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# The Role of Expert Knowledge

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## ABSTRACT

# Why Do Leaders Matter? The Role of Expert Knowledge*

Why do some leaders succeed while others fail? This question is important, but its complexity makes it hard to study systematically. We examine an industry in which there are well-defined objectives, small teams, and exact measures of leaders' characteristics. We show that a strong predictor of a leader's success in year T is that person's own level of attainment, in the underlying activity, in approximately year T-20. Our data come from 15,000 professional basketball games. The effect on team performance of the coach's 'expert knowledge' is large and is discernible in the data within 12 months of his being hired.

JEL Classification: J24, M51

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**Why Do Leaders Matter? The Role of Expert Knowledge**

## 1. Introduction

Leaders matter. Little is known, however, about why some leaders are successful while others are not. This paper argues that leaders draw upon their deep technical ability in, and acquired expert knowledge of, the core business of their organization. In a setting where productivity can be measured in an unambiguous way, the paper shows that how well an organization performs in year T depends on the level of attainment -- in the underlying activity -- of its leader in approximately year T-20. Perhaps surprisingly, this idea has not been emphasized in the management literature on leadership.

Bertrand and Schoar (2003) demonstrate that CEO fixed effects are correlated with firms' profitability. Their study is important because it suggests that individuals themselves can shape outcomes. However, as the authors explain, it is not clear why this happens. Their evidence establishes that MBA-trained managers seem particularly productive (in the sense that they improve corporate returns), but cannot reveal the mechanisms by which this happens. Jones and Olken (2005) examine the case of national leaders. By using, as a natural experiment, 57 parliamentarians' deaths, and economic growth data on many countries between the years 1945 and 2000, the authors trace linkages between nations' leaders and nations' growth rates. The authors reject 'the deterministic view … where leaders are incidental'. Despite its creativity, this paper also leaves open the intellectual question: what is it about leaders that makes them effective or ineffective? Work by Bennedsen, Perez-Gonzalez and Wolfenzon (2007) spans these two earlier papers by establishing, in Danish data, that the death of a CEO, or a close family member, is strongly correlated with a later decline in firm profitability[1]. This, again, seems to confirm that leaders matter to the performance of organizations.

[1] Focusing on family businesses, Pérez-González (2006) and Bennedsen et. al. (2007) also show that firms that select CEOs from among family members, as compared to those hired from outside, are more likely to have poor performance.

Theoretical explorations of leadership are offered by Hermalin (1998, 2007), who focuses on the incentives used by leaders to induce followers to follow; by Majumdar and Mukand (2007), who construct a model in which a key role is played by followers' willing to put their faith in the their leader; by Dewan and Myatt (2008), who concentrate on the role played by a leader's ability, and willingness, to communicate clearly to followers; by Rotemberg and Saloner (2000), who study the theoretical effects of a visionary leader in setting incentives for innovation; and by Dai, Lewis and Lopomo (2006), whose theoretical model stresses the superior information held by expert managers. However, closer in spirit to our later results is empirical work on the role of expert knowledge by Goodall (2006, 2008). She studies the performance of the world's top research universities. Goodall finds a positive cross-section correlation between the scholarly quality of presidents and the academic excellence of their institutions, and some evidence, for a set of British universities, that those led by highly cited scholars show improved performance over the ensuing decade.

In complex settings, where leaders command thousands or even millions of people, it is likely to be difficult to discern the reasons for those individuals' effects. The remainder of the paper therefore draws on an industry in which team size is small and objective data are plentiful. Our setting is that of US professional basketball. We measure the success of National Basketball Association (NBA) teams between 1996 and 2003, and then attempt to work back to the underlying causes. We have information on 15,040 regular season games for 219 coach-season observations, for which we compute winning percentages; in addition, we study post-season playoff success for these coaches. Perhaps unsurprisingly, a main explanatory factor is the quality of the group of players. But, less predictably, there seem also to be clear effects from the nature of a team's coach. Teams perform substantially better if led by a coach who was, in his day, an outstanding player. This correlation is, to our knowledge, unknown even to experts in basketball (perhaps because, without statistical methods, it is hard to glean from even detailed day-to-day observation of the sport).

The paper's empirical contribution is to document the existence of a correlation between brilliance as a player and the (much later) winning percentage or playoff success of that person as a coach. Such a correlation, no matter how evocative of cause and effect, might be an artefact. When we probe the data, however, there seem strong grounds for believing in a causal chain.

First, we demonstrate that the correlation is robust to the inclusion of team fixed-effects and other inputs affecting team success.

Second, once we isolate the exact years in a team's history when a new coach arrived, we find evidence of an immediate effect. The extent of improvement in the team over the ensuing 12 months is strongly correlated with whether the new appointee had himself once been a top player. The size of the effect is substantial: for the performance of a team, the difference between having a coach who never played NBA basketball and one who played many years of NBA allstar basketball is, on average, approximately six extra places up the NBA league table. This is a large effect given the league's size of 29 teams during our sample period.

Third, our results are robust to adjustments for the endogeneity of coaching and playing quality, as indicated by instrumental variables (IV) analyses. When, for example, the top-player variable is instrumented by ones for height, position on the court, and whether the coach was born or went to college in the state where the team is located, robust results are found. We also show in an Appendix that re-doing the analysis with birth-year dummies as additional instruments yields the same basic findings.

## 2. A framework

Our ultimate goal is to estimate the impact of expert leaders on an organization's output. However, factors of production, including the quality of leadership, are chosen by the firm, potentially leading to endogeneity biases in estimating production functions. One therefore needs a framework for understanding the economics of this choice before turning to the data. Let coaches be indexed by i, players by j, and teams by $\tau$. Teams play in locations that have variable amenity (that is, non-pecuniary) value to everyone. Through the season, luck matters. There is some random element, e, with density function f(e). A team at the outset buys a pool of players with total ability a, and buys coaching quality q. Players' ability is rewarded at wage w; coaching quality is rewarded at rate per-unit-of-quality at salary s. The performance of a team is given by function $p = p(a, q, e)$ which is increasing in players' total ability a, and coach quality q, and is affected by the random shock e.

Entrepreneur owners run teams. They have a utility function $R = r(p) - wa - sq$ where r(p) is an increasing concave function of performance, wa is the player wage bill, and sq is the coach salary bill. Ceteris paribus, the entrepreneurs like to win, but do not like paying the costs of team and coach. Players playing for team $\tau$ get utility $v = v(w, \tau)$ where $\tau$ stands in for amenity factors like the niceness of the local climate in that team's geographical area. Without loss of generality, we can order teams in such a way that higher $\tau$ stands for higher utility ceteris paribus. For simplicity only, assume a separable utility function $v = \mu(w) + \tau$. Here the utility element $\mu(.)$ is assumed concave in income.

Coaches get utility $u(s, \tau, i) = \mu(s) + \tau + n(\tau, i)$ where n is to be thought of as a small idiosyncratic non-pecuniary preference, by coach i, for a particular team $\tau$. Assume that these n(..) preferences are observable to the entrepreneur owners of the teams; they might be due to nostalgia, caused by the past, for a particular area. In many cases the value of $\tau$ will be zero, meaning that coaches are indifferent across such teams. Coaches as a whole are a 'thin' market, so individual n(..) preferences may matter. By contrast, the market for players is a thick market. The $\tau$ non-pecuniary preferences are known by everyone, and common to coaches and players.

While leagues control the number of teams allowed in (thus potentially producing monopoly profits), we assume that individual entrepreneurs are free to buy and sell their teams (this is approximately true in the case of professional sports, where the league gives approval to team sales). Thus, including the costs of purchasing the team, there will be an equilibrium utility R* for potential entrepreneurs seeking to enter the industry. Coaches are mobile and in principle can go anywhere. Thus, there will also be an equilibrium utility u* for coaches of a given quality. The same reasoning will apply to free-agent players, who are comprised of those with at least 3-4 years of NBA playing experience (Kahn and Shah 2005). For players who are not free agents, we make the Coasian assumption that, through trades and sales of player contracts, they will be allocated efficiently, after taking into account their preferences for location as well as their playing ability.[2] These assumptions lead to the conclusion that player allocation will be the same as if all players were free agents and had achieved the same equilibrium utility level v* given their ability.[3]

The entrepreneur can, if wished, tie wage w and salary s to the random component e. Call these functions w(e) and s(e). Consider the benchmark case where the n(τ, i) preferences are zero. The entrepreneur chooses player-pool ability a, coach quality q, wage function w(e) and salary function s(e), to

$$Maximize \int [r(p(a,q,e)) - wa - sq] f(e) de$$

*subject to*

$$\int uf(e)de \geq u^*(a) \qquad (1)$$

$$\int \mathrm{vf(e)de} \geq \mathrm{v^*(q)}, \qquad (2)$$

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[2] Our assumption of the separability of player (and coach) utility with respect to income and location implies that there will be no wealth effects on player location. Therefore, free agency, which is expected to raise player wealth, will not affect the willingness to pay to be located in a particular area. Kahn (2000) surveys evidence on the Coase Theorem in sports and concludes that most research indeed finds that the advent of free agency has not affected competitive balance, as the Coase Theorem predicts.

[3] While coaches' and players' salaries are undoubtedly much greater than those in the outside world, in our sample period, there were only roughly 400 playing and 29 head coaching jobs in the NBA. Thus, an equilibrating mechanism that leads to a relationship between utility in other jobs and in the NBA features

where u* and v* are written as functions of the two kinds of ability, a and q. These constraints hold for each a and q. In equilibrium, we have four first-order conditions:

$$\int [\partial r / \partial q - s] f(e) de = 0 \qquad (3)$$

$$\int [\partial r / \partial a - w] f(e) de = 0 \qquad (4)$$

$$-q + \lambda \partial u / \partial s = 0 \quad \textit{for each state of nature e} \qquad (5)$$

$$-a + \rho \partial v / \partial w = 0. \quad \textit{for each state of nature e} \qquad (6)$$

Here lambda and rho are multipliers on the two expected utility conditions above.

The optimal wage w and the salary s will thus not be contingent on e in this setup. From the mathematics, q and a are fixed before the state of nature e is revealed, and lambda and rho are independent of e, so the last two first-order conditions are independent of e. Intuitively, because owners are risk neutral and because our simplified model assumes away problems eliciting effort from players or coaches, compensation will not be state-contingent. There may in principle be rents here that have to be divided between entrepreneurs and coaches. Although everyone has to be rewarded or penalized for the amenity value of the team's location, rents could flow from the small n(..) preference of coaches. One route is to assume entrepreneurs get to keep the whole rent. The characteristics of the framework are then: People get hired at the season's start, before e is known. The optimal player wages w and coach salary s are independent of the state of nature, e. There is a version of an expected marginal product = marginal cost condition. Player wages are higher in worse locations. Coach salaries are higher in worse locations.

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the very low probability of entry into the league, counterbalanced by the high earnings in the NBA given entry. Aidt et al (2007) show that sports managers' tenures generically follow a power law.

Better players (higher ability a) earn more (higher w). Better coaches (higher quality q) also earn more (higher s).[4]

With one exception, coaches spread themselves evenly geographically. The exception is that they have a small non-pecuniary preference for certain teams, and are thus willing to accept a lower salary at a team for which they have a positive non-pecuniary preference, in a way that is determined by the rate of substitution between income and amenities along an iso-utility level in the implicit function: $\mu(s) + \tau + n(\tau, i) - u^* = 0$.

These idiosyncratic n(..) preferences provide a way to think about how econometrically to identify the p equation. Whenever rents are partially divided between the coaches and the entrepreneur owners -- in the spirit of the rent-sharing evidence in other labor markets, such as in Blanchflower et al (1996) and Hildreth and Oswald (1997) -- then coaches will take jobs disproportionately with the teams for which they have some n-preference. These n-preferences, by assumption, are features of the utility function alone, and do not directly affect coaches' productivity.

## 3. Data and Empirical Procedures

To study the impact of playing ability on coaching success, we use data drawn from *The Sporting News Official NBA Guide* and *The Sporting News Official NBA Register*, 1996-7 through 2003-4 editions, as well as the basketball web site: http://www.basketball-reference.com/. These sources have information on coaches' careers as well as current team success and other team characteristics. We supplement this information with data on team payroll, taken from Professor Rodney Fort's website, http://www.rodneyfort.com/SportsData/BizFrame.htm.

### A. Basic Approach

[4] Since players and coaches are willing to take less money to play in better locations (with a higher $\tau$), teams can make more money there, all else equal. We assume that the league will allow team relocation to proceed to take advantage of the coaches' and players' locational preferences. As more teams enter the favorable locations, the revenues per team there will deteriorate, providing an equilibrating mechanism.

The main empirical setup, which mirrors the p(a, q, e) function assumed in the previous section, is a production function approach:

$$wpct_{\tau t}=a_0+a_1 playerpay_{\tau t}+a_2 coachexpert_{\tau t}+b_\tau+u_{\tau t}, \qquad (7)$$

where for each team τ and year t, we have: wpct is the team's regular season winning percentage, playerpay is the log of the team's payroll for players minus the log of the mean team payroll for all teams for that season, coachexpert is a dummy variable indicating whether the coach was ever an allstar player in the NBA minus the mean value for that variable across teams for that year, b is a team fixed effect, and u is a disturbance term. Win-percentage equations, with the wage bill included as a variable, are discussed for a range of sports settings in, for example, Szymanski (2000, 2003).

In equation 7), the measure of output, the team's regular season winning percentage, is a clear measure of team success. However, as discussed below, we also experimented with an alternative measure of output—playoff performance in the current season. Both of these dependent variables are relative measures of success. Specifically, the mean winning percentage for a season must be .5, and in each season, exactly sixteen teams make the playoffs, which operate as a single elimination tournament with four rounds. Inputs include the team's playing ability and the coach's playing expertise. Because the dependent variables are defined as within-year relative success (regular season or playoff), we define the inputs similarly. Our maintained hypothesis is that better quality players earn higher salaries, which can then be used as an indicator of playing skill.[5] The measure of playing skill is that team's payroll relative to the league average for that year.

Our measure of playing expertise of the coach is intuitive as well: we wish to test whether ability as a player leads to greater success for a coach controlling for other

[5] Several studies of individual player salaries in the NBA over the 1980s, 1990s and 2000s support the idea that playing ability is amply rewarded. See, for example, Kahn and Sherer (1988), Hamilton (1997), or Kahn and Shah (2005). The classic original article on sport labor markets is Rottenberg (1956); modern analyses are provided by Kahn (2000) and Rosen and Sanderson (2001).

inputs. As was the case for the dependent variable, we also experimented with various measures of the coach's playing expertise, including the number of times the coach was named to the NBA allstar team, and also the number of NBA seasons played. In each of these alternative specifications, the coach's playing ability is measured relative to other coaches that season. The incidence or total of allstar team appearances is an indicator of playing excellence. In addition, the total years of playing experience is likely to be a mark of playing skill because of learning on the job; moreover, only the best players are continually offered new playing contracts and thus the opportunity to play for many seasons. Because of the high level of player salaries relative to other occupations, we can infer that player exit from the NBA is typically caused by injury or insufficient skill rather than by the location of better earning opportunities in other sectors (for healthy players offered NBA contracts). Hence players with longer careers will be positively selected.

Equation 7) also includes a vector of individual team dummy variables. These can be interpreted as measuring other factors of production such as arena type (some arenas may produce a greater advantage to the home team, for example) or influence of the front office in selecting players, trainers, etc.

As in basic production function analyses, all inputs are endogenous, since the firm chooses them and the output level, and there may be nonrandom matching between coaches and teams, as suggested in the equilibrium model outlined earlier. In addition, our measure of coaching quality may contain errors. Therefore, in some analyses, we provide instrumental variable (IV) estimates, where we use the following instruments for relative player payroll and coaching playing expertise: i) lagged relative payroll, ii) the coach's height if he played in the NBA (defined as zero for those who did not play in the NBA), iii) a dummy variable for playing guard in the NBA, iv) a dummy variable for having been born in the state where the current team is located; and, v) a dummy variable for having attended college in the state where the current team is located. As above, these variables are all defined relative to their within-season means. Lagged payroll may be an indicator of the underlying fan demand for team quality, which will then affect the level of the inputs chosen, while player height and position together may influence a player's being named to the allstar game or career length and thus serve to correct measurement errors in relating allstar status or career length to true underlying playing ability. Having been born in or attended college in the current team's state may be an indicator of willingness to supply coaching talent.

As a robustness check, we also report in the Appendix further results where the list of instruments is augmented with a series of birth-year dummy variables for the coach. The idea here is that changes in league size as well as the opening of new sources of playing talent such as foreign players exogenously affect opportunities to accumulate NBA playing experience. We use a full set of birth-year dummy variables in order to allow such factors to take the most flexible functional form possible. For example, coaches whose prime playing ages occurred when there were more jobs available (relative to the available supply of playing talent) are expected to have longer NBA playing careers, all else equal. In these supplementary analyses, we control in the performance equations for age and age squared so that there may be no direct effect of the birth year dummies on performance through age, although the results were very similar when we did not add these age and age squared controls. League size has a more ambiguous effect on allstar appearances than on NBA career length, since the size of the allstar team has remained constant over time. Thus, on the one hand, as the league grows, individuals may have longer careers (giving them more chances to be an allstar); on the other hand, a larger league size reduces the likelihood of being selected to the allstar team in any given year (reducing one's chances of being an allstar). Therefore, these birth-year instruments are more conceptually appropriate for the NBA playing career length specification of the coach's playing expertise, although, as will be seen below, the results are similar using any of the three indicators of the coach's playing ability.

**B. Alternative Specifications**

As noted, team regular season winning percentage is our basic measure of output. However, since, ultimately, winning the championship is the highest achievement a team can attain, we also in some models define output as the number of rounds in the playoffs a team survives in a particular season. As mentioned, in each season, 16 teams make the playoffs. We therefore define a playoff round variable:

playoffrd=

0 if the team did not make the playoffs that year

1 if the team lost in the first playoff round

2 if the team lost in the second round

3 if the team lost in the third round

4 if the team lost in the league finals

5 if the team won the championship.

Because of the ordinal nature of the playoff-round variable, we estimate its determinants using an ordered logit analysis. For the instrumental variables analysis with the playoff-round dependent variable, we form the predicted values of team relative payroll and coach's playing expertise. We then use these predicted values in the ordered logit and construct bootstrapped standard errors, with 50 repetitions.

Our basic two-factor production function model assumes that all information about coaching expertise is contained in the coachexpert (or playing experience) variable. However, we have a variety of information on coaches' careers that in some analyses we use as controls. These include coach's race (a dummy variable for white coaches), age, age squared, years of NBA head coaching experience and its square, years of college head-coaching experience, years of head-coaching experience in professional leagues other than the NBA, and years as an assistant coach for an NBA team, all measured as deviations from the within-season mean. We do not include these in the basic model because they are also endogenous in the same way that the other inputs are. Moreover, since playing occurs before coaching, these additional controls themselves can be affected by the coach's playing ability. Their inclusion, therefore, may lead to an understatement of the full effects of the coach's playing expertise. As shown below, however, our results for the coach's playing ability hold up even when we add these detailed controls for coaching experience, although with such a large number of potentially endogenous variables, IV estimates cannot be implemented.

**4. Empirical Results**

Figures 1-6 show descriptive information on coaching success and two of our measures of the coach's playing ability: i) an indicator for having been an NBA allstar player, and, ii) an indicator for having been an NBA player. Our basic sample includes 219 coach-season observations on a total of 68 NBA coaches. Fifty-two of these coaches were never NBA allstars, and they account for 153 of the 219 observations, or about 70%; the other 16 coaches were allstar players, accounting for 66 coach-seasons. There were 26 non-players, accounting for 75 observations (34% of the sample) and 42 former NBA players making up the remaining 144 cases. These Figures are consistent with Kahn's (1993) findings for baseball that managers (who are in an equivalent position to head coaches in basketball) with more highly rewarded characteristics (such as experience and past winning record) raise the performance of teams and individual players. Like the work cited earlier on leader effects, Kahn (1993) does not explore the possible mechanisms through which successful coaches raise player performance.

Figure 1 provides simple evidence that outstanding players go on to be the most effective coaches. It shows gaps of 6-7 percentage points in team winning percentage favoring former NBA allstar players vs. non-allstars (whether or not they played in the NBA) or former NBA players vs non-players. These differentials are both statistically significant at better than the 1% level (two tailed tests) and are about 1/3 of the standard deviation of winning percentage of about 0.17. Figure 2 shows similar comparisons of playoff success by the coach's playing ability. Coaches who were allstars go an average of 0.13 rounds further than non-allstars in the playoffs, a small differential that is statistically insignificant. However, former NBA players who now coach advance 0.4 rounds further in the playoffs than non-players, a difference that is statistically significant at the 3.2% level.

Figures 3 and 4 reveal the same pattern as Figures 1 and 2. Here the sample is restricted to coaches who are in their first year with the team. For this subgroup, any accumulated success or failure of the team prior to the current season is not directly due to the current coach's efforts as a head coach. First-year coaches have worse success than average coaches, as indicated by the lower values of winning percentage and playoff success in Figures 3 and 4 compared to those in Figures 1 and 2. But, strikingly, playing ability apparently helps new coaches by at least as much as it does for the average coach. The differentials in Figures 3 and 4 all favor former allstars or former players and are larger in magnitude than those in Figures 1 and 2. For example, Figure 3 shows winning percentage differentials favoring better players of 7-12 percentage points, effects which are significant at 1% (allstars vs. non-allstars) or 10% (players vs. non-players). Figure 4 shows that among coaches in their first year with the team, better players advance 0.31 (allstars vs. non-allstars) to 0.54 (players vs. non-players) rounds further in the playoffs, with the latter differential significant at 4%. In fact, the figure shows that, of the (seventeen) cases where a team was taken over by a new coach who was a non-player, none made the playoffs in the coach's first year with the team.

Finally, Figures 5 and 6 contrast team winning percentage (Figure 5) and playoff success (Figure 6) before and after the arrival of a new coach by the coach's playing experience. In order to smooth out the data, given the small number of cases in which a team is taken over by a new coach (56), we present two-year moving averages in Figures 5 and 6. For example, the values for 2 years before the arrival of the new coach ("-2") are the average outcomes for 2 and 3 years before the coach's arrival. The values for year 1 are the average outcomes for one and two years after the coach's arrival. Figure 5 shows that before the new coach arrived, the team winning percentage was similar for teams that were about to hire nonplayers (0.42-0.45) vs. teams that were about to hire former NBA players (0.43-0.46). After the coach arrived, the team's winning percentage rose steadily over the next 3-4 years from an initial pre-arrival level of 0.43 to a level of 0.51 if the coach was a former NBA player; however, if the new coach was not a former NBA player, winning percentage initially fell by one percentage point to 0.41, with no apparent trend over the next 3-4 years.[6]

Figure 6 provides complementary evidence. It shows that before the coach's arrival, the teams that were about to hire nonplayers actually had slightly higher playoff success (0.71-0.79) than teams that were about to hire former NBA players as their coach (0.56-0.72). After the coach's arrival, playoff success rose steadily to 1.09 for teams hiring former NBA players; in contrast, for teams hiring coaches who never played in the NBA, playoff success initially plummeted to 0.29 in the first two years before rising to roughly 0.6 in years 2-4. Both Figures 5 and 6, then, indicate that teams hiring former NBA players show steady improvement in the 4 regular seasons and playoff competitions after the new coach's arrival relative to their performance before hiring the new coach. But when a team hires a coach who never played in the NBA, team performance immediately deteriorates, and even after 3-4 years does not reach the levels attained before the coach's arrival.

While Figures 1-6 show evidence suggesting that expert players make better coaches, the figures do not control for other influences on team success or for the endogeneity of matching between coach and team. We now turn to regression evidence that accounts for these factors. Table 1 contains ordinary least squares (OLS) results for team winning percentage (standard errors are clustered at the coach level). The top portion of the table measures the coach's playing ability as the total years as an NBA player, while the next portion uses the number of times he was an NBA allstar player, and the last panel uses a dummy variable indicating that he was ever an NBA allstar player. For each of these definitions of playing ability, there are four models shown: i) excluding other coach characteristics and excluding team dummies; ii) excluding other coach characteristics and including team dummies; iii) including other coach characteristics and excluding team dummies; iv) including both.

[6] Figures 5 and 6 give winning percentages and playoff success for each team for 3-4 years after the coach's hiring regardless of whether the new coach stayed with the team. We follow this procedure

For the two allstar specifications, greater playing ability among coaches is associated with a raised team winning percentage, usually by a highly statistically significant amount. For example, hiring a coach who was at least once an NBA allstar player raises team winning percentage by 5.9 to 11.4 percentage points. To assess the magnitude of these effects, we estimated a simple regression of 2003-4 gate revenue (millions of dollars) on team winning percentage (ranging from 0 to 1) and obtained a coefficient of 46.5 (standard error 15.3). According to this estimate, hiring a coach who was an allstar player at least once raises team revenue by $2.7 million to $5.3 million, all else equal, relative to one who was never an NBA allstar. This estimate of the marginal revenue product of the coach's playing ability of course does not control for other potential influences on revenue. However, it does illustrate the size of the estimates. In addition, a 5.9-11.4 percentage point effect on winning percentage is sizeable relative to the standard deviation of winning percentage in our sample of 17 percentage points. Recall that the raw differential in winning percentage between allstars and non-allstars as shown in Figure 1 is about seven percentage points. The 5.9-11.4 range of regression estimates in Table 1 implies that the raw differential is not caused by spurious correlation with other variables.

In the specifications in Table 1 using total years as an NBA allstar player, the effects range from 0.7 to 2.3 percentage points and, as mentioned, have small standard errors. Compared to hiring a coach who was never an NBA allstar player, hiring a coach who was an NBA allstar player for the average number years among allstars (4.9) appears to increase the winning percentage by 3.4 to 11.3 percentage points. The implied marginal revenue products of a coach who was an NBA allstar player for the average number of allstar appearances among this group are $1.6 million to $5.3 million, relative to a non-allstar.

Finally, using total years as an NBA player, we find coefficient estimates in Table 1 ranging from 0.003 to 0.009, effects which are significant twice, marginally significant once, and insignificant twice. The average playing experience among former players is

because the coach's future tenure with the new team is endogenous to the team's success.

10.47 years. Thus, Table 1 implies that hiring a former player with average playing experience raises winning percentage by 3.1 to 9.4 percentage points relative to hiring a nonplayer. These effects are slightly smaller than the effects of hiring a former allstar.

In other results in Table 1, a higher team payroll has significantly positive effects on winning percentage. The implied marginal revenue products of a 10 percent increase in team relative payroll are $539,400 to $1.288 million. Since the mean payroll is about $44 million, this result could imply that teams overbid for players. Potentially, players may have entertainment value beyond their contribution to victories. Among other results in Table 1, prior coaching experience at the professional level appears to contribute positively to victories. This may be due to actual on-the-job learning or to selectivity effects in which the good coaches are kept in the league. In either case, the impact of the coach's playing ability is robust to inclusion of these other controls. Controlling for the team's payroll implicitly takes account of a possibly spurious relationship between hiring a coach who was an allstar or a former NBA player and team success. Specifically, it is possible that a coach who was a famous player attracts new fans who have a high demand for winning. The team may then find it profitable to hire better players than otherwise. However, since we have controlled for team payroll, our findings for the coach's playing expertise cannot be explained by this possible phenomenon.

Table 2 contains instrumental variables (IV) estimates for the effects of the coach's playing ability and team payroll on victories. Whether or not we control for team fixed effects, the impact of the coach's playing ability is larger than in the OLS results. When we do not control for team fixed effects, the impact of the coach's playing ability is significantly different from zero at all conventional confidence levels; when we do control for team fixed effects, the positive impact of the coach's playing ability is significant at levels between 3.6 and 9.1%. Team payroll effects are positive in each case and are larger than in the OLS results. They are significant in each case except for the specification which includes team fixed effects and total years as an NBA allstar player, in which case the coefficient is about the same size as its asymptotic standard error. Overall, Table 2 suggests that the positive point estimates for the impact of the coach's playing ability on team winning percentage are robust to the possible endogeneity of the team's inputs.[7]

Table 3 provides ordered logit estimates for playoff performance, an alternative indicator of team output. As mentioned earlier, the dependent variable has a minimum value of 0 (not making the playoffs), and increases by 1 for each round a team survives, up to a maximum of 5 for the league champion. The effects of the coach's playing ability are always positive, and they are usually statistically significant for the number of all star teams specification. When we measure coaching ability by number of seasons played, the impact on playoff success is highly significant twice and marginally significant twice, but the impact is only marginally significant twice in the "Coach Ever an NBA Allstar Player" specification. To assess the magnitude of the coefficients, it is useful to note the cutoffs for the ordered logit function. Looking at the first column, the effect on the logit index of being on at least one NBA allstar team is 0.575. The difference in the cutoff for making it to the league finals (2.868) and losing in the semifinals (2.055) is 0.813. Therefore, this estimate of the impact of coaching ability implies that adding a coach who was an NBA allstar player at least once is enough to transform the median team that loses in the semifinals (i.e. is at the midpoint of cutoffs 3 and 4) into one that makes it to the finals and then loses. In general, this effect is large enough to increase the team's duration in the playoffs by at least one half of one round. The other point estimates in Table 3 are qualitatively similar to this one: adding a coach who was an allstar player (or one who has the average number of allstar appearances among the allstars) is sufficient to raise the playoff duration usually by at least one half round, and in the last specification, by one round. Hiring a former player at the mean years of playing time usually is enough to increase one's playoff success by a full round.

Table 4 shows IV results for the determinants of playoff success. The point estimates are considerably larger than Table 3's ordered logit results. Moreover, the effects are statistically significant whether or not we include team dummy variables. Overall, the

[7] Table A1 shows first stage regression results for the determinants of coach playing ability and team relative payroll. It shows that coach height and lagged relative payroll are especially strong instruments.

point estimates in Table 4 show that adding an allstar coach or adding a coach who played in the NBA is associated with a longer expected duration in the playoffs, usually by at least one full round.

As noted, we also in some analyses used individual birth year dummy variables as additional instruments for the coach's playing ability. The results are shown in Appendix Tables A2 (current winning percentage) and A3 (playoff success). The results are very strong in each case where we do not control for team dummy variables: specifically, they reveal a sizable and highly significantly positive effect of the coach's playing ability on team performance. When we control for team dummies in Tables A2 and A3, we obtain qualitatively similar results, although the coefficients are now only about 1.5-2.1 (winning percentage in Table A2) or 1.28-1.68 (playoff success in Table A3) times their asymptotic standard errors. But the basic findings are robust to this alternative set of instruments.

Another way to try to understand causality is to examine what happens immediately after a new coach arrives. In our data, we have 56 coach-season observations on coaches who are in their first year with the team. This sample size limits the degree to which we can control for other influences on team success. Nonetheless, it is instructive to study the impact of the playing ability of the new coach on these teams in the first year of the team-coach match. In Tables 5 and 6, we show the results of regression models for team regular season winning percentage (Table 5) and playoff success (Table 6) during these seasons. Because average winning percentage among this sample is no longer 0.5 and because playoff success among this group can vary across years, we include raw variable values (i.e. not differences from the within-year mean) and include year dummies in the statistical models. In addition to these, we control for the previous season's winning percentage (top panel) or this variable plus the current season's relative payroll for players (bottom panel). By holding constant the team's past success and its current relative payroll, we effectively correct for the resources the new coach has to work with when he takes over. When we do not control for current payroll, we allow the coach to influence the quality of players through trades, drafting of rookies and free-agent signings.

Table 5 shows that adding coaches who were allstars seems immediately to improve the winning percentage over what the team had accomplished in the previous year, whether or not we control for current payroll.[8] Adding a former player as the coach also has a positive coefficient, although it is only slightly larger than its standard error. Finally, Table 6 reveals that adding a coach who was an allstar player or who had played in the NBA previously is always associated with a positive effect on playoff success in the first year, although this effect is significantly different from zero only when we measure playing ability as the number of years the coach was an NBA allstar.[9] Tables 5 and 6 together provide evidence that adding a coach who was an expert player is correlated with later improved team performance, all else equal, as also suggested in the raw data shown in Figures 5 and 6.

An alternative interpretation of the results in Tables 5 and 6 is that teams having temporarily bad results deliberately hire a former allstar player as their next coach. In the following year, the team's success reverts to its long run trend, and this produces a potentially positive, spurious correlation between having a former allstar player as one's new coach and the team's improvement. However, our earlier IV analyses control for the endogeneity of the coach's playing ability.[10] Moreover, unless the paper's key idea -- that better players make better coaches -- were true, it is not easy to see why such teams would systematically seek out the former top players from the pool of potential coaches.

## 5. Conclusion

[8] Estimating the basic regression models in Tables 1 and 3 excluding the current payroll yielded very similar results.

[9] As Table 6 shows, none of the new coaches led a team that lost in the finals in his first year. There are therefore only four possible playoff rounds achieved in this sample in addition to the no-playoff outcome. Further, results for the coach's playing ability were virtually identical when we replaced past winning percentage with past playoff success.

[10] Moreover, even this scenario in which the correlation in Tables 5 and 6 is spurious requires that the team believes that hiring an expert will rectify the team's poor performance.

New work in economics seeks to understand whether leaders matter. The evidence suggests that they do. What is not understood, however, is exactly why and how. To try to make progress on this research question, we draw on data from an industry where there are clear objectives, small teams of workers, and good measures of leaders' characteristics and performance. Our work confirms, in a setting different from those of papers such as Bertrand and Schoar (2003) and Jones and Olken (2005), that leader fixed-effects are influential. However, the principal contribution of the paper is to try to look behind these fixed effects. We find that a predictor of a leader's success in year T is that person's own level of attainment, in the underlying activity, in approximately year T-20. Our data are on the outcomes of approximately 15,000 US professional basketball games. Ceteris paribus, we demonstrate, it is top players who go on to make the best coaches. This 'expert knowledge' effect appears to be large, and to be visible in the data within the first year of a new coach arriving (see, for instance, Figures 3, 5 and 6). For the typical team, the difference between having a coach who never played NBA basketball, and one who himself played many years of allstar basketball, is approximately six extra places up the league table.

Might it be that the level of a coach's acquired skill and deep knowledge is not truly the driving force behind these results, but rather merely that some 'tenacious personality' factor (or even a genetic component) is at work here, and this is merely correlated with both a person's success as a coach and having been a top player in his youth? It could. There are, however, reasons to be cautious of such an explanation. One is that it is hard to see why mystery personality factor X should not be found equally often among those particular coaches -- all remarkable and extraordinarily energetic individuals -- who did not achieve such heights as players. A second is that every social-science discovery is subject to some version of this -- essentially unfalsifiable -- claim. A third is that we have found, in a way reminiscent of the education-earnings literature in economics, that extra years of the 'treatment' are apparently related in a dose-response way to the degree of success of the individual.

Finally, even if we accept the finding that the coach's skill as a player is the driving force behind our major finding, there are several routes through which this effect can operate. First, it is possible that great players have a deep knowledge of the game and can impart that to the players they coach. It is also possible that this expert knowledge allows coaches who were better players to devise winning strategies since they may be able to "see" the game in ways that others cannot. Second, formerly great players may provide more credible leadership than coaches who were not great players. This factor may be particularly important in the NBA where there are roughly 400 production workers recruited from a worldwide supply of thousands of great basketball players. These 400 earn an average of $4-$5 million per year.[11] To command the attention of such potentially large egos, it may take a former expert player to be the standard bearer, who can best coax out high levels of effort. Third, in addition to signaling to current players that the owner is serious about performance by hiring a coach who was a great player, there may also be an external signaling role for such a decision. Specifically, having a coach who was a great player may make it easier to recruit great players from other teams.

While the setting for our study is a particular industry -- professional basketball -- our findings may be relevant to a range of high-performance workplaces where the employees are experts. These potentially include professional-service firms such as law and accounting practices, universities, cutting-edge technology companies, and R&D organizations.

[11] See, for the example the *USA Today* salaries database at: http://content.usatoday.com/sports/basketball/nba/salaries/default.aspx.

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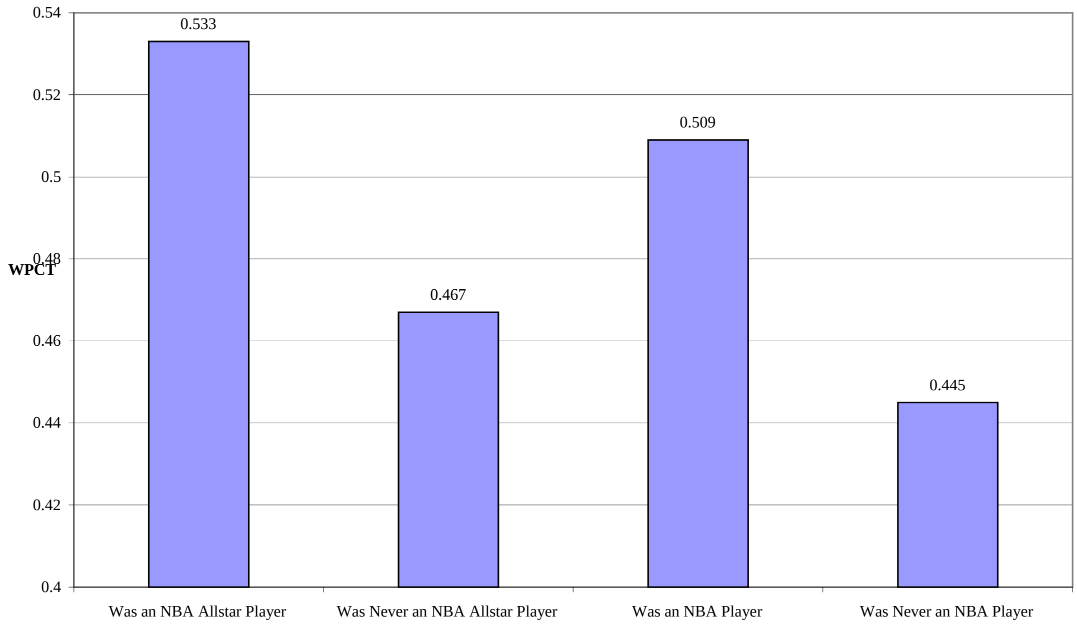
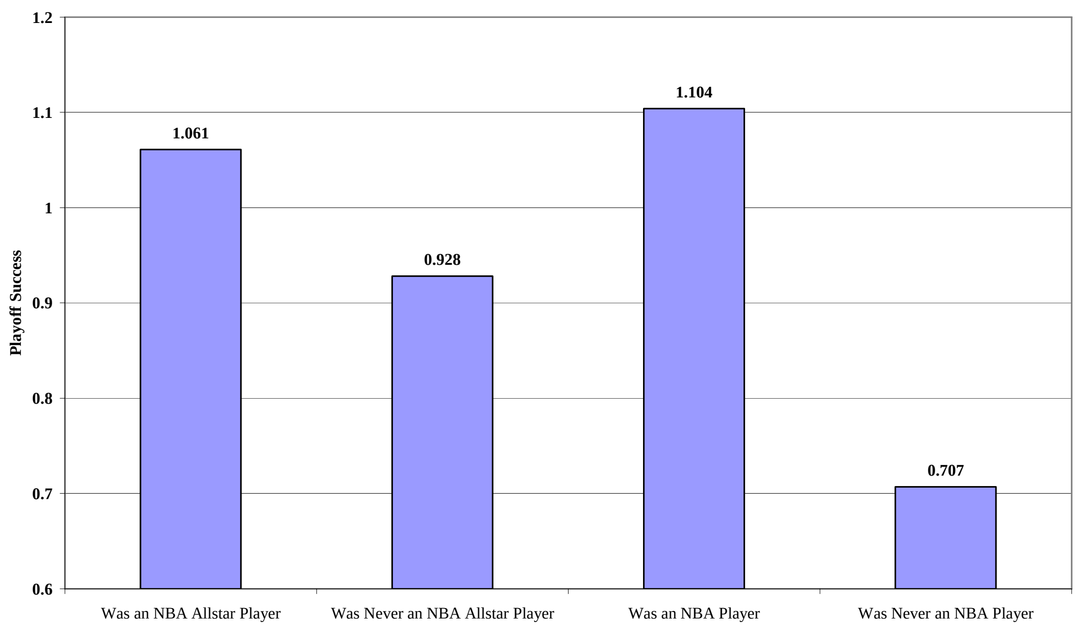
**Figure 1**
**Team's Regular-Season Winning Percentage (WPCT) by Coach's Former NBA Allstar and Player Status**



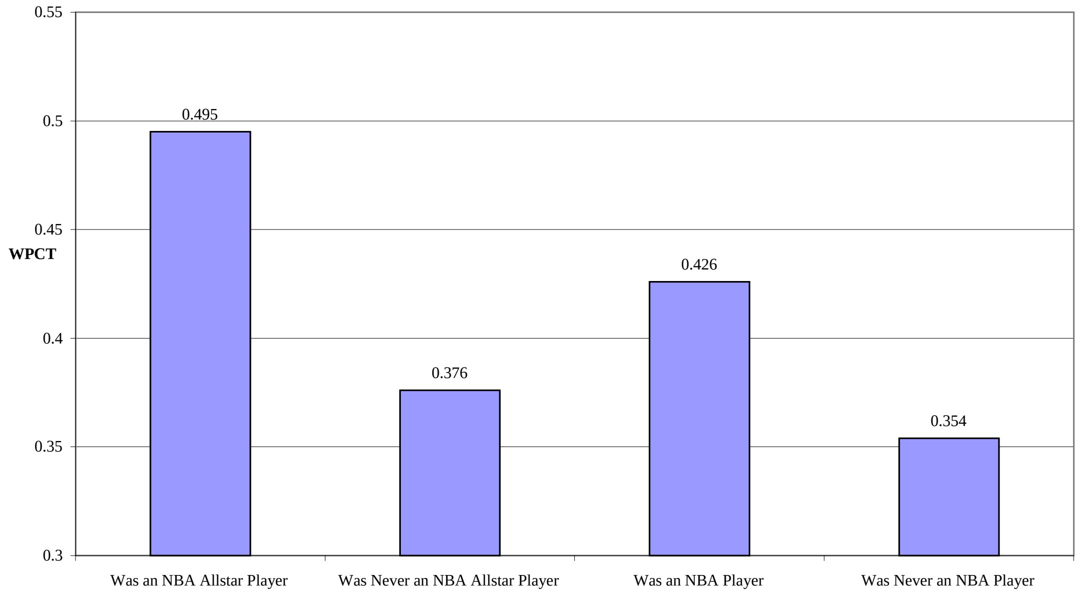

Note to Figure 1: both differences are statistically significant at the 1% level (two-tailed tests).

**Figure 2**
**Playoff Team Success by Coach's NBA Allstar and Player Status**



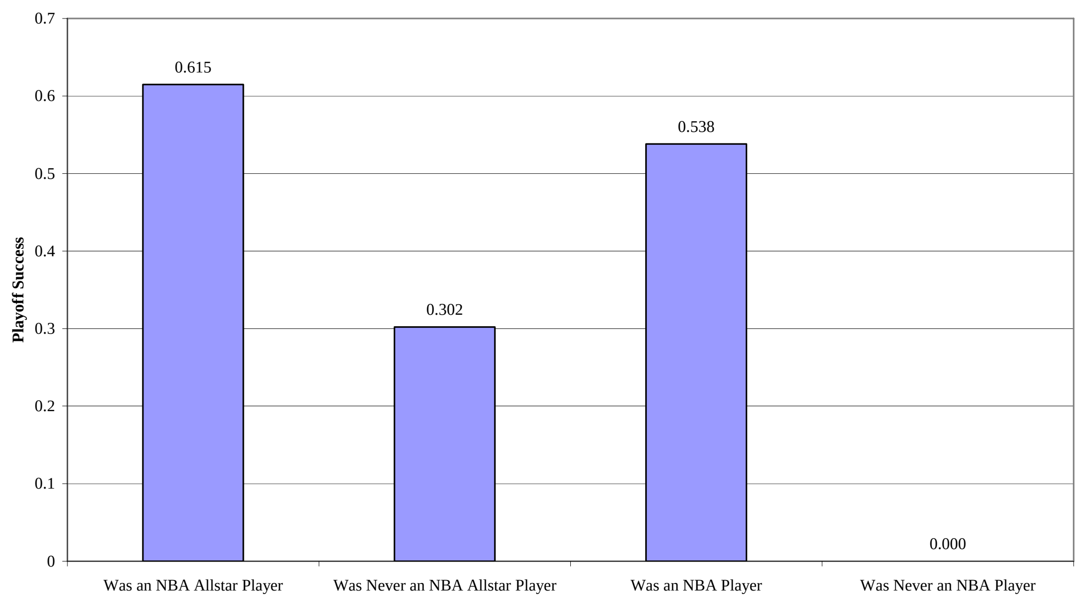

Notes to Figure 2: the Allstar vs. Non-allstar difference is not statistically significant, and the Player vs. Non-player difference is significant at the 3.2% level (two tailed test). Playoff success takes on 5 values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship.

**Figure 3**
**Team's Regular-Season Winning Percentage (WPCT) by Coach's NBA Allstar and Player Status: Coaches in Their First Year with the Team**



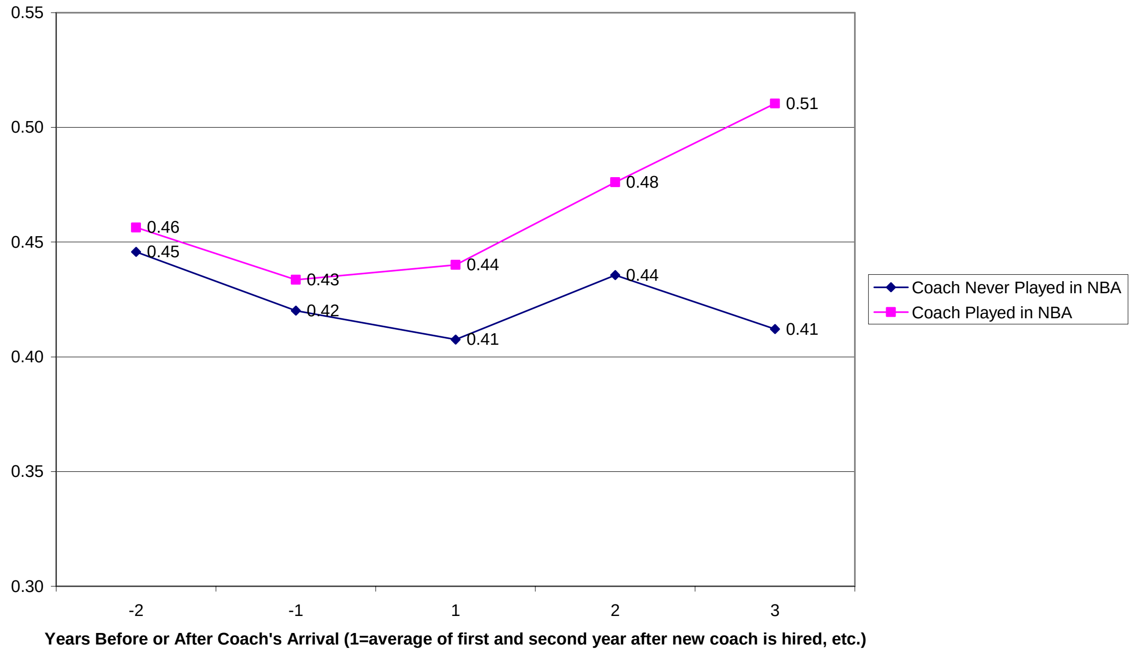

Notes to Figure 3: the Allstar vs. Non-allstar difference is significant at the 1% level, while the Player vs. Non-player difference is significant at the 10% level (two-tailed tests).

**Figure 4**
**Playoff Team Success by Coach's NBA Allstar and Player Status: Coaches in Their First Year with the Team**



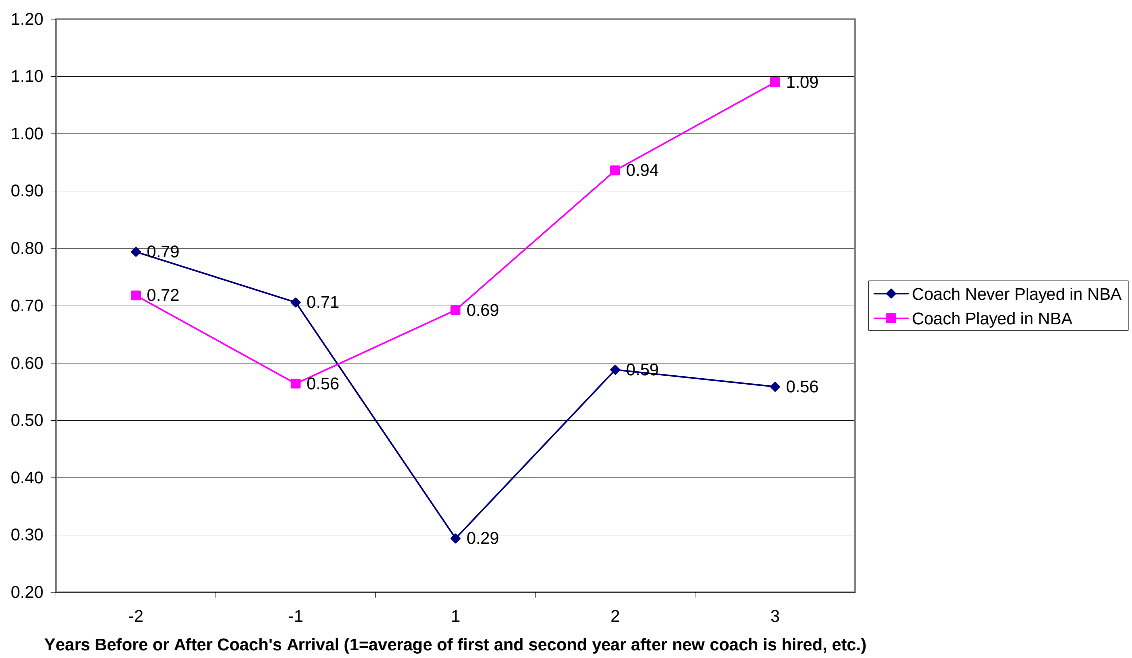

Notes to Figure 4: the Allstar vs. Non-allstar difference is not statistically significant, while the Player vs. Non-player difference is significant at the 4% level (two-tailed test). Playoff success takes on 5 values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship.

**Figure 5: Team Winning Percentage (WPCT) Before and After Arrival of New Coach (2 year moving average)**




Note to Figure 5: for negative years (i.e., before the coach's arrival), values are the average of that year's WPCT and the previous one; for positive years, values are the average of that year's WPCT and the subsequent one.

**Figure 6: Team Playoff Success Before and After Arrival of New Coach (2 year moving average)**




Notes to Figure 6: Playoff success takes on 5 values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship. For negative years, values are the average of that year's playoff success and the previous one; for positive years, values are the average of that year's playoff success and the subsequent one.

**Table 1: Ordinary Least Squares (OLS) Results for Team's Regular-Season Winning Percentage**

| Variable | Coef | SE | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|---|---|---|---|
| Coach's Total Years as NBA Player | 0.006 | 0.003 | 0.006 | 0.003 | 0.003 | 0.003 | 0.009 | 0.005 | 0.007 | 0.005 |
| Team Relative Payroll | | | 0.258 | 0.055 | 0.185 | 0.096 | 0.189 | 0.059 | 0.116 | 0.075 |
| White | | | | | | | 0.071 | 0.038 | 0.069 | 0.029 |
| Age | | | | | | | -0.022 | 0.020 | -0.042 | 0.021 |
| Age squared | | | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| NBA Head Coaching Experience (exp) | | | | | | | 0.018 | 0.008 | 0.022 | 0.008 |
| Exp squared | | | | | | | -0.001 | 0.000 | -0.001 | 0.000 |
| Years of College Head Coaching | | | | | | | 0.002 | 0.004 | 0.002 | 0.005 |
| Years of Other Pro Head Coaching | | | | | | | 0.012 | 0.007 | 0.014 | 0.007 |
| Years as NBA Assistant Coach | | | | | | | 0.005 | 0.005 | 0.008 | 0.005 |
| Team fixed effects? | no | | no | | yes | | no | | yes | |
| R squared | 0.039 | | 0.158 | | 0.447 | | 0.259 | | 0.517 | |
| Coach's Total Years as NBA Allstar Player | 0.007 | 0.004 | 0.007 | 0.003 | 0.010 | 0.004 | 0.010 | 0.004 | 0.023 | 0.009 |
| Team Relative Payroll | | | 0.265 | 0.059 | 0.191 | 0.103 | 0.196 | 0.058 | 0.139 | 0.076 |
| White | | | | | | | 0.054 | 0.038 | 0.043 | 0.027 |
| Age | | | | | | | -0.015 | 0.018 | -0.054 | 0.019 |
| Age squared | | | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| NBA Head Coaching Experience (exp) | | | | | | | 0.018 | 0.008 | 0.027 | 0.008 |
| Exp squared | | | | | | | -0.001 | 0.000 | -0.001 | 0.000 |
| Years of College Head Coaching | | | | | | | -0.004 | 0.003 | 0.002 | 0.004 |
| Years of Other Pro Head Coaching | | | | | | | 0.009 | 0.006 | 0.019 | 0.007 |
| Years as NBA Assistant Coach | | | | | | | 0.003 | 0.005 | 0.010 | 0.005 |
| Team fixed effects? | no | | no | | yes | | no | | yes | |
| R squared | 0.016 | | 0.159 | | 0.451 | | 0.245 | | 0.527 | |
| Coach Ever an NBA Allstar Player | 0.065 | 0.033 | 0.075 | 0.029 | 0.059 | 0.028 | 0.086 | 0.034 | 0.114 | 0.047 |
| Team Relative Payroll | | | 0.277 | 0.058 | 0.200 | 0.103 | 0.215 | 0.055 | 0.150 | 0.080 |
| White | | | | | | | 0.056 | 0.036 | 0.049 | 0.024 |
| Age | | | | | | | -0.014 | 0.018 | -0.053 | 0.021 |
| Age squared | | | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| NBA Head Coaching Experience (exp) | | | | | | | 0.016 | 0.007 | 0.023 | 0.007 |
| Exp squared | | | | | | | 0.000 | 0.000 | -0.001 | 0.000 |
| Years of College Head Coaching | | | | | | | -0.003 | 0.003 | 0.002 | 0.004 |
| Years of Other Pro Head Coaching | | | | | | | 0.010 | 0.007 | 0.017 | 0.007 |
| Years as NBA Assistant Coach | | | | | | | 0.004 | 0.005 | 0.010 | 0.005 |
| Team fixed effects? | no | | no | | yes | | no | | yes | |
| R squared | 0.031 | | 0.157 | | 0.451 | | 0.262 | | 0.524 | |

Sample size is 219. Standard errors clustered by coach. All explanatory variables are measured as deviations from the season mean.

**Table 2: Instrumental Variable Results for Team's Regular-Season Winning Percentage**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.229 | 0.081 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.045 | 0.019 | | |
| Coach's Total Years as NBA Player | | | | | 0.009 | 0.003 |
| Team Relative Payroll | 0.367 | 0.092 | 0.288 | 0.104 | 0.337 | 0.083 |
| Team fixed effects? | no | | no | | no | |
| | | | | | | |
| Coach Ever an NBA Allstar Player | 0.170 | 0.099 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.056 | 0.026 | | |
| Coach's Total Years as NBA Player | | | | | 0.006 | 0.003 |
| Team Relative Payroll | 0.332 | 0.150 | 0.171 | 0.170 | 0.279 | 0.134 |
| Team fixed effects? | yes | | yes | | yes | |

Sample size is 219. Standard errors clustered by coach. Instruments include lagged team relative payroll, coach's height if he played in the NBA (0 otherwise) , a dummy variable for having been an NBA guard, and dummy variables for having been born in and having attended in college in the same state in which the team is located. Except for team dummies, all explanatory variables and instruments are measured as deviations from within year mean.

**Table 3: Ordered Logit Results for Team's Playoff Performance**

| Variable | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|---|---|
| Coach's Total Years as NBA Player | 0.059 | 0.036 | 0.101 | 0.057 | 0.141 | 0.067 | 0.187 | 0.080 |
| Team Relative Payroll | 2.925 | 0.853 | 2.561 | 1.596 | 2.390 | 0.760 | 1.335 | 1.003 |
| White | | | | | 0.920 | 0.479 | 1.485 | 0.570 |
| Age | | | | | -0.390 | 0.307 | -0.686 | 0.458 |
| Age squared | | | | | 0.003 | 0.003 | 0.005 | 0.004 |
| NBA Head Coaching Experience (exp) | | | | | 0.137 | 0.127 | 0.204 | 0.169 |
| Exp squared | | | | | -0.003 | 0.004 | -0.001 | 0.006 |
| Years of College Head Coaching | | | | | 0.050 | 0.058 | 0.057 | 0.108 |
| Years of Other Pro Head Coaching | | | | | 0.256 | 0.125 | 0.566 | 0.174 |
| Years as NBA Assistant Coach | | | | | 0.086 | 0.079 | 0.131 | 0.082 |
| Cutoff: 1 | 0.005 | 0.204 | -0.706 | 0.870 | 0.033 | 0.202 | -1.761 | 1.104 |
| Cutoff: 2 | 1.163 | 0.223 | 0.780 | 0.877 | 1.320 | 0.286 | -0.048 | 1.056 |
| Cutoff: 3 | 2.061 | 0.244 | 1.825 | 0.932 | 2.281 | 0.325 | 1.123 | 1.085 |
| Cutoff: 4 | 2.883 | 0.407 | 2.735 | 0.840 | 3.140 | 0.435 | 2.138 | 1.018 |
| Cutoff: 5 | 3.653 | 0.707 | 3.609 | 0.858 | 3.971 | 0.683 | 3.245 | 1.146 |
| Team fixed effects? | no | | yes | | no | | yes | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Coach's Total Years as NBA Allstar Player | 0.075 | 0.044 | 0.162 | 0.081 | 0.122 | 0.055 | 0.364 | 0.224 |
| Team Relative Payroll | 2.916 | 0.830 | 2.526 | 1.886 | 2.391 | 0.807 | 1.372 | 1.023 |
| White | | | | | 0.718 | 0.520 | 0.873 | 0.662 |
| Age | | | | | -0.248 | 0.235 | -0.862 | 0.546 |
| Age squared | | | | | 0.002 | 0.002 | 0.007 | 0.005 |
| NBA Head Coaching Experience (exp) | | | | | 0.132 | 0.111 | 0.310 | 0.206 |
| Exp squared | | | | | -0.003 | 0.004 | -0.006 | 0.008 |
| Years of College Head Coaching | | | | | -0.045 | 0.050 | -0.043 | 0.113 |
| Years of Other Pro Head Coaching | | | | | 0.176 | 0.099 | 0.588 | 0.185 |
| Years as NBA Assistant Coach | | | | | 0.042 | 0.069 | 0.204 | 0.138 |
| Cutoff: 1 | 0.007 | 0.201 | 0.350 | 1.151 | 0.040 | 0.195 | 1.132 | 2.500 |
| Cutoff: 2 | 1.156 | 0.224 | 1.837 | 1.153 | 1.308 | 0.274 | 2.854 | 2.517 |
| Cutoff: 3 | 2.051 | 0.246 | 2.870 | 1.211 | 2.250 | 0.305 | 4.007 | 2.580 |
| Cutoff: 4 | 2.870 | 0.427 | 3.756 | 1.129 | 3.089 | 0.453 | 4.990 | 2.514 |
| Cutoff: 5 | 3.627 | 0.739 | 4.582 | 1.184 | 3.867 | 0.727 | 6.037 | 2.563 |
| Team fixed effects? | no | | yes | | no | | yes | |

**Table 3: Ordered Logit Results for Team's Playoff Performance (ctd)**

| Variable | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.575 | 0.367 | 0.377 | 0.529 | 0.796 | 0.417 | 0.702 | 0.799 |
| Team Relative Payroll | 3.037 | 0.846 | 2.594 | 1.869 | 2.586 | 0.785 | 1.325 | 1.074 |
| White | | | | | 0.715 | 0.493 | 1.115 | 0.583 |
| Age | | | | | -0.202 | 0.230 | -0.537 | 0.539 |
| Age squared | | | | | 0.002 | 0.002 | 0.004 | 0.005 |
| NBA Head Coaching Experience (exp) | | | | | 0.098 | 0.110 | 0.175 | 0.163 |
| Exp squared | | | | | -0.001 | 0.004 | 0.000 | 0.006 |
| Years of College Head Coaching | | | | | -0.042 | 0.051 | -0.079 | 0.099 |
| Years of Other Pro Head Coaching | | | | | 0.183 | 0.101 | 0.521 | 0.221 |
| Years as NBA Assistant Coach | | | | | 0.044 | 0.069 | 0.125 | 0.122 |
| Cutoff: 1 | 0.012 | 0.201 | -0.982 | 0.913 | 0.045 | 0.191 | -1.902 | 1.146 |
| Cutoff: 2 | 1.167 | 0.224 | 0.489 | 0.909 | 1.317 | 0.278 | -0.202 | 1.120 |
| Cutoff: 3 | 2.055 | 0.250 | 1.521 | 0.968 | 2.250 | 0.315 | 0.948 | 1.165 |
| Cutoff: 4 | 2.868 | 0.414 | 2.406 | 0.889 | 3.081 | 0.445 | 1.923 | 1.117 |
| Cutoff: 5 | 3.626 | 0.736 | 3.233 | 0.917 | 3.860 | 0.728 | 2.940 | 1.151 |
| Team fixed effects? | no | | yes | | no | | yes | |

Dependent variable takes on five values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship. Sample size is 219. Standard errors clustered by coach. All explanatory variables measured as deviations from within-season mean.

**Table 4: Instrumental Variable Results for Team's Playoff Performance (ordered logit)**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 3.321 | 0.653 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.630 | 0.104 | | |
| Coach's Total Years as NBA Player | | | | | 0.126 | 0.035 |
| Team Relative Payroll | 4.336 | 1.003 | 3.110 | 0.971 | 3.775 | 0.860 |
| Cutoff: 1 | 0.032 | 0.159 | 0.033 | 0.126 | 0.025 | 0.139 |
| Cutoff: 2 | 1.226 | 0.155 | 1.273 | 0.185 | 1.199 | 0.170 |
| Cutoff: 3 | 2.137 | 0.164 | 2.231 | 0.236 | 2.095 | 0.204 |
| Cutoff: 4 | 2.964 | 0.303 | 3.099 | 0.302 | 2.912 | 0.270 |
| Cutoff: 5 | 3.736 | 0.476 | 3.873 | 0.423 | 3.675 | 0.443 |
| Team fixed effects? | no | | no | | no | |
| Coach Ever an NBA Allstar Player | 5.961 | 2.857 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 1.771 | 0.437 | | |
| Coach's Total Years as NBA Player | | | | | 0.212 | 0.080 |
| Team Relative Payroll | 5.973 | 3.294 | 1.561 | 3.318 | 4.099 | 3.162 |
| Cutoff: 1 | 3.559 | 2.276 | 15.047 | 4.004 | 0.131 | 1.114 |
| Cutoff: 2 | 5.078 | 2.342 | 16.642 | 4.003 | 1.653 | 1.105 |
| Cutoff: 3 | 6.131 | 2.402 | 17.732 | 4.098 | 2.705 | 1.012 |
| Cutoff: 4 | 7.060 | 2.479 | 18.705 | 4.149 | 3.634 | 0.933 |
| Cutoff: 5 | 7.981 | 2.581 | 19.698 | 4.208 | 4.551 | 1.062 |
| Team fixed effects? | yes | | yes | | yes | |

Dependent variable takes on five values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship. Sample size is 219. Bootstrapped standard errors (50 replications). Instruments include lagged team relative payroll, coach's height if played (0 otherwise), a dummy variable for having been an NBA guard, and a dummy variables for having been born in and having attended college in the same state in which the team is located. Except for team dummies, all explanatory variables and instruments are measured as deviations from within year means.

**Table 5: OLS Results for Team's Regular-Season Winning Percentage (Coaches in Their First Season with the Team)**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.091 | 0.040 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.015 | 0.006 | | |
| Coach's Total Years as NBA Player | | | | | 0.005 | 0.004 |
| Last Season's Team Winning Percentage | 0.392 | 0.123 | 0.370 | 0.128 | 0.417 | 0.122 |
| Year effects? | yes | | yes | | yes | |
| R squared | 0.347 | | 0.366 | | 0.315 | |
| | | | | | | |
| Coach Ever an NBA Allstar Player | 0.092 | 0.041 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.015 | 0.006 | | |
| Coach's Total Years as NBA Player | | | | | 0.005 | 0.004 |
| Last Season's Team Winning Percentage | 0.374 | 0.132 | 0.358 | 0.135 | 0.406 | 0.128 |
| This Season's Team Relative Payroll | 0.034 | 0.097 | 0.022 | 0.094 | 0.021 | 0.104 |
| Year effects? | yes | | yes | | yes | |
| R squared | 0.349 | | 0.367 | | 0.316 | |

Sample size is 56. Standard errors clustered by coach. Variables measured in absolute levels except for team relative payroll.

**Table 6: Ordered Logit Results for Team's Playoff Success, Coaches in Their First Season with the Team**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.757 | 0.885 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.288 | 0.108 | | |
| Coach's Total Years as NBA Player | | | | | 0.120 | 0.084 |
| Last Season's Team Winning Percentage | 4.639 | 1.953 | 3.956 | 2.299 | 4.942 | 2.158 |
| Year effects? | yes | | yes | | yes | |
| Cutoff: 1 | 4.243 | 1.272 | 4.391 | 1.165 | 4.996 | 1.497 |
| Cutoff: 2 | 5.409 | 1.298 | 5.703 | 1.207 | 6.188 | 1.574 |
| Cutoff: 3 | 6.437 | 1.343 | 6.900 | 1.235 | 7.238 | 1.533 |
| Cutoff: 5 | 7.180 | 1.461 | 7.724 | 1.656 | 8.000 | 1.668 |
| | | | | | | |
| Coach Ever an NBA Allstar Player | 0.760 | 0.891 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.290 | 0.110 | | |
| Coach's Total Years as NBA Player | | | | | 0.120 | 0.086 |
| Last Season's Team Winning Percentage | 4.578 | 2.239 | 4.046 | 2.529 | 4.868 | 2.294 |
| This Season's Team Relative Payroll | 0.140 | 2.187 | -0.212 | 2.033 | 0.187 | 2.306 |
| Year effects? | yes | | yes | | yes | |
| Cutoff: 1 | 4.205 | 1.380 | 4.464 | 1.383 | 4.949 | 1.455 |
| Cutoff: 2 | 5.371 | 1.390 | 5.776 | 1.378 | 6.140 | 1.508 |
| Cutoff: 3 | 6.399 | 1.579 | 6.969 | 1.545 | 7.192 | 1.605 |
| Cutoff: 5 | 7.143 | 1.625 | 7.790 | 1.905 | 7.956 | 1.680 |

Sample size is 56. Standard errors clustered by coach. Variables measured in absolute levels except for team relative payroll. Dependent variable takes on four values in this sample: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 5=won championship.

**Table A1: First Stage Regression Results for Coach's Playing Quality and Relative Payroll Variables**

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Coach Ever an NBA Allstar Player | | | | Coach's Total Years as an NBA Allstar Player | | | |
| Variable | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Played Guard | -0.086 | 0.170 | 0.008 | 0.126 | -0.990 | 1.048 | -0.595 | 0.805 |
| Height for NBA Players (inches) | 0.007 | 0.002 | 0.005 | 0.002 | 0.041 | 0.013 | 0.028 | 0.010 |
| Lagged Team Relative Payroll | -0.102 | 0.156 | -0.129 | 0.145 | -0.088 | 1.037 | 0.614 | 0.713 |
| Born in Current Team's State | -0.176 | 0.241 | -0.135 | 0.148 | 0.038 | 2.781 | -0.908 | 1.007 |
| Attended College in Current Team's State | 0.121 | 0.109 | 0.099 | 0.128 | 2.142 | 1.536 | 1.653 | 1.120 |
| Team fixed effects? | no | | yes | | no | | yes | |
| R squared | 0.196 | | 0.635 | | 0.184 | | 0.655 | |

| | Team Relative Payroll | | | | Coach's Total Years as an NBA Player | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Played Guard | -0.005 | 0.028 | -0.054 | 0.053 | -0.003 | 1.605 | 0.425 | 1.243 |
| Height for NBA Players (inches) | 0.000 | 0.000 | 0.001 | 0.001 | 0.131 | 0.019 | 0.129 | 0.014 |
| Lagged Team Relative Payroll | 0.674 | 0.060 | 0.425 | 0.095 | 0.465 | 1.134 | 0.325 | 0.797 |
| Born in Current Team's State | 0.047 | 0.048 | 0.078 | 0.052 | -1.066 | 1.403 | -2.480 | 1.265 |
| Attended College in Current Team's State | 0.029 | 0.043 | -0.030 | 0.077 | 0.473 | 0.637 | 2.996 | 1.721 |
| Team fixed effects? | no | | yes | | no | | yes | |
| R squared | 0.476 | | 0.581 | | 0.635 | | 0.851 | |

Sample size is 219. Standard errors clustered by coach. Explanatory variables other than team dummies are defined as deviations from within-season means.

**Table A2: Instrumental Variable Results for Team's Regular-Season Winning Percentage with Coach's Birth Year Dummies as Additional Instruments**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.088 | 0.043 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.012 | 0.005 | | |
| Coach's Total Years as NBA Player | | | | | 0.008 | 0.003 |
| Team Relative Payroll | 0.374 | 0.075 | 0.354 | 0.075 | 0.345 | 0.078 |
| Coach's age and age squared included? | yes | | yes | | yes | |
| Team fixed effects? | no | | no | | no | |
| | | | | | | |
| Coach Ever an NBA Allstar Player | 0.068 | 0.036 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.011 | 0.005 | | |
| Coach's Total Years as NBA Player | | | | | 0.004 | 0.003 |
| Team Relative Payroll | 0.350 | 0.146 | 0.336 | 0.144 | 0.302 | 0.135 |
| Coach's age and age squared included? | yes | | yes | | yes | |
| Team fixed effects? | yes | | yes | | yes | |

Sample size is 219. Standard errors clustered by coach. Instruments include lagged team relative payroll, coach's height if he played in the NBA (0 otherwise) , a dummy variable for having been an NBA guard, dummy variables for having been born in and having attended in college in the same state in which the team is located, and coach's. birth year dummies. Except for team dummies, all explanatory variables and instruments are measured as deviations from within year means.

**Table A3: Instrumental Variable Results for Team's Playoff Performance with Coach's Birth Year Dummies as Additional Instruments (ordered logit)**

| Variable | Coef | SE | Coef | SE | Coef | SE |
|---|---|---|---|---|---|---|
| Coach Ever an NBA Allstar Player | 0.866 | 0.415 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.121 | 0.049 | | |
| Coach's Total Years as NBA Player | | | | | 0.101 | 0.025 |
| Team Relative Payroll | 3.854 | 1.101 | 3.609 | 1.006 | 3.788 | 1.020 |
| Cutoff: 1 | 0.007 | 0.118 | 0.005 | 0.180 | 0.009 | 0.164 |
| Cutoff: 2 | 1.178 | 0.136 | 1.173 | 0.163 | 1.210 | 0.161 |
| Cutoff: 3 | 2.075 | 0.203 | 2.077 | 0.201 | 2.117 | 0.182 |
| Cutoff: 4 | 2.892 | 0.283 | 2.898 | 0.291 | 2.936 | 0.222 |
| Cutoff: 5 | 3.643 | 0.423 | 3.651 | 0.461 | 3.703 | 0.414 |
| Coach's age and age squared included? | yes | | yes | | yes | |
| Team fixed effects? | no | | no | | no | |
| Coach Ever an NBA Allstar Player | 1.496 | 1.170 | | | | |
| Coach's Total Years as NBA Allstar Player | | | 0.223 | 0.170 | | |
| Coach's Total Years as NBA Player | | | | | 0.134 | 0.080 |
| Team Relative Payroll | 7.094 | 3.243 | 6.711 | 2.848 | 5.759 | 2.749 |
| Cutoff: 1 | 0.952 | 1.433 | 2.014 | 2.170 | 0.205 | 1.197 |
| Cutoff: 2 | 2.482 | 1.464 | 3.536 | 2.168 | 1.727 | 1.205 |
| Cutoff: 3 | 3.531 | 1.460 | 4.583 | 2.215 | 2.776 | 1.148 |
| Cutoff: 4 | 4.459 | 1.492 | 5.512 | 2.173 | 3.721 | 1.104 |
| Cutoff: 5 | 5.391 | 1.570 | 6.450 | 2.147 | 4.720 | 1.255 |
| Coach's age and age squared included? | yes | | yes | | yes | |
| Team fixed effects? | yes | | yes | | yes | |

Dependent variable takes on five values: 0=missed playoffs; 1=lost in first round; 2=lost in second round; 3=lost in third round; 4=lost in finals; 5=won championship. Sample size is 219. Bootstrapped standard errors (50 replications). Instruments include lagged team relative payroll, coach's height if played (0 otherwise), a dummy variable for having been an NBA guard, dummy variables for having been born in and having attended college in the same state in which the team is located, and coach's birth year dummies. Except for team dummies, all explanatory variables and instruments are measured as deviations from within year means.