Jonathan Liu

Are Higher Paid NBA Players More Inclined to Misbehave During Games Because They Are Difficult to Replace?

Introduction

It is not uncommon to see professional basketball players get angry during a game. Perhaps they are upset at a call, upset at their own performance, or even upset at opposing players. Which types of players are the most likely to "act up" on the court? Perhaps stars (i.e. higher paid players) are more willing to engage in extracurricular activity on the court because they know that they cannot be replaced regardless as to how they act. Such substitution theory in the NBA was analyzed in *Celebrity Misbehavior* by Todd D. Kendall (2004). The main question Kendall investigated was: Are NBA players more inclined to misbehave on the court as their salaries increase because they are less substitutable? In particular, NBA players who are paid more are generally more talented, so they are less substitutable. Hence, it is possible that they have more freedom to act however they want during games. After all, it is very difficult for a team to find another player of similar talent, allowing these players more leeway in the manner in which they act during basketball games. This paper will replicate the results of *Celebrity Misbehavior* by Todd D. Kendall (2004).

The original paper analyzed regular season data from the 1996-1997 season to the 2000-2001 season. Kendall used the propensity for players to earn technical fouls as a proxy for misbehavior on the court. Players can be assigned technical fouls for misconduct on the court (e.g. arguing with the referees, use of profanity, getting in a fight with other players etc.). Kendall found that players with greater incomes tend to receive more technical fouls. Kendall initially proposed different theories to explain the finding aside from the substitution theory. One was the income effects theory where misbehavior is a normal good. Perhaps demand for bad behavior increases as one earns more money. For example, it is possible that higher paid NBA players lose less utility from a fall in their public image after engaging in misbehavior on the court whereas lower-paid NBA players need their jobs, so they lose much more utility if their public image declines as a result of misbehaving. Another was the stress theory. Star NBA players may feel stressed from how their every move on the court are being watched by thousands of people. Thus, they can suddenly crack under pressure and engage in an outburst on the court when provoked (e.g. by a bad call, poor performance, irritating opposing players etc.).

Kendall ultimately found much evidence in support of the substitution theory. However, when replicating the results of Kendall's paper for the 1996-1997 season to the 2000-2001 season, little evidence was found in support of the theory that higher paid NBA players tend to misbehave more on the court because they are less substitutable. Furthermore, analyzing data from the 2018-2019 regular season produced similar results.

Empirical Strategy

To replicate the analyses in Kendall's paper, six different weighted least squares were ran on panel data for NBA players from the 1996-1997 season to the 2000-2001 season (regular season data only):

1. $Techs_{it} = a_1 * Log(Salary_{it}) + YearFixedEffects + \epsilon_{it}$
2. $Techs_{it} = a_1 * Log(Salary_{it}) + a_2 * Flags_{it} + a_3 * Center_{it} + a_4 * Guard_{it} + YearFixedEffects + \epsilon_{it}$
3. $Techs_{it} = a_1 * Log(Salary_{it}) + a_2 * Flags_{it} + a_3 * Center_{it} + a_4 * Guard_{it} + a_5 * Rank_{it} + a_6 * Rank_{it}^2 + YearFixedEffects + \epsilon_{it}$
4. $Techs_{it} = a_1 * Log(Salary_{it}) + a_2 * Flags_{it} + a_3 * Rank_{it} + a_4 * Rank_{it}^2 + YearFixedEffects + PlayerFixedEffects + \epsilon_{it}$
5. $Techs_{it} = a_1 * Log(Salary_{it}) + a_2 * Flags_{it} + a_3 * Rank_{it} + a_4 * Rank_{it}^2 + a_5 * FGA_{it} + a_6 * MP_{it} + YearFixedEffects + PlayerFixedEffects + \epsilon_{it}$
6. $Techs_{it} = a_1 * Log(Salary_{it}) + a_2 * Flags_{it} + a_3 * FTP_{it} + a_4 * FGP_{it} + YearFixedEffects + PlayerFixedEffects + \epsilon_{it}$

The dependent variable in each regression, *Techs*, is the number of technical fouls per 1000 minutes played. *Log(Salary)* is the natural log of a player's salary adjusted for inflation (i.e. in 2020 USD). *Flags* is the number of flagrant fouls per 1000 minutes played. *Center* takes on a value of 1 if a player played the center position during the season; 0 otherwise. *Guard* takes on a value of 1 if a player played a guard position (i.e. either point guard or shooting guard) during the season; 0 otherwise. *Rank* is a player's salary rank on his team (i.e. 1 if the player is the highest paid on his team, 2 if the player is the next highest paid player, and so on). Note that if there were ties, all players involved in the tie were given the highest rank possible, where 1 is the highest rank. For example, if two players were tied for the highest paid player on a team, both players were given a rank of 1. The next highest paid player was given a rank of 3. *FGA* is the number of field goal attempts per 100 minutes. *MP* is the total minutes a player played during the season. *FTP* is a player's free-throw percentage (on a scale from 0 to 1). *FGP* is a player's field goal percentage (on a scale from 0 to 1).

Note that even though only regression 5 controls for minutes played, all six regressions are weighted by minutes played. This is so players who played more minutes had a greater effect on the regressions than those who did not play many minutes.

Furthermore, all six regressions control for year fixed effects, or the season the players played in. The year for every season was the ending year for that season. For example, a player who played in the 1996-1997 season was assigned a year of 1997.

Kendall ran all six regressions in his paper; however, he also controlled for the experience of every player in the league (i.e. the number of years a player played in the NBA) in each of the regressions.[1] The results in the replication, however, will show that despite omitting the experience variable, there is still little evidence in support of the substitution theory in the NBA.

The purpose of regression 1 is to see whether there is a positive correlation between one's salary and his propensity to commit technical fouls, controlling for the season. Regression 2 also controls for the rate of which a player commits flagrant fouls as well as the position a player played in. It is possible that players who receive more technical fouls are simply more physical. Physical players can wear out opposing players, thus they are typically paid more than those who are not as physical. One way to measure a player's physicality is through his propensity to commit flagrant fouls. Flagrant fouls are typically assessed when a player uses excessive and/or unnecessary contact/force against an opposing player. The physicality of a player can also differ by position. For example, centers are often the biggest and/or heaviest players on a team. Thus, their style of play often involves much more physicality than that of guards and/or forwards. This can make centers really valuable to a team, yet also have a high tendency to receive technical fouls based on their style of play.

Regressions 3, 4, and 5 includes the rank and squared rank of a player's salary on his team in order to find more evidence in support of (or against) the substitution theory. Kendall

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[1] I was unable to find reliable data for every player's experience.

mentions that even if the coefficient for the *log(salary)* variable is significantly positive in regressions 1 and 2, this can be due to the income effects theory. However, if the coefficient for the *log(salary)* variable is not significantly positive after including the two variables, and the coefficients for the rank and/or squared rank variables is/are significantly and substantially negative, then such a finding would contradict the theory that misbehavior is simply normal good for NBA players. Rather, it would provide more credibility to the theory that players who are paid the most on a team are the least substitutable, thus they decide to act more freely on the court knowing that they are very difficult to replace.

Instead of controlling for the position of each player like in regression 3, regressions 4 and 5 control for player fixed effects. This is to better control for characteristics about each player that can be correlated to how much he is paid and his tendency to receive technical fouls. For example, a player's style of play can be dependent on his overall athleticism, which can be difficult to measure. Or, players can react to pressure differently. For instance, some players may play very well in practice but not in front of thousands of fans with the game on the line. Those who play the best under pressure likely receive higher salaries and inherently receive fewer technical fouls as they are much more poised.

Regression 5 also controls for how involved a player is in a game. A player's field goal attempts per 100 minutes and his minutes played are used as proxies for how much action a player sees during games. In particular, players who play more minutes and attempt more shots per game are generally paid more, and they likely have more opportunities to be provoked during games such as being assessed with fouls that they believe they did not deserve. This can cause players to argue with the referees, resulting in a technical foul.

Regression 6 attempts to separate out the substitutability theory from the stress theory. Even if it is found that higher ranked players in terms of salary earn more technical fouls, this can be because such players are under greater pressure. The media and fans can be focused on these players. Opposing players may choose to play more physically against the most talented players on a team. This can cause higher paid players to have emotional outbursts on a court, making them more likely to receive technical fouls. The main variable of interest is the free-throw percentage. Kendall argues that a player's substitutability can be measured with his free-throw percentage. This makes sense as teams generally need players very accurate at free-throws to close out games. For example, teams losing at the end of games typically resort to fouling opposing players to stop the clock and to get more possessions. Teams without accurate free-throw shooters will have a hard time sealing a game that is otherwise won. Regression 6 controls for a year and player fixed effects. It also controls for a player's overall talent by including his salary and field goal percentage. More talented players generally are more accurate at free-throws, and such players typically see more playing time, allowing them more opportunities to be provoked during games. Furthermore, it controls for a player's propensity to commit flagrant fouls. More physical players are typically fouled more as they try to "muscle their way" to score points. Thus, they receive more free-throw attempts, so they are more likely to practice free-throws than other players.

As an extension, data for the 2018-2019 regular season was analyzed to see if results from a more recent season are similar to that from about two decades ago. The five regressions were ran using the data from the 2018-2019 season:

$$7.\quad Techs_i = a_1 * Log(Salary_i) + \epsilon_i$$

$$8.\quad Techs_i = a_1 * Log(Salary_i) + a_2 * Center_i + a_3 * Guard_i + \epsilon_i$$

$$9.\quad Techs_i = a_1 * Log(Salary_i) + a_2 * Center_i + a_3 * Guard_i + a_4 * Rank_i + a_5 * Rank_i^2 + \epsilon_i$$

$$10.\ Techs_i = a_1 * Log(Salary_i) + a_2 * Center_i + a_3 * Guard_i + a_4 * Rank_i + a_5 * Rank_i^2 + a_6 * FGA_i + a_7 * MP_i + \epsilon_i$$

$$11.\ Techs_i = a_1 * Log(Salary_i) + a_2 * Center_i + a_3 * Guard_i + a_4 * FTP_i + a_5 * FGP_i + \epsilon_i$$

Like regressions 1-6, regressions 7-11 were also weighted by minutes played. Since the dataset only includes data from one season, none of the regressions control for year fixed effects and/or player fixed effects. Furthermore, the data did not have information on the number of flagrant fouls each player was assessed, so none of the regressions controlled for that factor.[2] Otherwise, regression 7 mirrors that of regression 1. Regression 8 mirrors that of regression 2. Regression 9 mirrors that of regression 3. Regression 10 mirrors that of regression 5. Note that since player fixed effects cannot be controlled for (nor could the number of flagrant fouls a player received), regression 10 controlled for a player's position in order to account for the fact that some player's

[2] The data source, http://dougstats.com/index2.html, did have a flagrant fouls column for each player in the 2018-2019 season, but every player had 0 flagrant fouls, which is clearly incorrect.

playing style may be more physical/aggressive than others.[3] Similarly, regression 11 mirrors that of regression 6.

Data

In order to replicate Kendall's results, data for player salary by season (i.e. the 1996-1997 season to the 2000-2001 season as well as the 2018-2019 season), in 2020 USD, was taken from HoopsHype at https://hoopshype.com/salaries/players/. All other data was taken from dougstats at http://dougstats.com/index2.html. This includes seasonal data for the team each player played on[4], the number of technical fouls each player received, the number of flagrant fouls each player received[5], the total minutes each player played, each player's position, the number of field goal attempts for each player, the number of made field goals for each player, the number of free throw attempts for each player, and the number of made free throws for each player. Note that in the NBA, any two-point or three-point shot counts as a field goal. Field goal percentage was calculated by dividing the number of made field goals by the number of field goal attempts. Free-throw percentage was calculated similarly.

Table 1 shows the summary statistics of the data used in Kendall's paper (note that while not shown in the table, there were 2056 observations). Table 2 shows the summary statistics of the data collected to attempt to replicate the results Kendall found (i.e. from the 1996-1997 season to the 2000-2001 season). One key difference is that there were only 1854 observations in the collected data as opposed to 2056. This is likely the main reason as to why the results from the replication in this paper differed from what Kendall found. Otherwise, most of the variables used in the replication had similar means and standard deviations to that in Kendall's paper. One variable that had considerable differences was the salary variable. In the replication, all salary was in 2020 USD, whereas Kendall used the salaries of every player without adjusting for

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[3] Perhaps a more ideal method was to take panel data across multiple recent seasons (e.g. from the 2014-2015 regular season to the 2018-2019 regular season). This is so player fixed effects could be controlled for, instead having to rely on player position to control for how some players have more aggressive playing styles than others. The advantage of using only 2018-2019 data is that one can see trends relevant to that specific season (i.e. the most recent completed NBA regular season).

[4] It is possible for a player to be traded to another team in the middle of a season. In that case, the player was assigned the team in which he ended the season with.

[5] Flagrant foul data was only analyzed for the 1996-1997 season to the 2000-2001 season as it was missing for the 2018-2019 season.

inflation. This can cause a small difference in the results as the amount of inflation accumulated over the course of five years from 1996 to 2001 can somewhat alter the results.

Table 3 shows the breakdown of the collected data from the 1996-1997 season to the 2000-2001 season by position. Comparing with Table 1, the dataset Kendall used had a bit more power forwards. While only 18.6% of all observations were power forwards in the collected dataset, that proportion was 22.6% in the dataset used in Kendall's analysis.

Table 4 shows the breakdown of the collected data by season. Overall, all five seasons were well-represented in the dataset used to replicate Kendall's analysis. Each of the seasons represented about 20% of the observations.

Figure 1 shows the average rate of which players committed technical fouls (i.e. technical fouls per 1000 minutes) by salary rank in Kendall's paper. Figure 2 plots the same information using the data collected for replication. The points in Figure 2 are higher than that for Figure 1, especially for salary ranks between 1 and 6 inclusive. The propensity for players to commit technical fouls in Figure 2 was greater than 1.5 technical fouls per 1000 minutes for ranks 1 to 6, reaching as high as 2.6 for the highest paid player. On the other hand, the highest propensity for players to commit technical fouls in Figure 1 was around 1.5 technical fouls per 1000 minutes for the highest paid player. That value was slightly less than 1 for ranks 4 to 6 inclusive. Furthermore, in Figure 1, the propensity to commit technical fouls is decreasing between ranks 1 and 5, but then appears to level off for all subsequent ranks. However, in Figure 2, the propensity to commit technical fouls appears to be decreasing between ranks 1 and 15. The differences in the figures can likely be explained by the fact that the dataset used in Kendall's paper had 202 more observations than that in the replication.

In regards to the data for the 2018-2019 regular season, Table 5 shows the summary statistics of the relevant variables. There were a total of 460 players in the dataset. One big difference between Table 5 and Tables 1 and/or 2 is that the average salary for players in the 2018-2019 season was much greater. After adjusting for inflation, players were paid, on average, almost $3 million more than around two decades ago.[6]

Another difference between Table 5 and Tables 1 and/or 2 is that the average rate of which players commit technical fouls was much smaller in the 2018-2019 season. On average,

[6] This is likely due to the increase in demand for watching NBA games on television over the course of 20 years. As a result, total NBA revenue has been increasing.

players received 1 technical foul per 1000 minutes played in the 2018-2019 data, but that number was about 1.5 in Tables 1 and 2. Furthermore, while the greatest rate of which a player received technical fouls was 43 per 1000 minutes from the 1996-1997 season to the 2000-2001 season, that value was only 10 per 1000 minutes in the 2018-2019 season. One likely cause for this was that in the 2018-2019 season, players got suspended for one game after receiving 16 unsportsmanlike technical fouls in a regular season, and they were suspended for one more game for every two additional unsportsmanlike technical fouls they accumulated ("How Many Technical Fouls Before a Suspension in NBA?"). This likely served as a deterrence for NBA players to misbehave on the court. This could also cause referees to be more lenient in handing out technical fouls, especially if they did not want to be targeted by the media for causing a star player to be suspended.

Table 6 shows the breakdown of the 2018-2019 data by position. The data is composed of more shooting guards (about 25% of the observations) and fewer power forwards and centers (about 14% of the observations). This could indicate that teams have gradually signed less big-men over the course of 20 years. Perhaps teams have gradually began placing greater value on smaller, but faster players who can make plays and/or shoot three-pointers as opposed to slower but bigger players who rely on their size to score in the paint.

Lastly, Figure 3 shows the average rate of which player commit technical fouls by salary rank in the 2018-2019 data. Like in Figure 2, the propensity to commit technical fouls appears to be gradually decreasing by rank (with the exception of small spike at the 13th rank in Figure 3).

It is important to note that technical fouls is not a perfect proxy for misbehavior on the court. Kendall mentions that a player can receive technical fouls for non-unsportsmanlike reasons such as delay of game, calling a timeout when his team does not have any left, an illegal substitution (e.g. checking into the game without notifying the scorer's table). In general, however, players receive technical fouls for misconduct on the court (i.e. arguing with referees, taunting, fighting with other players etc.). Another issue with using technical fouls is that assessing technical fouls can be subjective depending on the referee. Some referees can be more lenient than others. Furthermore, since players are ejected after receiving a second technical foul in a game, referees may refrain from assessing a technical foul to a player who already has one, even if he is clearly acting up, in order to avoid potential backlash from the media and fans. A more ideal dataset would contain the number of times a player "acted up" during a game, regardless if he was punished for it. Even then, it would be difficult classify some incidents. For example, if a player misses a shot and utters profanity under his breath, is that considered "acting up?" Thus, even though using technical fouls is not the perfect way of measuring misbehavior on the court, it is a highly practical method.

Empirical Results

Table 7 shows the regression results in Kendall's paper, and Table 8 shows the regression results using the collected data from the 1996-1997 season to the 2000-2001 season. Due to a lack of data, the regressions in Table 8 did not control for player experience. Even so, column 1 of both tables indicate that players with a higher salary have a greater propensity to commit technical fouls. For Table 7, a 1% increase in a player's salary increases the rate of which he commits technical fouls by 0.0037 per 1000 minutes played. In Table 8, a 1% increase in a player's salary increases the rate of which he commits technical fouls by 0.0048 per 1000 minutes played. Both estimates were significant at the 5% level. Since Table 8 did not control for player experience, that estimate is likely biased upwards. Players with more experience in the NBA typically are paid more. Furthermore, more experienced players tend to commit more technical fouls, evident from all the regression results of Table 7. One possible explanation for this is that more experienced players are more directly involved in games (e.g. touch the ball more frequently, shoot the ball more frequently, are responsible for defending the more talented/aggressive players etc.), thus receive more opportunities to be provoked.

Column 2 of Tables 7 and 8 both provide stronger evidence that higher paid players have a greater propensity to commit technical fouls. Even after controlling for a player's position and his propensity to be overly physical and commit flagrant fouls, in Table 7, a 1% increase in a player's salary increases the rate in which he commits technical fouls by 0.0036 per 1000 minutes played. In Table 8, a 1% increase in a player's salary increases the rate in which he commits technical fouls by 0.0047 per 1000 minutes played. Again, both estimates were significant at the 5% level, and since Table 8 omits player experience, the estimate in Table 8 is likely biased upwards.

Column 3 of Table 7 provides evidence in support of the substitution theory as opposed to the income effects theory. After including a player's salary rank and squared salary rank on his team, Kendall found that the coefficient for the *log(salary)* variable was still positive, but no longer significant at the 5% level. Thus, Kendall suggested that it is likely not the case that demand for misbehavior increases as salary increases. On the other hand, the estimated coefficient for the salary rank variable was significantly negative at the 5% level and somewhat substantial. Even after considering the fact that the estimated coefficient for the squared salary rank variable was significantly positive at the 5% level, holding other factors constant, the highest paid player on a team is expected to commit about 0.19 more technical fouls than the next highest paid player. This result supports the theory that highest paid players are the least substitutable, and thus commit significantly more technical fouls than the next highest paid players on their teams.

The results in Column 3 of Table 8, however, fails to support the substitution theory over the income theory. Like with the results in Column 3 of Table 7, the estimated coefficient for the salary rank variable was significantly negative at the 5% level and somewhat substantial. Even after considering the fact that the estimated coefficient for the squared salary rank variable was significantly positive at the 5% level, holding other factors constant, the highest paid player on a team is expected to commit about 0.19 more technical fouls than the next highest paid player. The gap will likely be smaller if player experience was also controlled for. After all, players with more experience are likely paid the most on their teams (and thus have a “higher” salary rank) while also having a greater tendency to commit technical fouls. Meanwhile, the estimated coefficient for the *Log(salary)* variable was still significantly positive at the 5% level. A 1% increase in a player’s salary still increases the rate in which he commits technical fouls by 0.00315 per 1000 minutes played. While the estimate is likely biased upwards since experience was not controlled for, the estimated coefficient was still substantially larger than what was found in Kendall’s paper (the estimated coefficient for the *Log(salary)* variable was 0.14 in Column 3 of Table 7, less than half of that in Column 3 of Table 8). Thus, the replicated results fail to provide stronger evidence in support of the substitution theory.

When Kendall controlled for player fixed effects instead of the position he played as in Column 4 of Table 7, he found greater evidence in support of the substitution theory. Again, the estimated coefficient for the *Log(salary)* variable was still not significant at the 5% level. In fact, it was slightly negative at -0.05, further contradicting the income effects theory. Meanwhile, the estimated coefficient for the salary rank variable was still significantly negative at the 5% level.

Even though the estimated coefficient for the squared salary rank variable was significantly positive at the 5% level, the highest paid player on a team is expected to commit about 0.12 more technical fouls per 1000 minutes than the next highest paid player, which is still slightly substantial.

Column 4 of Table 8 reported different results from Column 4 of Table 7. Like in Kendall's paper, the estimated coefficient for the *Log(salary)* variable was not significant at the 5% level, contradicting the income effects hypothesis. However, the estimated coefficient of the salary rank variable was not significantly negative at the 5% level. After taking into consideration of the estimated coefficient of the squared salary rank variable, the results indicate that the highest paid player on a team is expected to commit about 0.1 more technical fouls per 1000 minutes than the next highest paid player (the gap will likely be even smaller after controlling for the experience variable), slightly lower than what was found in Column 4 of Table 7.

Column 5 of Table 7 and Table 8 differed in a similar manner. After controlling for field goal attempts per 1000 minutes and minutes played, the estimated coefficient for the salary rank variable in Column 5 of Table 7 was significantly negative at the 5% level. Even though the estimated coefficient for the square salary rank variable was significantly positive, the highest paid player on a team is expected to commit about 0.1 more technical fouls per 1000 minutes than the next highest paid player. Meanwhile, the estimated coefficient for the *Log(salary)* variable remained not significant at the 5% level. However, in Column 5 of Table 8, none of the estimated coefficients were significant at the 5% level except for the one on the rate of field goal attempts. In fact, the expected difference between the propensity of the highest paid player on a team to commit technical fouls and that of the second highest paid player was only 0.075 per 1000 minutes, and this is without controlling for the experience variable.

Lastly, Column 6 of Table 7 and Table 8 produced different results. In Kendall's paper, he found that an increase in a player's free-throw percentage by 1 percentage point increased his expected propensity to commit technical fouls by 0.0136 per 1000 minutes, which was significant at the 5% level. Thus, Kendall suggested that less substitutable players (i.e. more accurate free-throw shooters) have a greater to tendency to receive technical fouls. However, in Column 6 of Table 8, an increase in a player's free-throw percentage by 1 percentage point increased his expected propensity to commit technical fouls by 0.0143 per 1000 minutes, which was not significant at the 5% level even though the estimate was higher than in Column 6 of Table 7. Note that the estimate in Table 8 is likely biased upwards since experience was not controlled for. After all, more experienced players are generally more accurate free-throw shooters.

Overall, the results in Table 8 do not support the substitution theory, unlike those in Table 7. This is mainly due to differences in the datasets used, as discussed in the data section. Despite the differences in the data and results, there is one striking similarity between the two tables: in Column 5 of Tables 7 and 8, the coefficient for field goal attempts per 100 minutes was significant at the 5% level. In both tables, if a player takes an additional field goal attempt per 100 minutes, his expected propensity to commit technical fouls increases by about 0.03 per 1000 minutes. In other words, suppose a player plays around 20 minutes per game (which is rather reasonable considering that a game is 48 minutes long), then if he takes an additional shot attempt per game, his propensity to commit technical fouls rises by about 0.15 per 1000 minutes, which is rather substantial. This is after controlling for player and year fixed effects, a player's talent (i.e. his salary), a player's tendency to play physically and receive flagrant fouls, and the number of minutes played. This suggests that players who are more directly involved in a game (e.g. players who touch and shoot the ball more often) have more opportunities to be provoked. For example, opposing defenders may decide to be extra physical when defending such players, opposing players may start "trash-talking" such players with the intent of "throwing them off", referees may unintentionally make questionable calls against such players (e.g. assess a charging foul on a player when a blocking foul against an opposing player should have been called). As a result, a more plausible explanation as to why higher paid players had a greater tendency to commit technical fouls in the 1996-1997 season to the 2000-2001 season is that higher paid players experience more action on the court, thus they have greater opportunities to be provoked into receiving technical fouls.

Table 9 shows the regression results using data from the 2018-2019 regular season. Column 1 indicates that a 1% increase in a player's salary increases his propensity to commit technical fouls by 0.00395 per 1000 minutes, which was significant at the 5% level. After controlling for a player's position in Column 2, a 1% increase in a player's salary increases his propensity to commit technical fouls by 0.0036 per 1000 minutes, which was still significant at the 5% level. Note that Column 2 did not control for player experience nor a player's propensity to receive flagrant fouls, so the estimate is likely biased upwards. Column 3 includes each player's salary rank and squared salary rank. The estimated coefficients for salary rank and squared salary rank were close to zero and highly insignificant whereas the estimated coefficient for *Log(salary)* remained positive and significant at the 5% level (at 0.338). Thus, there is very little evidence supporting the substitutability theory in the 2018-2019 NBA regular season.

After controlling for minutes played and field goal attempts per 100 minutes in Column 4 of Table 9, the estimated coefficients for salary rank and squared salary rank were still close to zero and highly insignificant. Furthermore, the estimated coefficient for the *Log(salary)* variable was not significant at the 5% level. Surprisingly, the coefficient for field goal attempts for 100 minutes was also not significant at the 5% level. One possible explanation is that higher paid players and/or players who see more action on the court in the 2018-2019 season have shown more restraint in their behavior than players in the late 1990s/early 2000s. For example, players may avoid expressing their emotions even when provoked since they know that they get suspended after accumulating 16 technical fouls. Another explanation is that referees have gotten more lenient over time, particularly towards star players. Referees may decide to give more famous/talented players "the benefit of the doubt" and refrain from assessing technical fouls on them in order to avoid any backlash from the media and/or fans.

Lastly, in Column 5 of Table 9, not only was the estimated coefficient for the free-throw percentage variable not significant at the 5% level, but it was also negative. Holding other factors constant, if a player's free-throw percentage increased by 1 percentage point, his expected propensity to commit technical fouls decreased by about 0.009 per 1000 minutes. If it was the case that more accurate free-throw shooters were less substitutable, and less substitutable players have a greater propensity to receive technical fouls, then the coefficient for the free-throw percentage variable should have been significantly positive. Overall, the results from the analysis of the 2018-2019 season do not support the theory that higher paid players are more inclined to receive technical fouls because they are less substitutable.

Conclusion

While *Celebrity Misbehavior* by Todd D. Kendall (2004) concludes that there is strong evidence that higher paid NBA players are more inclined to misbehave and receive technical fouls because they are less substitutable, a replication of Kendall's analysis suggests otherwise.

Especially after controlling for player fixed effects when analyzing the gathered data for the 1996-1997 season to the 2000-2001 season, the effect of a player's salary rank on his propensity to commit technical fouls was found to be insignificant. In fact, the effect will likely be even smaller if the collected data also included the experience of each of the players. The differences between Kendall's findings and that of the replicated results is likely mainly due to the fact that the dataset Kendall worked with had 202 more observations than the one used in the replication. Furthermore, there were likely other minor differences between the dataset Kendall used and the one used in the replication (e.g. differences in the entries for each of the players). Despite the differences in the data used, both the results of Kendall's analysis and that in the replication suggest that high-volume shooters have a greater propensity to commit technical fouls. Thus, a more plausible explanation as to why higher paid players tend to receive more technical fouls is that they are more involved during games. Such players are likely the stars of their teams, so they generally touch and shoot the ball more often. As a result, there are more opportunities for such players to be provoked on the court. Opposing teams may send their most physical and/or irritating players to guard them. Referees may occasionally make a mistake and call a foul and/or violation against a star player, causing him to object to the call, which can likely result in a technical foul. More advanced data can be used to further investigate the validity of this explanation. For example, future research can collect data on every player's usage rating, which is a metric that estimates the percentage of all team plays involving the player whenever he is on the court. Usage rating is likely a much better variable than field goal attempts per 100 minutes used in Tables 7, 8, and 9.

However, in the analysis of the 2018-2019 NBA regular season, not only was there no evidence found in support of the substitution theory, but there was also very little evidence suggesting that higher paid players were more likely to receive technical fouls because they were provoked more often. Perhaps more recent star NBA players have shown more restraint in their behavior on the court, especially if they know that they get suspended after accumulating 16 technical fouls. They could understand their value to their teams and control their tempers even when provoked. Another possibility is that referees have become more lenient about assessing technical fouls over time, especially to star players. Hence, even when a star player acts up in the middle of their game, referees may refrain from assessing a technical foul in order to avoid potential backlash from the fans, the media, and even from the player's teammates and/or coaches. One topic for future research is to analyze technical foul data for all of the seasons from the 1996-1997 season to the 2018-2019 season in order to get a better idea of the temporal trend of technical fouls over the course of about two decades.

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Tables and Figures

Table 1: Summary Statistics from Kendall (2004)

Variable		Mean	S.D.	Max
Technical fouls per season (actual)		2.29	3.72	40
Tech. fouls per 1000 minutes played (rate)	All Seasons	1.46	2.61	43
	96-97 season	1.38	2.24	20
	97-98 season	1.42	2.61	33
	98-99 season	1.42	3.09	43
	99-00 season	1.36	2.04	18
	00-01 season	1.71	2.90	33
Ejections per season (actual)		0.20	0.57	7
Ejections per 82 games played (rate)	All Seasons	0.26	0.91	20.5
	96-97 season	0.23	0.67	4.5
	97-98 season	0.25	0.91	13.7
	98-99 season	0.26	0.95	11.7
	99-00 season	0.31	1.22	20.5
	00-01 season	0.25	0.69	7.5
Salary (millions)		2.59	3.03	33.1
Minutes played		1204.3	934.98	3464
Games played		50.48	25.56	82
Age		28.88	4.42	44
Experience		5.89	4.11	21
Flagrant fouls per 1000 minutes (rate)		0.28	1.38	38.46
Free throw %		0.72	0.14	1.00
Field goal %		0.43	0.09	1.00
Position = Power Forward		.226	-	-
Position = Point Guard		.200	-	-
Position = Small Forward		.189	-	-
Position = Shooting Guard		.197	-	-
Position = Center		.184	-	-
Position = Unknown		.003	-	-

Note: the "actual" rates for technical fouls and ejections use only the four sample years in which a full 82 game season was played. There was a work stoppage in the 1998-99 season, such that only 50 games were played that year.

Figure 1: Average Propensity to Commit Technical Fouls by Salary Rank on Team from Kendall (2004)

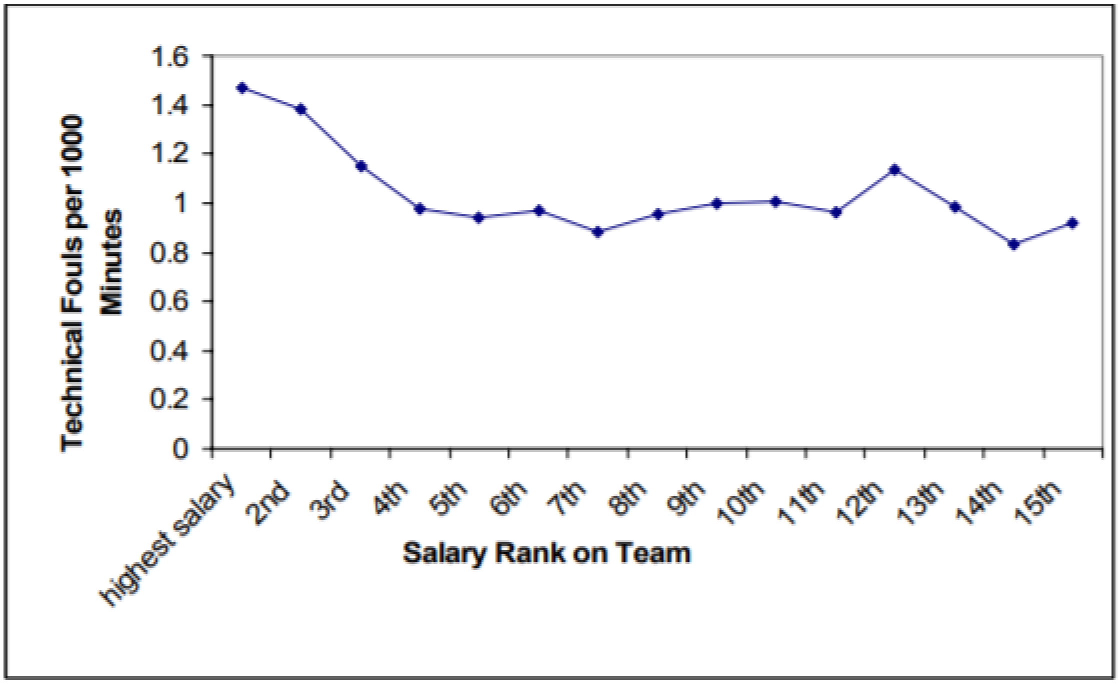

Table 2: Summary Statistics from Collected Data Used in Replication (1996-1997 Season to 2000-2001 Season)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Tech. Fouls per 1000 Minutes Played	1,854	1.50	2.50	0.00	0.00	2.29	43.48
Salary (in millions of 2020 USD)	1,854	4.28	4.88	0.01	1.12	5.59	52.95
Log(Salary)	1,854	14.71	1.15	8.85	13.93	15.54	17.78
Minutes Played	1,854	1,278.90	919.31	1	468	1,945.5	3,464
Flagrant Fouls Per 1000 Minutes	1,854	0.27	1.09	0	0	0	27
Free Throw Percentage	1,797	0.72	0.14	0.00	0.66	0.81	1.00
Field Goal Percentage	1,849	0.43	0.09	0.00	0.40	0.47	1.00
Field Goal Attempts Per 100 Minutes	1,854	31.30	9.62	0.00	25.00	36.90	100.00

Table 3: Breakdown of Collected Data from the 1996-1997 Season to the 2000-2001 Season by Position

	Observations	Proportion of Observations
Power Forward	345	0.186
Point Guard	370	0.200
Small Forward	348	0.188
Shooting Guard	364	0.196
Center	345	0.186
Unknown	4	0.002

Table 4: Breakdown of Collected Data by Season

	Observations	Proportion of Observations
1996-1997	332	0.179
1997-1998	375	0.202
1998-1999	363	0.196
1999-2000	398	0.215
2000-2001	386	0.208

Figure 2: Average Propensity to Commit Technical Fouls by Salary Rank on Team from Collected Data for the 1996-1997 Season to the 2000-2001 Season

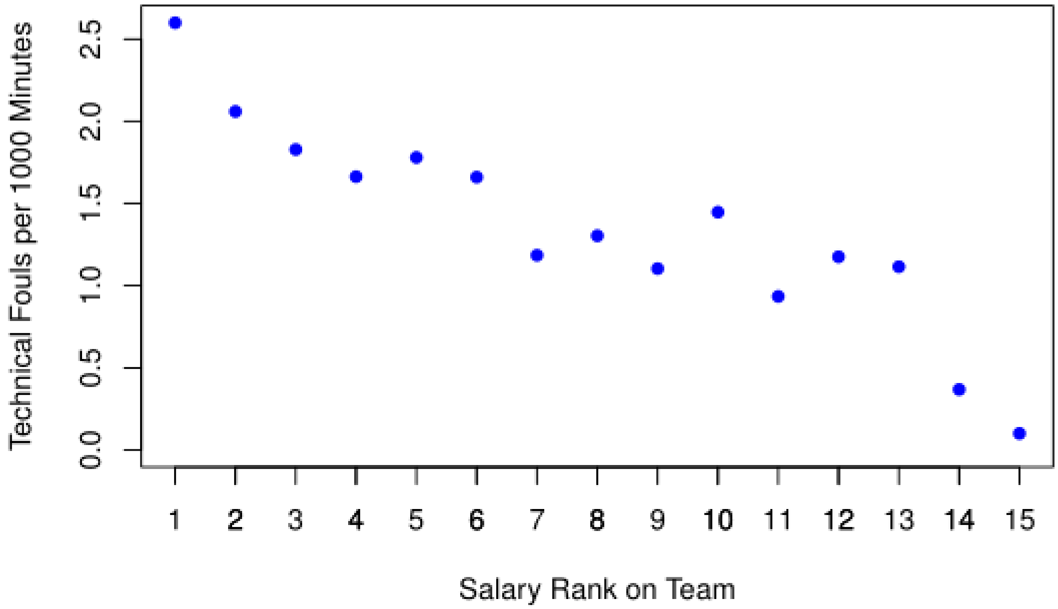

Table 5: Summary Statistics of Collected Data from the 2018-2019 Season

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Tech. Fouls per 1000 Minutes Played	460	1.02	1.65	0.00	0.00	1.45	10.09
Salary (in millions of 2020 USD)	460	6.92	8.15	0.05	1.40	10.65	38.07
Log(Salary)	460	14.80	1.72	10.78	14.15	16.18	17.46
Minutes Played	460	1,144.09	837.88	1	342.2	1,840	3,025
Free Throw Percentage	435	0.74	0.13	0.00	0.69	0.82	1.00
Field Goal Percentage	456	0.44	0.11	0.00	0.40	0.49	1.00
Field Goal Attempts Per 100 Minutes	460	34.92	10.93	0.00	28.22	40.68	100.00

Table 6: Breakdown of Collected Data from the 2018-2019 Season by Position

	Observations	Proportion of Observations
Power Forward	65	0.141
Point Guard	94	0.204
Small Forward	92	0.200
Shooting Guard	116	0.252
Center	65	0.141

Figure 3: Average Propensity to Commit Technical Fouls by Salary Rank on Team for the 2018-2019 Season

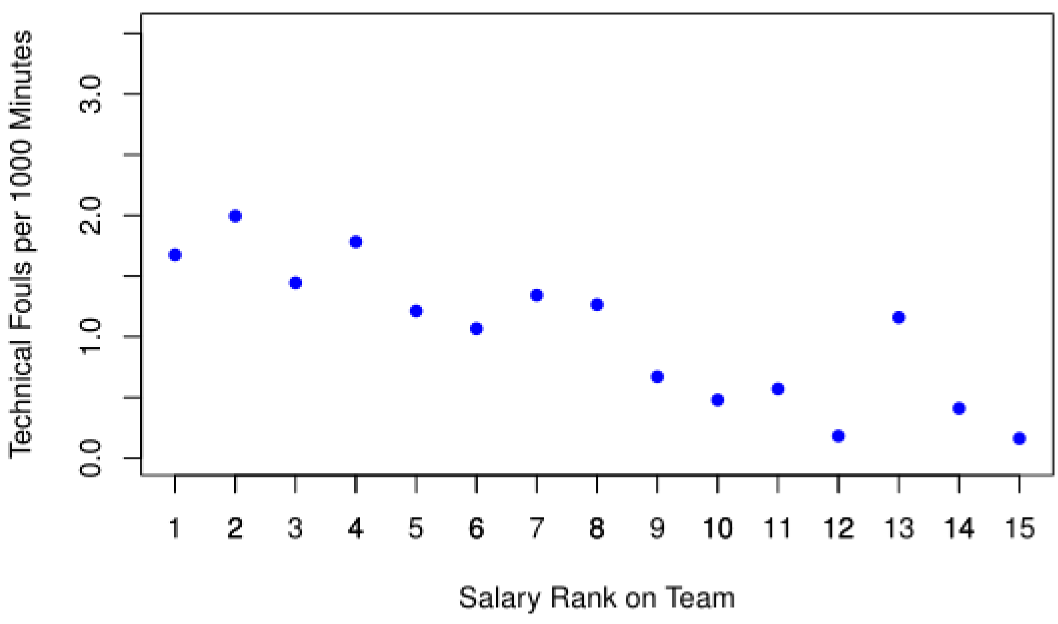

Table 7: Regression Results from Kendall (2004)

Dependent Variable: Technical Fouls Committed Per 1000 Minutes Played

	[1]	[2]	[3]	[4]	[5]	[6]
Log (Salary)	0.37*	0.36*	0.14	-0.05	-0.05	0.03
	(4.22)	(4.32)	(0.89)	(0.34)	(0.35)	(0.39)
Experience	0.06*	0.05*	0.05*	0.49	0.46	0.44
	(2.32)	(2.19)	(2.25)	(0.90)	(0.81)	(0.59)
Flagrant Fouls per 1000 Minutes		0.68*	0.68*	0.19**	0.18**	0.19**
		(5.62)	(5.66)	(1.90)	(1.90)	(1.94)
Position = Center		-0.09	-0.12			
		(0.40)	(0.51)			
Position = Guard		-0.59*	-0.57*			
		(3.22)	(3.14)			
Salary Rank on Team (1 = highest paid)			-0.22*	-0.15*	-0.13*	
			(3.47)	(2.39)	(2.08)	
Salary Rank Squared			0.01*	0.01*	0.01*	
			(2.89)	(2.15)	(1.97)	
FG Attempts per 100 Minutes					0.03*	
					(2.54)	
Minutes Played					0.00	
					(0.82)	
Free Throw %						1.36**
						(1.81)
Field Goal %						-0.32
						(0.25)
Constant	1.02*	1.19*	2.35*	-1.46	-2.35	-2.50
	(6.65)	(7.30)	(6.08)	(0.32)	(0.51)	(0.51)
Year Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Player Fixed Effects?	No	No	No	Yes	Yes	Yes
R^2	0.07	0.13	0.14	0.73	0.74	0.73
N	2056	2056	2056	2056	2056	1989

Notes – t-statistics in parentheses. * indicates significance at 5% level, while ** indicates the 10% level. All regressions are weighted by minutes played, and standard errors are robust to clustering by player.

Table 8: Regression Results Using Collected Data from the 1996-1997 Season to the 2000-2001 Season

	Dependent variable:					
	Technical Fouls Per 1000 Minutes					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Salary in 2020 USD)	0.482***	0.471***	0.315**	0.082	0.062	0.088
	(0.086)	(0.085)	(0.138)	(0.162)	(0.156)	(0.112)
Flagrant Fouls Per 1000 Minutes		0.792***	0.797***	0.199*	0.197*	0.205**
		(0.137)	(0.138)	(0.104)	(0.103)	(0.104)
Center		−0.112	−0.142			
		(0.248)	(0.246)			
Guard		−0.617***	−0.609***			
		(0.196)	(0.194)			
Salary Rank on Team			−0.228***	−0.129*	−0.099	
			(0.079)	(0.069)	(0.066)	
Squared Salary Rank on Team			0.014***	0.010**	0.008*	
			(0.005)	(0.005)	(0.005)	
Field Goal Attempts Per 100 Minutes					0.029**	
					(0.012)	
Minutes Played					0.0001	
					(0.0001)	
Free Throw Percentage						1.430*
						(0.779)
Field Goal Percentage						−0.441
						(1.364)
Constant	−5.601***	−5.301***	−2.285	−0.099	−0.685	−1.227
	(1.256)	(1.227)	(2.176)	(2.593)	(2.618)	(2.046)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Player Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	1854	1854	1854	1854	1854	1796
R Squared	0.062	0.137	0.146	0.739	0.742	0.739
Adjusted R Squared	0.059	0.134	0.141	0.616	0.619	0.616

Note: *p<0.1; **p<0.05; ***p<0.01
All regressions are weighted by minutes played and clustered by player.

Table 9: Regression Results Using Collected Data from the 2018-2019 Season

	Dependent variable:				
	Technical Fouls Per 1000 Minutes				
	(1)	(2)	(3)	(4)	(5)
Log(Salary in 2020 USD)	0.395***	0.364***	0.338**	0.281*	0.375***
	(0.071)	(0.068)	(0.140)	(0.144)	(0.071)
Center		0.720**	0.714**	0.747**	0.700**
		(0.304)	(0.308)	(0.307)	(0.343)
Guard		−0.226	−0.223	−0.270	−0.210
		(0.175)	(0.176)	(0.183)	(0.186)
Salary Rank on Team			−0.036	−0.027	
			(0.088)	(0.087)	
Squared Salary Rank on Team			0.002	0.002	
			(0.005)	(0.005)	
Field Goal Attempts Per 100 Minutes				0.012	
				(0.011)	
Minutes Played				0.0001	
				(0.0001)	
Free Throw Percentage					−0.946
					(0.942)
Field Goal Percentage					−0.390
					(1.605)
Constant	−4.882***	−4.384***	−3.854	−3.570	−3.648**
	(1.072)	(1.027)	(2.424)	(2.402)	(1.434)
Observations	460	460	460	460	435
R Squared	0.082	0.12	0.12	0.127	0.122
Adjusted R Squared	0.08	0.114	0.11	0.114	0.112

Note: *p<0.1; **p<0.05; ***p<0.01
All regressions are weighted by minutes played.
All standard errors are robust.