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Mixing the princes and the paupers: Pay and performance in the National Basketball Association

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Abstract:

We investigate how team and individual performances of players in the National Basketball Association respond to variations in intra-team pay inequality. By breaking down team dispersion into conditional and expected components, we find that expected pay dispersion has a positive effect on team and individual performance. We find that team and individual performances are essentially orthogonal to conditional pay inequality, counter to the hypotheses of fairness and cohesion proposed in the literature both for sports and general occupations. A change in collective bargaining regime in 1996 had little impact on either team or player productivity.

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1. Introduction

This paper will analyze the relationship between pay disparity and individual player performance in particular team sports setting, the National Basketball Association (NBA). NBA franchises have the choice of setting pay levels for players with low or high degrees of pay inequality. A policy of pay inequity within teams involves hiring a small number of superstars ('princes') alongside a larger number of less able players ('paupers'). Alternatively, teams can hire a roster of players who are perceived to be similarly gifted, and hence adopt a more equitable pay structure. Our focus will be on *individual* response of player productivity to changes in pay structure within teams. As we shall show below, it appears that teams have diverged in their pay setting policies with some franchises offering fairly equal pay structures and others offering unequal pay scales with a mix of princes and paupers.

The relationship between pay inequality and worker performance has attracted much attention amongst labor economists and industrial relations specialists. This is largely because the theoretical literature is sharply divided as to the likely impacts of increased pay inequality on worker performance. The seminal theoretical contribution of Lazear and Rosen (1981) established tournament theory in which a salary scale that is convex in hierarchical job grades could promote optimal effort of workers in response to perceived increase in relative rewards through promotion. A hierarchical pay system can deliver incentives to provide effort that a uniform, egalitarian system cannot. Moreover, a hierarchical pay structure with increased wage dispersion over another, otherwise similar, pay structure can induce incentives for greater effort and higher future performance, since the returns to higher performance are increased (Milgrom and Roberts, 1992).

Hicks stated the contrarian argument that "it is necessary that there should not be strong feelings of injustice about the relative treatment of employees since these would diminish the efficiency of the firm"(1963, p317). This gives rise to the 'pay compression' hypothesis whereby increased pay inequality reduces satisfaction over both pay and job and generates feelings of unfairness, envy and resentment that in turn cause workers not to perform as well as they might under a more equal salary structure. In this vein, Levine (1991) argued that narrow wage dispersion could foster group cohesion in organizations which in turn could raise labor productivity. In a variation of the pay compression theory, Ramaswamy and Rowthorn (1991) argued that workers could even interfere with and harm co-worker productivity through 'sabotage' induced by adverse feelings caused by high levels of pay dispersion. Some workers could possess 'damage potential' to harm co-workers. To avoid reduced group performance and output, these workers would need to be paid an efficiency wage so as to deter sabotage behavior.

Testing between alternative theories of the relationship between pay dispersion and worker performance is not easy principally because each theory is mediated through worker effort and worker productivity. Worker effort is rarely observed and the worker productivity is at best imprecisely observed in the employer-employee data sets that are used in the empirical literature. Indeed, the empirical evidence typically relates to *organizational* rather than individual performance (Grund and Westergaard-Nielsen, 2008; Heyman, 2005; Lallemand *et al.* 2004; Winter-Ebmer and Weissmüller,1999).

A setting where individual worker productivity is more precisely observed is professional team sports, since these typically deliver publicly observed, disseminated and verifiable performance measures for athletes. These performance statistics, and accompanying salary data, are widely available for the major North American sports.

The case that we analyze in this paper is the National Basketball Association (NBA) over the period 1990 to 2008. This League is interesting for several reasons. First, output in the form of team wins depends on successful team production. Each team has a small roster of players, usually of the order of 12 to 15 'core' players who take up the majority of playing time. Just five players appear on court at any time and teamwork is essential for success. Unlike Major League Baseball, for example, there is relatively little inter-team player mobility within seasons so teams have identifiable rosters of regular players. This is important for assessing the impact of pay inequality on worker performance. Moreover, the NBA introduced a radical new collective bargaining agreement in 1996 that encouraged some, but not all, teams to increase payroll inequality. This new agreement can be viewed as a natural experiment that can be modeled using a difference-in-difference method. Hence, an empirical relationship between pay disparity and worker productivity can in principle be identified.

Our paper will proceed as follows. Section 2 will address theoretical concerns. Section 3 will introduce the models and estimation procedures to be applied to team performance in the NBA. This section will also show how the collective bargaining agreement of 1996 led to a fundamental change in intra-team pay dispersion. Section 4 will present our models of individual worker performance while section 5 reports the results of our estimations of these models. Section 6 will conclude. To anticipate our primary result, we will show increased intra-team payroll dispersion based on *predicted* (not actual) salaries is associated with increased team and player productivity. However, the 1996 collective bargaining agreement had a marginally significant negative effect on player, but not team, productivity that mitigated the positive effect of predicted salary dispersion.

2. Theoretical concerns

One way of modeling the impact of pay structure on worker productivity is to examine contrasting effects through a team production framework. The analysis follows Lazear (1989) and an adaptation of that model to the National Hockey League by Stefanec (2010). Within a basketball franchise, higher pay will typically be awarded to starting players on a team, with lower pay awarded to 'benchwarmers' or fringe players who appear less regularly. Players can be viewed as competing, in an abstract sense, for starting or benchwarmer positions. We need not be concerned about positional categories, as we would in European soccer or American football, as basketball is a fluid game in which each player has attacking an defensive responsibilities. We assume that both the numbers of starting positions and starting salary slots are fixed. To fix ideas, we consider two players *j* and *k* who compete for a starting position. We define wage disparity as the salary gap between players, $w_j - w_k, = \lambda$, which is assumed to be exogenous to player productivity.

Player productivity can be thought of as having an individual dimension and a co-operative dimension. For example, the ability to convert shots into points is an individual attribute while the ability to pass to teammates is a co-operative attribute. On the court, this distinction becomes blurred since, for example, the ability to convert a shot into points depends on how close to the basket the shot is taken, which in turn depends on successful passes by team-mates to get the shooter into a good position. Nevertheless, we proceed with the distinction as a convenient abstraction.

A risk-neutral basketball player has the production function $f(e, h)$ where e denotes individual effort while h denotes effort directed to towards helping teammates. We assume $f(0, h) = f(e, 0) = 0$, $e > 0$, $h > 0$, $f_e > 0$, $f_h > 0$ (so cooperation is mutually beneficial), $f_{ee} < 0$ and

$f_{hh} > 0$ or < 0. Again following Lazear (1989) and Stefanec (2010), the individual outputs of players j and k are given by:

$$q_j = f(e_j, h_k) + \varepsilon_j \tag{1a}$$

$$q_k = f(e_k, h_j) + \varepsilon_k \tag{1b}$$

These equations capture the essence of player productivity in a team sport such as basketball: player A's performance statistics depend on his own individual effort and also the co-operative effort of his team-mates. Similarly, the performance statistics of a team-mate B depend on his own individual effort and also how much effort player A undertakes to aid his performance. The players' respective outputs will also depend on random factors (principally luck) summarized in the stochastic ε terms, which may also include any measurement error in outputs.

The probability that player j beats player k in a contest for a starting position is given by:

$$p = \Pr(q_j > q_k) = G[f(e_j, h_k) - f(e_k, h_j)] \tag{2}$$

where G[.]is the cumulative distribution function. Players incur cost (disutility) of effort given by $C(e, h)$ where C_e, C_{ee}, C_h, C_{hh} for all players. Players maximize expected utility by choice of individual and cooperative effort. The maximization problem is:

$$\text{Max } w_j + (1 - p(.))\lambda - C(e_j, h_j) \tag{3}$$

Let g be the probability density function corresponding to G. From tournament theory, the equilibrium will be Cournot-Nash and g will be evaluated at zero. Assuming the profit function to be concave, the first-order conditions for maximization of (2) are;

$$\lambda g(0) = C_e(.)/f_e(e_j, h_k) \tag{4a}$$

$$\lambda g(0) = C_k(.)/f_h(e_k, h_j) \tag{4b}$$

We then examine the signs of partial derivatives $\partial e/\partial\lambda$ and $\partial h/\partial\lambda$ by comparative statics:

$$\partial e/\partial \lambda = g(0)f_e/[C_{ee} - \lambda g(0)f_{ee}] > 0 \quad (5a)$$

$$\partial h/\partial \lambda = -g(0)f_h/[C_{hh} - \lambda g(0)f_{hh}] < 0 \text{ if } C_{hh} - \lambda g(0)f_{hh} > 0 \quad (5b)$$

From (4a) we see that an increase in pay disparity (greater pay gap) raises individual effort, given own cooperative effort and that of teammates. This is the standard tournament result carried over to a team production setting (Lazear and Rosen, 1981). Widening of the salary structure motivates players to provide greater individual effort (Ehrenberg and Bognanno, 1990). From (4b) we observe that if the production function exhibits diminishing returns to co-operative effort ($f_{hh} < 0$) then an increase in pay disparity lowers a player's co-operative effort. As players compete for starting positions, they engage in less co-operative treatment of rivals resulting in lower co-operative effort, holding individual effort constant. But, as Stefanec (2010) points out, if instead the production function has sufficiently strong increasing returns to cooperative effort, such that the denominator of (4b) becomes positive, without violating second-order conditions, then increased pay disparity results in *greater* co-operative effort. Then the theoretical prediction that greater pay disparity reduces 'teamwork' will break down.

The foregoing theory applies to player choice of effort in two dimensions, individual and co-operative. It ignores several confounding factors. First, firms make selection choices in their hiring policies, including choice of drafted young players from college. Players are not randomly assigned to teams and teams choose their levels of pay disparity through the mix of free agents and drafted players in the composition of the team roster. We assume that the teams select their pay disparity levels through the notion of a 'pay structure' and that players are able to some extent to vary their performance (productivity) levels in response to an exogenous degree of pay disparity. Second, we abstract from dynamic concerns emanating from use of multi-period contracts. These dynamic concerns could include shirking behavior immediately after signing a long-term contract (Berri and Krautmann, 2006). The previous model ignored intertemporal allocations of effort over a long contract period. Third, we have not considered the particular NBA institutional feature of a soft salary cap. This may reduce pay disparities below levels intended by team owners.

3. Team performance and pay inequality in the NBA

The theoretical model above suggests that the impact of payroll disparity should be observed on the performance of individual players. The empirical literature on the subject [see DeBrock *et al.* (2004) and Depken (2000) on baseball, Frick *et al* (2003) on the four major North American sports, Berri and Jewell (2004) on basketball, Mondello and Maxcy on the National Football League, Franck and Nüesch (forthcoming) on German soccer and Gomez (2002), Kahane (forthcoming), Sommers (1998) and Stefanec (2010) on the National Hockey League], though, has often examined the issue of pay disparity in professional sports at the team level.[1] Of these papers, all but De Brock *et al.* (2004) and Kahane (forthcoming) use an unconditional measure of wage inequality.[2] But the hypotheses in the literature point to a need to investigate whether changes in intra-team pay inequality lead to changes in team performance for a given quality of co-workers (teammates) in the team. For this purpose, we need a *conditional* measure of pay inequality that controls for the quality of a worker's

[1] In an interesting variation on this literature, Katayama and Nuch (forthcoming) model the impact of salary dispersion on team performance in the NBA at game level. They find, in line with Berri and Jewell (2004), no effect of within-team pay disparity on team performance, using estimation methods similar to this paper.
[2] DeBrock *et al.* (2004) use a Herfindahl index to measure pay inequality while Kahane (forthcoming) uses standard deviation and inter-quartile range.

teammates (Winter-Ebmer and Zweimüller, 1999; Lallemand *et al.*, 2004).[3] Such a measure can be extracted from a salary model.

In this section we estimate a team-based model of pay inequality and performance. We begin with a simple salary model for player *i* in year *t*:

$$Log\ salary = \alpha_0 + \boldsymbol{\alpha_1 X_{it-1}} + \text{year effects} + \varepsilon_{it} \qquad (6)$$

where $\boldsymbol{X}_{it-1}$ is a vector of observable player skills and attributes at the season prior to assessment of salary and $\boldsymbol{\alpha_1}$ is a vector of characteristics to be estimated. The predicted part of the estimates of equation (6) is used to generate a Gini measure of pay inequality for each team-year, $GINI\ PREDICTED_{jt}$ where *j* suffix denotes a team. The residuals from estimates of equation (6) represent differences between actual salary and expected salaries. These differences could arise either from unobserved quality or could reflect overpaid or underpaid players but we are unable to distinguish these two effects (De Brock *et al.* 2004). The residuals are used to compute a second measure of pay inequality, $GINI\ RESIDUAL_{jt}$. An increase in *GINI PREDICTED* implies an increase in dispersion of expected salaries while an increase in *GINI RESIDUAL* indicates a greater dispersion of salaries around their expected values.

Our two measures of pay inequality are then inserted into a model of team performance, here measured by regular season win percent:

$$Win\ percent_{jt} = \beta_0 + \boldsymbol{\beta_1 Z_{jt}} + \beta_2 GINI\ PREDICTED_{jt} + \beta_3 GINI\ RESIDUAL_{jt} + Team\ effects + \nu_{jt} \qquad (7)$$

[3] Winter-Ebmer and Zweimüller (1999) used ‘standardised’ wages as a proxy for worker productivity. An inverted U-shaped relationship was found between conditional wage dispersion and worker productivity for white-collar workers while there was a positive relationship between pay dispersion and worker productivity for blue-collar workers. The study by Lallemand *et al.* (2004) was at firm level with profits per employee as proxy for firm performance. There results point to a positive relationship between this measure of firm performance and conditional pay inequality. In our sports application we can measure team and worker performance directly without the need for proxies.

In the estimation of our player salary model we need reliable measures of player productivity. We could have used a composite measure of productivity. The conventional measure of productivity used by the National Basketball Association is *NBA EFFICIENCY* and this is the sum of player positive statistics, comprised as points, rebounds, steals, assists and blocked shots, minus the sum of performance metrics that reduce wins (turnovers and missed shots). Berri (1999, 2008) points out that this measure imposes equal weights on each performance statistic and overvalues the positive impact of inefficient scoring.

Despite the problems with *NBA EFFICIENCY*, it does a surprisingly good job of explaining the variation in NBA salaries. Berri, et. al. (2007), though, noted that one can explain slightly more by employing specific individual productivity variables. Specifically, we find – essentially consistent with Berri, *et. al.* (2006, 2007) and Berri and Schmidt (2010) – that salaries can be explained with per game measures of points, rebounds, blocks and assists (shooting efficiency, turnovers, and steals tend not to explain player salaries in the NBA). To these variables we add age, age squared, minutes per game to capture variation in playing time (we predict that players who remain on court for longer periods will be rewarded with greater salary) and win percent of the team that the player was contracted to in the previous season. These are all observable and known attributes of players. We deliberately exclude player fixed effects as these represent unobservable characteristics. We do include year effects to capture salary inflation in the NBA, which was considerably greater than consumer price inflation over the period examined, 1990 to 2008. We confine the sample of players to those who have at least 20 games per season and 12 minutes per game in a given season. This filter, applied throughout the paper, eliminates fringe players who contribute little to team wins. The estimated salary model is shown in Table 1 and is similar to that estimated by Berri *et al.* (2007).

TABLE 1 HERE

In the team performance model, we control for team quality by using *RELATIVE SALARY*, defined as total payroll of a team divided by the League average team payroll in a given season thus centering the metric at a mean of 1. We hypothesise that teams may encounter diminishing returns in win percent to team payroll (quality) and so introduce a squared term in *RELATIVE SALARY* to allow for this possibility (Simmons and Forrest, 2004). Our estimated model of team performance is shown in Table 2, column (1).

TABLE 2 HERE

In this model, the coefficients of *RELATIVE SALARY* and *RELATIVE SALARY SQUARED* are significantly positive and negative, respectively, in line with the diminishing returns hypothesis and consistent with Simmons and Forrest (2004). The measure of pay inequality taken from predicted (expected) salaries has a positive and significant coefficient. Essentially, this result shows that NBA teams which employ a roster of players that are more unequal in talent (as proxied by market salaries) perform better in the regular season than teams that are more equal in quality. This finding is the complete opposite of the result of DeBrock *et al.* (2004). These authors estimated a comparable to ours for Major League Baseball and obtained a significant negative coefficient on their measure of predicted pay inequality.

The 1995 Collective Bargaining Agreement

The 1995 collective bargaining agreement between players and team owners in the National Basketball Association brought about a radical change in pay equity. This bargaining agreement raised the team cap on payrolls to 45% of eligible league revenues as from the 1996 close season. It also eliminated the right of teams to match offers from other organizations to their own free agents. Hence, all free agents without a contract at the conclusion of the 1995-96 season were free to negotiate and sign with any team in the NBA. As a result, several teams began the summer in 1996 with relatively empty rosters and large amounts of money to spend on the acquisition of talent. Several teams opted to spend their money on a few star athletes, the NBA 'princes'. Having acquired these stars, teams filled the remaining places in their rosters with NBA 'paupers', many of whom were prepared to play for the NBA minimum wage on offer. This minimum wage still exceeded these players' reservation wages.

Hill and Groothuis (2001) presented evidence that the distribution of salaries in the NBA became increasingly unequal after 1996. They did so using basic descriptive statistics: standard deviation, skewness, kurtosis and Gini coefficient. All of these measures showed a more unequal salary distribution immediately after the 1995-96 season. Table 3 reports unconditional Gini coefficients for NBA teams over the whole sample period and over the 1990-96 and 1996-2008 subperiods. Focusing on the average Gini coefficients for 1994-95 and 1995-96 on the one hand, and 1996-97 and 1997-98 on the other, we find an increase in mean Gini coefficient across all teams from 0.336 to 0.411. We also observe that 15 out of 29 teams experienced an increase in Gini coefficient of at least 20% between 1994 and 1998; some of these teams had very large increases in pay inequality, most notably Atlanta, Chicago and Los Angeles Lakers. This substantial increase in salary inequality for around half of NBA teams is a valuable aid to identification of impacts of changes in pay inequality on player performance.

Some teams restructured playing rosters and contracts so as to generate increased pay inequality. We propose to term these teams, denoted by asterisk in Table 3, as 'treated' teams which are coded as '1' in the dummy variable, *TREAT*. The remaining teams are correspondingly 'untreated'; these are teams which decided not to raise pay inequality around the 1996 period. Another dummy variable, *POST 1996*, is coded as '1' for all seasons from 1996/97 onwards and 0 otherwise.

Without inclusion of control variables to allow for potentially confounding factors, we can observe the differences in mean differences between treated and untreated teams before and after the 1996 watershed when the new collective bargaining agreement was enforced. These differences are shown in Table 4. If we use a pair of broad time periods for comparison, 1990-95 and 1996-2007, we see that the raw difference-in-difference estimate of variation in win percent attributable to the new CBA is -0.036. However, if a narrower time period is chosen, 1994-96 and 1996-98, with two seasons either side of the new union agreement, we find a much less difference-in-difference estimate of 0.002, effectively zero. The larger negative estimate in the broader time periods is probably picking up other changes in the basketball players' labor market, such as variations in salary cap rules.

TABLE 4 HERE

We can estimate the treatment effect from a team-level regression as follows:

$$Win\ percent_{jt} = \beta_0 + \boldsymbol{\beta_1 Z_{jt}} + \beta_2 GINI\ PREDICTED_{jt} + \beta_3 GINI\ RESIDUAL_{jt} + \beta_4 TREAT_{jt} + \beta_5 POST\ 1996_{jt} + \beta_6 TREAT*POST\ 1996_{jt} + Team\ effects + v_{jt} \quad (8)$$

In equation (8), *TREAT*POST 1996* is an interaction term between treated teams (those that were substantially affected by the collective bargaining agreement through a change in pay policy) and the post-1996 period dummy. The coefficient on this variable then registers the difference-in-difference estimate of treatment of teams before and after the collective bargaining watershed.

Regression estimates of equation (8) are reported in column (2) of Table 2. We find no significant treatment effect. Varying the selection of treated teams, e.g. by making the required increase in Gini coefficient to be 10% rather than 20%, thereby adding two extra teams (Detroit and San Antonio), does not affect the result. Overall, the extra variables in equation (8) fail to add significant explanatory power to those in equation (7). Hence, the impact of increased pay inequality on team performance cannot be identified from our suggested natural experiment. Of course, the 'experiment' here is somewhat unusual in that we are imposing investigators' judgement on what constitutes a substantial change in team pay inequality. In most natural experiments in economics, the changed is externally driven as in law changes across states or countries.

It is possible that variations in pay dispersion could affect team performance (win percent) directly through some collective team effort effect; successful teams may generate powerful synergies from their players. In this respect, the team-based approach presented thus far is of interest. But the hypotheses surrounding impact of pay inequality on performance- envy, team cohesion, emulation, prospects of tournament-type rewards and so on- are fundamentally about *workers'* responses to pay structures.

A worker-level approach can take advantage of the immense data on player productivity available to researchers in professional sports. The team (firm) outcomes observed in sports are entirely a function of the actions the players take upon the field of play. The player's actions are in turn a function of a list of factors that includes a player's talent, a player's age, the productivity of teammates – and as the literature suggests – the level of pay disparity on the team. The impact of this latter factor, though, is unclear. Hence the need for a properly designed empirical investigation that focuses on individual worker productivity. The next section takes up this theme.

4. Modeling player performance in the National Basketball Association

Using data from 1987 to 2007, Berri (2008) offered an alternative metric to *NBA EFFICIENCY* – which we will label *PROD* -- in which the weights on each performance statistic are derived from a regression of team wins on the full set of player performance statistics. The coefficients from this regression – shown in Table 5 -- are used to compile *PROD*. This reveals that three point field goals made and offensive and defensive rebounds have higher weights among the positive performance statistics than blocked shots and free throws made. One should note that *PROD* is adjusted for the set of team statistics reported in Table 5. To allow for variations in playing time, a further adjustment is made by calculating player performance per 48 minutes. This gives our dependent variable for player performance, *ADJP48*. A version of this productivity metric has been applied in a number of studies of player performance in basketball (e.g. Berri and Krautmann, 2006; Berri, et. al. 2006, Berri *et al.* 2009, Berri and Schmidt 2010, Price and Wolfers, forthcoming).

TABLE 5 HERE

Our full model of player performance in the NBA is:

$$ADJP48_{it} = \gamma_0 + \boldsymbol{\gamma_1}\,'\boldsymbol{X_{it}} + \gamma_2 GINI\ PREDICTED_{jt} + \gamma_3 GINI\ RESIDUAL_{jt} + \gamma_4 TREAT_{jt} + \gamma_5 TREAT*POST\ 1996_{jt} + \theta_i + team\ dummies + \varepsilon_i \quad (6)$$

ADJP48 is our player performance metric just described. Included in the ***X*** vector of control variables are lagged *ADJP48*, *AGE* and *AGE SQUARED*. We include a dummy variable, *NEWTEAM*, to denote whether a player moved between teams between beginning of previous season and beginning of current season. We also include a variable to denote the sum of playing experience over the last two seasons, *TOTAL GAMES*. This variable helps control for the extent and frequency of player injuries. Our ***X*** vector contains an additional variable, *ROSTER STABILITY*. This captures team stability; we identify the set of players who appeared for a team in both current and prior seasons. We then compute the average of percentage of team minutes accounted by these consistent roster members. *ROSTER STABILITY* is then the average of the percentages of playing time of these players over the current and prior seasons. We hypothesize that a team with a stable group of players who interact regularly on the court will better incorporate learning and peer effects compared to a team with a greater roster turnover. Players who regularly play together will learn and anticipate each other's moves thus facilitating more shots and points earned in a game. Our prior is that increased *ROSTER STABILITY* is associated with increased player performance.

In addition to *ROSTER STABILITY*, we have a measure of teammate productivity, *TMWP48*, defined as team wins minus the contribution of a particular player given by *ADJP48*. This eliminates the 'reflection problem' by which team productivity across all players is affected by a particular player's productivity (Manski, 1993). Basketball teams have small rosters, as only five players take the court at any time, so removing player *i* from the team productivity measure is particularly important.

In basketball, shot attempts in a game are finite; if a player takes more shots, his teammates must take fewer shots since only one ball and limited playing time. The same argument applies to rebounds and steals, which also contribute to player productivity. To some extent, peer effects of teammates on player productivity are already captured by *ROSTER STABILITY*. But with diminishing returns, a player's productivity will *fall* if he plays on a better team since his teammates are contributing a greater amount to the total team effort. Hence, it is possible that increased teammate productivity will lead to reduced individual productivity in basketball. Berri and Krautmann (2006) offer evidence, albeit with marginal significance, that such a negative effect exists in basketball.

We use the two intra-team Gini coefficients derived earlier from salary equations, *GINI PREDICTED* and *GINI RESIDUAL*, as our measures of pay inequality. As in our model of team performance we introduce *TREAT* and *TREAT*POST 1996* to test for effects of the 1995 Collective Bargaining Agreement on player performance via the same set of teams in *TREAT* as for the team-based model. A set of player, team and year fixed effects completes the model. Table 6 shows descriptive statistics for our sample of basketball players, prior to inclusion of lags.

TABLE 6 HERE

5. Empirical results of individual performance models

Table 7 reports our regression results. Column (1) begins with a set of pooled OLS estimates, in which *GINI PREDICTED* has a positive coefficient that is significant at the 1 percent level. At this stage, we exclude lagged performance and also take no account of the structural break in 1996. The model is estimated over the full sample of eligible players who had 20 games and 12 minutes per game in a given season. Column (2) brings in player fixed effects, which are clearly significant. Column (3) then adds lagged performance, where we find that a single lag of performance delivers a significant coefficient, showing some persistence in performance.[4]

[4] Ordinary least squares estimation with a lagged dependent variable and a serially correlated error term will lead to inconsistent parameter estimates. Consistent estimators can be obtained by instrumental variables estimation of the parameters of a first-difference model, where lags of regressors are used as instruments. This is the Arellano-Bond estimator, available in Stata 11 software (Cameron and Trivedi, 2009). We applied this dynamic difference GMM estimator to the models in Table 6, columns (3) and (4). We note the risk of biased results from this estimator where instruments are weak (Blundell and Bond,

Turning to our set of control variables, *AGE* and *AGE SQUARED* deliver significant coefficients, positive and negative in line with priors Moreover, performance in basketball is maximized at 26 years of age which appears plausible and as such gives us greater confidence in our model.[5] As would be predicted, *TOTAL GAMES* has a significant positive effect on player productivity. Players who appear in more games deliver better performances, suggesting an element of rationality in team selection decisions. *ROSTER STABILITY* has a significant, positive effect on player productivity, as predicted. We interpret this as suggesting that team chemistry has spillover effects on player performance.

However, when we control for what teammates do on the court in their performances, we find a significant *negative* effect of teammate productivity, *TMWP48*, on player performance. Literature on peer effects from other sports (baseball, as shown by Gould and Winter (2009) and from supermarket checkout operators (Mas and Moretti, 2009) points to positive effects of teammate or co-worker productivity on individual worker performance. Our contrary result can be rationalized by the fact that there is only one ball in basketball and limited playing time. In basketball as noted above, scoring opportunities are both finite and constrained by teammates. Hence, it is plausible for basketball- unlike baseball- that increased productivity for one player will diminish the opportunities, and productivity of others. Our result also suggests that a superstar in our data set such as

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1998) and so we also used a dynamic difference system estimator. These two approaches gave unsatisfactory results in different ways. In the Arellano-Bond approach, the Sargan test of over-identification restrictions rejected the null on each variant of lag structure of endogenous variable(s). In the systems GMM approach, the model delivered very few significant coefficients on our control variables and the coefficient on lagged productivity was also insignificant. In neither approach were the coefficients on either *GINI PREDICTED* or *GINI RESIDUAL* statistically significant.

[5] Berri and Schmidt (2010) report that performance peaks in the NBA at age 24. These authors, though, examined performance from 1977 to 2008. We suspect that the slightly later peak in our sample is due to improvement in player training and conditioning methods over time. This allows players to maintain peak performance longer.

Michael Jordan, who dominated the game statistically during his career, did not positively impact the productivity of his teammates (as noted in Berri, et. al. 2006).

Turning to our focus variables, *GINI PREDICTED* and *GINI RESIDUAL*, we find contrasting effects of pay inequality on player productivity. Increases in *GINI PREDICTED* appear to lead to greater player performance, while changes in *GINI RESIDUAL* have no effect. We would argue that *GINI PREDICTED* can be thought of as "justified inequality". In other words, if a player is on a team with players he perceives to be better, he will accept that salaries should be unequal. In contrast, *GINI RESIDUAL* can be thought of as "unjustified inequality", which could generate perceptions of envy and fairness that in turn induce diminished player effort and performance.

Our results indicate that "justified inequality" – or playing with players who are perceived to be much better – makes a player better. Recall that we have found that diminishing returns exists in the NBA. So better teammates should make a player offer less. Salaries, though, are primarily driven by scoring. In other words, although salaries capture perceptions of performance, they do not fully capture productivity [see Berri, et. al.(2006, 2007) and Berri-Schmidt (2006)]. Consequently, our results indicate that when a player perceives his teammates are better, he plays better.

There is no significant effect of conditional pay dispersion on player performance. The fixed effects model with lagged performance reveals a significant, positive effect of predicted pay dispersion on player performance. Player productivity is positively related to dispersion of expected salaries. Players in teams that have greater salary dispersion measures perform better than comparable players on teams with more uniform dispersion. This result is consistent with emulation effects (players aspire to the performance levels of highly paid stars) or tournament-type incentives (players are motivated by a less uniform structure to perform better so as to earn more lucrative contracts). Our results do not give any support to the cohesion and morale effects supposedly induced by a more uniform or 'fairer' pay structure.

To test for the particular effects of the change in collective bargaining regime imposed in 1996, we first return to examination of differences in means between players on treated and untreated teams before and after 1996. The results, shown in the bottom panel of Table 4, point to an impact of the change in bargaining regime on player performance that is zero, regardless of time window selected for comparison.

Turning to a regression analysis of the change in bargaining regime, we undertake two modifications of the fixed effects model with lagged performance. First, beginning with the model in (column (3) of Table 7), we interact the Gini variables, *GINI PREDICTED* and *GINI RESIDUAL* with the post-1996 dummy variable, *POST 1996* and re-estimate the model over the full sample. These interaction terms (not reported to save space) yield insignificant coefficients and fail to add significant explanatory power to the model. The descriptive statistics in Table 6 show why. Quite simply, although the unconditional Gini coefficient rises after 1996, *GINI PREDICTED,* derived from expected salaries does not. Actually, this measure shows a slight mean reduction after 1996. So expected salaries adjusted to the new bargaining regime in such a way that the degree of pay inequality attached to these predicted salaries remained unchanged.

Second, we apply a difference-in-difference methodology similar to that used in the team performance model by adding the dummy variables *TREAT* and *TREAT*POST 1996* with estimation over the restricted sub-sample of players who were present in both 1995 and 1996. *TREAT* has an insignificant coefficient so players on 'treated' teams are no more or less productive than players with similar attributes on non-treated teams. But the coefficient on *TREAT*POST 1996* is negative and significant at the 10 percent level. This is tentative evidence that the change in bargaining regime implemented in 1996 may have reduced player productivity for players employed by teams that had substantial changes in pay structure resulting in greater observed pay inequality. This result must be considered alongside the similarly marginally significant coefficient on *GINI PREDICTED* and also the very small effects shown in the differences in means in Table 4. The effect of the implementation of the new bargaining agreement was then to offset the positive effect of increased pay dispersion based on predicted salaries.

6. Conclusions

The key questions posed in this paper were: Does increasing disparity in salary impact team and worker performance positively or negatively? Our answers focus on a specific natural experiment from the NBA. In the 1990s a number of teams dramatically increased their level of salary inequality. Did this increase in inequality impact the performance of individual players or their teams?

To address our questions we first looked at the factors that determine salary in the NBA. As has been demonstrated previously in the literature, we find that player salary in the NBA is primarily driven by points scored. Fundamental factors that determine team wins (i.e. shooting efficiency, rebounds, and turnovers) are less important for player salaries. In sum, there appears to be a difference between teams' perceptions of productivity and a player's actual production of wins in the determination of player salaries. Understanding what factors determine player salaries allows us to examine inequality from two perspectives. The first perspective – "justified inequality" – is derived from an estimation of inequality taken from predicted salaries out of our model of player salaries. We suspect that players might accept the notion that some players are better than others; and that players who are perceived to be better should be paid more money, with no response in terms of individual player effort and productivity. The other component og pay inequality, though, is what we call "unjustified inequality", or inequality not justified by and conditional upon perceptions of performance embedded in our model of salary determination. This measure of conditional pay inequality is derived from the residuals of our salary model.

When we looked across the entire time period examined, justified inequality did not appear to change very much. In particular, the effects of the natural experiment of a radical change in collective bargaining agreement implemented in 1996 were primarily to raise unjustified (conditional) pay inequality.

Interestingly, though, both team and player performances appear to respond positively to changes in justified inequality based on expected salaries over the whole sample period.. We interpret these results as confirmation of tournament theory. But one can also argue that if a player plays with teammates he perceives as better, he will also perform better. This aspect of teammate interaction deserves greater attention in future research and team sports offer useful settings in which to pursue this analysis.

Our results with respect to unjustified (conditional inequality) are somewhat harder to interpret. Previous literature from team sports suggests that changes in unjustified inequality has impacts on team performance via the response of player performances, possibly driven by concerns over 'fairness' in the salary distribution. Our contribution in this paper has been to examine the relationship between pay inequality at both individual and team levels, and our focus on the player level is new here. But, although we looked at the role of conditional pay inequality in performances at the team and player levels we failed to find any impact at all, regardless of choice of empirical estimator.

All of this suggests that the natural experiment that initially caught our attention was not as important as first suggested by the sharp increases we found in observed total Gini coefficients for many teams. The changes in pay inequality we observed in the mid-1990s did not affect the basic argument suggested above. Using a difference-in-difference methodology we found no evidence of any difference in mean differences of either team or player productivity. We suggest that teams successfully accommodated the 1996 change in collective bargaining agreement by making changes in team composition that widened actual pay inequality without affecting pay inequality based on expected salaries that are in derived from perceptions of player performance. Although actual pay inequality widened for many teams, pay inequality based on predicted salaries did not fundamentally change.

We also found little evidence of a role for conditional pay inequality in either team or player performances. In contrast, justified inequality appears to have a positive impact on player performance in the NBA. This result holds both before and after the natural experiment that the NBA conducted. We suggest that players in the NBA – across the entire time period examined – behave in a fashion consistent with tournament theory.

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Table 1
Salary model for NBA players 1990/01 to 2007/08
Dependent variable: Log salary

Variable	Coefficient (absolute t statistic)
Age	0.369 (10.97)
Age squared	-0.0058 (9.82)
Points per game	0.043 (13.76)
Rebounds per game	0.055 (9.30)
Blocks per game	0.193 (9.58)
Assists per game	0.026 (4.07)
Minutes per game	0.014 (4.76)
Team win percent	0.571 (8.48)
Year dummies	Yes
Adjusted R^2	0.606

Note: The null hypothesis of equal coefficients on defensive and offensive rebounds could not be rejected so these are combined into total rebounds. All performance measures are lagged one season.

Table 2 Team performance regressions, dependent variable is team win percent 1990/91 to 2007/08

Variable	Coefficient (absolute t statistic)	Coefficient (absolute t statistic)
	(1)	(2)
Relative salary	0.648 (5.78)	0.616 (5.58)
Relative salary squared	-0.169 (4.12)	-0.159 (3.97)
Gini predicted	0.474 (5.36)	0.494 (5.08)
Gini residual	-0.038 (0.50)	-0.054 (0.72)
Post 1996		-0.024(0.95)
*Treat*post 1996*		-0.024 (0.68)
Team fixed effects	Yes	Yes
Adjusted R^2	0.343	0.343
N	516	503

Table 3 Gini coefficients by NBA team

Team	1990-2007	1990-1995	1996-2007
Atlanta*	0.411	0.277	0.479
Boston	0.411	0.337	0.449
Charlotte	0.356	0.326	0.374
Chicago*	0.403	0.338	0.435
Cleveland*	0.411	0.395	0.419
Dallas*	0.385	0.343	0.406
Denver*	0.398	0.333	0.430
Detroit	0.314	0.275	0.334
Golden State	0.377	0.385	0.373
Houston*	0.442	0.388	0.470
Indiana*	0.386	0.334	0.412
Los Angeles Clippers	0.343	0.312	0.359
Los Angeles Lakers*	0.442	0.274	0.527
Miami*	0.442	0.356	0.485
Memphis			0.350
Milwaukee	0.353	0.273	0.393
Minnesota	0.427	0.342	0.469
New Jersey	0.426	0.363	0.458
New Orleans			0.422
New York	0.373	0.378	0.370
Orlando*	0.419	0.330	0.463
Philadelphia	0.402	0.381	0.412
Phoenix	0.425	0.362	0.456
Portland*	0.348	0.279	0.383
Sacramento*	0.380	0.295	0.422
San Antonio	0.415	0.384	0.431
Seattle*	0.393	0.277	0.451
Toronto			0.348
Utah*	0.389	0.292	0.438
Vancouver	0.371		0.380
Washington*	0.426	0.387	0.445
All	**0.395**	**0.334**	**0.423**

Note: * denotes a treatment team as defined in the text

Table 4

Treatment effects on team and player performance

Teams: win percent	1990-95	1996-2007	Δ	1994-95	1996-97	Δ
Treated	0.513	0.498	-0.015	0.542	0.530	-0.012
Untreated	0.484	0.505	0.021	0.452	0.466	-0.014
Difference	-0.029	0.007	**-0.036**	-0.090	-0.064	**0.002**
Players: ADJP48						
Treated	0.328	0.301	-0.027	0.322	0.296	-0.026
Untreated	0.319	0.281	-0.038	0.294	0.273	-0.021
Difference	0.009	0.020	**0.011**	-0.028	-0.023	**-0.005**

Table 5

The impact of various player and team statistics on wins in the NBA

Player variables	**Coefficient**
Three point field goal made	0.0644
Two point field goal made	0.0318
Free throw made	0.0176
Missed field goal	-0.0334
Missed free throw	-0.0150
Offensive rebounds	0.0334
Defensive rebounds	0.0333
Turnovers	-0.0334
Steals	0.0333
Opponent's free throws made	-0.0175
Blocked shot	0.0174
Assists	0.0223
Team variables	
Opponent's three point field goals made	-0.0641
Opponent's two point field goal made	-0.0317
Opponent's turnovers	0.0333
Team turnover	-0.0334
Team rebounds	0.0333

Table 6

Descriptive statistics: mean (standard deviation)

Variable	Whole sample	Pre-1996	Post-1996
Player productivity	0.299 (0.121)	0.314 (0.123)	0.293 (0.120)
Team productivity	0.099 (0.032)	0.100 (0.034)	0.099 (0.031)
Age	27.98 (3.89)	27.91 (3.34)	28.01 (4.11)
Total games	135.0 (23.6)	141.6 (21.1)	132.0 (24.0)
Roster stability	0.692 (0.156)	0.732 (0.147)	0.674 (0.157)
Gini	0.394 (0.097)	0.332 (0.079)	0.422 (0.092)
Gini Predicted	0.276 (0.078)	0.280 (0.091)	0.274 (0.071)
Gini Residuals	0.262 (0.075)	0.249 (0.071)	0.268 (0.076)

Table 7 Individual performance regressions, dependent variable is *ADJP48*

Variable	(1) Pooled OLS	(2) Fixed effects	(3) Fixed effects	(4) Fixed effects; treated players only
ADJP48 t – 1			0.136 (6.26)	0.183 (5.74)
Age	-0.0081 (1.30)	0.044 (7.46)	0.036 (6.26)	0.033 (4.43)
Age squared	0.00016 (1.50)	-0.00084 (8.16)	-0.00069 (6.94)	-0.00060 (4.92)
Total games	0.0012 (13.58)	0.0007 (9.44)	0.0006 (8.74)	0.0006 (6.53)
Change team	0.013 (1.66)	0.017 (3.32)	0.011 (3.43)	0.015 (2.25)
Roster stability	0.083 (6.24)	0.021 (2.71)	0.018 (2.35)	0.018 (1.74)
Team productivity	-0.698 (10.15)	-0.110 (2.41)	-0.104 (2.39)	-0.130 (2.15)
Gini predicted	0.197 (6.97)	0.036 (1.96)	0.035 (2.00)	0.039 (1.75)
Gini residuals	-0.025 (0.94)	0.016 (1.00)	0.019 (1.15)	0.025 (1.14)
Treat				0.019 (0.77)
*Treat*Post 1996*				-0.013 (1.88)
Team effects	No	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Player effects	No	Yes	Yes	Yes
N (observations)	3871	3871	3871	1969
N (players)	802	802	802	270
R^2	0.085	0.252	0.358	0.353