Celebrity Misbehavior in the NBA

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ABSTRACT

I compare and contrast theories of why NBA players misbehave on the court, then test them empirically. I find evidence that earnings are positively correlated with misbehavior, and that both absolute and relative salary matter. For instance, I find that a player who is highest paid on his team misbehaves roughly 7% more than one who is second-highest paid, even at the same salary level. This relative effect I interpret as due to lack of good substitutes for top players. I also find some evidence that personal preferences may be important in understanding misbehavior, but no evidence that immaturity or peer effects are important determinants of misbehavior in the NBA.

KEYWORDS: Celebrity, basketball, technical fouls, substitutability

I. Introduction

Famous people are "leaders", where trends in social behavior begin. One prominent facet of celebrity is the apparently high propensity to engage in socially disapproved behavior, including boorishness and general snobbery, as well as more pernicious misbehavior such as substance abuse and debauchery.[1] Compared with other celebrities, professional basketball players are even more frequently accused of engaging in and promoting anti-social behavior.

In this paper, I analyze data on National Basketball Association players in order to derive empirical relationships between individual misbehavior and player characteristics. I measure misbehavior by the propensity to receive "technical" fouls and to be ejected from games, but I also show that this propensity is correlated with players' off-court legal incidents. This suggests that these results might also have implications for misbehavior among other classes of celebrity, or for worker misbehavior generally.

The results indicate that factors related to salary are important determinants of misbehavior in the NBA. I also find that unmeasured aspects of personal character likely explain a substantial fraction of the variation in misbehavior between players. I find little evidence that age and peer effects matter, however.[2]

In particular, I find strong evidence in favor of the importance of *relative* salary levels. A player's salary, relative to that of others on his team or in the league generally, may be at least partially indicative of how well other available players may substitute for him; thus, teams and fans may put up with more misbehavior from the top paid players on a team because of a lack of good alternatives. This lack of substitutability may be derived from the fact that the market for

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[1] This does not seem to be driven entirely by the greater media focus on stars' lives; see Fowles (1992) for evidence on causes of mortality by celebrities in comparison to non-celebrities.
[2] A number of recent articles have attempted to disentangle individual and group effects as causes for worker misbehavior generally (Ichino and Maggi, 2000, Costa and Kahn, 2003, Ferris, et al, 2003).

very highly skilled players is usually quite thin, or from the fact that fans associate their team closely with particular "star" players, and cannot easily switch their loyalties to new players. If players enjoy misbehavior (or find it costly to repress), top-paid players may then engage in more misbehavior.[3]

In Section II, I discuss this theory, and contrast it with several others that also may explain misbehavior among NBA stars and other celebrities. Section III presents empirical tests of some of these theories.

II. Six Factors Influencing Misbehavior among Celebrities

In this section, I briefly consider six simple theories of celebrity misbehavior generally, with special application to professional athletes. I make no claim that this is an exhaustive list of reasons why stars misbehave, but I focus on factors I can empirically address with the data at hand.

(1) *Personal preferences.* Much anti-social behavior may simply represent odd preferences (Caplan, 2006). Success as a professional athlete is usually associated with many years of tedious practice in adolescence and beyond. The individual who is willing to undertake such an extreme commitment may be unusual in other aspects as well. Thus, if there is some exogenous, possibly even genetic, factor that leads individuals to be unusual both in their employment and in their personal preferences, then the brilliant performances that make one a celebrity would be more likely to originate from people who also have preferences considered outside of social norms.

(2) *Pure income effects*. It is possible that misbehavior is simply a normal good, so that star athletes, who are among the best paid workers in the world, lose less utility from the fall in demand for their services associated with bad behavior. Alternatively but equivalently, high-earners may be

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[3] Rosen (1981) also emphasizes consumer's inability to substitute across persons of differing talent levels. My argument is that the nature of celebrity magnifies this aspect of consumption.

able to hire better legal counsel and publicity representatives after misbehaving, lowering their effective price of bad behavior.[4] Under this theory, however, one would expect CEOs of major corporations to engage in as much or more illicit drug use, marital infidelity, and public oafishness as movie stars, pro athletes, and rock stars. I know of no empirical work on this subject that addresses this question, though the stereotype is certainly that they do not.

(3) *Lack of substitutability*. Star players are difficult to replace for several reasons. First, Shaquille O'Neal, Dennis Rodman, Rasheed Wallace, and other top players are unique world-class talents, and sufficiently qualified replacements are very difficult to come by. This problem is compounded by the relative indivisibility of their labor effort; two players, each half as talented as Michael Jordan, are not anywhere near as productive as one Michael Jordan.[5]

Second, team output is intrinsically tied to the team's stars. Fans do not simply follow the Cleveland Cavaliers; they also care about the particular players who *are* the Cavaliers. Similarly, in a non-sports context, the demand for a recording of the song "Yesterday", originally performed by the Beatles, is many orders of magnitude greater than the demand for the same song, as recorded by a Beatles "cover" band, even a very talented one. Therefore, it is generally difficult to replace celebrity labor output with non-celebrity output, even at par quality.[6]

(4) *Publicity*. Misbehavior may be a means of increasing fame, and raising demand for one's work. Dennis Rodman's frequently changing hair colors attracted worldwide interest to the mid-

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[4] In a study of 40 professional athletes sentenced to community service for crimes committed, McCarthy and Upton (2006) found that much of the punishment "involved activities such as throwing out a ceremonial first pitch at a Major League Baseball game, posing for pictures or attending or coaching at youth sports camps". In only four of the cases did star athletes serve the type of menial labor typically required of non-celebrity defendants.

[5] For a variety of reasons, including technical issues in the production process (e.g., there is only one ball in play at a given time, and only five players allowed on the floor), and fixed costs of consumption (e.g., fans may enjoy wearing a replica Jordan jersey more than alternating between two less talented player jerseys). Neale (1964) refers to this aspect of sports production as "Bobby Layne" rigidity.

[6] By contrast, purchasers of non-celebrity products, such as dry cleaning services, may care about the quality of a particular dry cleaner's services, but are usually indifferent as to who owns the plant or what technology was used to produce a given level of quality.

1990s Chicago Bulls, independent of their on-court success, and certainly increased the demand for Rodman's autobiography, his replica jerseys, and probably other Bulls-related paraphernalia. Similarly, if fans enjoy seeing celebrities misbehave, or live vicariously through their favorite star's exploits, stars will naturally respond to this demand by supplying more misbehavior.

(5) *Youthful Immaturity*. With few exceptions, the ranks of professional athletes are constituted overwhelmingly by men between the ages of 18 and 35. Young celebrities may be less risk-averse, or may misunderstand the potential consequences of bad behavior, leading them to engage in activities towards which more mature individuals would be less inclined.

(6) *Peer Effects*. High-profile athletes, (and similarly, movie stars and top musicians) may be pestered or even mobbed by fans asking for autographs and other favors when they make public appearances. For this reason, many celebrities employ professional assistants to do their grocery shopping and other tasks that non-celebrities typically would do themselves.[7] This leads celebrities to engage in a disproportionate number of social interactions with other celebrities. This is particularly true for athletes, who travel with their teammates to away games, and practice together when at home. Such a tight-knit group may lead to different social norms than those that arise among non-celebrities, who interact frequently with persons from a variety of walks of life.[8]

III. Empirical Application

1. Introduction

In this section, I test the theories considered in the previous section by analyzing a measurable form of misbehavior among an important class of celebrities, professional basketball

[7] This is especially problematic for basketball players, whose height cannot be easily disguised in the way a movie star can use dark sunglasses or a scarf to hide from the public.

[8] Similarly, Becker and Murphy (2000) suggest that peer effects can explain different norms in speech patterns among teenagers and the different social norms regarding smoking that exist in Japan and the U.S.

players. Specifically, I examine the propensity of players to commit technical fouls and to be ejected from games.[9]

2. Rules governing technical fouls and ejections

Technical fouls may be assigned to individual players by referees any time during the play of an NBA game. Though there are other possible reasons for receiving a technical foul, by far the most common is unsportsmanlike conduct, including: fighting with other players or officials, disrespectfully addressing an official, overt actions indicating resentment to a call, use of profanity, taunting, hanging on the basketball rim excessively, or deliberately-thrown elbows or fists.[10] The available data do not, however, distinguish the precise offense for which the foul was called, limiting the extent to which different degrees of misbehavior can be distinguished. Technical fouls may also be called on an entire team for illegal defense formations, but I do not count these fouls in the analysis below.

Technical fouls are penalized, making them usually counter-productive to team success. For each offense, the opposing team receives an opportunity to take a free throw.[11] Players are automatically ejected upon receiving two technical fouls during the same game, and it is possible for two technical fouls to be called simultaneously for especially egregious offenses. Such cases may also involve suspension from some number of future games. The longest suspensions levied are

[9] McCormick and Tollison (1984) and Goff and Tollison (1992) also consider basketball players' propensity to commit fouls, though they focus on personal (not technical) fouls, which more often represent player mistakes or, sometimes, productive strategies. Heckelman and Yates (2003) find that increasing enforcement did not lead to less violence in hockey, although there is clearly a productive element to violent behavior in hockey (Jones, et al, 1997), which is not clearly the case with technical fouls in basketball.

[10] According to the official rulebook of the NBA, technical fouls can also be assigned for excessive time-outs, delay-of-game, or illegal substitutions (for instance, inserting a player into a game without notifying the scorer's table). Such fouls are exceedingly rare.

[11] In some cases, such as fights where technical fouls are called on both teams, no free throws are awarded. In addition, for excessive time-out situations, the ball changes possession, and for delay-of-game situations, additional time may be added to the shot clock. The ball does not change possession for other types of technical fouls.

around five games, although in a few exceptional cases they have been much longer[12]. The median suspension is 1 game. Individual teams and coaches may also assess additional fines and penalties at their own discretion.

3. Are technical fouls and ejections a meaningful measure of misbehavior?

One may ask whether technical fouls and ejections, representing misbehavior on the court, are correlated with general misbehavior *off* the court. Table 1 provides a list of the "worst on-court offenders" – as measured by technical fouls per 1,000 minutes played and ejections per 82 games – during the sample years. Most of these players have had very turbulent off-court careers. For instance, Rasheed Wallace has been arrested on drug charges and once physically threatened an NBA official outside the stadium. Anthony Mason has been charged with statutory rape, attacking a police officer, and assault on two occasions. Charles Barkley, whose autobiography is entitled "Outrageous", has joked on-camera about violence towards women, and has been involved in a number of bar fights, including one in which he threw a man through a glass window. Dennis Rodman, whose autobiography is entitled "Bad As I Wanna Be", has been arrested for DUI, spousal abuse, and public drunkenness, and was twice married for durations less than six months. Vin Baker has struggled with alcoholism, and Derrick Coleman has faced criminal charges for two DUIs as well as for public urination in the dining room of an Italian restaurant.

Admittedly, a few players on this list, such as Jerome Kersey, have exhibited mostly nondescript off-court behavior, so the relationship between on-court and off-court misbehavior is not

[12] The only suspensions in league history greater than 10 games are (1) Ron Artest, Stephen Jackson, and Jermaine O'Neal (Indiana Pacers) were suspended for 73, 30 and 25 games, respectively, for fighting with fans during a game, (2) Latrell Sprewell (Golden State Warriors) was suspended for 68 games during the 1997-98 season for assaulting his coach, (3) Kermit Washington (Los Angeles Lakers) was suspended for 26 games in 1977 for punching (and nearly killing) another player, and (4) Dennis Rodman (Chicago Bulls) was suspended for 11 games in 1997 for kicking a courtside TV photographer.

one of perfect correlation.

As another test, I also collected the number of criminal arrests or other publicized off-court misbehavior incidents for each player from a website tallying such cases among athletes, *cracksmoker.com*.[13] The number of arrests listed on the website for a player is positively and significantly correlated with the number of technical fouls, and the number of technical fouls per minute played by players in my sample ($\rho = 0.28$, significant at the >99% level).[14]

4. Testing theories of misbehavior

I propose to use these data to test some of the theories discussed in Section II above. Some summary statistics on the sample are provided in Table 2; a given player in a given year may have multiple observations if he is traded between teams during the season.

Despite the presence of players like those listed in Table 1, technical fouls are generally rare; the mean is 2.47 per season, and the median player commits just one per season. Figure 1 illustrates this fact even more starkly by presenting the distribution of technical fouls in the sample (truncated at a maximum of 20 for readability). Nearly 44% of these observations involve zero technical fouls, and many players who do commit technical fouls have only a few. Despite this potential limitation in the measurement of misbehavior, it will be seen that technical fouling can still be explained to some degree by observable variables.

One important variable I will concentrate on is salary. Since the top players are usually the most highly paid, both the substitutability and pure income effects theories presented in the previous section predict a positive relationship between salary and technical fouls. Figure 2 presents a simple

[13] As of May, 2006, the site now appears to be defunct. Data are available upon request from the author.
[14] I could have simply used *cracksmoker.com*'s lists as the measure of player misbehavior in lieu of technical fouls, but public reporting of arrests is likely to be strongly correlated with a player's level of fame and salary, generating bias in the results. Nevertheless, the results below hold when I use this variable as the measure of misbehavior.

scatterplot of these two variables for one year in the sample, the 2000-01 season. Two stylized facts are immediately clear from Figure 2: first, there are some well-behaved players at all salary levels with no technical fouls; and second, on average there is a prominent positive relationship between salary and misbehavior. Of course, this simple analysis cannot control for many potential confounding factors, including the fact that higher paid players usually play more minutes on the floor, but we will see that a more sophisticated analysis retains this basic result.

In order to distinguish substitutability from pure income effects, I estimate the effects of salary on the number of technical fouls a player commits in a season, distinguishing between a player's salary *level*, and his salary *rank* on his team.[15] The effect of salary rank, holding constant salary level, provides evidence on the importance of the substitutability theory. To illustrate, suppose player A and player B have identical salaries, but that player A is the best-paid player on his team, while player B is the second-highest paid on his team. The substitutability theory predicts that player A will commit more technical fouls than player B, because player A is usually more of a "star" than player B. For the reasons discussed in Section II, deterring player A from misbehavior will generally involve higher costs on the part of teams and fans than player B.

On the other hand, if pure income effects are an important determinant of misbehavior, this should be empirically determinable in the effect of salary level on technical fouls, holding constant salary rank.

Since technical fouls are rare, discrete events, linear regression methods are inefficient relative to models built explicitly for count data in the dependent variable. Poisson regression is one possible model to organize the data; however, as is clear from the mean and standard deviation on

[15] Salary rank is calculated by comparing the yearly salaries of all players who played any minutes on a given team in a given year. It may be argued that players who played fewer games should be less relevant in computing salary rankings; calculating salary rank based only on players with more than 500 minutes played in a year does not change the results substantially, however.

technical fouls and ejections in Table 2, there appears to be substantial overdispersion in the dependent variable. Therefore, assuming equality in conditional mean and variance for these variables may be inappropriate. A common alternative, which I employ below, is the negative binomial model (see Cameron and Trivedi, 1986, for alternative models of count data). Thus, I estimate the following equation:

[1] $$\ln(\lambda_{iky}) = \ln(\min_{iky}) + \alpha(Salary\ Rank_{iky}) + \beta \ln(Salary_{iky}) + \gamma X_{iky} + \eta_k + \lambda_y + \varepsilon_{iky}$$

where λ_{iky} is the expected number of technical fouls committed by player *i* on team *k* in season *y*, $\min_{iky}$ is the seasonal number of minutes played by this player on team *k* (his potential "exposure" to technical fouls), $Salary\ Rank_{iky}$ is the rank order (with 1 being the highest) of player *i*'s salary on team *k* in season *y*, X_{iky} is a matrix of covariates, and η_k and λ_y are team and year fixed effects, respectively. ε_{iky} is a stochastic disturbance term, and $\exp(\varepsilon_{iky})$ is assumed to be drawn from a gamma distribution. It can be shown that the conditional distribution of technical fouls will then be negative binomial (Cameron and Trivedi, 1986).

In some specifications of equation [1], I will also include player-level fixed effects, so that only variation in a given player's characteristics are used to estimate coefficients.

As discussed above, the pure income effects theory predicts $\beta > 0$. Distinctly, the substitutability theory should be reflected in the estimated value of α. This is so in the data if we find $\alpha < 0$ (recall that the highest-paid player has salary rank = 1).

For covariates, I include the player's experience level (in years) in the NBA, dummy variables for the player's position[16], and a measure of his physical stature, body mass index.[17] These latter two variables are intended to control for the fact that centers and forwards, as well as bigger players generally, tend to be involved in aspects of the game with more physical contact, such as dunking the ball or waiting under the basket for rebounds, and physical contact may lead to more opportunities for fighting, and thus, technical fouls. The inclusion of year and team fixed effects sorts out any secular changes over time in the number of technical fouls (perhaps due to changes in referee stringency, e.g.), and any effects of team-wide "bad-boy" strategies, which might bias the results.

I now address five important factors that may bias the findings presented below. First, since technical fouls may lead to ejection from games, they are generally more costly when committed by "star" players, since these players' performances are more crucial to the team's chances of winning. Therefore, a natural expectation would be that coaches should exert more effort to reign in badly behaved stars. If so, this effect would bias the results against finding evidence for the substitutability theory.

Second, there is the widely-held suspicion that star players are allowed to get away with more by referees. Under this theory, when a referee is uncertain about a call, he may give top players the benefit of the doubt, either under the assumption that high-talent players are less likely to be truly guilty, or due to pressure from teams, who wish to satisfy fans' desire to see star athletes play. This effect, too, would bias the results against finding evidence for the substitutability theory.

Third, player salaries may be determined by factors other than talent and productivity. Players usually sign contracts based primarily on *expected* productivity; injuries or other unanticipated factors may cause real productivity to differ. Moreover, racial discrimination and

[16] I include controls for centers, forwards, and guards. Separating shooting guards from point guards, and small forwards from power forwards does not change the results.
[17] Body mass index, or BMI, is calculated as a person's weight (kgs.), divided by the square of his height (m).

other unique features of the labor market for players may also play a part in determining salaries (Berri, 1999, Kahn and Sherer, 1988). To the extent such factors are important, they will add measurement error to the independent variables in the analysis, leading to a bias against finding statistically significant results.

Fourth, it may be difficult to distinguish fully the pure income effects theory from the "publicity" theory discussed in the previous Section, or from other productive aspects of misbehavior, such as team cohesion-building. Both imply a positive relationship between earnings and misbehavior; the difference is the direction of causality. Therefore, income effect estimates may be biased upwards; we will see below that there is very little evidence for income effects in any case, however. There is no obvious reason why "publicity" misbehavior would affect a player's salary rank, separate from his salary level, however, so estimates of the substitutability theory should be unaffected.

Finally, it is possible that some players play a more aggressive style of basketball than others. To the extent such a strategy is successful, these players will earn more, but may also cause more fights and frustrated outbursts due to their aggression. To ameliorate this bias, I include in the covariates the player's rate of "flagrant" fouls, which indicate play that is overly aggressive, but not malicious in the eyes of the referees. Nevertheless, this may not fully account for strategic aspects of misbehavior.

Column 1 in Table 3 estimates equation [1], with standard errors adjusted to allow correlation among different observations for a given player.[18] Allowing for a quadratic term in salary rank appeared to fit the data better than a simple linear model, a fact that will be made clearer below when I allow for a fully non-parametric form for salary rank. The coefficients in Table 3 may be interpreted as semi-elasticities, i.e., the effect of a linear increase in the dependent variable on

[18] Alternatively, allowing intragroup correlation only at the team level does not change the results.

technical fouls, measured in percentage points. For instance, the estimated coefficient on salary rank implies that, holding constant salary level and other factors, a player who is the best paid on his team will typically collect around 7% more technical fouls than one who is second-highest paid.[19] This effect is (jointly) statistically significant, as is indicated in the third row.

The coefficient on salary indicates that there may also be a separate income effect; however, this coefficient is only of marginal statistical significance. We will see that in some robustness checks, this effect does become statistically significant; thus, we cannot fully discount the role of pure income effects in determining misbehavior, although the evidence for this theory must be considered weak and rather fragile.

Since the estimated effect is quadratic, there is a larger estimated difference between the first and second-highest paid players than there is between the second and third-highest paid, and so on. In fact, the form of the equation implies that the relationship between salary rank and misbehavior actually turns positive around the 12th best-paid player. However, there are usually not more than 15 different players on a team in any given year, and most of the lowest-paid players rarely ever play, so one should take estimates regarding their behavior with a grain of salt.

In unreported analysis, the quadratic form imposed on the relationship between salary rank and misbehavior seemed to fit the data better than linear or other functional forms; however, it may be that this assumption constrains the true effect, and so biases the results. To test for this, I performed the same estimation as in column 1, but allowed salary rank to enter in a fully non-parametric way, with a separate indicator variable for each rank. Figure 3 graphs the expected number of technical fouls for each salary rank, calculated at mean values of the other covariates

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[19] Technically, since salary rank is discrete, the effect of an increase of one rank is not exactly the same as the infinitesimal marginal effect. If α is the estimated coefficient on salary rank, the true effect of an increase of one in rank is $\exp(\alpha) - 1$. For small α, this is well approximated by α. Thus, the actual effect of changing salary rank from 1 to 2 (and thus, changing the quadratic term from 1 to 4) is $\exp(-0.074) - 1 + \exp(4*0.003) - 1 = -0.0593$, or a 5.9% decline in technical fouls.

(coefficients on other variables are suppressed).[20] Figure 3 illustrates that the relationship between salary rank and misbehavior seems to be concentrated over the highest salary ranks, with little effect on salary ranks after the seventh or eighth. This result is quite similar to that previously estimated with a parametric quadratic form.

Returning to Table 3, one alternative hypothesis to explain the results in columns 1 and 2 is that, due to the fixed time for each game (ignoring overtime), there is a roughly fixed number of plays a team has the opportunity to run. Thus, while it is clear that better paid players generally touch the ball more often, there will also tend to be a rank distribution of "touches" on any given team, with the highest paid player on a team being involved in more plays independently of his absolute salary level. If a player's salary rank is independently correlated with the number of times he touches the ball, and touching the ball more leads to more opportunities to be drawn into fights or other unruly behavior, then this might explain the results presented so far. In other words, touches, not minutes played, may be the correct exposure variable for technical fouls.

Column 2 addresses this concern by including as a covariate the natural log of a player's touches, calculated as the sum of field goal attempts, rebounds, and assists. This specification is not as clean a test of the substitutability theory, however, since salary rank and touches are likely to be collinear, and thus the estimated effect of touches may pick up some of the true effect of substitutability. Nevertheless, column 2 shows that, even when touches are included in the regression, salary rank is still statistically significant and the measured effect is not much lower than before.

Another hypothesis is that the estimates in columns 1 and 2 actually represent the effects of some unmeasured variable correlated with innate ability. Therefore, the apparent validation of the

[20] Only the estimates for salary ranks 1-14 are shown, since very few teams employ more than 15 players in a season, and so estimation of effects after rank 14 is based on very small sample sizes.

substitutability theory may in fact be a spurious composition or sample selection issue. As a check of this hypothesis, column 3 estimates equation [1] once again, but includes player fixed effects, which control for all unmeasured factors associated with a particular player which do not change over time, such as personal character. On the other hand, inclusion of 3,376 new covariates reduces substantially the amount of variation in the dependent variable left to explain, so this specification may not be optimal. I do not include the positional and body mass index variables in this regression, since these variables rarely change over a player's career.[21] The result in column 3 suggests that when the *same player* moves from a team where he is the second highest paid player to a team where he is the highest paid player, he is expected to increase his misbehavior by 2.9%. This effect is smaller than that estimated in the cross sectional results from the first two columns, but is still statistically significant. These results suggest that the relationships estimated in Table 3 do not seem to be driven (at least primarily) by composition or sample selection issues.

In the short run, a given player is substitutable only with other players on the same team – if A misbehaves too much, the coach may only reduce his playing time in favor of teammate B – however, over a longer horizon, firing and hiring are possible, and so all players in the league who play the same position may be thought of as substitutes to some greater or lesser degree. To estimate this effect, column 4 continues a similar analysis, but calculates salary rank according to a player's order in the salary distribution of players of the same position across all teams.[22] The coefficients reported are multiplied by 10 for readability. Consistent with the theory, the results show that the measured effect of this "overall" ranking is smaller, but still statistically significant. The result implies that the best paid center, for example, in the league will commit around 0.49% more technical fouls than the second best paid center.

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[21] And when they do, it is more often due to measurement error than an actual change. Including these variables, however, does not change the results.

[22] Again, positions are defined as "center", "forward", and "guard".

Column 5 replicates these "league-wide" substitutability estimates, but includes player fixed effects. The estimated effect of salary rank is essentially unchanged.

Finally, in columns 6 and 7, I estimate equation [1] once more, but use ejections as the measure of misbehavior in lieu of technical fouls. Since one can only be ejected once per game, I use games played per season, instead of minutes played, as the exposure variable, although the same results hold under either specification. The results in columns 6 and 7 suggest that the same effect evidenced for technical fouls is also apparent for ejections: the best paid player on a team will be ejected between 4.4% and 11.9% more times per 82 games than the second-best paid player, depending on whether player fixed effects are included or not. Earlier, I argued that the existence of "publicity"-style misbehavior might bias the coefficient on salary levels, but would be unlikely to bias the estimated effects of salary rank. These results for ejections validate this argument to some degree, since it is difficult to imagine that being ejected from games is productive in basketball, especially for star players.[23]

Table 4 presents some further robustness checks on the substitutability and income effects theories tested in Table 3. The "baseline" row replicates the results from column 1 in Table 3. In the second row, I drop the twenty players most prone to committing technical fouls; the results are essentially unchanged, indicating that the estimated effects are not being driven primarily by outliers. In the third row, I allow the coefficient on the exposure variable, ln(min), to vary from unity; this does not seem to affect the estimates on the salary variables either.[24] In the fourth row, I adjust the negative binomial model to allow for "excess" zeros in the distribution of technical fouls, as might be appropriate given the histogram in Figure 1. This does not seem to change the results

[23] It might be unproductive in producing wins, but productive in producing revenue if fans enjoy seeing egregious misbehavior. In unreported analysis, I compared the probability of election to the NBA all-star team, which is determined by fan balloting, to a player's propensity for ejection, controlling for other player statistics. Ejections seem to reduce, not increase, the probability that a player is elected to the all-star team, ceteris paribus.

[24] The estimated coefficient on ln(minutes) is 1.176.

substantially. Since salary rank and salary level might be collinear, in rows 5 and 6, I allow for different functional forms with respect to salary level, excluding it altogether in row 5, and allowing it to enter quadratically in row 6. In both cases, the estimated effects of salary rank are stronger than in the baseline case. Finally in rows 7 and 8, I ignore the count-data aspect of technical fouls, and simply run a log-linear regression, with zero values in technical fouls converted to 0.5 in order to take the natural log. In row 8, player fixed effects are included, but in both cases, the effects of salary rank are stronger than in the baseline. However, in the log-linear regressions, salary level is statistically significant.

The log-linear regressions also allow me to estimate an upper bound on the importance of the "personal preferences" theory, as discussed in Section II. The log-linear regression in row 7, without player fixed effects, had a goodness-of-fit statistic of 0.41, while the regression in row 8, with player fixed effects, had a goodness-of-fit statistic of 0.74.[25] Thus, the player fixed effects explain 33% of the observed variation in misbehavior. Preferences are likely to constitute the bulk of fixed player attributes affecting misbehavior; if so, then personal preferences can explain up to 33% of the misbehavior seen in the NBA.

Therefore, to summarize the results so far, I find an important role for substitutability in understanding misbehavior in the NBA, and a smaller, more speculative role for pure income effects. Moreover, personal preferences may explain a significant fraction of misbehavior, as much as 33%.

In Table 5, I use the same data to address other theories of misbehavior discussed in Section II. First, I consider the "immaturity" theory – that celebrity misbehavior is driven by youth. While this theory is popular in sports writing (e.g., Redeker, 2003), Column 1 of Table 4, which includes player age as a covariate, shows that there appears to be no significant relationship between a player's age and his propensity to commit technical fouls. I include both a linear age term and an

[25] There is no natural goodness-of-fit statistic for negative binomial regression.

indicator variable for players under age 22, although the results are unchanged under a variety of alternative specifications. The latter variable is intended to pick up any special effect of players who enter the NBA without completing college, as these players have been a special focus of league efforts to reduce misbehavior.[26] Neither of these variables is significant.[27] The point estimates, in fact, suggest that younger players behave better. This may, however, be a selection effect, since the pool of talent among younger players generally has wider variance than among veterans, who have succeeded in the league for a number of years. In order to separate out selection effects from the real effect of age, column 2 includes player fixed effects. Thus, the effect of age is estimated by following individual player's careers, instead of comparing different players of different ages. Again, however, there is no evidence that younger players have a higher rate of misbehavior. In fact, players under age 22 commit 35% *fewer* technical fouls, and this effect is statistically significant.

Interestingly, and consistent with these results, it is notable that the coefficient on years of experience in Table 3 is generally positive (though not always significantly so), suggesting again little role for immaturity in determining misbehavior.[28]

In columns 3 and 4, I deal with the "peer effects" theory, in which social norms evolve differently among small groups of people who interact mostly within the group. If a peer effect exists, it should be the case that a given player's propensity to commit technical fouls is correlated with his teammates' technical fouling rate. Columns 3 and 4 include teammates' technical fouls in the regression model, with column 4 also including player fixed effects. In neither case, however, is there any statistically significant relationship between a player's misbehavior and that of his

[26] The creation of the National Basketball Development League for such players was motivated, in part, by a belief that players were entering the league too early, to the detriment of both players and the game generally.
[27] Nor are they jointly significant.
[28] Excluding experience as a covariate, which tends to be collinear with age, does not change the results on age effects appreciably.

teammates.

IV. Conclusion

Although there are many reasons why celebrities might engage in a disproportionately large amount of bad behavior, the empirical evidence from the NBA analyzed in this paper suggests a significant role for lack of substitutability in the production process. Players who are sufficiently unsubstitutable can "get away" with more misbehavior simply because team and fan options are so limited.

These results may even hold lessons for worker misbehavior generally. As a specific example, janitorial services within firms are likely to be more easily substitutable than, say, computer assistance services, as working in a dirty environment or cleaning up one's own workspace constitute relatively low-cost substitutes to good janitorial services, while most people cannot fix their own computers. The results presented in this paper suggest that janitors should have friendlier personalities than IT professionals, an observation which fits at least the stereotypes for these two professions[29]. As another example, higher rates of malfeasance with students among tenured than among non-tenured university faculty would also be a prediction of this theory, one that has some justification in survey data by List (2001).

[29] In its discussion of IT professionals in the US economy, a government report states, "[A] lack of social skills contributed to their public reputation as 'nerds', 'geeks', 'bit heads', 'propeller-heads', and the like" (Commerce Department, 2003).

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Table 1: Worst Offenders in Sample

Player	Season	Technical Fouls per 1000 Minutes Played
Dennis Rodman	1998-99	19.79
Rasheed Wallace	2000-01	13.61
Rasheed Wallace	1999-00	13.36
Dennis Rodman	1996-97	12.84
Bimbo Coles	2000-01	11.19
Gary Payton	1998-99	10.95
Charles Barkley	1996-97	10.95
Chris Gatling	2000-01	10.78
Vin Baker	2002-03	10.62
Shawn Bradley	2003-04	10.35

Player	Season	Ejections per 82 games played
Rasheed Wallace	2000-01	7.45
Dennis Rodman	1998-99	7.13
Rasheed Wallace	1999-00	7.09
Charles Barkley	1997-98	6.03
Shaquille O'Neal	2001-02	4.89
Anthony Mason	1996-97	4.49
Dennis Rodman	1996-97	4.47
Jerome Kersey	1997-98	4.43
Chris Gatling	2000-01	4.43
Derrick Coleman	1997-98	4.17

Notes: Player-year observations over sample seasons 1996-97 through 2003-04. Ejections per 82 games played is calculated as [82 x (ejections/games played)]. To avoid small sample size problems, only observations with more than 600 minutes played (significantly below the mean) are included in these tables.

Table 2: Summary Statistics

Variable	Mean	S.D.
Technical fouls	2.47	3.75
Ejections	0.20	0.54
Salary (millions of 2003 dollars)	2.94	3.41
Minutes played	1357.59	959.66
Games played per season	56.42	24.56
Age	27.80	4.48
Experience (years in NBA)	4.68	3.71
Body mass index (BMI=weight/height^2)	24.98	1.83
Flagrant fouls per 1,000 minutes	0.29	1.27
Position = Center	0.19	---
Position = Guard	0.39	---
Position = Forward	0.42	---
Position = Undefined	0.003	---

Notes: Means based on 3,376 player-year observations from the 1996-97 season through 2003-04, with the exception of technical fouls, ejections, minutes played, and games played, which are based on 2,967 observations, excluding the 1998-99 season, in which there was a work stoppage such that only 50 games were played.

Table 3: "Substitutability" Theory of Misbehavior

Dependent Variable:	-------------Technical Fouls---------------					Ejections	
Ranking on:	------Own Team------			League (x10)		Own Team	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Salary rank (1 = highest)	-0.074 (2.83)	-0.067 (2.58)	-0.049 (2.38)	-0.059 (2.82)	-0.049 (2.42)	-0.119 (2.11)	-0.044 (0.67)
Salary rank^2	0.003 (2.36)	0.003 (2.28)	0.001 (1.03)	0.000 (0.95)	0.001 (1.11)	0.003 (1.05)	-0.003 (0.71)
p-value	0.02	0.03	0.01	0.00	0.01	0.06	0.06
ln (salary)	0.089 (1.55)	-0.002 (0.004)	-0.046 (0.94)			0.201 (1.63)	-0.049 (0.32)
Flagrant foul rate	0.164 (4.65)	0.191 (5.05)	0.074 (4.16)	0.161 (4.81)	0.074 (4.12)	0.163 (3.63)	0.105 (2.85)
Experience (years)	0.039 (3.81)	0.050 (4.86)	-0.014 (0.28)	0.041 (3.98)	-0.014 (0.28)	0.038 (1.99)	0.103 (0.39)
Center	0.064 (0.78)	0.142 (1.69)		-0.100 (1.12)		-0.293 (2.02)	
Guard	-0.346 (4.12)	-0.373 (4.44)		-0.398 (4.76)		-0.342 (2.19)	
Body mass index	0.035 (1.90)	0.034 (1.82)		0.034 (1.89)		0.040 (1.09)	
ln ("touches")		0.269 (5.63)					
Player fixed effects?	No	No	Yes	No	Yes	No	Yes
Constant	-8.431 (8.13)	-8.943 (8.67)	-4.005 (3.76)	-6.910 (11.60)	-3.397 (4.21)	-10.45 (4.41)	11.24 (0.01)

Notes: Test statistics in parentheses. Columns [1]-[5] use technical fouls as the dependent variable, while columns [6] and [7] use ejections. "Salary rank" refers to the player's rank on his team for all columns except [4] and [5], where it refers to rank among all players of the same position in the league. All regressions based on 3,376 player-year observations, and are implemented in a negative binomial model, with either minutes played or games played as the exposure variable (depending on whether technical fouls or ejections are the dependent variable). The error term is allowed to be correlated across years for a given player. "Touches" is measured as the sum of field goal attempts, assists, and rebounds.

Table 4: Robustness Checks

	Salary Rank	Salary Rank^2	ln(salary)
Baseline	-0.074**	0.003**	0.089
Drop outlier players	-0.073**	0.003**	0.078
Allow coefficient on ln(min) to be $\neq 1$	-0.074**	0.004**	0.035
Zero-inflated regression	-0.078**	0.004**	0.064
Exclude ln(salary)	-0.096**	0.003**	
Salary level enters quadratically	-0.083**	0.003*	Salary: 0.055 Salary^2: 0.001
Log-linear regression	-0.125**	0.004**	0.220**
Log-linear regression with player fixed effects	-0.075**	0.002**	0.082**

Notes: Regressions include same variables as in column 1 of Table 3, except as noted. See Table 3 notes for details on sample and methodology.

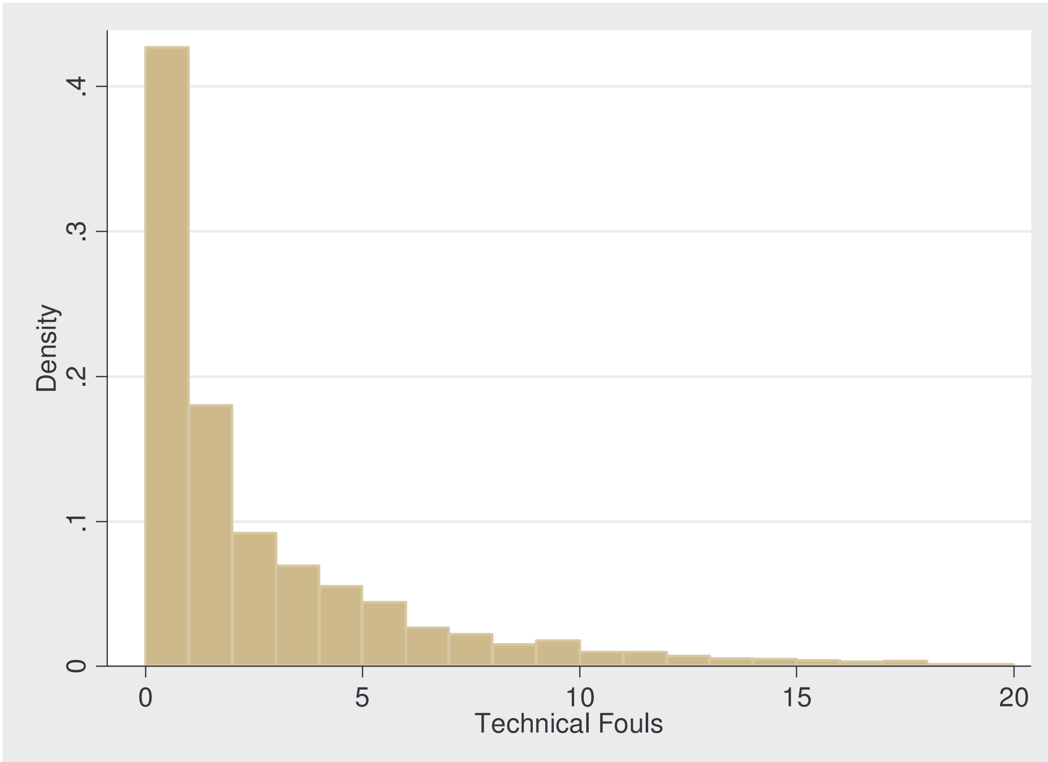
Table 5: Other Factors Influencing Misbehavior

Dependent Variable: Technical fouls committed per season

	[1]	[2]	[3]	[4]
Age	-0.021 (0.98)	-0.023 (0.32)	-0.016 (0.80)	0.003 (0.05)
Age ≤ 22 indicator	-0.024 (0.22)	-0.347 (4.34)	-0.046 (0.41)	-0.343 (4.30)
Teammates' technical fouls			0.001 (0.33)	0.000 (0.46)
Salary rank on team (1 = highest)	-0.073 (4.16)	-0.040 (1.94)	-0.063 (2.41)	-0.042 (2.16)
Salary rank^2	0.003 (2.35)	0.001 (0.57)	0.003 (2.28)	0.001 (0.71)
Log (salary)	0.082 (1.42)	-0.059 (1.23)	0.144 (2.25)	-0.050 (1.11)
Flagrant fouls per 1,000 minutes	0.166 (4.59)	0.074 (4.20)	0.204 (4.94)	0.072 (4.10)
Experience	0.063 (2.44)	-0.005 (0.07)	0.053 (2.25)	-0.022 (0.33)
Position = center	0.078 (0.93)		0.079 (0.89)	
Position = guard	-0.343 (4.06)		-0.344 (3.83)	
BMI	0.035 (1.93)		0.033 (1.65)	
Player fixed effects?	No	Yes	No	Yes
Constant	-7.911 (6.62)	-3.031 (1.53)	-8.300 (7.31)	-3.672 (2.05)

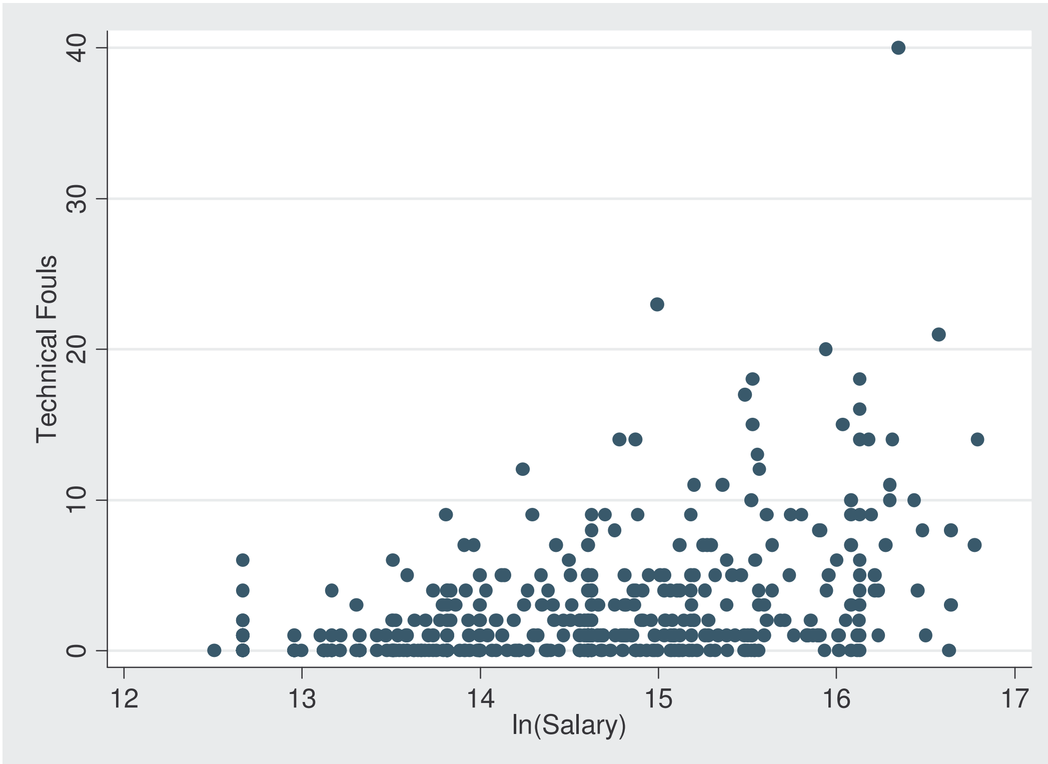
Notes**:** Test statistics in parentheses. See Table 3 notes for details on sample and methodology.

Figure 1: Distribution of Technical Fouls



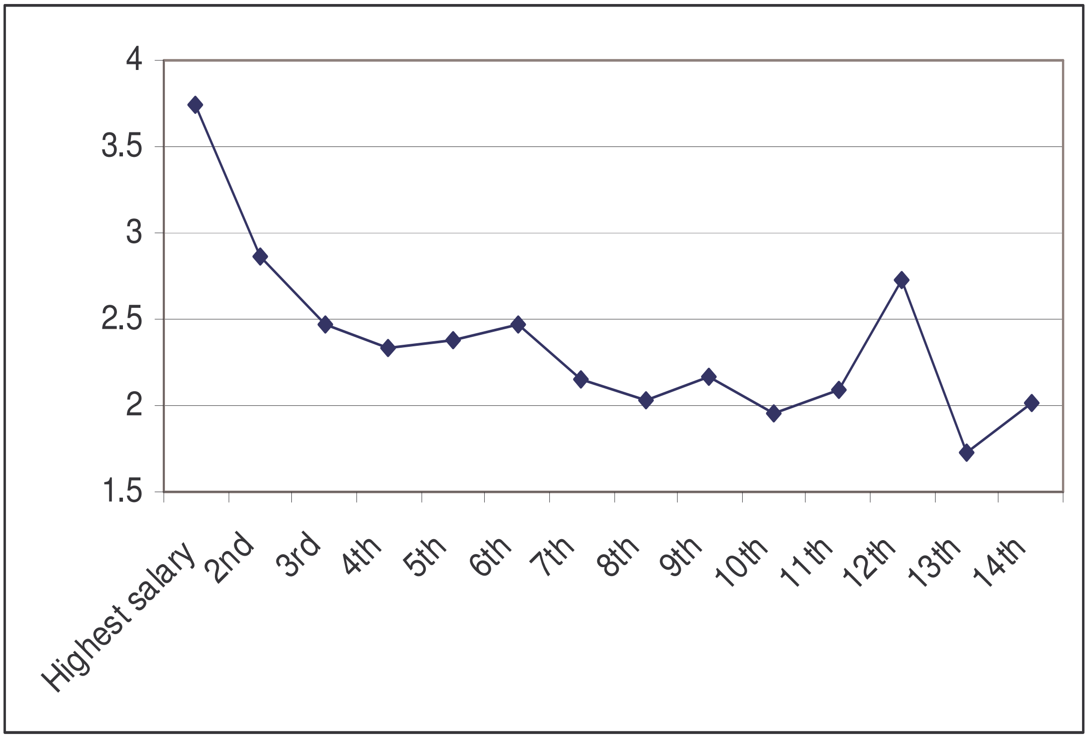
Notes: 2,967 player-year observations from the 1996-97 through 2003-04 seasons, excluding the shortened 1998-99 season. There are a small number of players with more than 20 technical fouls in a season (see Table 1); the horizontal axis is truncated for readability.

Figure 2: Technical Fouls vs. Salary, 2000-01 NBA Season



Notes: 428 player observations from the 2000-01 NBA basketball season.

Figure 3: Non-Parametric Estimation of Relationship between Technical Fouling Rate and Salary Rank



Notes: Points in the figure represent predictions from a negative binomial regression of technical fouls against dummy variables for each salary rank. Data are 3,376 player-year observations from the 1996-97 through 2003-04 seasons. Covariates include ln(salary), flagrant fouls per 1,000 minutes, experience, body mass index, and position, year, and team fixed effects. Standard errors are robust to clustering at the player level.