Sub-Perfect Game:

Profitable Biases of NBA Referees*

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Abstract

This paper empirically investigates three hypotheses regarding biases of National Basketball Association (NBA) referees. Identification of basketball referee bias is typically difficult as changes in observed statistics may be caused by either changes in referee bias or player behavior. We identify bias by exploiting the fact that referees have varying degrees of discretion over different types of a particular statistic–turnovers. This allows us to conduct a treatment and control-style analysis, using the less discretionary turnovers as the player behavior control. The results provide evidence that referees favor home teams, teams losing during games, and teams losing in playoff series. All three biases are likely to increase consumer demand.

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1 Introduction

All firms face rules, such as tax laws, health regulations, and ethical codes, that constrain the actions they may take to maximize profits. How firms respond to these rules is theoretically ambiguous, as there is a tradeoff between compliance and illicit actions that directly enhance profits. In view of this tradeoff, we examine the behavior of National Basketball Association (NBA) referees (refs). There are a number of ways in which the NBA may benefit from its refs favoring certain teams or players; yet, fans likely value the integrity of the sport and may lose interest if they perceived the officiating to be systematically skewed. We empirically test for several types of ref bias that could be profitable to the league.[1] The results shed light on the general question of whether firms "bend the rules" despite being observed closely by consumers and the media.

The main challenge to the analysis is disentangling referee and player behavior. The basketball statistics most directly affected by refs, fouls and turnovers, are simultaneously influenced by the players' actions, which makes identification of bias difficult. To account for this issue, we use play-by-play data. This type of data includes more detailed description of statistics than the more commonly used game-level data. It also allows us to exploit the fact that referees have varying degrees of discretion over different types of turnovers.[2] We use the play-by-play detail to classify turnovers into two groups: "discretionary" (mainly traveling violations and offensive fouls) and "non-discretionary" (mainly bad passes and lost balls). There is a clear dichotomy between these two groups, as discretionary turnovers (DTOs) are always caused by refs blowing the whistle while the ball is in play, while non-discretionary turnovers (NTOs) are either determined directly by the players and without a ref whistle, or by the ball going out of bounds. In other words, only discretionary turnovers involve active ref behavior while the ball is in bounds.

[1] We use "the league" to refer to team owners and any other actors who may be residual claimants on revenues and have some control over the management of refs.

[2] A turnover is a play in which the team with possession of the ball loses possession before taking a shot at the basket.

To test for the presence of ref bias we compare how DTOs are affected by variables associated with possible bias relative to how NTOs are affected. The analysis is thus in the spirit of a treatment and control design. While the distinction between turnover types is not clean, as both types are affected by both player and ref behavior, identification of bias only rests on the assumption that, on average, refs have a larger (percentage) effect on DTOs than they have on NTOs. To be clear, we are not claiming that refs have little or no influence over NTOs, just *less* influence than they have over DTOs. A formal model and detail on this argument are provided in Section 3. As the discretionary/non-discretionary distinction can be drawn for turnovers but not fouls, the paper's discussion is focused on the estimates regarding bias effects on turnovers. We caution that the results on fouls are only suggestive, though still important.[3]

We find evidence of three biases: favoritism of home teams, teams losing during games, and teams that are behind in a multi-game playoff series. All three biases are plausibly profit-enhancing for the league. Home favoritism increases the home court advantage, which likely increases ticket demand, as most fans who attend games enjoy them more when the home team performs better. Biasing calls in favor of teams losing during games keeps games close and more competitive, likely improving television viewership. Favoring teams losing in playoff series may extend series, which would lead to higher ticket sales and television revenues. We provide a more detailed discussion of the relation between these biases and profits in Section 2, along with a discussion of the psychology and incentives of biases from the refs' perspective.

Each type of favoritism results in an approximately 10% advantage in DTOs, and the first two types are associated with a slightly smaller advantage in fouls. Most of the NTO effects are close to zero. In the playoffs the home DTO bias is larger, as compared to the regular season, and is increasing in attendance. The advantage of teams losing in games and the playoffs is greater when the teams are losing by larger margins.

Our statistical tests are designed to identify the existence of the biases so we do not claim to make precise estimates regarding the effects of the biases on game outcomes.

[3]The absence of foul effects would be strong evidence of a lack of bias.

A rough estimate of the magnitude of the DTO home bias effect on games is that teams are about 2.2% more likely to win at home, as compared to on the road, due to DTO bias. This effect would approximately double in a playoff game with high attendance and more than double if we were to also attribute the estimated foul effects to ref bias. The effects of the other biases on game and series outcomes are smaller.

Previous research, and some of our auxiliary empirical results suggest that the biases are mainly psychological and social in nature. However, we do find evidence linking ref incentives to the biases. Although we do not have data on ref compensation, we observe the refs assigned to playoff games. Since working playoff games is lucrative, considered prestigious, and generally limited to refs who have higher career status, we can use playoff games as a proxy for compensation. We find that refs who work more playoff games are more likely to be assigned to regular season games involving weak home teams playing strong opponents. Since these are the games in which the benefits to the league of home favoritism would be relatively high, this indicates the league makes ref assignments in a strategic way, and rewards refs who help home teams when they need it most.

Regardless of the interpretation of this evidence, among major professional sports, the NBA has been particularly outspoken about the degree to which its refs are monitored.[4] This suggests the league has implemented the type of system needed to detect these biases. The fact that they persist suggests the league has at least not created strong disincentives for them, and tacitly condones them.[5] It is also possible that league management is unaware of the biases. If that is the case, then our paper provides an empirical strategy that they (and similar organizations) might use to monitor these type of biases.

[4]NBA commissioner David Stern said in 2008, "We decided five years ago that we would track literally every call in order to help develop our officials and make them better, and they really effectively are the most measured and metricized group of employees in the world," (Stern (2008)).

[5]Despite the league's statements that they have made efforts to improve the consistency of officiating starting in 2003, we find that the biases have not decreased since that time.

2 Background and Hypotheses

Biased rule enforcement is not unique to the NBA, as several related issues have arisen in other sports in recent years. For example, in the 2002 Winter Olympics pairs figure skating competition there was a scandal involving the French judge being accused of favoring the Russians, causing them to win the gold medal. Zitzewitz (2006) provides evidence of a much broader pattern of nationalistic voting and vote-trading by figure skating judges. The French judge was subsequently banned from the sport for three years, and the judging system has been reformed.[6] In soccer, there have been major gambling-related match-rigging scandals involving refs in the Italian and Chinese top leagues.[7] There is also a substantial recent economics literature showing soccer referees systematically favor home teams, although the bias is usually attributed to social pressure from fans, and not economic incentives.[8]

NBA officiating has been especially controversial since the emergence of its own major scandal involving the former ref Tim Donaghy. Donaghy admitted to using inside information to bet on NBA games and providing confidential information to other gamblers and bookies. After being investigated by the FBI, Donaghy alleged that many other NBA refs have several biases, including favoritism of star players, teams losing during games and teams losing in playoff series, and that the league sometimes knowingly turns a blind eye to these biases, and sometimes even subtly encourages them. In response, the league commissioned Pedowitz (2008), which comprehensively reviews the league's officiating program, with a focus on the influence of gamblers and bookies and the biases alleged by Donaghy. The report's overall conclusion is that the league was not guilty of any wrongdoing, and says it found no evidence of any of the specific biases alleged by Donaghy.[9]

[6] See, e.g., BBC (2002).

[7] See Delaney (2006) and Yue (2010). Duggan and Levitt (2002) conduct an interesting empirical analysis of match-rigging by sumo wrestlers, but they did not study biased rule enforcement by officials. The economics literature on this type of rule violation is part of the broader forensic economics literature; see Zitzewitz (2009) for a review.

[8] See Sutter and Kocher (2004), Garicano et al. (2005), Dohmen (2008), and Pettersson-Lidbom and Priks (2010).

[9] The report states in its executive summary: "NBA management sends a clear and consistent message to referees that they are to make accurate and consistent calls and favor no team or player. We have found no evidence that the League has ever deviated from this message."

Pedowitz (2008) does not conduct any empirical analysis, however. In this paper we empirically study the team-related ref biases alleged by Donaghy (and others), and the home bias. It is one of the first papers to study the home bias in a sport other than soccer.[10] We also hope to contribute to the economics literature by studying two other ref biases that are not well established in any sport.[11] The three biases can be stated as hypotheses as follows.

Hypothesis 1: Referees favor home teams (*home bias*).
Hypothesis 2: Referees favor teams losing during games to keep games close (*close bias*).
Hypothesis 3: Referees favor teams losing in playoff series (*playoff bias*).

Why would refs have these biases? What benefits and costs for the refs might they entail? As mentioned above, there is a substantial literature on why social pressure may cause the home bias. Refs may want to please home fans due to altruistic motives–to enhance their experience attending games–or for self-serving motives–to avoid being heckled or booed. For the former case, we expect bias would be more likely to increase late in games, when its effect on fan experiences could be greatest.[12] There is also evidence that refs are persuaded by crowd reactions to plays; i.e., refs "learn" from the crowd what the correct call is in some situations. Since crowds are biased towards the home team, if refs do not fully filter out the crowd's partisanship, this would also cause a home bias.[13] If refs are influenced by the crowd due to either pressure or learning,

[10]It is important to examine the home bias in other sports since, for one thing, social pressure from soccer fans may be relatively intense. For example, soccer fans (from outside the US) stand throughout games, while US fans usually sit (Kelley (2009)). On the other hand, Dohmen (2008) found that bias is larger at soccer games that do not have a track separating the fans from the field, and interpreted this as evidence that bias is greater when fans are closer to the playing action. This would cause NBA home bias to be greater than that of other sports, since NBA fans sit relatively close to the action.

[11]Anderson and Pierce (2009) and Zimmer and Kuethe (2009) empirically study basketball ref biases. The former find college basketball refs call more fouls against the visiting team and teams losing during games, and the latter find evidence that NBA refs have biases that extend playoff series and favor teams from larger television markets in the playoffs. The key difference between their papers and ours is our empirical strategy for identifying ref bias separate from player behavior. Rodenberg and Lim (2009) examine the hypothesis that refs were biased against one particular team, the Dallas Mavericks, and found little evidence in support of the hypothesis.

[12]In the latter case, where refs favor the home team to avoid heckling, bias may increase late in games when heckling becomes more intense, or decrease when there is less benefit of pleasing fans to reduce future heckling.

[13]Nevill et al. (2002) indicates ref bias can exist independent of social pressure, as the authors conduct

we would expect the influence to increase with the level of attendance and strength of crowd support for the home team. Social-psychological factors could also cause the close and playoff biases, as refs might feel sympathy for, and thus favor, the "underdog" teams–teams losing during games and in the playoffs. These teams might also plead harder for calls, which also (like home crowds) could persuade refs to make calls favoring them if refs are somewhat naive in interpreting the teams' arguments. The close and playoff biases could also be caused by the refs' incentives to build "goodwill" with teams, as refs are evaluated in part by coaches and other members of teams (Pedowitz (2008)).[14] If the goodwill benefit from favoring losing teams is greater than the cost of disfavoring winning teams, which is plausible, then it could be rational to favor losing teams. Regardless of the source of close or playoff bias we would expect each bias to increase when teams are losing by larger margins, since this should both increase sympathy and goodwill benefits.[15]

Thus, refs may trade off psychosocial or personal economic benefits of bias against the costs. Costs might result from critical media coverage or punishment from the league, if the league promotes purely objective officiating. However, it is also possible the league rewards bias–or at least only provides a weak disincentive for bias–if bias benefits the league. And indeed, all three biases are plausibly profitable, especially if fans were not fully aware of them.[16] The home bias could cause attending games to become more enjoyable, or cause fans to think their presence and support have a greater effect on the team's outcome, thereby increasing ticket demand. The close bias would increase television viewership demand, and possibly ticket demand as well, if close games are more entertaining to watch. The playoff bias would have the most direct impact on the league's bottom line. Playoff series are best-of-seven; i.e., the first team to win four games wins the series. Thus, if the team leading in the series has won three games, the

experiments showing that soccer refs watching game footage on videotape are influenced by crowd reactions in isolated, laboratory settings.

[14]Donaghy (2009) also discusses other benefits refs may obtain from goodwill, such as avoiding arguments with players and obtaining personal perks from players such as autographs.

[15]Refs would not directly benefit economically by extending a playoff series since refs are assigned to playoff games one at a time, and not for the entire series (Beck (2008)).

[16]We do not examine the star favoritism bias in this paper, although it could also be revenue-enhancing as it could make star players more marketable. We limit our scope to team-related biases.

series only continues if the trailing team wins the subsequent game. The league benefits from longer series through greater ticket sales and television revenues.[17] In fact, games that result from a series being extended would often be particularly lucrative, since both ticket and television viewer demand is higher for games that occur late in playoff series.[18]

Explicit league encouragement of the biases could take the form of direct communication, e.g. the league telling refs to enforce some rules more or less strictly in particular playoff series, or indirectly via the league financially rewarding refs who exhibit the biases without attributing the rewards directly to bias. The league does supervise and monitor refs carefully (Pedowitz (2008)), and could use the tools of promotion and playoff assignments, worth tens of thousands of dollars or more (Donaghy (2009)), to motivate refs to behave in the desired way. Although Pedowitz (2008) describes the league's ref monitoring and evaluation program in detail, it is unclear how the evaluation works and how it is linked to ref economic outcomes.[19]

If the biases were caused by this type of explicit encouragement, we would expect refs who exhibit the biases to be assigned to more playoff games. We would also expect these refs to be more likely to be assigned to regular season games where the league's returns to bias are greater, and the magnitude of the biases should increase in situations where the returns to the league are higher, and decrease in situations where detection is more likely. For example, if the close bias was more severe in games that are nationally televised, this would indicate explicit bias. Although both returns and probability of detection would increase in those games, we expect the first effect would be dominant, while other factors causing close bias should not change.[20] Similarly, we would expect

[17] We were unable to determine whether league television revenues are directly tied to the number of playoff games. However, even if they are not, there is a strong indirect relationship, as the value of television contracts would depend on the expected number of games.

[18] It is worth noting that the league changed the format of the first round of the playoffs from best-of-five to best-of-seven starting in the 2003 playoffs. This change was ostensibly made to prevent flukish, or undeserved, upsets, but had the side effect of increasing the total number of playoff games. The change has affected a small percentage of series outcomes; since then, 45 of the 48 teams to first win three games in first round series have proceeded to win a fourth game.

[19] While ref calls and non-calls are comprehensively recorded and evaluated as correct or incorrect, it is possible that the evaluators are biased themselves and use different standards in different situations to allow for ref bias. It is also unclear how the league teams together and assigns refs to regular season games, although this is ostensibly done in an arbitrary way (Price and Wolfers (2007)).

[20] The league would not obtain higher revenues as a direct result of the bias, but would get more revenues in

the home and playoff biases to increase in situations where they have the greatest effect on the favored team winning–the end of close games. But since both league returns and detection probability change in all of these situations, the predictions are somewhat ambiguous. Furthermore, league returns from the home bias may also increase in the playoffs and when attendance is higher, since the bias would reach more fans in both cases and series go to their maximal length when the home team wins every game. Therefore finding the home team's advantage increases in those situations would not provide clear evidence of the source of bias.

In summary, given the somewhat opaque and potentially subjective nature of the league's system for evaluating and compensating its officials, it is difficult to say what the precise costs and benefits of the biases are for the refs. It is clear that the league has the tools to both be informed about ref performance and to influence their performance; it is unclear how the league uses these tools. It is possible refs are rewarded only for objectivity and may still be biased due to the personal benefits; it is also possible refs are given leeway to have a limited degree of bias, or even that the biases are rewarded. One thing we can say is that it does not seem likely that the psychosocial benefits refs get from bias are large. Moreover, the goodwill benefits of bias are indirectly sanctioned by the league. Thus, if we do find the biases exist, this implies the disincentive for bias created by the league must also not be large. We have also noted a few testable comparative statics that may provide some insight into the causes of the biases.

3 Data and Empirical Strategy

3.1 Data

We use play-by-play data obtained from ESPN.com for all NBA regular season and playoff games from the 2002-03 through 2007-08 seasons. The play-by-play data provide more detailed description of game events than game-level box-score data. This extra detail is necessary for us to disaggregate turnovers, which is the key to our empirical

the future from television contracts as a result of the higher viewer ratings caused by the bias.

strategy. Pertinent basketball turnover terms are defined in Table 1. The play-by-play data also include the exact time at which each game event occurred, allowing us to analyze the effects of score changes within games. The downside to using play-by-play data is that they are not official league statistics and may have more measurement error than box score data (we drop games with missing minutes due to possible error). This is not too concerning, since when we aggregate the play-by-play data to the game-level the numbers are very similar to the official box score data, and the error should not bias our results towards ref favoritism regardless.

As discussed in the introduction, the primary challenge to our analysis is that nearly all basketball statistics are simultaneously affected by both ref and player behavior. We address this problem by classifying turnovers into two categories: discretionary and non-discretionary. Traveling violations, offensive fouls, three second violations, and offensive goal tending are classified as discretionary. These are all turnovers that are called by a ref blowing his or her whistle while the ball is in play, and hence would not have occurred without active ref behavior. Both traveling violations and offensive fouls, which comprise the vast majority of the DTOs, are notoriously subjective and inconsistently called in the NBA, which also suggests they are relatively susceptible to bias.[21] Three second and offensive goal-tending violations are also categorized as discretionary, as they are called by a ref whistle with the ball in play, but occur infrequently and bear little weight on the results.

Bad passes, lost balls, and shot clock violations are classified as non-discretionary turnovers. These turnovers are determined either directly by player behavior, such as when a defensive player steals the ball from the offense, or when refs make a call either because the ball has gone out of bounds or the shot clock has expired. In the latter case refs have no discretion since the shot clock is publicly viewable and a loud buzzer goes

[21] After the 2008-2009 season, Joe Borgia, the NBA's vice president of ref operations said the traveling rule was confusing (sports.espn.go.com/nba/news/story?id=3951002) and league management did in fact clarify the rule prior to the 2009-2010 season, which is outside of our sample. The offensive foul is prone to manipulation due to players "flopping" (pretending to fall down due to contact from offensive players), and there were reports that league management said that it would begin punishing floppers in May of 2008 after receiving pressure from fans and analysts (stoptheflop.net/) but the policy was not actually implemented (nba.fanhouse.com/2008/12/29/so-much-for-the-nbas-flop-crackdown/).

off when it expires. In the former case, refs often have little discretion in making the call, for example, when one player throws a pass that directly goes out of bounds. But sometimes the ref may have a great deal of discretion; e.g., when a player steps near the sideline, the ref may be able to call the player out or make no call at all. Ideally, we would separate bad passes and lost balls into those that are due to the ball going out of bounds and are called by the ref, and those that are not, but our dataset does not allow this. Thus, refs do have some discretion over what we call NTOs. Still, there is a clear distinction between the two types of turnovers: discretionary ones are *always* called by refs when the ball is in play and non-discretionary ones are either *not called* by the ref or called out of bounds. We describe formally how this distinction is used to test for bias in the following subsection.[22]

In addition to the turnover analysis, we also examine fouls, which are the more frequently used measure of ref behavior (e.g., see Price and Wolfers (2007)). Unlike turnovers, it is more difficult to classify foul types by the degree of discretion refs have to judge them. Fouls are still split into two categories for the analysis, shooting and non-shooting, since this is also a natural distinction; however, it is not clear, *a priori*, which type is affected more by player or ref behavior.

Table 2 presents summary statistics for the turnover and foul types. We aggregate these statistics to the team-game-minute level and present the results separately for the home and away team and also for the winning and losing team (based on the score at the start of the minute). The table provides a preview of the econometric results, as both home and losing teams generally have greater advantages in DTO and foul statistics than they do in the NTOs.[23]

[22]The names of the types of turnovers ("bad passes", "lost balls", etc.) are those used in the ESPN.com play-by-play data. One type of turnover, double dribble violations, is dropped from the analysis. Although, according to the definition above, they are discretionary, they are arguably less subjective than the other DTO types. However, these violations occur infrequently, and results are robust to including them in either turnover group.

[23]Despite their name, offensive fouls are indeed turnovers, both by definition and in practice. By definition, offensive fouls result in the offensive team turning the ball over to the defensive team without taking a shot. In practice, the style of play which makes other turnovers more likely (aggressive, risky play on offense) also makes offensive fouls more likely. Regardless, the estimated biases are actually stronger when offensive fouls are dropped from the analysis.

3.2 Formal Model

The following is a formal presentation of our identification strategy. We show how ref bias can be cleanly detected using the DTO/NTO distinction with a few weak assumptions. Let T_{Dit} be DTOs, T_{Nit} be NTOs for team i in game-minute t. We henceforth suppress i and t. Suppose ref favoritism can be quantified and is measured by X_R (ref favoritism is increasing in X_R), and player "ball control" behavior, or aversion to turnovers, is measured by X_P (an increase in X_P corresponds to a change in player behavior that causes turnovers to decrease). Let Z be a variable that takes higher values in situations in which favorable bias is hypothesized to occur; for example, Z could be a dummy equal to one when the team is at home, losing during the game, or trailing in the playoff series. As both X_R and X_P may be affected by Z, assume:

$$X_R = \gamma_0^R + \gamma_1^R Z + \epsilon_1 \tag{1}$$

$$X_P = \gamma_0^P + \gamma_1^P Z + \epsilon_2. \tag{2}$$

Z is assumed to be independent of ϵ_1 and ϵ_2. The hypothesis of interest is that $\gamma_1^R > 0$; the causal effect of Z on ref bias is positive. The parameters γ_0^R and γ_0^P can be interpreted as ref bias and player behavior when $Z = 0$ (for the case of Z being a home dummy, they would be the mean X_R and X_P for the road team).

The problem is that neither X_R nor X_P are observable and, consequently, equation (1) cannot be directly estimated. Therefore, to test the hypothesis, additional assumptions are required. Suppose T_D and T_N are affected by both ref and player behavior as follows:

$$lnT_D = \beta_0^D + \beta_1^D X_R + \beta_2^D X_P + u_1 \tag{3}$$

$$lnT_N = \beta_0^N + \beta_1^N X_R + \beta_2^N X_P + u_2. \tag{4}$$

The X's are assumed to be independent of the u's. Equations (3) and (4) are specified as log-linear so that the coefficients can be interpreted as percentage effects. To identify ref bias, two additional assumptions are made.

Assumption 3.1. $\beta_1^D < \beta_1^N \leq 0$.

Assumption 3.2. $\beta_2^N \leq \beta_2^D \leq 0$.

These assumptions seem highly plausible. Assumption 3.1 implies that, on average, ref behavior has a greater percentage effect on DTOs than NTOs. Assumption 3.2 states that when player behavior changes in a way affecting turnovers in general, the DTO percentage effect is not larger than the non-discretionary effect.

Then, by substituting (1) and (2) into (3) and (4) we obtain:

$$lnT_D = \widetilde{\beta}_0^D + (\beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P)Z + \widetilde{u}_1 \tag{5}$$

$$lnT_N = \widetilde{\beta}_0^N + (\beta_1^N\gamma_1^R + \beta_2^N\gamma_1^P)Z + \widetilde{u}_2. \tag{6}$$

Here, $\widetilde{\beta}_0^D = \beta_0^D + \beta_1^D\gamma_0^R + \beta_2^D\gamma_0^P$ and $\widetilde{u}_1 = \beta_1^D\epsilon_1 + \beta_2^D\epsilon_2 + u_1$ and $\widetilde{\beta}_0^N$, and $\widetilde{u}_2$ are defined analogously. Equations (5) and (6) can be estimated directly, as Z, T_D and T_N are observable and the single right-hand side (RHS) variable in each equation is independent of the error term.

To test for the presence of ref bias, we first test whether Z is associated with an advantage in DTOs. That is, we test whether the coefficient on Z in (5) is negative:

$$\begin{aligned} \beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P &< 0 \leftrightarrow \\ \gamma_1^R &> -\frac{\beta_2^D}{\beta_1^D}\gamma_1^P. \end{aligned} \tag{7}$$

Evidence of this inequality holding would be evidence of ref bias if $\gamma_1^P \leq 0$. This is because $\frac{\beta_2^D}{\beta_1^D} \geq 0$ by Assumptions 3.1 and 3.2, so if $\gamma_1^P \leq 0$, then $\gamma_1^R > -\frac{\beta_2^D}{\beta_1^D}\gamma_1^P$ implies $\gamma_1^R > 0$, which is equivalent to the existence of ref bias.

This test will not be sufficient, however, if $\gamma_1^P > 0$. To account for this case, the coefficients on Z from equations (5) and (6) can be employed to test the following:

$$
\begin{aligned}
\beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P &< \beta_1^N\gamma_1^R + \beta_2^N\gamma_1^P \leftrightarrow \\
\frac{\beta_2^D - \beta_2^N}{\beta_1^N - \beta_1^D}\gamma_1^P &< \gamma_1^R.
\end{aligned} \tag{8}
$$

By Assumptions 3.1 and 3.2 $\frac{\beta_2^D-\beta_2^N}{\beta_1^N-\beta_1^D} \geq 0$, therefore, if $\gamma_1^P > 0$ then $\frac{\beta_2^D-\beta_2^N}{\beta_1^N-\beta_1^D}\gamma_1^P < \gamma_1^R$ implies $\gamma_1^R > 0$. Thus, for all γ_1^P, testing (7) and (8) is sufficient for testing $\gamma_1^R > 0$ and, thereby, identifying the existence of ref bias.

Practically speaking, to perform the hypothesis tests, equations (5) and (6) must first be separately estimated. Then, the coefficient on Z from (5), $\beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P$, must be significantly greater than zero *and* greater than the coefficient on Z from (6), $\beta_1^N\gamma_1^R + \beta_2^N\gamma_1^P$. It important to note that this test does not require that player behavior affects both types of turnovers in the same way (i.e. it is not assumed that $\beta_2^D = \beta_2^N$). However, in order to isolate the magnitude of the bias, $\beta_1^D\gamma_1^R$, additional (strong) assumptions are required. By assuming $\beta_2^D = \beta_2^N$ and $\beta_1^N = 0$, we can difference the estimates of $\beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P$ and $\beta_1^N\gamma_1^R + \beta_2^N\gamma_1^P$ to obtain $\beta_1^D\gamma_1^R$.

4 Analysis

The analysis is based almost entirely on team-game-minute level data sets. Our samples includes two observations for each minute of each game, one for each team. The final three minutes of the fourth quarters are dropped, as game play often changes dramatically in those situations. For example, losing teams sometimes intentionally commit more fouls in those minutes for strategic reasons. Standard errors are clustered by game or match-up to account for the repetition of game-minutes in the sample.

Although the home and playoff biases are game-level, suggesting we could use game-level data to test for them, we need to use a finer time-scale to avoid the hypothesized biases possibly interacting with each other, which would confound the estimation results. For example, if refs indeed favor both home teams and teams losing during games, failing to control for within-game scores could cause the varying biases to nullify each other. Home teams would be favored at the beginning of games when neither team is losing, then home teams would be disfavored after taking the lead; therefore, in game-level data home bias would be under-estimated.

The analysis of each hypothesis is performed using four dependent variables: shooting fouls, non-shooting fouls, DTOs, and NTOs. As they are all count variable–each only takes non-negative integer values–Poisson regression is the most appropriate estimation technique. The Poisson model is estimated via maximum likelihood, under the assumption that the dependent variable takes a Poisson distribution with log-expectation equal to a linear function of the regressors.[24] Log-linearity allows for coefficient estimates to be interpreted as percentage effects.

The Poisson model also has the advantage of not requiring observations in which the dependent variable equals zero to be dropped, unlike typical log-linear models, since in the Poisson model the dependent variable is a log-expectation (and not just a log). However, a disadvantage of using this model is that we are unable to obtain estimates of covariances of the coefficients across equations. For this reason, results of across-equation tests are not reported. However, we are often able to show coefficients are significantly different across equations for all feasible covariances (those with absolute value less than the product of the standard errors). Thus, any discussion of across-equation differences refers to significance levels for all feasible covariances.

We use dummy variables to test many of the hypotheses of interest; "Home" is a dummy for whether a team is playing at home, "Playoff" is a dummy for the game occurring in the playoffs, "Score Diff $<$ -10","-10 $\leq$ Score Diff $\leq$ -4", ..., "10 $<$ Score Diff" are dummies for whether the team is losing at the start of the minute by more than 10 points, by 4 to 10 points, etc. The omitted category is winning or losing by 3 or fewer points. We use dummies to allow for a non-linear relation between bias and score difference; results are similar when we vary the way the cutoffs are

[24]The Poisson distribution assumption for a variable requires that its mean and variance are equal. Table 2 indicates that this is not problematic for our data. Results are very similar when we use other model specifications.

defined. "Attendance" (measured in thousands) is included in all models, along with an interaction of Attendance and Home, Playoff and Home, and quarter and match-up (team-opponent-season) fixed effects (FEs). We de-mean attendance so the coefficient on Home is the effect for average attendance. The match-up FEs imply our estimated effects are solely a result of the variation in a team's performance from their mean performance against the same opponent, in the same season. Including these FEs allows us to tightly control for variation in team quality and the composition of game pairings. The details of the playoff bias analysis are somewhat different; they are described in Section 4.3.

The magnitude of the home bias may vary throughout the game. For example, the home crowd may be strongest at the game's start, leading to large home team favoritism followed by a decline in home bias, which may even become an away bias if refs want to compensate for their initial bias. This could confound the close bias estimation results. If refs favor away teams late in games after home teams have (on average) taken the lead, the data would indicate teams losing in games are favored. We account for this by reporting results for a second specification in which we allow the home bias to vary throughout the game by interacting Home with the quarter dummies.[25]

4.1 Home Bias

Table 3 presents the results from the Poisson regressions for the full sample. The home team has a greater than 11% advantage in DTOs on average, but a less than 3% advantage in NTOs, in the models without home-quarter interactions. The DTO coefficient is significantly different from both zero and the NTO coefficient at the 1% level, which, according to the argument detailed in Section 3.2, implies the existence of ref bias. In the models with quarter interactions, the non-interacted Home term represents home bias in the fourth quarter. The DTO advantage then is only around

[25] We have also examined specifications with interactions of the Score Diff variables with Home; the coefficients are mostly insignificant indicating the close bias is the same for home and away teams. In a previous version of the paper we analyzed quarter-level data and included controls for points scored in the quarter, minus opponent's points scored. This is an endogenous variable, since it is simultaneously determined by the dependent variable, but still provides a "proxy control" for unobserved style of play. Results were generally similar with this specification.

8%, but the non-discretionary advantage is very close to zero, and they are different from each other at the 5% level. These results indicate the home bias declines in the fourth quarter. The home team also has an over 8% advantage in shooting fouls and a 2.9% advantage in non-shooting fouls, both significantly different from zero at the 1% level, in the models without quarter interactions.

The home advantage in DTOs increases by close to 10% in the playoffs, which is significantly different from zero at the 1% level. The shooting foul playoff-home effect is close to 5% and significant at the 5% level, while the NTO playoff-home effect is less than 4% and insignificant. The only significant home-attendance effect is for non-shooting fouls; the home team's advantage goes up by 0.6% for every 1,000 home fans. The match-up FE specification controls for the possibility that player behavior and game attendance are both correlated with the quality and type of game opponent. Consequently, the significant playoff and attendance results are not simply caused by teams playing differently against, say, better opponents, which also attract larger and more ardent crowds. Additionally, in results not reported, we find the home bias is not affected by whether the game is televised or whether the game took place in the 2005-06 season or later.

4.2 Close Bias

Table 3 also supports the close bias hypothesis, as it shows teams trailing at the start of a minute are systematically favored in the subsequent minute. When a team trails by more than 10 points its expected DTOs decline by around 15%, relative to teams who are trailing or winning by no more than three points. Losing by more than 10 points is associated with teams committing slightly more NTOs. The estimates for the two types of turnovers are different from each other at the 1% level, so there is very strong evidence of bias in favor of teams down by large margins. Furthermore, teams losing by 4-10 points have a significant 3.7% advantage in DTOs, while teams winning by 4-10 points have a disadvantage of 11% more DTOs than baseline teams, which is significantly different from zero and the NTO estimate of a 4.9% effect at the 1% level.

Results are highly robust to whether or not Home-quarter interactions are included, which indicates the close bias is not just an artifact of the home bias changing during the game. Winning teams commit 14-27% more shooting fouls and 12-18% more non-shooting fouls than teams in close games. We do not find any differences in the close bias based on whether the game is nationally televised or occurs in a more recent season (results again unreported).

4.3 Playoff Bias

Although the playoff bias hypothesis is especially well known, investigating it is relatively difficult due to the limited sample of playoff games.[26] We start by looking at mean game-level turnover differences, categorized by playoff series score, which are presented graphically in Figure 1. The different values of the horizontal axis variable correspond to different home team win-loss records for the series coming into the game. The values (i.e., home records) are ordered by the approximate degree to which the home team winning would affect the length of the series.[27] Points on the left part of the figure represent games in which home team wins are more likely to extend the series, and points on the right represent games in which away team wins are more likely to extend the series. The sample sizes are represented by the sizes of the points in the graph; they are especially small for games in which the home team is up 2-0 and 3-0 (four and two, respectively), as the visiting team rarely wins the first two games of a series.[28]

Figure 1 indicates two patterns. First, most of the points for discretionary fouls lie below zero (the horizontal axis), which is consistent with the home bias discussed earlier. Second, the home team's advantage is larger in games in which the home team winning would be more likely to extend the series. Both of these patterns are weaker for NTOs. As a rough statistical check, two linear predictions are fitted to the data,

[26] We have also tested for another alleged playoff bias: that the league favors large market teams in all playoff games, not just those that would extend the series, to increase television ratings of the later playoff rounds. We find no evidence that large market teams have an advantage in DTOs and, therefore, do not report results.

[27] There are 16 playoff teams and four playoff rounds. Each round consists of paired match-ups between the teams, each of which consists of a best-of-seven series. Thus, there are 16 possible series scores (home wins-away wins) at the start of each playoff game.

[28] The team with the better regular season record is the home team for the first two games of each playoff series. Thus, in cases when the home team is leading 2-0 or 3-0, the team with the worse regular season record has won the first two games of the series despite being on the road, which happens very rarely.

one for each type of turnover. The DTO line is positively sloped and steeper than that of NTOs, which supports the playoff bias hypothesis. Neither line is substantially influenced by a point with a small sample size.

To formally test the hypothesis, we again use Poisson regression models, but now restrict the sample to only include playoff games and introduce a new regressor, "Series Diff," which equals the number of games the team has won thus far in the series prior to the current game, minus the games won thus far by the opponent. For example, Series Diff=0 for both teams in the first game of every series, and if a team is up 2-0 or 3-1 in the series, then Series Diff=2. This specification is somewhat restrictive, as it implies bias is the same when, say, a team is up 1-0 or 3-2. The ideal approach would be to use different dummies for different playoff series situations, but the limited playoff sample implies that doing this would reduce statistical power substantially. The variable Series Diff is attractive because it is parsimonious, analogous to the Score Diff variable used to test close bias, and allows bias effects to increase for teams losing by more games in the series, as we discuss in Section 2.

Table 4 presents estimation results from models that incorporate the full set of control variables, replacing match-up FEs with a match-up control.[29] For each game a team is down (up) in the series, it gains (loses) a 3.4% advantage in DTOs, significant at the 5% level. The advantage is not significant for the other statistical category, except for non-shooting free throws, which has a substantially smaller effect of 1.3%, which is only significant at 10%. The DTO estimates are not significantly different from those for NTOs for all feasible covariances. This is likely due to the relatively small sample. Still, the results provide evidence that teams are favored in ways consistent with our hypothesis. We should also note the results show the home DTO advantage is increasing in attendance, and the close bias appears to be smaller in the playoff-only sample.

[29]The match-up control is equal to the mean of the dependent variable from regular season games against the opponent, for the same season. Results are similar using FEs, but it may be preferable to avoid them since the within-group estimator in this context could be problematic. For example, if teams down in the playoffs had above average turnovers in the games they lost, as we would expect, they would naturally have below average turnovers in the subsequent game(s). This would cause it to appear as if teams down in playoff series have a turnover advantage, when it would not be caused by ref bias.

Since the playoff bias has potentially more direct effects on revenues than the other biases, we also examine whether the bias changes in more pivotal game situations. To do this we interact Series Diff with the number of minutes remaining in the game ("Mins Remaining"), a dummy for the score difference going into the minute being weakly less than 10 points ($|\text{Score Diff}| \leq 10$), and the interaction of these two variables. We are implicitly defining the important situations as calls that occur with less time remaining and/or when the score is within 10 points. This definition is admittedly *ad hoc*, but the results are robust to defining it in different ways. The estimation results are also reported in Table 4. The interaction terms are mostly insignificant. The signs for the DTO estimates imply the effect is greater when the score is somewhat close, but this effect does not increase late in games, as the triple-interaction term coefficient is negative and close to zero. Results for most other variables are insignificant as well, except one indicating NTOs decline when games are close and time remaining decreases, which is what we would expect due to player behavior changes. We also test whether the bias is larger in series between large television market teams, and if the bias has changed over time; results are generally neither statistically nor economically significant.[30]

Because the analysis reported in Table 4 comes from a smaller sample than that of Table 3, we conduct a complementary analysis of playoff bias using game-level data, which we have for a much longer time-frame (1992-2007).[31] We estimate Poisson regressions with various dependent variables, and use Series Diff, Home, match-up regular season means (as defined above) as RHS variables with a playoff-only sample. Since we cannot separate the turnover types for these data, we expect the results to be depressed towards zero, and need to examine other statistics as dependent variables to substitute for NTOs as "placebos." We also cannot separate foul types. Table 5 reports results; teams down in series again have a significant turnover advantage. The magnitude of the turnover effect is larger than that of any other statistic, again suggesting the turnover effect is not driven just by changes in player behavior. This supports the existence of

[30]To examine the connection between television market size and playoff bias, we test whether the advantage of teams hypothesized to be favored increases as the total Nielsen television market size of the two teams increases. We do not report these results in the interest of brevity, but they are available upon request.

[31]We use box score data from ESPN.com and basketballreference.com.

a persistent playoff bias that affects turnovers only, and not fouls.[32]

5 Extensions

5.1 Economic Significance

As discussed above, our empirical strategy does not allow us to precisely estimate the magnitudes of the biases. Still, we can provide a few remarks on this subject. We first note that home teams have a winning percentage in the regular season of 60.6% (Schuhmann (2009)), so being the home team increases the probability of winning by 21.2 percentage points. This effect could be considered an upper bound on the magnitude of home bias. We also run a logit regression on game level data for all games (including the playoffs) from the 1992-2007 seasons, in which our dependent variable is whether the team wins.[33] We include Home, Series Diff and match-up FE as controls. The estimated marginal effect of Series Diff is -0.088, and significant at the 1% level. This implies the upper bound for the playoff bias effect for teams down two or more games is even greater than the home bias upper bound, since Series Diff = 2 or 3 for the teams up in the series and Series Diff = -2 or -3 for the teams down. But we should be even more cautious with these estimates, since teams likely play especially hard when down in playoff series.

To convert our estimated biases into measures of game outcomes, we use the estimated marginal effects of various statistics on wins from Berri et al. (2006).[34] They report that each turnover is associated with 0.034 fewer wins in their Table 6.5. Since away (home) teams commit 3.7 (3.4) DTOs per game (implied by our Table 2), if home teams have a 9.1% advantage,[35] this equates to win probability changing by approxi-

[32]It is possible that the playoff bias is caused mainly by increased home bias, since the home crowd is maybe stronger in playoff games in which the home team is near elimination. We analyze this issue by recoding Series Diff =-1 for home teams when the series score is 3-3, and recoding Series Diff=1 for away teams. In these situations, the home crowd should be very strong since it is a double-elimination situation. The recoding causes the Series Diff estimate to weaken, indicating playoff bias is not just caused by increased home bias.

[33]Since these regressions are based on game-level data we are able to use data from prior to the 2002-03 season.

[34]A similar approach was used by Price and Wolfers (2007) to provide a measure of the economic significance of the effect of racial bias on the part of referees.

[35]Home teams have an 11.5% advantage in DTOs, and a 2.4% advantage in non-discretionary, as reported

mately 2.2% when a team switches from away to home status, just due to the DTO effect.[36] The effect would be substantially greater if we attributed the foul advantage to bias as well. To be conservative, we only use the shooting foul advantage difference, which is 6.4% (8.8% - 2.4%), and assuming each foul results in two shots, with 1.5 made, this would yield a marginal effect of 2.5% on wins.[37] The home DTO effect also nearly doubles in the playoffs. However, there is no evidence of the playoff bias affecting fouls. While the DTO playoff bias is estimated to be greater than the overall home bias for teams down two or three games, the playoff bias effect on the outcomes of playoff series is likely to be very small on average, since even if the favored team wins one game due to bias it still may not go on to win the series.

Berri et al. (2006) do not analyze the effects of changes in statistics within games on outcomes. To provide approximations of these effects, we estimate simple logit models, with the dependent variable being a dummy for winning the game. These logit regressions use two samples: one restricted to second half observations for teams down 4-10 points at halftime and the other restricted to teams down by 11 or more points at halftime. We use each type of turnover and foul advantage as RHS variables, with and without controls for other game statistics, which are determined prior to the dependent variable in this context. For example, one RHS variable is the difference in DT0s during the second half of the game between the losing and winning team (based on the score at halftime). Our preferred specifications are those with the full set of controls. These imply (results unreported) an increase in turnover advantage by one increases the probability of winning around 3.5% for teams down 4-10 at halftime, and 0.5% for teams down by 11 or more; both effects are significant at the 1% level. However,

in Table 3. The end of Section 3 describes how under certain assumptions we can difference these estimates to get an estimate of the magnitude of ref bias.

[36]This effect comes from $0.034 \times 0.091 \times 3.7 + 0.034 \times 0.091 \times 3.4$. We sum the home and away effects since the away team gains an advantage, and the home team loses it, due to the switch in home status. This effect is similar to that found by Garicano et al. (2005); they estimated that home soccer teams down one goal were given an extra one minute of injury time, in which the probability of scoring was 0.015, and away teams down one goal, who had a lower probability of scoring of 0.01, were given 0.82 less minutes.

[37]In reality, the vast majority of shooting fouls result in two shots, but some result in just one, while others result in three. The league average free throw shooting percentage is approximately 75% and Berri et al. (2006) estimates marginal effects of 0.018 wins per free throw made and -0.015 wins per free throw missed. In our data, away (home) teams commit 10.5 (9.9) shooting fouls per game. Thus the effect is calculated as $(10.5 + 9.9) \times 0.064 \times (1.5 \times 0.018 - 0.5 \times 0.015)$.

teams losing by 4-10 would only obtain a total advantage of around 0.18 turnovers from the bias, even if losing the entire second half, which would only improve the chance of winning by 0.61%.[38] Attributing the foul advantage to bias would again cause the effect to increase, but minimally, as our logit estimate for shooting fouls is 1.8%. But we note that these results are very crude. Exploring the effects of within game changes on wins more carefully is a topic for future work.

5.2 Bias and Ref Incentives

We do not have data on individual ref calls or ref pay, so it is difficult for us to analyze the relation between individual ref biases and compensation. However, the number of playoff assignments a ref receives may be a good observable proxy for his compensation. Thus, we can use playoff assignment data to gain additional insight into the refs' incentives for, and league's policy towards, the biases.

For this analysis, we use a two-stage procedure. We first estimate three regressions for each season using a game-level dataset: one with a dummy dependent variable for the home team winning the game, one with the dependent variable being the absolute value of the game's final score margin, and one with the dependent variable being the home team's (home) win percentage for the season minus the away team's (away) season win percentage. As controls, we include ref, home team, and away team FEs, except for the win percentage regressions where we only use ref FEs.[39] We then use the coefficient from each referee's FE from the first stage regressions as variables in a separate ref-season level dataset. We refer to these variables as "Home Coefficients," "Close Coefficients," and "Matchup Coefficients," respectively.

These three variables provide noisy measures of home bias, close bias, and the degree the home team was *ex ante* favored for games the ref was assigned to, for each ref-season. The associations between these variables and playoff assignments provide evidence on whether the league rewards or punishes bias. If the Home Coefficients

[38] Teams commit 3.53 DTOs per game, so 1.77 DTOs per half, and Table 2 implies teams down 4-10 have a 3.7% advantage, and teams up 4-10 have a 11.1% - 4.9% = 6.2% disadvantage. Thus the 0.18 effect comes from $(0.037 + 0.062) \times 1.77$. The effect on winning probability is calculated as $0.18 \times 3.5\%$.

[39] The home and away FEs would be collinear with that dependent variable.

are positively related to playoff assignments, that indicates home bias is rewarded. If Close Coefficients are negatively related to playoff games, that indicates close bias is rewarded. And if Matchup Coefficients are negatively related to playoff games, that indicates the league rewards the refs more likely to work regular season games in which, *ceteris paribus*, the home team is likely to lose by a large margin. We use various specifications for this analysis as the robustness of results is especially questionable given that our measures of referee bias are estimates from separate regressions. We also use both current season, and next season playoff games (worked by the ref in that season) as dependent variables, since compensation for bias in a given season may occur with a lag.

Results are presented in Table 6 . We obtain multiple significant results indicating home biased refs are rewarded; however, there is also one significant result indicating refs that keep games close are actually punished. Neither of the results on home or close bias are consistently significant across specifications, however. The results for Matchup Coefficients, on the other hand, seem very robust: they always indicate refs who worked more games in which home teams faced stronger opponents are also refs assigned to more playoff games, at 1% significance. This is only indirect evidence on the incentives the league provided for bias, since it does not show those refs actually inordinately favored the home teams in those games. Still, it does provide strong evidence the assignments the league made between refs and regular season games were non-random and consistent with the hypotheses regarding the profitability of biases described above.

6 Discussion

We have presented evidence that home teams, teams losing during games and teams losing in playoff series have an advantage in DTOs, and almost no advantage in NTOs. This is likely due to ref bias, since the first type of turnover is determined more directly by ref actions than the second type. While we cannot completely rule out both DTO and NTO effects being caused entirely by player actions (and referees being on average completely neutral), we think it is extremely unlikely that this is the case, especially since the pattern is consistent for the three game situations.

The biases may be caused by psychosocial factors or the desire of refs to build goodwill with teams, and not explicit encouragement from the league. Home bias increases in the playoffs and with higher attendance, which is consistent with the bias being caused by social pressure and/or persuasion from the crowd (we cannot distinguish these factors). The decline of the home bias in the fourth quarter indicates refs want to be impartial when it matters most, and do not want their calls to be closely linked to game outcomes. The insignificant effect of televised status on the close bias also is consistent with non-explicit bias. The findings that the playoff bias does not increase in critical minutes of games or in series between large television market teams are also consistent with the bias not being an intentional means of increasing profits.

The personal benefits to refs of bias are likely low, however, so the fact that bias persists suggests the league has at least not created strong disincentives for bias. Moreover, we know the league does monitor refs closely, the biases have not declined in the second half of our sample, when monitoring was more intense, and that the league rewards with more playoff assignments the same refs more likely to be assigned to regular season games involving weak home teams and strong opponents, where bias may be most beneficial. Still, our discussion of the relation between the persistence of the biases, and our hypotheses that the biases may be profitable, is somewhat speculative. An ideal additional test would be to identify a psychosocial bias that would *reduce* the league's profits. If this bias also persisted, it would suggest all of the biases exist independent of their profitability. If the unprofitable bias did not persist, this would suggest the biases we study are condoned or encouraged by the league because they are profitable. Unfortunately we are not aware of any such bias. Perhaps this could be an avenue for future work.

The estimated DTO advantages are generally substantially larger than those of both types of fouls. We do not draw formal conclusions from these results due to the identification problem for fouls, but speculate it is unlikely that player behavior systematically affects DTOs more than fouls. Thus, even if the foul effects were caused by bias, the bias affecting DTOs would seem to be more severe. It is unclear how to interpret these results with respect to the league's profit motive, however. It is possible the league allows greater bias for DTOs since they are not reported in box scores and, thus, less observable to fans and analysts. On the other hand, it is possible DTOs are more difficult to judge and inherently more subjective than fouls, and consequently it is more costly for the league to eliminate DTO bias.

We should note that while the league may reduce future bias by modifying its ref monitoring and compensation practices, it is possible to monitor excessively. Overzealous monitoring could create a host of new problems, as, for example, referees might feel compelled to make calls in one game to make up for perceived disparities in previous games. Hopefully, simply calling attention to and raising awareness of the biases will help to alleviate them. The league's clarification of the traveling rule in 2009 may also be beneficial. Similarly, clarifying rules regarding offensive fouls (increasing the penalties for flopping) could help in the future. Finally, it might be helpful to report traveling and offensive foul violations separately from other turnovers in box-scores and for the league to make public its internal reports and/or data on officiating. In general, being sure rules are defined clearly and appropriately, and making data on rule compliance public may be the lowest cost way for both the NBA and organizations in general to improve compliance and reduce suspicion about lack of compliance.

Our findings on difficult to detect biases also relate to a larger class of rule-based goods and services beyond sports. For example, the television quiz shows in the 1950s used biased rule enforcement to make their shows more entertaining, by giving the most charismatic contestants answers in advance Van Doren (2008). This type of blatant violation of the rules is likely a thing of the past. However, our results suggest that even today it is possible that game show firms favor some contestants in a more subtle manner, perhaps by feeding them questions on subjects they are known to be strong on or giving them weaker opponents.

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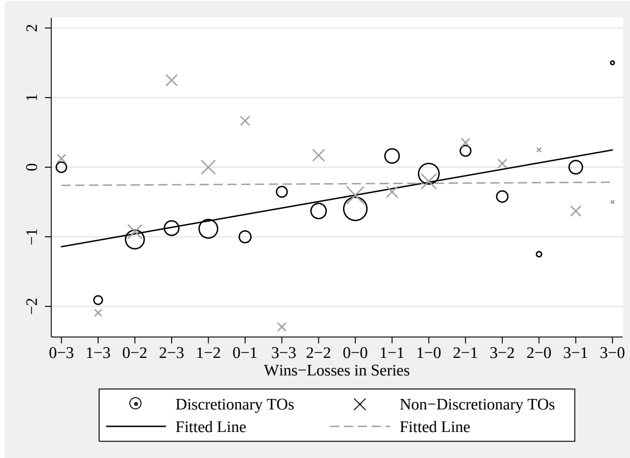

Figure 1: Mean turnover differences (home team's turnovers minus away team's turnovers, for the game) by playoff series score (home team's wins in the series prior to game start–home team's losses in the series prior to game start). Number of observations for each series score represented by the size of the points (X's and O's).

Table 1: Turnover Definitions

Turnover Type	Definition
Discretionary Turnovers	
Travel*	Progressing in any direction while in possession of the ball [without dribbling], which is in excess of prescribed limits as noted in Rule 10-Section XIV.
Three seconds	An offensive player remains in the painted lane in front of the basket for more than three consecutive seconds.
Offensive Goal-Tend	A player interferes with the ball when it is on a downward trajectory or is in an extended cylinder-shaped region above the rim.
Offensive foul*	Illegal contact committed by the offensive player.
Non-Disc. Turnovers	
Bad pass	A pass that either is stolen by the defensive team or goes out of bounds.
Lost ball	Having the ball either directly stolen by the defensive team or stepping out of bounds with possession of the ball.
Shot clock	The offensive team fails to take a shot that hits the rim within 24 seconds of possession.

Notes: Definitions for terms with * from: http://www.basketball.com/nba/rules/rule4.shtml#IV (definitions for other terms unavailable from that website as they are unofficial terms used in play-by-play transcripts).

Table 2: Minute-Level Summary Statistics

	Home Mean (SD)	Away Mean (SD)	Diff (Home - Away)	Winning Mean (SD)	Losing/Tied Mean (SD)	Diff (Losing - Winning)
Discretionary Turnovers						
Travel	0.0202 (0.142)	0.0241 (0.155)	-0.0039 ***	0.0235 (0.153)	0.0210 (0.144)	-0.0025 ***
Three seconds	0.0073 (0.085)	0.0066 (0.081)	0.0007 ***	0.0082 (0.090)	0.0059 (0.077)	-0.0022 ***
Offensive foul	0.0416 (0.203)	0.0451 (0.211)	-0.0035 ***	0.0452 (0.211)	0.0418 (0.203)	-0.0034 ***
Offensive goal-tend	0.0011 (0.033)	0.0012 (0.034)	-0.0001	0.0011 (0.033)	0.0011 (0.034)	0.0000
Non-Discretionary Turnovers						
Bad pass	0.1285 (0.353)	0.1261 (0.350)	0.0024 ***	0.1308 (0.356)	0.1242 (0.347)	-0.0066 ***
Lost ball	0.0603 (0.244)	0.0635 (0.251)	-0.0032 ***	0.0614 (0.247)	0.0624 (0.248)	0.0010
Shot clock	0.0052 (0.072)	0.0057 (0.075)	-0.0005 ***	0.0057 (0.075)	0.0052 (0.072)	-0.0005 ***
Non-Shooting Fouls						
Personal	0.1556 (0.393)	0.1556 (0.393)	0.0000	0.1649 (0.404)	0.1476 (0.383)	-0.0173***
Loose ball	0.0275 (0.166)	0.0283 (0.168)	-0.0008 **	0.0298 (0.173)	0.0263 (0.162)	-0.0035 ***
Inbounds	0.0002 (0.015)	0.0007 (0.026)	0.0000	0.0003 (0.016)	0.0002 (0.014)	0.0000
Clearing	0.0005 (0.023)	0.0007 (0.026)	-0.0001 **	0.0007 (0.026)	0.0005 (0.023)	-0.0001 **
Away from ball	0.0004 (0.020)	0.0004 (0.020)	0.0000	0.0004 (0.021)	0.0003 (0.018)	-0.0001 **
Shooting Fouls						
Non-flagrant	0.2058 (0.433)	0.2167 (0.443)	-0.0109 ***	0.2267 (0.452)	0.1981 (0.425)	-0.0286 ***
Flagrant	0.0009 (0.029)	0.0010 (0.032)	-0.0002 **	0.0008 (0.028)	0.0011 (0.033)	0.0003 ***

Notes: Sample includes all games from 2002-2003 - 2007-2008 seasons with play-by-play data available on ESPN.com; overtime periods and last three minutes from fourth quarters dropped from all games, and games with missing minutes dropped. "Winning" = winning by one or more points at start of quarter; "Losing/Tied" = losing or tied at quarter start. In total there are 632,880 observations; 316,440 minutes, with two observations for each minute (one for each team). *, **, *** denote 10%, 5% and 1% significance, respectively (for differences; two-tailed tests, unequal variances).

Table 3: Home and Close Bias Poisson Regression Results

	Discretionary Turnovers		Non-Discretionary Turnovers		Shooting Fouls		Non-Shooting Fouls	
Home	-0.1152***	-0.0824***	-0.0238***	-0.0128	-0.0877***	-0.0759***	-0.0293** *	-0.0449***
	(0.0101)	(0.0215)	(0.0061)	(0.0133)	(0.0055)	(0.0111)	(0.0061)	(0.0123)
Attendance	-0.0050	-0.0050	-0.0005	-0.0005	-0.0005	-0.0005	0.0039*	0.0039*
	(0.0034)	(0.0034)	(0.0020)	(0.0020)	(0.0018)	(0.0018)	(0.0021)	(0.0021)
Attendance $\times$ Home	-0.0028	-0.0028	0.0026	0.0026	0.0017	0.0017	-0.0063**	-0.0063**
	(0.0044)	(0.0044)	(0.0027)	(0.0027)	(0.0024)	(0.0024)	(0.0027)	(0.0027)
Playoff	0.0823**	0.0822**	-0.0109	-0.0109	0.0316	0.0316	0.1094** *	0.1094***
	(0.0347)	(0.0347)	(0.0225)	(0.0225)	(0.0210)	(0.0210)	(0.0197)	(0.0197)
Playoff $\times$ Home	-0.0981**	-0.0981**	-0.0335	-0.0336	-0.0478**	-0.0479**	-0.0214	-0.0214
	(0.0382)	(0.0382)	(0.0232)	(0.0232)	(0.0205)	(0.0205)	(0.0214)	(0.0214)
Score Diff < - 10	-0.1505***	-0.1498***	0.0075	0.0070	-0.0482***	-0.0489***	-0.0217**	-0.0220**
	(0.0179)	(0.0179)	(0.0104)	(0.0104)	(0.0098)	(0.0098)	(0.0110)	(0.0110)
-10 $\leq$ Score Diff ≤ -4	-0.0369***	-0.0369***	-0.0015	-0.0017	-0.0278***	-0.0279***	0.0171**	0.0172**
	(0.0138)	(0.0138)	(0.0082)	(0.0082)	(0.0076)	(0.0076)	(0.0085)	(0.0085)
4 $\leq$ Score Diff $\leq$ 10	0.1109***	0.1109***	0.0488***	0.0489***	0.1427***	0.1427***	0.1254** *	0.1253***
	(0.0133)	(0.0133)	(0.0080)	(0.0080)	(0.0075)	(0.0075)	(0.0086)	(0.0086)
10 < Score Diff	0.1817***	0.1810***	0.1622***	0.1627***	0.2708***	0.2714***	0.1758** *	0.1761***
	(0.0169)	(0.0170)	(0.0103)	(0.0104)	(0.0090)	(0.0090)	(0.0105)	(0.0105)
Q1 $\times$ Home		-0.0275		0.0045		-0.0029		0.0100
		(0.0281)		(0.0171)		(0.0148)		(0.0167)
Q2 $\times$ Home		-0.0469*		-0.0274		-0.0054		0.0259
		(0.0269)		(0.0169)		(0.0145)		(0.0159)
Q3 $\times$ Home		-0.0452*		-0.0178		-0.0348**		0.0220
		(0.0268)		(0.0171)		(0.0143)		

Notes: N = 632,700; unit of observation = game-minute-team. All models include match-up (team-opponent-season) fixed effects, quarter fixed effects and a constant as RHS variables. Attendance is de-meaned and measured in thousands. Score Diff = start of minute own score minus opponent score (dummy variables for difference being less than -10, between -10 and -3, etc.). Q1/Q2/Q3 = dummies for 1st/2nd/3rd quarter; Home = dummy for home game. Robust standard errors clustered by match-up in parentheses. *, **, *** denote 10%, 5% and 1% significance.

Table 4: Playoff Bias Poisson Regression Results

	Discretionary Turnovers		Non-Discretionary Turnovers		Shooting Fouls		Non-Shooting Fouls	
Series Diff	0.034**	-0.073	-0.005	-0.025	0.004	0.015	-0.013*	0.006
	(0.014)	(0.055)	(0.010)	(0.035)	(0.008)	(0.027)	(0.008)	(0.027)
Home	-0.165***	-0.164***	-0.040	-0.040	-0.113***	-0.113***	-0.064***	-0.065***
	(0.039)	(0.039)	(0.026)	(0.026)	(0.020)	(0.020)	(0.020)	(0.020)
Attendance × Home	-0.073***	-0.073***	-0.006	-0.006	0.004	0.004	-0.020*	-0.020*
	(0.022)	(0.022)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)
Score Diff < - 10	-0.075	-0.108	0.064*	0.183***	0.040	-0.016	0.060	-0.018
	(0.063)	(0.107)	(0.039)	(0.066)	(0.035)	(0.054)	(0.039)	(0.062)
-10 $\leq$ Score Diff ≤ -4	0.002	-0.011	-0.012	-0.017	-0.014	-0.036	0.043	0.021
	(0.051)	(0.052)	(0.032)	(0.032)	(0.030)	(0.030)	(0.032)	(0.032)
4 $\leq$ Score Diff $\leq$ 10	0.013	0.004	0.008	0.006	0.119***	0.098***	0.154***	0.133***
	(0.053)	(0.053)	(0.030)	(0.030)	(0.028)	(0.028)	(0.030)	(0.030)
10 < Score Diff	0.116*	0.082	0.103***	0.222***	0.264***	0.207***	0.189***	0.112*
	(0.064)	(0.107)	(0.039)	(0.067)	(0.032)	(0.054)	(0.035)	(0.060)
Series Diff × Mins Remaining		0.003		0.000		-0.001		-0.000
		(0.003)		(0.002)		(0.001)		(0.002)
Series Diff ×|Score Diff| $\leq$ 10		0.081		-0.020		-0.023		-0.037
		(0.070)		(0.045)		(0.033)		(0.035)
Series Diff ×|Score Diff | $\leq$ 10 × Mins Remaining		-0.001		0.001		0.001		0.001
		(0.003)		(0.002)		(0.002)		(0.002)
|Score Diff| $\leq$ 10 × Mins Remaining		-0.001		0.006**		-0.001		-0.002
		(0.004)		(0.003)		(0.002)		(0.002)

Notes: N = 42,480 (playoff games only). Series Diff = own games won in series thus far minus opponent's games won in series thus far. Attendance is de-meaned for playoffs and measured in thousands. Match-up (team-opponent-season) regular season means, quarter fixed effects, and a constant included as RHS variables in all models. Score Diff = start of minute own score minus opponent score (dummy variables for difference being less than -10, greater than -11 and less than -3, etc.); Q4 = dummy for 4th quarter; Home = dummy for home game; Mins Remaining = regulation minutes remaining in the game. Mins remaining included as stand-alone regressor in models including it in interactions. Robust standard errors clustered by game in parentheses. *, **, *** denote 10%, 5% and 1% significance.

Table 5: Playoff Bias, Game-Level Sample: Poisson Regression Results

	Turnovers	Fouls	Blocks	Rebounds	Assists	Field Goals Made
Series Diff	0.012**	-0.004	0.011	0.007**	0.010**	-0.001
	(0.005)	(0.003)	(0.009)	(0.003)	(0.004)	(0.002)

Notes: N= 2,350 ; unit of observation = game-team; sample includes only playoff games from 1992-2007. Series Diff = own games won in series thus far minus opponent's games won in series thus far. Match-up (team-opponent-season) regular season means, home game dummy and a constant included as RHS variables in all models. Robust standard errors in parentheses. *, **, *** denote 10%, 5% and 1% significance.

Table 6: Estimation Results for Analysis of Ref Playoff Assignments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Home Coefficients	0.022	0.625	1.536*	2.526***	0.182	0.829*	0.529	1.755**
	(0.445)	(0.418)	(0.791)	(0.822)	(0.492)	(0.456)	(0.958)	(0.847)
Close Coefficients	0.031	0.004	0.123***	0.069	-0.003	-0.015	0.027	0.027
	(0.022)	(0.027)	(0.041)	(0.050)	(0.022)	(0.024)	(0.044)	(0.046)
Matchup Coefficients	-4.297***	-3.446***	-7.607***	-5.423***	-4.778***	-2.937***	-10.184***	-6.717***
	(0.696)	(0.942)	(1.601)	(1.610)	(0.765)	(0.770)	(1.364)	(1.264)
N	344	205	344	205	287	159	287	159

Notes: Sample consists of data from the 2002-03 to 2007-08 seasons; unit of observation is a ref-season. The dependent variable equals zero if the ref worked zero playoff games that season, and one if the ref worked one or more playoff games for models (1) and (2), which are estimated via logit. The dependent variable is the number of playoff games the ref worked that season for models (3) and (4), estimated via Poisson regression. Models (5)–(8) are analogous, with the dependent variable defined by the number of playoff games the ref worked in the subsequent season. Home Coefficients and Close Coefficients are estimated ref-season effects on the home team's probability of winning and |Score Diff|. Matchup Coefficients is the estimated association between ref-season and the difference in winning percentage (for the season) between home and away teams for games the ref-season works. See Section 5.2 for details on how these variables are constructed. Models (1), (3), (5), and (7) are estimated using samples restricted to refs who worked at least 40 regular season games; the other models use samples restricted to refs who worked at least 60 regular season games. Logit models report marginal effects. Season fixed effects included in all models. Robust standard errors clustered by ref in parentheses. *, **, *** denote 10%, 5% and 1% significance.