more favorably. Another

[6] For example, the Poll's Wikipedia entry states that "The coaches poll has come under criticism for being inaccurate, with some of the charges being that coaches are biased toward their own teams and conferences, that coaches don't actually complete their own ballots, and that coaches are unfamiliar with even the basics, such as whether a team is undefeated or not, about teams they are voting on" (November 7, 2011). Similar statements are made in hundreds of popular commentaries throughout each college football season, especially when individual ballots are released for the end of the regular season poll.

[7] Coleman et al. (2010) and Logan (2011) find similar biases in the Associated Press College Football Writers poll.

[8] Interestingly, coaches are not the only ones who have been accused of showing bias for personal gain when ranking college football teams. Following the 1969 season, long before there was an official national championship game, President Nixon declared undefeated Texas as the national champion, despite the fact that Penn State was undefeated as well. Many commentators suggested that the President's unusual proclamation was in pursuit of the Lone Star state's electoral votes.

[9] Conference television contracts are substantial, such as the $2.25 billion 15-year contract between ESPN and the Southeastern Conference, and the $2.8 billion 25-year contract between the Big Ten Network (part of Fox Sports) and the Big Ten Conference.

reason for promoting one's own conference reputation is to improve recruiting prospects. Within conference match-ups are most common, and even for less competitive teams, being in a conference with higher-ranked teams helps recruiting prospects because players are likely attracted to more prestigious and highly visible conferences.

Along with some of incentives describe here, coaches may also bias their rankings of teams in their same group (BSC versus non-BCS), same conference, and teams they have played because they are more familiar with them. In other words, there may be familiarity bias or other cognitive biases (e.g., confirmatory or self-serving biases) that are difficult to disentangle from financial incentives. In other cases, however, we have data to test the financial incentives more directly, as we will show.

The selection method for BCS bowl games creates what is perhaps the most direct private incentive that may distort how coaches rank teams. As described previously, the Coaches Poll is an important part of the BCS formula for determining eligibility for at large invitations, and the payoffs are substantial to the conferences of teams receiving these invitations. Each season there are a set of teams considered contenders for an at large invitation, which we refer to as "bubble teams." We expect that all of the reputation benefits already discussed apply in particular to coaches ranking teams on the bubble because of the high profile of BCS bowl games.

At large BCS invitations have direct financial incentives as well. Financial payoffs to universities vary significantly depending on which of the bubble teams receives an invitation. These differences are based on the BCS rules for revenue allocation, with the payoff to any given university depending on several factors, including whether a team is from the same conference as the coach, whether other teams from the coach's conference also receive a BCS invitation, whether the coach's team and the team being ranked are both from a BCS Conference or a non-BCS Conference, and on conference rules for allocating revenue among member teams. The differences can often be significant; for example, the 2010 payoff rules imply that a coach from a BCS Conference ranking two bubble teams, one from his own conference and one from a non-BCS Conference, would face an $8 million difference in the payout to his conference. While BCS payouts were made to conferences, which then allocated funds among their university members, there is reason to believe that university athletic departments and football teams are the ultimate financial beneficiaries.[10] We thus hypothesize that greater financial payoffs lead to favoritism in the way that coaches rank bubble teams.

4. Data description

We use the ranking data from the final regular season ballots of coaches participating in the USA Today Coaches Poll from 2005 through 2010, that is, six years of ballots that are publicly available and posted online by USA Today. In each poll, participating coaches submit their ranking of the top 25 teams, where lower numbers correspond to better teams. The number of coaches submitting a ballot in each year is 62, 62, 60, 61, 59, and 59 for 2005 through 2010, respectively. The dataset consists of 9073 ranking observations, and the mean *Coach rank* is just under 13, as it should be, with a range between 1 and 25.[11] There are 139 different coaches in the sample, and the average number of years that a coach submits a ballot is 2.62, with a range between 1 and 6. Coaches in the sample sometimes change teams, which occurs 11 times, with one coach changing teams twice. The Poll also includes coaches that are coach of the same team in different years. It follows that the number coaches differs from the number of coach teams at 103.

The computer rankings used by the BCS provide an important variable for our analysis. These include those produced by Jeff Sagarin, Anderson & Hester, Richard Billingsley, Wesley Colley, Kenneth Massey, and Peter Wolfe. These rankings use different algorithms for ranking teams, taking into account a variety of factors such as win-loss records, the strength of opponents, and winning margins.[12] A particularly useful feature for our analysis is that the computer rankings provide an ordering of teams that is free of potentially distorting incentives, and thereby provide one way to control for team quality in our statistical models. To construct a single variable out of the six rankings, we follow the BCS protocol of dropping the highest and lowest ranking for each team and averaging the remaining four. We follow this procedure for every team in each year that was ranked in the top 25 by at least one coach, using the computer rankings for the corresponding week of the Coaches Poll. Table 1which includes all summary statistics, shows that the mean *Computer rank* is 14.4.

Fig. 1 plots a histogram of the difference between *Coach rank* and *Computer rank* for all of the observations in the dataset. The vast majority of the differences are clustered more or less symmetrically around zero, indicating the coaches and computers often agree, and in general are quite close. Further out in the tails, the asymmetry favoring the negative side corresponds with cases where coaches rank certain teams substantially more favorably than the computer rankings. The important observation to make from the histogram is that coaches appear to rank teams differently, and the primary aim of our empirical analysis is to determine whether coaches' private incentives help explain the heterogeneity.

[10] For example, when criticizing the BCS in testimony before the U.S. House of Representatives Subcommittee on Commerce, Trade and Consumer Protection, Mountain West Conference Commissioner Craig Thomas discussed how inequities in BCS payoffs disadvantaged non-BCS athletic programs, resulting in fewer athletic and academic opportunities for non-BCS conference athletes (U.S. House, Subcommittee on Commerce, Trade and Consumer Protection, 2009).

[11] The dataset is only two less than complete, as the 25th ranked team is missing for two coaches (Art Briles and Larry Blakeney) in 2006. It is unclear whether these missing observations were intentional on the part of the coaches or simply missing from the USA Today ballots posted online.

[12] While the six computer ranking produce different results, they are, not surprisingly, highly correlated. Pair-wise correlation coefficients among them range between 0.81 and 0.97.

Table 1
Summary statistics of all variables used in the empirical analysis.

Variable	Mean	Std. dev.
Panel A: coaches' ranking variables		
Coach rank	12.997	7.210
Computer rank	14.397	9.411
Coach rank – Computer rank	−1.399	5.049
Own team	0.012	0.111
Same conference	0.109	0.312
Season play	0.110	0.313
Coach win	0.087	0.282
Common recruits (%)	4.104	6.220
Bubble team	0.206	0.405
Coach bonus ($1000s)	17.810	29.490
Coach bonus share (%)	1.656	3.117
Panel B: bubble team variables		
Bubble × same group	0.557	0.497
Bubble × same conference	0.089	0.284
Bubble × same group × BCS	0.457	0.498
Bubble × same group × non-BCS	0.100	0.300
Bubble × same conference × BCS	0.072	0.258
Bubble × same conference × non-BCS	0.017	0.130
Bubble payoff ($100,000s)	−0.002	4.343
Bubble payoff share (%)	−0.001	3.077

Note: Variables are defined in the main text. Coaches' ranking variables are based on 9073 observations, with a few exceptions. *Common recruits* excludes observations when a coach ranks his own team, leaving 8960 observations for this variable. *Coach bonus* and *Coach bonus share* are only for observations when coaches rank their own team, and after missing data, there are 93 and 92 observations for each variable, respectively. Bubble team variables, which apply only for the bubble teams in each year, are based on 1872 observations.

As discussed previously, several financial and non-financial variables are hypothesized to have a potential effect on how coaches rank teams. To test these hypotheses, we create variables based on pairings between a coach's team and the teams he ranked in each year. *Own team* is an indicator for whether the observation is a coach ranking his own team. *Same conference* is an indicator for whether the coach's team is in the same conference as the team being ranked. *Season play* is an indicator for whether the coach's team played the team being ranked during the season, capturing some degree of familiarity. Because teams most often play other teams in their same conference, it is worth noting that the correlation between *Same Conference*

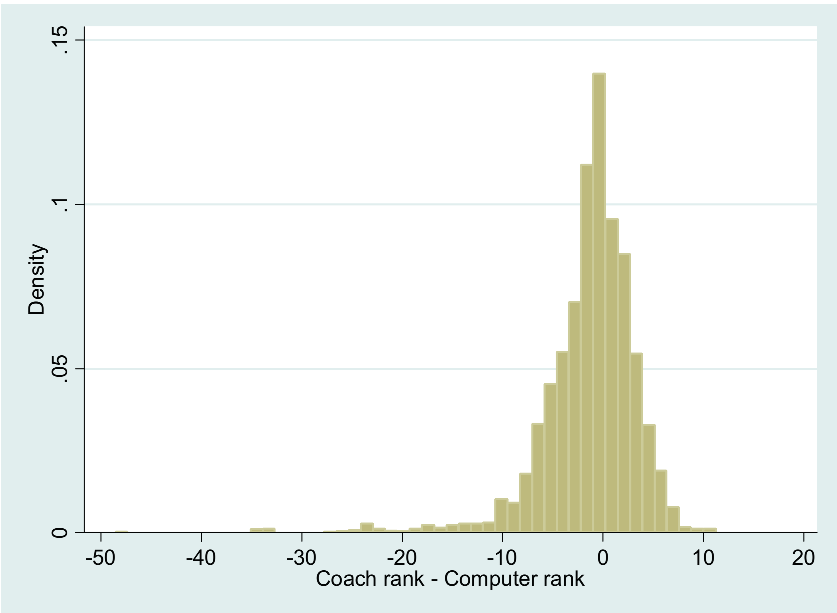

Fig. 1. Histogram of the difference between *Coach rank and Computer rank* for all 9073 observations.

and *Season play* is 0.67. *Coach win* is an indicator for whether the coach's team beat the team being ranked during the season.[13] Note that *Season play* must equal one in order for *Coach win* to equal one.

We create a variable to measure competition between teams to recruit high school players. We obtained data from Scouts.com, which includes a comprehensive listing of all high school players recruited to play Division I football. One of the online interfaces with the database reports for each team in each year all of the high school players that were offered scholarships. We downloaded these data for the 2004 through 2009 recruiting seasons and matched between schools based on player name. From this, we create *Common recruits* as the percentage of scholarship offers from a coach's team that also received an offer from the team being ranked. The recruiting competition is thus based on the percent of common scholarship offers between the coach's team and the team being ranked, and we investigate whether more common offers cause coaches to rank other teams less favorably. The average of *Common recruits* is 3.8% (range from 0 to 48%).

Other variables are based on financial payoffs. To focus on a coach's personal financial incentive for ranking his own team, we collected data on bonuses that a coach receives if his team ranks in the top 25. USA Today (2006, 2007, 2009) provides the contracts for 95 of the 132 (72%) of the cases in our data where a coach ranks his own team. Coaches' contracts generally list a base salary; a services compensation covering activities such as media and summer camp appearances; and a performance bonus covering items such as bowl appearances, graduation rates and achieving a top 25 or top 10 poll ranking. We create the variable *Coach bonus* as the average dollar amount of the bonus for achieving a top 25 ranking in the USA Today coaches' poll (range from $0 to $140,000). Bonus amounts were averaged in cases where the contract reports different bonuses for higher rankings. We also create *Coach bonus share* as the top 25 ranking bonus as a proportion of the coach's total compensation, which includes base salary plus services compensation (range from 0 to 16%).

Financial incentives also arise based on which teams receive BCS bowl invitations. We restrict attention to teams that were on the bubble of receiving a BCS invitation in each season. These are the teams in each year for which a more or less favorable ranking in the Coaches Poll could influence their chances of receiving a BCS bowl invitation. To systematically identify these teams, we first calculate rankings based on the average of the Harris Poll and the computer rankings during the week prior to the final regular season Coaches Poll. Recall that the Harris Poll and computer rankings contribute two-thirds of the overall BCS ranking and therefore provide the best indicator of the next BCS ranking independently of the Coaches Poll. We then eliminate all BCS conference champions, as they receive automatic invitations. We also assume that the remaining two most highly ranked teams will receive invitations, unless one of them is the third-ranked team in a conference, as only two teams from a conference are eligible for invitations. We then move down the ranking categorizing the more highly ranked teams as on the bubble until there appears a natural drop off accounting for other considerations.[14] Appendix Table 1 includes the list of these teams, along with the average ranking for the week prior and whether the team ultimately received a BCS invitation. With this classification, we create the variable *Bubble team* as an indicator for whether the team being ranked is in contention for a BCS at large invitation. This occurs 14% of the time coaches rank teams, and the number of bubble teams for 2005 through 2010 is 5, 4, 6, 5, 5, and 6, respectively.

We have discussed how coaches' universities receive different financial payoffs depending on which bubble team plays in a BCS bowl game. As a rough measure of these differences, we first create interactions that reflect how a coach's payoff differs categorically among the bubble teams, should the team receive a BCS invitation. These variables enable tests of whether direct financial incentives affect the way coaches rank teams. *Same group* is an indicator for whether the coach's team and the team being ranked are both in a BCS conference or both in a non-BCS conference. To further reflect how the payoffs may differ, we interact *Bubble team* with *Same conference* to indicate whether the coach's team and the team being ranked are from the same conference. Table 1 indicates that 56% of the coach ranks on bubble teams are pairings from the *Same group*, while 9% are from the *Same Conference*. Also shown in Table 1 is the further breakdown of whether *Same group* consists of pairings within BCS conferences or within non-BCS conferences, and whether *Same conference* consists of parings within the BCS or non-BCS conferences.

The last two variables are designed to capture the direct financial payoffs that arise because of BCS bowl invitations. Specifically, we estimate the financial payoff to each coach's university that would occur if the bubble team being ranked received a BCS invitation. To accomplish this, we consider the BCS payoffs to universities that would occur if the particular team being ranked received the invitation compared to the average payoff of the other bubble teams receiving the invitation. In general, these differences depend on several factors, including the categorical pairings described above, how the BCS allocated money to conferences, how non-BCS conferences allocated BCS revenues among themselves, and how conferences allocated money among their universities. In the Appendix, we describe the specific assumptions, steps, and data sources for estimating the payoffs and creating the variable *Bubble payoff*. The last row of Table 1 reports that the mean payoff is just under zero (range from −$3.4 to $13.6 million), and keep in mind that a negative payoff reflects the fact that a BCS invitation to the team being ranked lowers the payoff to the ranking coach's university, perhaps by reducing the chances that a team from the coach's conference receives an at large invitation. Finally, we collected data from the NCAA on the total size of the

[13] In only eight cases did teams play more than once during a season. In these cases, the variable was coded as a win only if the coach's team beat the team being ranked both times.

[14] Any third-ranked team in a conference, with a gap of at least 4 positions from the second-ranked team, is not considered on the bubble. Notre Dame is considered on the bubble if it was within 4 spots of the eighth-ranked team, the point at which it becomes an automatic qualifier.

football budget for each team in each year to scale BCS payoffs as a fraction of the overall football budget of the coach doing the ranking.[15] This variable, *Bubble payoff share*, is also close to zero on average (range from −23 to 70%).

5. Empirical analysis

We employ two different empirical strategies to investigate which variables explain the way coaches rank teams. The first is to estimate models of the form

$$Coach\,rank_{ijt} = \alpha + \boldsymbol{\beta}\mathbf{X}_{ijt} + f(Computer\,rank_{jt}) + \varepsilon_{ijt}, \tag{1}$$

where subscripts i denote coaches, j denotes teams being ranked, and t denotes year; $\mathbf{X}_{ijt}$ is a column vector of explanatory variables; α and the row vector $\boldsymbol{\beta}$ are coefficients to be estimated; $f(\cdot)$ leaves open the functional form of the relationship between coach and computer ranks; and ε_{ijt} is an error term. A key feature of specification (1) is the inclusion of *Computer rank* as an explanatory variable. This controls for the quality of each team in each year, and the control is immune to the potential distortionary incentives that confront coaches.[16] We estimate models with linear and quadratic functional forms, with the rationale to simply absorb variation and test robustness of the results.[17] Of primary interest are the coefficients in $\boldsymbol{\beta}$ because they relate directly to the hypotheses discussed in Section 3.

We estimate variants of specification (1) using ordinary least squares and report two-way clustered standard errors (Cameron et al., 2011), at the levels of team-year and coach-year. The two-way clustering ensures robust inference that takes account of two features of the data. The first is that *Computer rank* varies only at the team-year level. The second is that a coach's rankings of different teams are not independent within each year, because, for example, ranking one team higher means another must be lower. The two-way clustering accounts for the way that ε_{ijt} may be arbitrarily correlated within the two clusters and adjusts the standard errors accordingly.

Our second approach is less restrictive and based on fixed effects estimates of the general specification

$$Coach\,rank_{ijt} = \boldsymbol{\beta}\mathbf{X}_{ijt} + \mu_{jt} + \varepsilon_{ijt}, \tag{2}$$

where the difference is that μ_{jt} is a unique intercept for each team-year. These team-year fixed effects account for heterogeneity of team quality each season in a way that replaces the need for including *Computer rank*, which is perfectly colinear. The primary advantage of specification (2) is that it controls for team-year heterogeneity without requiring a functional form assumption between the coach and computer rankings. This is accomplished by pulling out into the intercept the average ranking, conditional on the model, that all coaches assign to each team in each year.[18] The result is that identification of the coefficients in $\boldsymbol{\beta}$ is based on how coaches for whom each variable applies differ from other coaches ranking the same team. With our estimates of the coefficients in specification (2), we again report standard errors that are two-way clustered on the team-year and coach-year levels. While the estimates based on specification (2) are preferable because of the more flexible functional form, comparison of the results across models provides useful robustness checks.

Table 2 reports the first set of results, with the explanatory variables of *Own team*, *Same conference*, *Season play*, and *Common recruits*. The first column includes the estimate of specification (1) with *Computer rank* entering as a linear function. Not surprisingly, *Computer rank* has a positive and statistically significant effect on *Coach rank*.[19] Other statistically significant results indicate that coaches rank a team more favorably if it is their own team, is in their same conference, and is a team they defeated during the season. Recruiting competition does not have a statistically significant effect. Before turning to the magnitude of these effects, let us consider robustness of the qualitative results across specifications. The model in column II has *Computer rank* entering as a quadratic function. The estimated relationship is increasing and concave, which one might expect given that *Coach rank*, unlike *Computer rank*, has an upper bound at 25. While this model fits the data better, increasing the R^2 from 0.72 to 0.83, the pattern of statistically significant results remains the same. Column III reports the fixed effects estimates of specification (2), the R^2 increases to 0.94, and the qualitative results are again the same.

[15] Data on the annual budgets of football programs at universities is made available by the Office of Postsecondary Education of the U.S. Department of Education. The data are collected as part of the Equity in Athletics Disclosure Act and can be downloaded at http://ope.ed.gov/athletics/GetDownloadFile.aspx.

[16] We use the current week's computer ranking as it includes the most recent information that coaches have available when filling out their ballots. Other studies (e.g., Coleman et al., 2010) use the previous week's ranking when explaining week-to-week changes in the aggregate poll throughout the season, but their analyses are structured differently than those developed here, which consider only one poll per year when the full coaches' ballots are available. Alternative specifications could also use the Harris Interactive Poll rather than the computer rankings, or possibly both. We estimated these alternatives and the results are very similar to those reported here. We use the computer rankings because they provide the best control that is free of alternative sources of bias that may be correlated with bias in the Coaches Poll. Research has shown, for example, that the Associate Press Poll is susceptible to different sources of bias (Coleman et al., 2010).

[17] Note that these functional form assumptions are less restrictive versions of a model in which the left-hand side variable is the difference between *Coach rank* and *Computer rank*, as this implicitly assumes a linear relationship with a coefficient equal to 1. We also estimate this alternative, but do not report the results for several reasons: the results are generally quite similar, there is evidence that assuming a linear coefficient equal to 1 is overly restrictive, and we prefer less restrictive specifications when possible.

[18] This approach controls year specific shocks common to all coaches, such as the addition of the fifth BCS bowl game following the 2006 season.

[19] With respect to the alternative specification mentioned in footnote 17, we test whether the coefficient of 0.652 on *Computer rank* is statistically different from 1. We reject the null hypothesis based on a Wald test ($F = 73.25$, $p < 0.01$).

Table 2
Regression models explaining how coaches rank teams.

	Model (I)	(II)	(III)
Own team	−1.391***	−0.851***	−1.394***
	(0.427)	(0.321)	(0.230)
Same conference	−0.695***	−0.754***	−0.704***
	(0.232)	(0.197)	(0.124)
Season play	0.249	0.278	−0.127
	(0.334)	(0.251)	(0.160)
Coach win	−1.100***	−0.846***	−0.430***
	(0.332)	(0.232)	(0.156)
Common recruits (%)	0.016	0.013	0.004
	(0.015)	(0.012)	(0.004)
Computer rank	0.652***	1.214***	–
	(0.041)	(0.042)	
Computer rank squared	–	−0.014***	–
		(0.001)	
Constant	3.709***	−0.168	
	(0.562)	(0.318)	
Team-year fixed effects	No	No	Yes
Observations	9073	9073	9073
R-Squared	0.722	0.825	0.938

Note: The dependent variable is *Coach rank*. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses.
* Statistical significance at the 90% level.
** Statistical significance at the 90% level.
*** Statistical significance at the 99% level.

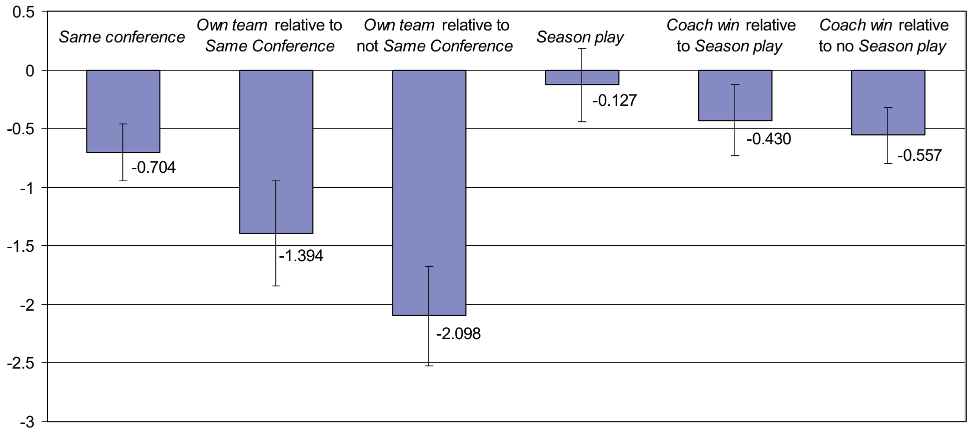

Fig. 2. Average magnitudes and 95% confidence intervals of how variables affect coach rankings based on the fixed effects estimates in column III of Table 3.

The coefficient magnitudes across the three models in Table 2 are relatively stable. While there are some differences, we focus on those from the preferred, fixed effects model. To facilitate interpretation, we illustrate the main results in Fig. 2, which shows coefficient estimates on the categorical variables along with 95% confidence intervals. When coaches rank teams in their own conference, they rank them, on average, 0.7 positions more favorably than teams not in their conference. Coaches rank their own team an additional 1.4 positions more favorably. Combining these results by summing the coefficients, we find that coaches rank their own team 2.1 positions more favorably than teams outside their conference. While having played a team during the season does not significantly affect rankings, having defeated a team during the season does. Coaches rank teams they defeated 0.43 positions more favorably compared to teams that defeated them. Compared to teams they never played, they rank teams they defeated 0.56 positions more favorably.[20]

We now turn to models that expand upon those in Table 2 in order to focus on incentives stemming from BCS bowl payoffs. While considering variants of Eq. (1), we report only the quadratic specification, as it is more flexible and improves the model's fit. The first column of Table 3 reports such a model with three additional variables specific to bubble teams.

[20] Since our data come only from the penultimate coaches poll, our season played measure captures the bias for recent games and for those earlier in the reason. We cannot rule out the possibility that coaches overate their opponents more immediately after playing them, with the bias dissipating over subsequent weeks.

Table 3
Regression models explaining how coaches rank teams, including categorical BCS bubble variables

	Model			
	(I)	(II)	(III)	(IV)
Own team	−0.842***	−1.374***	−0.845***	−1.387***
	(0.323)	(0.229)	(0.324)	(0.231)
Same conference	−0.682***	−0.633***	−0.670***	−0.625***
	(0.196)	(0.130)	(0.195)	(0.130)
Season play	0.263	−0.141	0.260	−0.140
	(0.247)	(0.159)	(0.249)	(0.158)
Coach win	−0.830***	−0.415***	−0.820***	−0.414***
	(0.230)	(0.156)	(0.229)	(0.156)
Common recruits (%)	0.013	0.004	0.011	0.003
	(0.012)	(0.004)	(0.012)	(0.004)
Computer rank	1.214***	–	1.213***	–
	(0.042)		(0.042)	
Computer rank squared	−0.014***	–	−0.014***	–
	(0.001)		(0.001)	
Bubble team	0.041	–	0.034	–
	(0.458)		(0.458)	
Bubble × *same group*	0.008	−0.072	–	–
	(0.171)	(0.139)		
Bubble × *same conference*	−0.412	−0.376*	–	–
	(0.275)	(0.209)		
Bubble × *same group* BCS	–	–	0.231	0.179
			(0.285)	(0.110)
Bubble × *same conf. BCS*	–	–	−0.507	−0.487**
			(0.313)	(0.222)
Bubble × *same group non-BCS*	–	–	−1.003*	−0.824***
			(0.567)	(0.267)
Bubble × *same conf. non-BCS*	–	–	0.060	0.125
			(0.429)	(0.452)
Constant	−0.177		−0.160	
	(0.344)		(0.343)	
Team-year fixed effects	No	Yes	No	Yes
Observations	9073	9073	9073	9073
R-Squared	0.825	0.938	0.825	0.938

Note: The dependent variable is Coach rank. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses.
* Statistical significance at the 90% level.
** Statistical significance at the 90% level.
*** Statistical significance at the 99% level.

The coefficient on *Bubble team* provides an estimate of how, after controlling for the other variables, coaches rank bubble teams in a season differently than other teams. *Bubble* × *Same group* estimates the effect on bubble team ranks of whether the coach's team and the team being ranked are both in a BCS conference or both in a non-BCS conference. The third variable, *Bubble* × *Same conference* measures the additional effect of having the paring within the same conference. Recall that these variables are designed to reflect the general pattern of how financial payoffs from the BCS bowl games are distributed between BCS and non-BCS conferences and among conferences themselves. While none of the new variables is statistically significant in the first model of Table 3 we do find significant results with the fixed effects model in column II. Coaches do not rank teams differently if they are from the same group, but the rankings are different when coaches rank bubble teams within their same conference. Rankings within the same conference are 0.38 positions more favorable than only within the same group, and 0.45 positions more favorable than those not within the same group ($t = 1.94$, $p = 0.05$).

The models in columns III and IV estimate the bubble effects separately for coaches in BCS and non-BCS conferences. The rationale is that payoffs are structured differently between the two groups. In particular, bonuses for receiving a bowl invitation are paid to individual conferences for those within the BCS, whereas part of the bonuses for non-BCS teams are paid to non-BCS conferences as an entire group. Consequently, one might expect BCS coaches to show more favoritism toward their own conference, while non-BCS coaches have a greater incentive to show favoritism toward all non-BCS teams. We find this general pattern in the results. The model in column III has a negative and statistically significant coefficient on *Bubble* × *Same group* for the non-BCS conferences. The magnitude is -1, indicating that coaches in non-BCS conferences rank non-BCS teams nearly one whole position more favorably on average. But these same coaches do not show additional favoritism toward teams in their particular conference. This result continues to hold in the fixed effects model (column IV), where we find nearly the opposite effect for coaches in BCS conferences. For them, favoritism is focused on teams in their own conference, by nearly half a position over teams only in their same group, reflecting the way payoffs are structured for the BCS conferences.

Table 4
Regression models explaining how coaches rank teams, including monetary payoff variables.

	Model	
	(I)	(II)
Own team	−1.018***	−1.172***
	(0.293)	(0.286)
Coach bonus ($1000s)	−0.021***	–
	(0.007)	
Coach bonus share (%)		(0.090)
Same conference	−0.669***	−0.676***
	(0.125)	(0.126)
Season play	−0.134	−0.139
	(0.159)	(0.159)
Coach win	−0.413***	−0.403***
	(0.155)	(0.155)
Common recruits (%)	(0.004)	(0.004)
Bubble payoff ($100,000s)	−0.051*	–
	(0.030)	
Bubble payoff share (%)	–	−0.050
		(0.032)
Team-year fixed effects	Yes	Yes
Observations	9041	9040
R-Squared	0.938	0.938

Note: The dependent variable is Coach rank. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses.
* Statistical significance at the 90% level.
** Statistical significance at the 90% level.
*** Statistical significance at the 99% level.

The next set of models focus directly on actual financial payoffs. We consider the variable *Coach bonus* to test whether the financial bonus that a coach receives for having his own team in the top 25 affects how he ranks his own team. Regarding the payoffs from invitations to BCS bowl games, we include our estimates of the financial incentives with the variable *Bubble payoff* instead of categorical variables reflecting the rules for revenue disbursement. Recall that this variable captures the payoff to a coach's university if the bubble team being ranked receives a BCS invitation compared to the average payoff of other bubble teams that year. Column I of Table 4 reports the first fixed effects estimates.[21] We find that *Coach bonus* has a negative and statistically significant effect, implying that a $10,000 increase in a coach's bonus is associated with a more favorable own-team ranking of 0.2 positions. Note that this is a direct financial effect for coaches that occurs beyond the full position more favorable ranking for one's own team that includes other direct and indirect incentives for coaches and universities captured in the variable *Own team*. Another way to express this result is that an additional bonus of $50,000 would be associated with ranking favoritism for one's own team by a full position. We find that the coefficient on *Bubble payoff* is negative and statistically significant. The magnitude implies that a $100,000 increase in the payoff produces more favorable rankings of 0.05 positions, or equivalently, boosting a coach's ranking of a bubble team one full position requires an additional payoff of $2 million to the coach's university. The model in column II reports results with the scaled variables *Coach bonus share* and *Bubble payoff share*, which convert the payoff amounts to a percentage of the coach's compensation and to the annual football budget of the coach's team, respectively. Both coefficients remain negative, but only the one for the coach's bonus is statistically significant. The magnitude implies, for example, that an increase in the coach's bonus payoff equal to 10% of his full compensation causes a more favorable ranking of his own team by 1.8 positions.

6. Conclusion

This paper provides evidence that private incentives distort public evaluations. While coaches participating in the USA Today Coaches Poll are tasked with providing unbiased rankings of teams, they face incentives that pose potential conflicts of interest. These arise because of reputation and financial rewards (to coaches and universities) that depend on how teams are ranked and whether teams are in position to receive an invitation to one of the high-profile and lucrative BCS bowl games. We find, using multiple empirical strategies, that conflicts of interest bias coach rankings in predictable ways.

The pattern of results is highly suggestive of the importance of both reputation benefits and direct financial payoffs. Coaches have clear incentives to rank more favorably both their own team and other teams in their athletic conference. We find that coaches' bonuses for having their own team ranked in the top 25 affect how they rank their own teams—up to two whole positions on average for a $50,000 increase in the bonus. Moreover, a coach's bonus payoff equal to 10% of his full compensation causes a more favorable ranking of his own team by a full 1.8 positions. We also find, on average, that coaches

[21] We find very similar results for models that include linear and quadratic specifications with *Computer rank*,in parallel with previous tables, though we report only the preferred fixed effects results here, and in subsequent tables, to reduce the amount of models presented.

rank teams from their own conference nearly a full position more favorably and boost their own team's ranking more than two full positions for non-bonus reasons. While it does not matter if a coach's team simply plays a team during the season, coaches rank teams they defeated more favorably by more than half a position. Coaches thus make their own team look better by ranking more favorably teams they defeated.

Above and beyond the effect of reputation and personal financial concerns, or perhaps other cognitive biases favoring one group of teams over another, coach rankings respond to the structure and amount of direct financial incentives created by at large invitations to the BCS bowl games. When it comes to ranking teams on the bubble of receiving an invitation to one of the BCS bowl games, coaches show favoritism to conferences and teams that generate higher financial payoffs to their own university. This is true both categorically and with respect to the actual magnitudes of the direct financial payoffs associated with each bubble team. While the former result could reflect confirmatory or self-serving biases on the part of coaches, the latter result focuses more directly on the effect of financial incentives. When a coach's university receives a greater financial payoff for a particular team receiving a BCS invitation, coaches rank that team higher, thereby increasing their chance of receiving the payoff. On average, an additional payoff of $2 million buys a more favorable ranking of one position. Finally, we find evidence that an increase in a bubble team's payoff to a coach as a percentage of his football budget causes coaches to rank the team more favorably.

It is important to mention that the NCAA replaced the BCS Bowl system with the College Football Playoff (CFP) starting with the 2014 football season. Four teams play in two CFP semifinal games, with the winners advancing to play for the national championship. Instead of the BCS selection formula, CFP teams are chosen by a thirteen-member selection committee made up of athletic directors from the five major conferences, other athletic directors, former coaches, and other notables such as former players and sportswriters. The committee produces weekly top 25 rankings, starting halfway through the season, with the final ranking selecting the playoff teams. The committee deliberates prior to submitting individual rankings via secret ballot. The selection committee's policy to address conflicts of interest is to recuse members from voting in cases where they or their family receive direct financial compensation from the university. These reforms are a clear step to address the types of bias identified in this paper.[22]

In conclusion, this study focuses on how private incentives distort public evaluations in the context of NCAA football; however, we think our methods and results should be of more general interest to economists. Conflicts of interest are ubiquitous through many spheres of economic and political activity, with credit rating agencies, third party certification, and the political process being just a few examples. Studying conflicts of interest in these areas is notoriously challenging because data are difficult to collect, incentives are not easy to define, and what constitutes a biased or distorted evaluation is hard to measure. In contrast, our study takes advantage of a unique field setting in which many agents are evaluating the same thing, private incentives to distort evaluations are clearly defined and measurable, and there exists an alternative source of evaluations that is bias free. The analysis provides strong statistical evidence on the distorting influence of private benefits based on reputation and financial incentives.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2014.07.018.

References

Ansolabehere, S., de Figueiredo, J.M., Snyder Jr., J.M., 2003. Why is there so little money in U.S. politics. J. Econ. Perspect. 17 (1), 105–130.
Ashcraft, A., Goldsmith-Pinkham, P., Vickery, J., 2010. MBS Ratings and the Mortgage Credit Boom, Federal Reserve Bank of New Work Staff Reports, No. 449.
Bowl Championship Series, 2011a. Bowl Championship Series Five Year Summary of Revenue Distribution 2005–06 through 2009–10, Downloaded from: http://www.ncaa.org (10.11.11).
Bowl Championship Series, 2011b. Bowl Championship Series Five Year Summary of Revenue Distribution 2006–07 through 2010–11, Downloaded from: http://www.ncaa.org (10.11.11).
Cameron, C.A., Gelbach, J.B., Miller, D.L., 2011. Robust inference with multiway clustering. J. Bus. Econ. Stat. 29 (2), 238–249.
Carey, J., 2005, June 7. ESPN Severs Ties to Coaches' Poll. USA Today.
Coleman, Jay B., Gallo, A., Mason, P., Steagall, J.W., 2010. Voter bias in the associated press college football poll. J. Sports Econ. 11 (4), 397–417.
Coleman, B.J., DuMond, M., Lynch, A.K., 2010b. Evidence of bias in NCAA tournament selection and seeding. Manag. Decis. Econ. 31 (7), 431–452.
Duggan, M., Levitt, S.D., 2002. Winning isn't everything: corruption in sumo wrestling. Am. Econ. Rev. 92 (5), 1594–1605.
Dumond, M.J., Lynch, A.K., Platania, J., 2008. An economic model of the college football recruiting process. J. Sports Econ. 9 (1), 67–87.
The Economist/YouGov Poll, 2010. Poll Conducted April 6, 2010, Results downloaded from: http://cdn.yougov.com/downloads/releases/econ/20100403_econToplines.pdf (20.11.11).
Fréchette, G.R., Roth, A.E., Ünver, M.U., 2007. Unraveling yields inefficient matchings: evidence from post-season college football bowls. RAND J. Econ. 38 (4), 967–982.
Griffin, J.M., Tang, D.Y., 2010. Did Subjectivity Play a Role in CDO Credit Ratings? University of Texas at Austin, McCombs Research Paper Series No. FIN-04-10.
Griffin, J.M., Tang, D.Y., 2011. Did credit rating agencies make unbiased assumptions on CDOs? Am. Econ. Rev. Pap. Proc. 101 (3), 125–130.
Langelet, G., 2003. The relationship between recruiting and team performance in division 1A college football. J. Sports Econ. 4 (3), 240–245.
Levitt, S.D., List, J.A., Sadoff, S.E., 2011. Checkmate: exploring backward induction among chess players. Am. Econ. Rev. 101 (2), 975–990.

[22] CFP selection committee procedures were designed to mirror those of the NCAA Division 1 men's basketball tournament selection committee, though even these procedures are not immune from bias similar to what we identify in this paper (Zimmer and Kuethe, 2008; Coleman et al., 2010b).

Logan, T.D., 2011. Econometric tests of American college football's conventional wisdom. Appl. Econ. 43, 2493–2518.
Malmendier, U., Tate, G., 2005. CEO overconfidence and corporate investment. J. Financ. 60 (6), 2661–2700.
Mehrana, H., Stulz, R.M., 2007. The economics of conflicts of interest in financial institutions. J. Financ. Econ. 85 (2), 267–296.
Mirabile, P.M., Witte, M.D., 2010. Not so fast, my friend: biases in college football polls. J. Sports Econ. 11, 443–455.
Munasinghe, L., O'Flaherty, B., Danninger, S., 2001. Globalization and the rate of technological progress: what track and field records show. J. Polit. Econ. 109 (5), 1132–1149.
O'Toole, T., 2006, December 6. $17M BCS payoffs sound great, but . . .. USA Today.
Paul, R.J., Weinbach, A.P., Coate, P., 2007. Expectations and voting in the NCAA football polls: the wisdom of point spread markets. J. Sports Econ. 8, 412–424.
Parsons, C.A., Sulaeman, J., Yates, M.C., Hamermesh, D.S., 2011. Strike three: discrimination, incentives, and evaluation. Am. Econ. Rev. 101, 1410–1435.
Price, J., Wolfers, J., 2010. Racial discrimination among NBA referees. Quart. J. Econ. 125 (4), 1859–1887.
Rittenberg, A., 2012, June 18. Transparency Need in New BCS, ESPN.com.
Romer, D., 2006. Do firms maximize? Evidence from professional football. J. Polit. Econ. 114 (2), 340–365.
Sanders, J., 2011. Raking patterns in college football's BCS selection system: how conference ties, conference tiers, and the designation of BCS payouts affect voter decisions. Soc. Netw., http://dx.doi.org/10.1016/j.socnet.2011.08.001 (in press).
U.S. House, Subcommittee on Commerce, Trade and Consumer Protection, 2009, May 1. The Bowl Championship Series: Money and Other Issues of Fairness for Publicly Financed Universities, Downloaded from: http://democrats.energycommerce.house.gov (14.11.01).
USA Today, 2006. Compensation for Div. I-A College Football Coaches, Downloaded from: http://usatoday30.usatoday.com/sports/graphics/coaches_contracts/flash.htm (02.08.13).
USA Today, 2007. Compensation for Div. I-A College Football Coaches, Downloaded from: http://usatoday30.usatoday.com/sports/graphics/coaches_contracts07/flash.htm (02.08.13).
USA Today, 2009. NCAA Football Coaches Contracts, Downloaded from: http://usatoday30.usatoday.com/sports/college/football/2009-coaches-contracts-database.htm (02.08.13).
Zitzewitz, E., 2012. Forensic economics. J. Econ. Lit. 50 (3), 731–769.
Zimmer, T., Kuethe, T., 2008. Major conference bias and the NCAA men's basketball tournament. Econ. Bull. 12 (17), 1–6.