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ABSTRACT

This paper provides a study on conflicts of interest among college football coaches participating in the USA Today Coaches Poll of top 25 teams. The Poll provides a unique empirical setting that overcomes many of the challenges inherent in conflict of interest studies, because many agents are evaluating the same thing, private incentives to distort evaluations are clearly defined and measurable, and there exists an alternative source of computer rankings that is bias free. Using individual coach ballots between 2005 and 2010, we find that coaches distort their rankings to reflect their own team's reputation and financial interests. On average, coaches rank teams from their own athletic conference nearly a full position more favorably and boost their own team's ranking more than two full positions. Coaches also rank teams they defeated more favorably, thereby making their own team look better. When it comes to ranking teams contending for one of the high-profile Bowl Championship Series (BCS) games, coaches favor those teams that generate higher financial payoffs for their own team. Reflecting the structure of payoff disbursements, coaches from non-BCS conferences band together, while those from BCS conferences more narrowly favor teams in their own conference. Among all coaches an additional payoff between $3.3 and $5 million induces a more favorable ranking of one position. Moreover, for each increase in a contending team's payoff equal to 10 percent of a coach's football budget, coaches respond with more favorable rankings of half a position, and this effect is more than twice as large when coaches rank teams outside the top 10.

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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 within financial markets. The famed magazine Consumer Reports rates thousands of household goods and services, and individuals concerned with things like corporate social responsibility, health, and the environment have a proliferation of ratings in these dimensions as well. Students choosing among colleges and universities can consult the well-known U.S. News and World Report Rankings along with numerous other references that compare alternatives. 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 private gain at the expense of those who rely upon them. Many have argued that credit rating agencies suffered from such a conflict of interest in the lucrative market for mortgage-backed securities, whereby inflated ratings ultimately contributed to the market's crash in 2007. The conflict arises in this industry because the principle source of revenue for rating agencies comes from the firms whose products they are rating. Recent empirical research has found that rating standards became progressively more lax between 2005 and 2007 (Ashcraft, Goldsmith-Pinkham, and Vickery 2010), subjectivity played an increasing important role in the ratings of collateralized debt obligations between 1997 and 2007 (Griffin and Tang 2010), and financial incentives explain biased assumptions within rating agencies (Griffin and Tang 2011). Reflecting more generally on the literature, however, Mehran and Stulz (2007) argue that research on conflicts of interest within financial markets often finds weaker and more benign conclusions than those communicated in the media.

Another area that has received considerable scholarly attention is the influence of campaign contributions on the behavior of legislators, whereby contributions produce private benefits for elected officials that may sway their policy positions and roll call votes away from the public interest. But, despite a substantial literature, the pattern of how and when campaign contributions influence elected officials remains unclear (Ansolabehere, de Figueiredo, and Snyder 2003). The research challenges of studying conflicts of interest, in all areas, stem not only from the need to persuasively identify causality, but also 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 executives 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, carries additional importance because it is 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 is not only prestigious, it also comes with substantial financial rewards for participating teams and conferences, as indicated by the $182 million of revenue that was disbursed within the NCAA after the 2010-11 season.

The 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. Because teams play significantly fewer games during a season than the number of potential match-ups, the ranking of teams requires judgment. Coaches, who are assumed to have expert knowledge, are thus relied upon to provide what is intended to be an unbiased and objective ranking. There are, however, a host of potentially distorting private incentives that pose a potential conflict of interest for coaches as they rank teams. These fall into the broad categories of improving the standing of one's own team and athletic conference, and receiving direct financial payoffs by influencing which teams are invited to play in BCS bowl games. The overall conclusion of our analysis, based on more than 9,000 ranking observations from 363 coach ballots between 2005 and 2010, is that private incentives have a significant and distorting influence on the way coaches rank teams.

We recognize that the rankings of NCAA football teams may not be of immediate scholarly concern, but we believe our study has methodological advantages and results that make it of broader interest. Studies on conflicts of interest are notoriously challenging because data are difficult to collect, incentives are not easy to define, and what constitutes 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. 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 is television contracts worth several billions of dollars.

Our study thus follows in the growing tradition of research that exploits the wealth of data and well-defined incentives often found in sports to investigate more general economic phenomena. These include studies on globalization and technological progress in track and field (Munasinghe, O'Flaherty, and Danninger 2001) corruption in sumo wrestling (Duggan and Levitt 2002), maximization behavior in football (Romer 2006), racial discrimination in basketball (Price and Wolfers 2010), game theory in chess (Levitt, List, and Sandoff 2011), and many others.

Beyond providing insight into conflicts of interest, our results have implications for the importance of information disclosure requirements. It was only after a wave of controversy about the integrity of the Coaches Poll, which we discuss later, that individual ballots for the final regular season poll were made publicly available starting in 2005. But disclosure does not occur for all other weeks of the season. Moreover, the American Football Coaches Association (AFCA), whose members make up the panelists in the USA Today Coaches Poll, attempted to revoke the disclosure rule during the 2010 season, until a public backlash caused officials to reconsider. Not surprisingly, the question of whether individual ballots of the Coaches Poll should be made public, and during which weeks, remains controversial. Knowing whether bias exists and in what form should thus inform continuing debate within NCAA football. More generally, the analysis provides a useful study on the potential importance of public disclosure and freedom of information regulations.

The analysis is based on all publicly available ballots of coaches participating in the Coaches Poll for the 2005-2010 seasons. The empirical strategy is based on regression models that exploit two distinct approaches to test how different variables affect the way that coaches rank teams. One approach uses a set of computer rankings to control for team quality from year to year, while the other uses fixed effects models that control more flexibly for team heterogeneity. Overall, we find robust evidence that private incentives introduce bias in the way that coaches rank teams. These arise because of reputation and financial rewards that depend on how teams are ranked and which teams are in position to receive an invitation to one of the high-profile and lucrative BCS bowl games. Among the main results are that coaches rank their own team more favorably and show favoritism to teams from their athletic conference. 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. The most direct economic result, however, is that financial incentives influence coach rankings. 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.

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.

2.1 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 twenty-five 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 twenty-five 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, they are also combined with other polls (described below) to produce an official BCS ranking.

The final regular season poll, conducted after the conference championship games around the first week of December, has added importance because it contributes to the BCS formula for selecting teams to play in the national championship and the eligibility of teams for invitations to other BCS bowl games.[1] 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

[1] A final Coaches Poll is conducted in January after the bowl games have been played.

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 final regular season 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, arguing that California had recently beaten Southern Mississippi, a team from a much less prestigious conference, by a disappointingly "narrow" margin of 26-10. 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 remains controversial, however, with the AFCA preferring not to make ballots public at all, and critics claiming that the restricted disclosure does not go far enough.

2.2 The BCS Bowl Games

College football bowl games are played in December and January, after the regular season, 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 may receive invitations to more prestigious and lucrative bowls. The BCS is a selection system that creates 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 in 2006.[2] The BCS method for selecting teams into these games has changed several times since its inception in the 1990, as has its formula for distributing revenue to conferences and teams.[3]

Beginning with the 2005 season, the BCS regular season rankings have been based on an equally weighted average of the Coaches Poll, the Harris Interactive College Football Poll,

[2] 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.

[3] 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, Roth, and Ünver 2007).

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 selection process of those participating in the Harris Poll aims to have valid representation of conferences and independent schools. The composite of computer rankings consists 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 current method for averaging the six computer programs is 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 is used to determine the two teams that receive invitations to play in the National Championship Game. The rankings are 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—receive automatic invitations to one of the four bowl games. The remaining at large BCS bowl invitations are selected by the administrators of the Bowl games themselves, with each game selecting two teams and the order of selection rotating each year. At large invitations are subject to some eligibility restrictions, such as a limit of two BCS invitations per conference, that Notre Dame automatically qualify if ranked in the top eight, and that a non-BCS conference team automatically qualify if ranked in the top 12 or if ranked in the top 16 and better than the champion of a BCS conference. While the BCS rankings are used for determining the eligibility of teams for at large BCS bowl invitations, the individual bowls have on occasion selected teams ranked in worse positions.[4]

Selection into one of the BCS bowl games has significant financial rewards for teams and conferences. Net revenues from the BCS games are substantial and continue to grow, having reached approximately $182 million for the 2010 season bowls and up from $126 million in 2005. The BCS allocates this money to each of the BCS conferences and to the non-BCS Division 1A conferences, who then divide the money amongst themselves based on an agreed upon formula. Universities then receive payments from their conference, with some conferences allocating funds more or less equally and others allocating them relatively unequally.

The BCS revenue allocation heavily favors the major BCS conferences with rules that are set out in advance of each season. Of all the payoffs from 2005 through 2010, just over 87 percent went to the BCS conferences and Notre Dame. Much of this money was dispersed

[4]In 2007, for example, Kansas received a BCS invitation despite a lower BCS ranking (8) than its Big 12 co-conferee Missouri (6)

in automatic payoffs to each of the BCS conferences, roughly $17 million for each conference in 2005 and $23 million in 2010. Moreover, when a BCS conference had a second team in one of the BCS bowl games, it received an additional payoff of $4.5 million during the 2005-2009 seasons and $6 million for 2010. The five non-BCS Division 1A conferences invariably received a base payment, which equaled approximately $5 million total for the 2005 season and nine percent of BCS revenue in 2006-2010. If one non-BCS team received a BCS bowl game invitation, the non-BCS conferences received an additional 9 percent of BCS revenue, and for a second invitation, they received a payment of $4.5 million in 2005-2009 and $6 million in 2010.

3 Criticism and Hypotheses

The USA Today Coaches Poll has a significant impact on the reputation and visibility of college football teams throughout the season, and on whether contending teams receive one of the highly sought after BCS bowl invitations. The Coaches Poll has nevertheless been the subject of continuing controversy and criticism. 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 towards 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. Although the AFCA's decision to begin partial disclosure in 2005 was intended to reduce such criticism, it was 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).

Despite such criticism, there is surprisingly little systematic evidence on whether the Coaches Poll is subject to bias. We are aware of only one paper that studies the question using the ballots from 2007 through 2010 aggregated at the conference level (Sanders 2011). The results are consistent with coaches showing favoritism to their own conference, especially when teams from a BCS conference are on the margin of receiving a BCS bowl game invitation. While we consider the same potential sources of bias in the present paper, our approach differs because we exploit the complete set of available data (years and ballots), test further hypotheses, and employ statistical methods more commonly accepted in the economics literature.

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 merchandise. More talented high school football players likewise favor higher-ranked teams when deciding where to play college football (Dumond, Lynch, and Platania 2008), and having better recruits makes for stronger teams (Langelet 2003). We thus predict, based on direct reputation benefits, that coaches are likely to have biased rankings in favor of their own teams.

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. 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. While we think this effect is plausible, though perhaps less direct, our empirical strategy tests whether coaches rank opponents differently depending on who won.

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. Using data between 2004-2009 on where all high school football players received scholarship offers and ultimately chose to play, we evaluate whether recruiting competition affects rankings. That is, we test whether coaches assign less favorable rankings to teams that offer scholarships to the same high school players.

The common assertion that coaches show favoritism to teams in their own conference resonates with many because coaches have several reasons to do so.[5] 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. 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 be-

[5] Interestingly, coaches are not the only ones who have been accused of showing favoritism in rankings for personal gain. Following the 1969 season, long before there was a 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.

tween the Big Ten Network (part of Fox Sports) and the Big Ten Conference. 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 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.

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. The payoff to a coach's university may differ 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 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 are often 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, depending on which team receives the BCS invitation.[6] While BCS payouts are made to conferences, which then allocate funds among their university members, there is reason to believe that university athletic departments and football teams are the ultimate financial beneficiaries. 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). To investigate whether such direct financial incentives influence the way coaches rank teams, we construct a data set of the payoffs to coaches

[6] See the Appendix for details about how this calculation is made.

based on whether different bubble teams receive a BCS invitation. We 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, all six years the ballots are publicly available and posted online by the USA Today. In each poll, participating coaches submit their ranking of the top 25 teams, where lower numbers correspond with 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 9,073 ranking observations, and the mean *Coach rank* is just under 13, as it should be, with a range between 1 and 25 (see Table 1).[7] 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. The specific distribution of the number of coaches with ballots from one to six years is, respectively, 42, 37, 17, 24, 12, and 7. 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.[8] 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.[9] Table 1 shows that the mean *Computer rank* is approximately 21, with a range between 1 and 73.

[7] 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 unclear whether these missing observations were intentional on the part of the coaches or simply missing from the USA Today ballots posted online.

[8] 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.

[9] The number of teams that at least one coach ranked in the top 25 for each of the years 2005 through 2010 is 38, 33, 38, 36, 42, and 34, respectively.

Figure 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 to cases where coaches rank 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 the private incentives of coaches help explain the heterogeneity.

As discussed previously, several variables are hypothesized to have a potential affect 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. *Coach win* is an indicator for whether the coach's team beat the team being ranked during the season.[10] Note that *Season play* must equal one in order for *Coach win* to equal one. Table 1 reports summary statistics for each of these variables along with others to which we turn now.

We create a variable for competition among 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.[11] The average of *Common recruits* is 3.8 percent, ranging between zero and 48 percent.

Other variables are based on the financial payoffs from 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

[10] 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.

[11] Using data from Scouts.com, we also created an alternative variable that measured the percentage of players offered a scholarship from the coach's team that ultimately signed to play at the team being ranked. With this variable, we found statistically insignificant results, and it is highly correlated with *Common recruits*. We therefore report results based on *Common recruits* rather than including both variables.

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 independent 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 ever receive a BCS invitation. We then move down the ranking categorizing the more highly ranked teams as on the bubble until there appears a natural drop off. Among these teams, 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.

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 percent 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. Table 2 includes the list of these teams, along with the average ranking for the week prior and whether the team ultimately received a BCS invitation

We have already discussed how coaches face 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 percent of the coach ranks on bubble teams are pairings from the *Same group*, while 9 percent 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 actual 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 coach's payoff 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 allocates money to conferences, how non-BCS conferences allocate BCS revenues among themselves, and how conferences allocate 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 payoffs range from a minimum negative value of -\$3.4 million to a maximum of \$13.6 million.[12] 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 football budget for each team in order to scale BCS payoffs as a fraction of the overall football budget of the coach doing the ranking.[13] This variable, *Bubble payoff share*, ranges from negative 23 percent to positive 70 percent.

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

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

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 from the potential distortionary incentives that confront coaches.[14] We estimate models with linear and quadratic functional forms, with

[12] It is worth mentioning that largest payoff values occur for the special case of Notre Dame's coach voting on Notre Dame, which is not affiliated with any conference and subject to special rules.

[13] 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.

[14] Alternative specifications could use the Harris Interactive Poll rather than the computer rankings, or possibly both. We estimate these alternatives and the results are very similar to those reported here. We chose to 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. 2009).

the rationale to simply absorb variation and test robustness of the results.[15] 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, Gelbach, and Miller 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_{it} 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. 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 3 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*.[16] Other

[15] 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.

[16] With respect to the alternative specification mentioned in footnote 15, 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 ($F = 73.25$, $p < 0.01$).

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.

The coefficient magnitudes across the three models in Table 3 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 Figure 2, which shows coefficient estimates on the categorical variables along with 95-percent 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.

We now turn to models that expand upon those in Table 3 in order to focus on incentives stemming from BCS bowl payoffs. While considering variants of equation (1), we report only the quadratic specification, as it is more flexible and improves the model's fit. The first column of Table 4 reports such a model with three additional variables specific to bubble teams. The coefficient on *Bubble team* provides and estimate of how, after controlling for the other variables, coaches rank bubble teams in a season differently than other teams. $Bubble \times Same\ group$ 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, $Bubble \times Same\ conference$ 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 BCS payoffs from the 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 4, 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 towards their own conference, while non-BCS coaches have a greater incentive to show favoritism towards 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 $Bubble \times Same\ group$ 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 towards 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 them.

The next set of models focuses directly on the actual financial payoffs of invitations to BCS bowl games. Instead of categorical variables reflecting the rules for revenue disbursement, we first include our estimates of the payoffs with the variable *Bubble payoff*. 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. Table 5 reports the two specifications in columns I and II. We find that the coefficients on *Bubble payoff* are negative and statistically significant. The magnitudes imply that a $100,000 increase in the payoff produces more favorable rankings of between 0.03 and 0.02 positions. Another way to express these results is that, after accounting for reputation benefits, boosting a coach's ranking of a bubble team one position requires an additional payoff between $3.3 and $5 million. Columns III and IV report the result of models with the scaled variable *Bubble payoff share*, which converts the payoff amount to a percentage of the annual football budget of the coach's team. The coefficient is negative and statistically significant for the fixed effects model, with a magnitude of -.05. This implies, for example, that an increase in the payoff equal to 10 percent of the revenue for a coach's football program causes a more favorable ranking of half a position on average.

The final component of our analysis tests whether the explanatory variables have different effects on the way that coaches rank the top teams compared to others. Consensus tends to emerge around the top teams each season, even though coaches have different opinions about the exact ranking. But the task of ranking 25 teams pushes coaches into areas of much greater heterogeneity in opinions about team quality. Figure 3 illustrates this point with a scatter plot of *Computer rank* against *Coach rank*. Notice the greater variability of computer rankings as coach ranks move from 1 to 25; that is, there is less consensus about lower ranked teams. Given the greater variability further down in the rankings, it is reasonable to question whether the estimated effects of our explanatory variables are constant between the more high- and low-ranked teams. One might expect, for example, that coaches have more latitude to distort rankings when there is less consensus outside of the elite teams.

Table 6 reports the results of models that expand on the fixed effects models in Table 5. The difference is inclusion of interactions between covariates and *Low rank*, which is an indicator for whether the team being ranked has *Computer rank* > 10. These specifications enable tests of whether coefficients differ depending on whether teams are highly ranked (*Computer rank* < 10) or lower ranked (*Computer rank* > 10).[17] The first column under each model includes the coefficient estimates. The second column includes the sum of the original estimate and the coefficient on the corresponding interaction. Hence estimates in the first column are for the highly ranked teams, and those in the second column are for the relatively low-ranked teams.

We find only one statistically significant difference based on model I. *Coach win* leads to more favorable rankings for low-ranked teams, but not high-ranked teams. Nevertheless, a Wald test of whether the coefficients on all the interaction terms are jointly equal to zero fails to reject the null hypothesis. This is not the case, however, for the model in which we include *Bubble payoff share*. Model II produces a statistically significant difference in the ranking between highly ranked and lower ranked teams in response to direct financial payoffs. In fact, the coefficient is almost four times as large for the low-ranked teams. While an increase in the payoff equal to 10 percent of the revenue for a coach's football program causes a more favorable ranking of a quarter of a position for elite teams, the same payoff has a full position effect for teams outside of the top 10. This result, along with those for *Coach win*, are consistent with the hypothesis that at least some distorting incentives are stronger for relatively low-ranked teams.

[17] The choice of where to set the cutoff between relatively high- and low-ranked teams is somewhat arbitrary. We chose the top 10 because it is often a focal point, and it produces bubble teams on both sides of the cutoff. We did, however, estimate models will different cutoff points, and the general pattern of results remains unchanged.

6 Discussion and Conclusion

This paper provides robust evidence that private incentives have a distorting influence on the way coaches rank teams in the USA Today Coaches Poll for college football. While coaches 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 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, based on two distinct identification strategies in our statistical analysis, that conflicts of interest bias coach rankings in predictable ways.

The pattern of results shows the importance of both reputation benefits and direct financial payoffs. Coaches have clear incentives to rank both their own team and other teams in their athletic conference more favorably. We find, on average, that coaches rank teams from their own conference nearly a full position more favorably and boost their own team's ranking more than two full positions. We also find that it does not matter if a coach's team simply plays a team during the season, but 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 concerns, 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. Reflecting the structure of BCS payoff rules, the non-BCS conferences band together such that when one of their teams is on the bubble, non-BCS coaches rank the teams one position more favorably on average. In contrast, coaches from BCS conferences show favoritism toward bubble teams from their own conference, though not to BCS conference teams more generally. These patterns are consistent with the distribution payoffs: all non-BCS conferences receive a portion of the payout when a non-BCS team receives an invitation, but for BCS conference teams, the payoffs go only to the participating team's conference.

All coaches, however, respond to the magnitude of the direct financial payoffs associated with bubble teams. When a coach's university receives a greater financial payoff if a particular bubble team receives a BCS invitation, coaches rank that team higher, thereby increasing their chance of receiving the payoff. On average, an additional payoff between \$3.3 and \$5 million buys a more favorable ranking of one position. Moreover, for each increase in a bubble team's payoff equal to 10 percent of a coach's football budget, coaches respond with more favorable rankings of half a position. Finally, this effect is strongest, more than twice as large, when coaches rank teams outside the top 10, where there is less consensus about the relative standing of teams.

We believe it is a stretch to interpret these results as evidence of corruption in the USA Today Coaches Poll. Instead, one interpretation is that coaches are intentionally gaming the system, but it is also possible that private incentives influence rankings in more subconscious ways. While distinguishing between these mechanisms is challenging, one way to gain traction is to consider the implications of disclosing individual coach's ballots. Our study is based on all of the publicly available ballots, and coaches knew their ballots would be made available when filling them out. Does the disclosure cause them to evaluate teams differently? We do not have undisclosed ballots to make direct comparisons, but as a rough measure, we can look at the pattern of aggregate Coaches Poll results compared to computer rankings, before and after disclosure began in 2005. Our goal is to see if coaches' rankings become more similar to the computer rankings when their ballots are subject to public scrutiny.

We assembled data on the aggregated Coaches Poll and the computer rankings used by the BCS for the last two regular season polls from 2000 through 2010.[18] Note that this is the poll we have studied throughout the paper, along with the previous week's pool and four years of earlier data. For each team in each poll we calculate the difference between the Coaches Poll and computer rankings and average the absolute difference among observations separately for all those before and after disclosure began in 2005. These averages are summarized in Table 7, where for example 2.494 is the average absolute difference between the coach and computer rankings of each team for the final regular season polls from 2000 through 2004. Given that adjacent polls are likely to have much in common, and can be used to account for overall differences before and after 2005, we calculate the difference between the final regular season poll and the previous week's poll, and then compare the difference in this difference between the pre- and post-disclosure periods. Note that the differences drop during both the pre and post-disclosure periods, but the drop is larger after disclosure by nearly twice as much. This implies that the difference between the Coaches Poll and the computer ranking, between two adjacent polls in the same year, is more than 100 percent smaller when the ballots are made public. It appears, therefore, that coaches are aware of their biases because their rankings move closer to the objective (computer) rankings when disclosed for public scrutiny. That coaches rankings are noticeably different under public disclosure raises further questions about how much stronger the biases are when there is no disclosure, and the result underscores the importance of public disclosure to minimize bias.

[18] The National Football Foundation archives these data and makes them available at http://www.footballfoundation.org/nff/page/379/bowl-championship-series-archive.

In conclusion, this study focuses on how private incentives distort public evaluations in the context of NCAA football, but 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 itself just a few examples. But 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 biased or distorted evaluation is hard to measure. In contrast, our study of the USA Today Coaches Poll provides a unique 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, along with the potential importance of information disclosure for managing conflicts of interest. Concern and debate about these issues has clear applicability beyond NCAA football, and the methodological approach that we apply here may inform research design is other areas.

7 Appendix

We describe our data sources and methods for deriving *Bubble payoff.* The variable measures the financial payoff to a coach's university if a particular bubble team receives an at large BCS bowl invitation, compared to the average payoff if one of the other bubble teams receives an invitation in that year. The first step is to calculate the direct payoff to coach conferences if each bubble team were to receive an invitation, assuming initially no effect on other bubble teams. Several factors affect the size of the direct conference payoffs, some of which are based on rules and others that require assumptions and estimation.

First, following BCS rules, if a team from a BCS conference receives an at large invitation, the team's conference receives \$4.5 million for the 2005-2009 seasons and \$6 million for 2010. If one team from a non-BCS conference receives an invitation, the non-BCS conferences receive 9 percent of the BCS net revenues to divide among themselves. If a second team from a non-BCS conference receives an invitation, the non-BCS conferences receive an additional 4.5 percent of the BCS net revenues to divide among themselves.

Second, we estimate how much of the payoff to non-BCS conferences goes to the qualifying team's conference. It is known that conferences of the invited teams received a larger payoff, with the remaining "share pool" divided among the other non-BCS conferences (O'Toole 2006). To back out the formula, we use data on actual payoffs reported by the BCS (Bowl Championship Series 2010, 2011). For example, the Mountain West received approximately \$3.7 million in 2007, when none of its teams qualified, and \$9.8 million in 2008, when Utah received the only non-BCS invitation. This comparison suggests that the Mountain West received a payoff of roughly \$6 million for Utah's qualification. Based on similar comparisons across years, along with information on the total amount paid to non-BCS conferences, we derive the following rules: The conference of the first qualifying team receives \$6 million in 2005-2009 and \$8 million in 2010, with respective share pools of \$3 million and \$4 million to be split among the other non-BCS conferences. Moreover, the conference of the second qualifying team receives \$4.5 million in 2005-2009 and \$6 million in 2010, with no additional revenue going to a share pool. First and second qualifiers are designated based on rankings reported in Table 2.

Third, we estimate the formula for how non-BCS conferences distribute the share pool among their conferences without a qualifying team. We again make inferences based on actual payoffs (Bowl Championship Series 2010, 2011). After netting out the payment to conferences for a qualifying team, we calculate the proportion of BCS payments that goes to each of the non-BCS conferences, using all years of data. We then assume that the share pool is split among the conferences in rescaled proportion after excluding the conference with the first qualifying team. For example, if a conference receives an average of 20 percent of the BCS payments (excluding a qualifying bonuses) over all years, then it receives 25 percent of the share pool, as there are five non-BCS conferences.

Fourth, Notre Dame is a special case as an independent, without conference affiliation. Notre Dame received $14,866,667 for its 2005 BCS bowl invitation and $4.5 million for its 2006 invitation, but the team was not on the bubble in any of the subsequent years.

Fifth, the direct payoffs need to account for the fact that money paid to the non-BCS conferences and/or Notre Dame for at large invitations often reduces the money available for automatic disbursement to the BCS conferences. When applicable, we make these adjustments to account for negative payoffs associated with some bubble teams and coach conferences. For example, the payoff to non-BCS conferences for Boise State's 2006 qualification ($9 million) was $4.5 million greater than the conference payoff for an at large qualifier from a BCS conference team. Hence, Boise State's invitation counts as a loss to all BCS conferences, and we calculate this loss as $750,000 per conference ($4.5 million/6 BCS conferences). In 2009, however, Boise State's qualification produced a non-BCS payoff equal to that of a BCS team ($4.5 million as the second non-BCS team) and therefore has no effect on the automatic disbursement to BCS conferences.

To summarize with examples, Appendix Table 1 lists the *Direct conference payoff* to all coach conferences for the five bubble teams in 2009: Texas Christian, Boise State, Iowa, Virginia Tech, and Penn State. Penn State and Iowa have direct payoffs of $4.5 million to the Big Ten, and Virginia Tech has a direct payoff of $4.5 million to the Atlantic Coast. Texas Christian, as the higher ranked bubble team from a non-BCS conference, has a direct payoff of $6 million to the Mountain West, with the remaining non-BCS conferences dividing the share pool in proportions observed in the data. Texas Christian has negative direct payoffs for the BCS conferences of $750,000. Finally, Boise State, as the lower ranked bubble team from a non-BCS conference, has a direct payoff of $4.5 million to the Western Athletic conference, and no effect on the payoffs to other conferences. We calculate a matrix like that in Appendix Table 1 for each year 2005-2010.

The next step is to adjust the *Direct conference payoff* to account for the way that bubble teams interact. Specifically, when considering the payoff of ranking one bubble team, coaches are likely to consider the comparative payoffs of other bubble teams. To capture this, we create a new variable *Conference bubble payoff*, which is defined as the difference between the *Direct conference payoff* for each bubble team and the average of *Direct conference payoff* for the other bubble teams in the same year.

The final step is to divide *Conference bubble payoff* by the number teams in each coach conference. We thus assume that conference revenues are distributed evenly among teams.

While this assumption is accurate for some conferences, others are known to have unequal distributions (e.g., the Big-12). We nevertheless use the average because other distribution rules specific to football are not available among conferences. The resulting variable is *Bubble payoff* as a measure of the financial consequences for each coach should the team he is ranking receive a BCS invitation relative to what he would receive on average for the other bubble teams receiving an invitation. The variable captures the fact that a coach has an incentive to rank a team more favorably if it produces a larger positive payoff and/or reduces the chances of a larger negative payoff. Similarly, the variable captures the fact that coaches have an incentive to rank teams less favorably if they are from other conferences.

Appendix Table 2 summarizes *Bubble payoff* reported in dollars, again for the example year 2009. Note that for coaches from conferences with teams on the bubble, their payoff for the other bubble teams are negative values, reflecting the fact that these coaches have incentives to give less favorable rankings to other bubble teams. Moreover, for coaches from conferences without teams on the bubble, there are incentives to rank teams higher or lower depending on whether the coach and team are both in BCS or non-BCS conferences.

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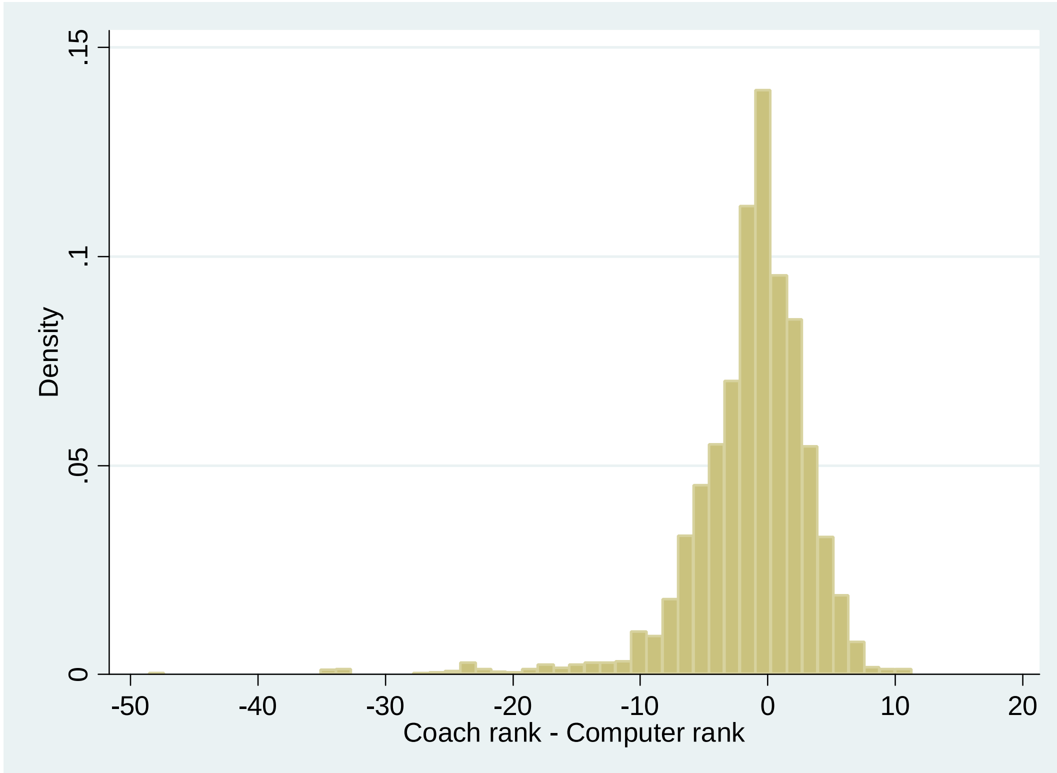

Figure 1: Histogram of the difference between *Coach rank* and *Computer rank* for all 9,073 observations

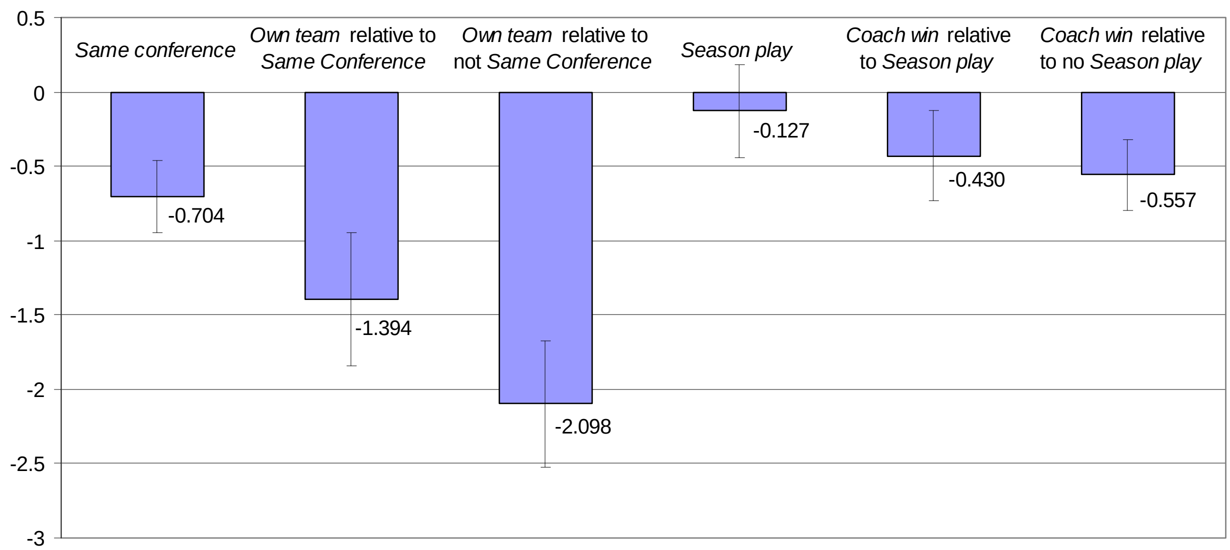

Figure 2: Average magnitudes and 95-percent confidence intervals of how variables affect coach rankings based on the fixed effects estimates in column III of Table 3

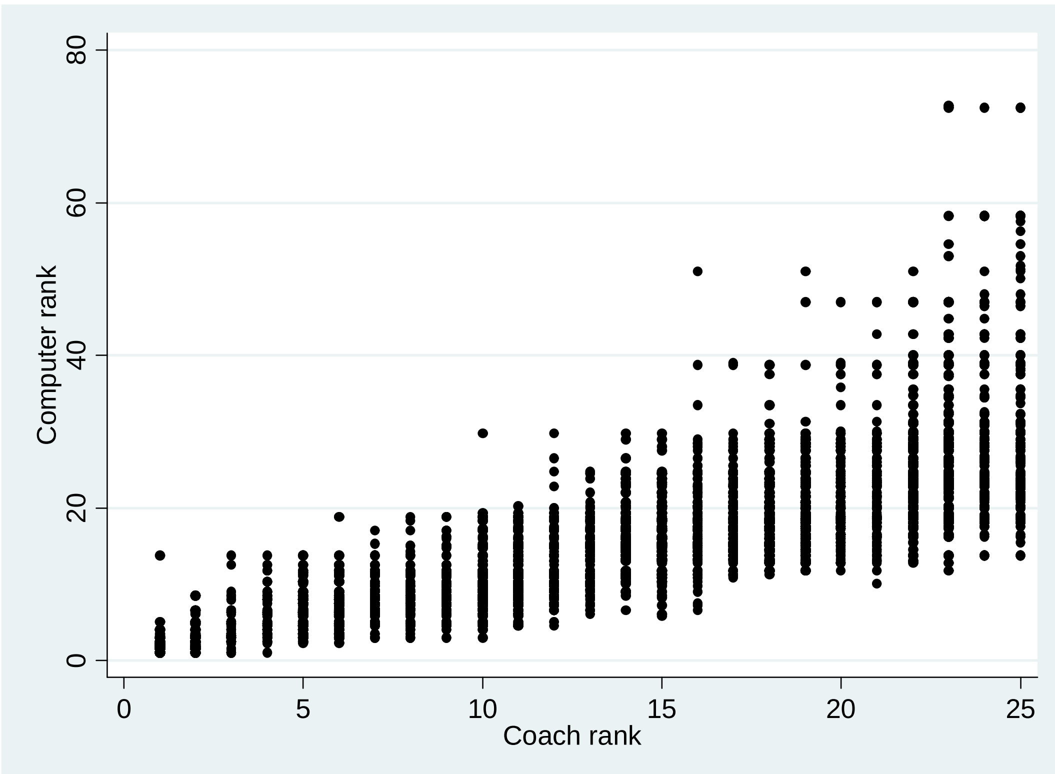

Figure 3: Scatter plot of *Computer rank* against *Coach rank* for all 9,073 observations

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

Variable	Observations	Mean	Std. Dev.	Min	Max
Coach rank	9073	12.997	7.210	1	25
Computer rank	13362	21.182	14.260	1	72.750
Coach rank – Computer rank	9073	-1.399	5.049	-49.750	11.250
Own team	13362	0.010	0.098	0	1
Same conference	13362	0.095	0.293	0	1
Season play	13362	0.098	0.298	0	1
Coach win	13362	0.074	0.262	0	1
Common recruits (%)	13232	3.828	5.938	0	48.077
Bubble team	13362	0.140	0.347	0	1
Bubble x *Same group*	1872	0.557	0.497	0	1
Bubble x *Same conference*	1872	0.089	0.284	0	1
Bubble x *Same group x BCS*	1872	0.457	0.498	0	1
Bubble x *Same group x non-BCS*	1872	0.100	0.300	0	1
Bubble x *Same conference x BCS*	1872	0.072	0.258	0	1
Bubble x *Same conference x non-BCS*	1872	0.017	0.130	0	1
Bubble payoff ($100,000s)	1872	-0.002	4.343	-37.167	148.667
Bubble payoff share (%)	1872	-0.001	3.077	-23.411	70.234

Notes: Variables are defined in the main text. The variable *Common recruits* excludes observations when coaches are ranking their own team. Statistics for the variables in the last eight rows apply only for the bubble teams in each year.

Table 2: Designated bubble teams for a BCS at large invitation, 2005 through 2010

Year	Team	Average rank	BCS bowl invitation
2005	Ohio State	4	Yes
2005	Oregon	5	No
2005	Miami	7	No
2005	Notre Dame	8	Yes
2005	Virginia Tech	9	No
2006	Boise State	7	Yes
2006	Notre Dame	10	Yes
2006	West Virginia	13	No
2006	Rutgers	14	No
2007	Missouri	6	No
2007	Kansas	7	Yes
2007	Hawaii	10	Yes
2007	Arizona State	11	No
2007	Boston College	13	No
2007	Illinois	14	Yes
2008	Utah	5	Yes
2008	Texas Tech	6	No
2008	Boise State	9	No
2008	Ohio State	10	Yes
2008	Texas Christian	11	No
2009	Texas Christian	5	Yes
2009	Boise State	6	Yes
2009	Iowa	10	Yes
2009	Virginia Tech	11	No
2009	Penn State	13	No
2010	Ohio State	7	Yes
2010	Arkansas	8	Yes
2010	Michigan State	9	No
2010	Louisiana State	10	No
2010	Boise State	11	No
2010	Missouri	12	No

Notes: Average rank reported in this table is based on the Harris Interactive Poll and the computer rankings in the week prior to the final regular season USA Today Coaches Poll.

Table 3: 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	9,073	9,073	9,073
R-squared	0.722	0.825	0.938

Notes: The dependent variable is *Coach rank*. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses. One, two, and three asterisk(s) indicate statistical significance at the 90-, 95- and 99 percent levels, respectively.

Table 4: 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 x *same group*	0.008	-0.072	--	--
	(0.171)	(0.139)		
Bubble x *same conference*	-0.412	-0.376*	--	--
	(0.275)	(0.209)		
Bubble x *same group BCS*	--	--	0.231	0.179
			(0.285)	(0.110)
Bubble x *same conf. BCS*	--	--	-0.507	-0.487**
			(0.313)	(0.222)
Bubble x *same group non-BCS*	--	--	-1.003*	-0.824***
			(0.567)	(0.267)
Bubble x *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	9,073	9,073	9,073	9,073
R-squared	0.825	0.938	0.825	0.938

Notes: The dependent variable is *Coach rank*. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses. One, two, and three asterisk(s) indicate statistical significance at the 90-, 95- and 99 percent levels, respectively.

Table 5: Regression models explaining how coaches rank teams, including monetary BCS payoff variables

	Model			
	(I)	(II)	(III)	(IV)
Own team	-0.776**	-1.340***	-0.825**	-1.371***
	(0.325)	(0.234)	(0.321)	(0.231)
Same conference	-0.744***	-0.696***	-0.717***	-0.676***
	(0.194)	(0.125)	(0.194)	(0.124)
Season play	0.284	-0.123	0.268	-0.134
	(0.251)	(0.159)	(0.250)	(0.159)
Coach win	-0.840***	-0.426***	-0.816***	-0.409***
	(0.231)	(0.156)	(0.228)	(0.155)
Common recruits (%)	0.013	0.004	0.013	0.003
	(0.012)	(0.004)	(0.012)	(0.004)
Computer rank	1.214***	--	1.214***	--
	(0.042)		(0.042)	
Computer rank squared	-0.014***	--	-0.014***	--
	(0.001)		(0.001)	
Bubble team	0.008	--	0.008	--
	(0.466)		(0.465)	
Bubble payoff ($100,000s)	-0.032***	-0.021*	--	--
	(0.010)	(0.011)		
Bubble payoff share (%)	--	--	-0.065	-0.049*
			(0.052)	(0.029)
Constant	-0.174		-0.173	
	(0.344)		(0.344)	
Team-year fixed effects	No	Yes	No	Yes
Observations	9,073	9,073	9,073	9,073
R-squared	0.825	0.938	0.825	0.938

Notes: The dependent variable is *Coach rank*. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses. One, two, and three asterisk(s) indicate statistical significance at the 90-, 95- and 99 percent levels, respectively.

Table 6: Regression models testing for heterogeneous effects between high- and low-ranked teams

	Model (I)		Model (II)	
	Coefficients	Coefficients if *Low rank*	Coefficients	Coefficients if *Low rank*
Own team	-0.964***	-1.544***	-1.058***	-1.560***
	(0.255)	(0.315)	(0.247)	(0.313)
Same conference	-0.711***	-0.619***	-0.687***	-0.648***
	(0.166)	(0.157)	(0.164)	(0.155)
Season play	-0.366	-0.097	-0.385	-0.098
	(0.306)	(0.171)	(0.308)	(0.172)
Coach win	0.010	-0.590***	0.026	-0.577***
	(0.298)	(0.179)	(0.299)	(0.179)
Common recruits (%)	0.005	0.003	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Bubble payoff ($100,000s)	-0.018**	-0.131	--	--
	(0.007)	(0.091)		
Bubble payoff share (%)	--	--	-0.026**	-0.098***
			(1.293)	(0.035)
Own team x *Low rank*	-0.580		-0.502	
	(0.402)		(0.395)	
Same conference x *Low rank*	0.092		0.040	
	(0.216)		(0.209)	
Season play x *Low rank*	0.268		0.288	
	(0.329)		(0.332)	
Coach win x *Low rank*	-0.599*		-0.603*	
	(0.336)		(0.337)	
Common recruits x *Low rank*	-0.002		-0.002	
	(0.007)		(0.007)	
Bubble payoff x *Low rank*	-0.113		--	
	(0.092)			
Bubble payoff share x *Low rank*	--		-0.072**	
			(3.083)	
Team-year fixed effects	Yes		Yes	
Observations	9,073		9,073	
R-squared	0.938		0.938	
Wald test of all interactions = 0	*F* = 1.22		*F* = 2.02	
	[*p* = 0.29]		[*p* = 0.06]	

Notes: The dependent variable is *Coach rank*. *Low rank* is an indicator for whether *Computer rank* > 10. Standard errors, with two-way clustering at the team-year and coach-year levels, are reported in parentheses. One, two, and three asterisk(s) indicate statistical significance at the 90-, 95- and 99 percent levels, respectively.

Table 7: Difference-in-differences comparison between coach and computer rankings by polls before and after public disclosure in 2005

	Years 2000 - 2004	Years 2005 - 2010
Previous week's Poll	2.567	2.931
Final regular season Poll	2.494	2.775
Difference	-0.073	-0.159
Difference-in-differences	--	-0.086

Notes: Differences may not be exact due to rounding. Numbers based on 192 rankings for Years 2000-2004 and 300 rankings for Years 2005-2010.

Appendix Table 1: *Direct conference payoff* to coach conferences for bubble teams 2009

	Bubble teams				
Coach conference	Penn State [Big Ten]	Iowa [Big Ten]	Virginia Tech [Atlantic Coast]	Texas Christian [Mountain West]	Boise State [Western Athletic]
BCS conferences					
Atlantic Coast	0	0	$4,500,000	-$750,000	0
Big East	0	0	0	-$750,000	0
Big Ten	$4,500,000	$4,500,000	0	-$750,000	0
Big-12	0	0	0	-$750,000	0
PAC-10	0	0	0	-$750,000	0
Southeastern	0	0	0	-$750,000	0
Independent	0	0	0	0	0
Non-BCS conferences					
Mountain West	0	0	0	$6,000,000	0
Western Athletic	0	0	0	$1,015,925	$4,500,000
Conference USA	0	0	0	$838,642	0
Mid-American	0	0	0	$627,727	0
Sun Belt	0	0	0	$517,707	0

Notes: Conference names in brackets are those corresponding to the bubble team. As described in the text, Texas Christian is treated differently than Boise State because it is the higher ranked non-BCS bubble team. This Table is only for an example year, as similar tables are created for all years 2005 through 2010.

Appendix Table 2: *Bubble payoff* to coach teams in conferences for bubble teams 2009

Coach conference	Bubble teams				
	Penn State [Big Ten]	Iowa [Big Ten]	Virginia Tech [Atlantic Coast]	Texas Christian [Mountain West]	Boise State [Western Athletic]
BCS conferences					
Atlantic Coast	-$78,125	-$78,125	$390,625	-$156,250	-$78,125
Big East	$23,438	$23,438	$23,438	-$93,750	$23,438
Big Ten	$323,864	$323,864	-$187,500	-$272,727	-$187,500
Big-12	$15,625	$15,625	$15,625	-$62,500	$15,625
PAC-10	$18,750	$18,750	$18,750	-$75,000	$18,750
Southeastern	$15,625	$15,625	$15,625	-$62,500	$15,625
Independent	$0	$0	$0	$0	$0
Non-BCS conferences					
Mountain West	-$166,667	-$166,667	-$166,667	$666,667	-$166,667
Western Athletic	-$153,220	-$153,220	-$153,220	-$12,120	$471,780
Conference USA	-$17,472	-$17,472	-$17,472	$69,887	-$17,472
Mid-American	-$12,072	-$12,072	-$12,072	$48,287	-$12,072
Sun Belt	-$9,956	-$9,956	-$9,956	$39,824	-$9,956

Notes: Conference names in brackets are those corresponding to the bubble team. As described in the text, Texas Christian is treated differently than Boise State because it is the higher ranked non-BCS bubble team. This Table is only for an example year, as similar tables are created for all years 2005 through 2010.