Why Do Leaders Matter? The Role of Expert Knowledge

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Abstract

Why do some leaders succeed while others fail? This question is important, but its complexity makes it hard to study systematically. We draw on a setting where there are well-defined objectives, small teams of workers, and exact measures of leaders' characteristics and organizational performance. 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 and reveal that former star players make the best coaches. This 'expert knowledge' effect is large.

Key words: Organizational performance, firms, leadership, fixed-effects, productivity.

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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 a negative performance.

Theoretical explanations of leadership are offered by Hermalin (1998, 2007), who focuses on the incentives used by leaders to induce followers to follow, and Dewan and Myatt (2008), who concentrate in their model on the role played by a leader's ability, and willingness, to communicate clearly to followers. 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 2004, 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 6 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 adjusting 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 had historically played for the team, robust results are found. We also show in an Appendix that re-doing the analysis with birth-year dummies as instruments yields the same basic results.

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 τ. 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, which has a 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 τ get utility $v = v(w, \tau)$ where τ 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 τ 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 τ. 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 team. In many cases the value of τ 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 τ 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, 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

[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. Thus the assumption of Coasian player movement may be valid.

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

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

$$s.t.$$

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

$$\int vf(e)de \geq v^*(q). \qquad (2)$$

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 4 first-order conditions:

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

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

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

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

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

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 state contingent in this setup. From the mathematics, the reason is that 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. 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 isoutility level in the implicit function: $\mu(s) + \tau + n(\tau, i) - u^* = 0$.

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the very low probability of entry into the league, counterbalanced by the high earnings in the NBA given entry.

[4] Since players and coaches are willing to take less money to play in better locations (with a higher τ), 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. There will thus be an equilibrium allocation of teams across locations in which the profits of the league are maximized.

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, and data on coaches' salaries, collected by Richard Walker of the *Gaston Gazette*.

A. Basic Approach

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.

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 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. 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, and, iv) a dummy variable for having played for the current team. 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 and are unlikely to be correlated with measurement errors in assessing playing ability. Having played for the current team may be an indicator of willingness to supply coaching talent; indeed, consistent with the theoretical framework described earlier, annual salaries are approximately 10% lower among the coaches who had played for their current team than among coaches who had not -- a pattern consistent with a relative-supply mechanism.

As a robustness check, we also report in the Appendix further results where the total years of NBA playing experience is instrumented by 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

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[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

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 are expected to have longer NBA playing careers, all else equal. In these supplementary analyses, we sometimes 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. 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 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.

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.

Kahn and Shah (2005).

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 1-4 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 <u>first year</u> 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). Finally, 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.

While Figures 1-4 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.

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 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 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 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 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 coach's playing ability and team payroll on victories. In models that do not control for team fixed effects, the impact of playing ability is larger than in the OLS results and is significantly different from zero at all conventional confidence levels. In models that do control for team fixed effects, coaching ability has positive effects that are larger in magnitude than the corresponding OLS results. However, they are at best about the same size as their asymptotic standard errors. 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 the coefficient is 1.66 times 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, although, perhaps unsurprisingly given the sample size, with team fixed effects the standard errors become large.[6]

Table 3 provides ordered logit estimates for playoff performance, an alternative indicator of team output. As mentioned earlier, the dependent variable ranges from 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, all the effects excluding team dummies are significantly different from zero. When we include team dummies, the impact of Total Years as NBA Allstar player is marginally significant, and the impact of Total Years as NBA Player remains highly significant. Overall, the 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 the individual birth year dummy variables as instruments for the coach's NBA playing experience, although with these additional variables it was not possible to control for team fixed effects. The results are shown in Appendix Tables A2 (current winning percentage) and A3 (playoff success). The results are very strong and in each show a sizable and highly significantly positive effect of the coach's NBA playing experience on team success. Specifically, this result is obtained whether we just use birth-year dummies as instruments or whether we use these and the

[6] Table A1 shows first stage regression results for the determinants of coach playing ability and team relative payroll. It shows that the indicator for having played for the current team, coach height and lagged

original set of instruments. Moreover, the finding holds up when we control for team relative payroll and for the coach's age and age squared.[7]

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

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relative payroll are especially strong instruments.

[7] When we used the allstar specifications, the instrumented results were always positive and of a similar magnitude to those presented in Tables 1-4; however, they were sometimes significant and sometimes not. As suggested earlier, the birth year dummies are likely to be more appropriate for explaining NBA playing career length rather than allstar appearances, and the IV results appear to bear this out.

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. An alternative interpretation of the results in Tables 5 and 6 is that teams having temporarily bad results panic and deliberately hire a former allstar player as their coach. In the next year, the team's success reverts to its long run trend, producing 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]

5. Conclusion

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, Figure 3).

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[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.
[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.

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 their youth? It could. There are, however, reasons to be cautious of such an explanation. One is pragmatic. Every social-science discovery is subject to some version of this -- essentially unfalsifiable -- claim. A second 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. A third 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.

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 players that 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.

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

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 employees are experts. These may include professional-service firms such as law and accounting practices, research universities, cutting-edge technology companies, and R&D units.

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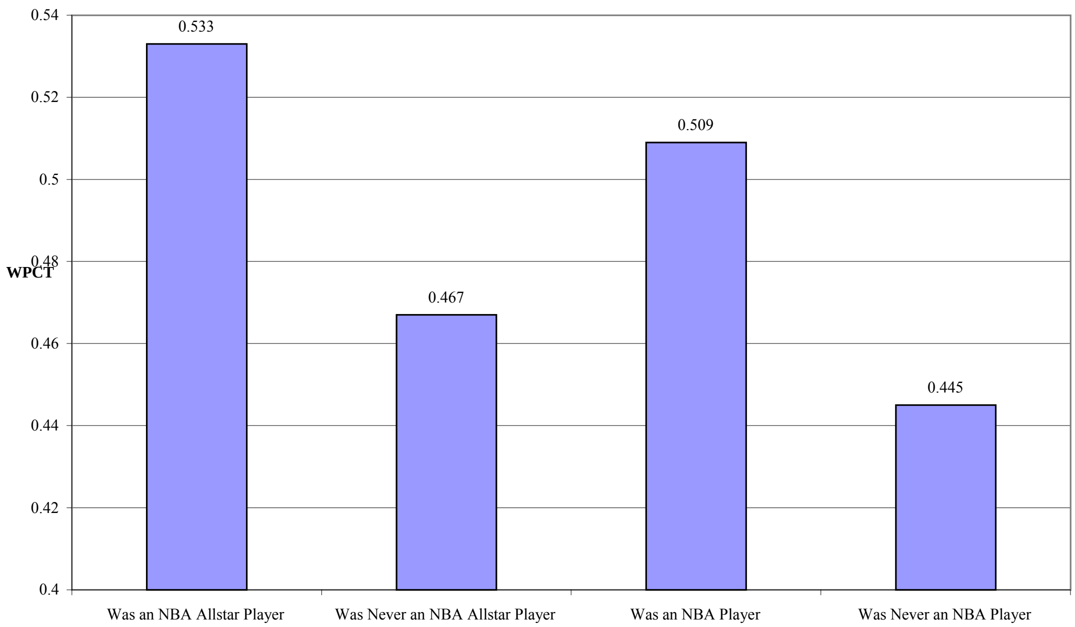
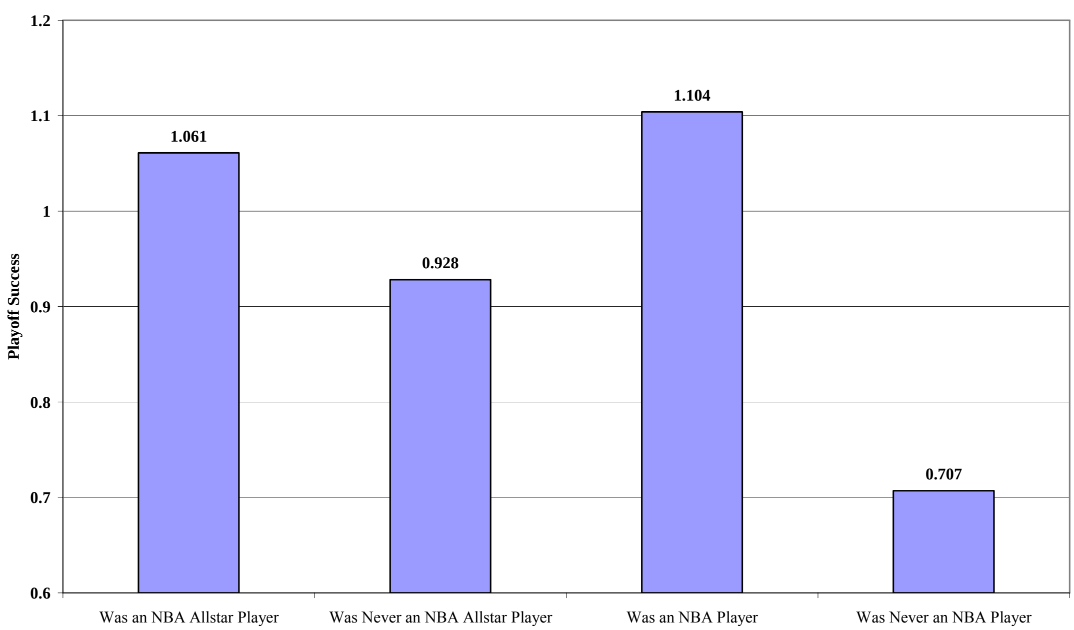
Figure 1
Team's Regular-Season Winning Percentage (WPCT) by Coach's Former NBA Allstar and Player Status



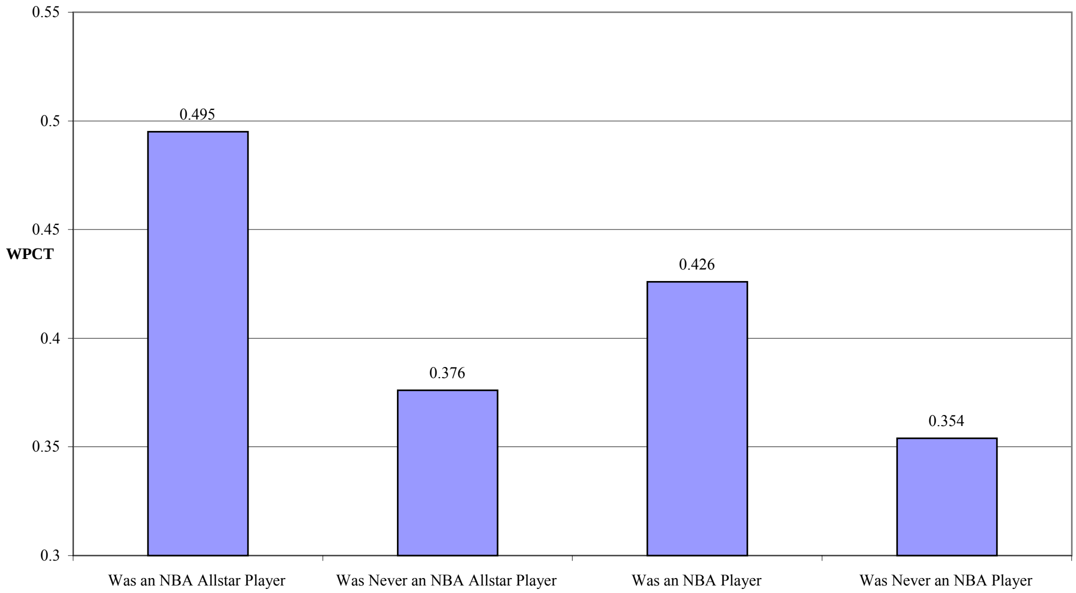
Note to Figure 1: both differences are statistically significant at the 1% level (two-tailed tests).

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



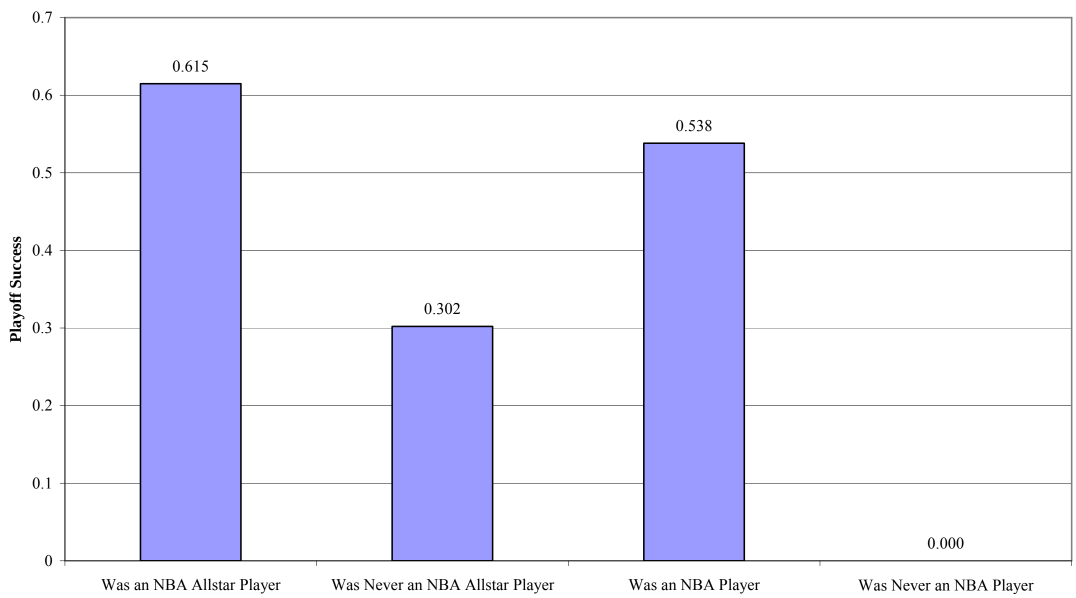
Note to Figure 2: the Allstar vs. Non-allstar is not significant, and the Player vs. Non-player difference is significant at the 3.2% level (two tailed test).

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



Note 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



Note to Figure 4: the Allstar vs. Non-allstar difference is not significant, while the Player vs. Non-player difference is significant at the 4% level (two-tailed test)

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	0.145	0.064				
Coach's Total Years as NBA Allstar Player			0.036	0.017		
Coach's Total Years as NBA Player					0.008	0.003
Team Relative Payroll	0.357	0.083	0.309	0.093	0.329	0.083
Team fixed effects?	no		no		no	
Coach Ever an NBA Allstar Player	0.054	0.087				
Coach's Total Years as NBA Allstar Player			0.021	0.022		
Coach's Total Years as NBA Player					0.004	0.004
Team Relative Payroll	0.352	0.143	0.291	0.175	0.320	0.148
Team fixed effects?	yes		yes		yes	

Sample size is 219. Standard errors clustered by coach. Instruments include lagged team relative payroll, player height, a dummy variable for having been an NBA guard, and a dummy variable for having played for the current team. 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	1.278	0.583				
Coach's Total Years as NBA Allstar Player			0.405	0.132		
Coach's Total Years as NBA Player					0.096	0.033
Team Relative Payroll	3.796	0.976	3.420	0.969	3.628	1.325
Cutoff: 1	0.012	0.124	0.009	0.162	0.017	0.141
Cutoff: 2	1.140	0.160	1.154	0.160	1.166	0.154
Cutoff: 3	2.012	0.182	2.041	0.173	2.047	0.217
Cutoff: 4	2.814	0.245	2.852	0.212	2.853	0.274
Cutoff: 5	3.568	0.422	3.615	0.393	3.610	0.409
Team fixed effects?	no		no		no	
Coach Ever an NBA Allstar Player	1.152	1.865				
Coach's Total Years as NBA Allstar Player			0.561	0.330		
Coach's Total Years as NBA Player					0.129	0.063
Team Relative Payroll	5.574	3.617	4.250	2.847	5.095	2.931
Cutoff: 1	0.185	1.629	4.322	2.930	-0.094	0.784
Cutoff: 2	1.643	1.590	5.788	2.944	1.387	0.759
Cutoff: 3	2.665	1.542	6.818	2.954	2.423	0.781
Cutoff: 4	3.558	1.506	7.720	2.950	3.331	0.801
Cutoff: 5	4.409	1.554	8.588	2.936	4.213	0.758
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). All explanatory variables and instruments are measured as deviations from within-season mean.

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				
Total Years as NBA Allstar Player			0.288	0.108		
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				
Total Years as NBA Allstar Player			0.290	0.110		
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 Allstar 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	-0.042	0.156	0.075	0.106	-0.687	1.065	-0.140	0.719
Height for NBA Players (inches)	0.005	0.002	0.003	0.001	0.031	0.013	0.019	0.009
Lagged Team Relative Payroll	-0.051	0.151	-0.039	0.132	0.570	1.234	0.893	0.731
Played for Current Team	0.323	0.181	0.501	0.183	0.953	1.074	1.440	0.822
Team fixed effects?	no		yes		no		yes	
R squared	0.234		0.672		0.135		0.656	

	Team Relative Payroll				Coach's Total Years as an NBA Player			
Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Played Guard	-0.006	0.027	-0.070	0.047	0.306	1.630	1.489	1.275
Height for NBA Players (inches)	0.000	0.000	0.001	0.001	0.121	0.021	0.109	0.016
Lagged Team Relative Payroll	0.682	0.054	0.416	0.089	0.764	1.108	1.203	0.795
Played for Current Team	-0.030	0.020	-0.057	0.055	2.608	1.210	4.768	1.070
Team fixed effects?	no		yes		no		yes	
R squared	0.472		0.581		0.654		0.868	

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: Further IV Results for Team's Regular Season Winning Percentage

Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Coach's Total Years as NBA Player	0.010	0.004	0.009	0.004	0.009	0.003	0.009	0.003
Age			-0.001	0.027			-0.001	0.027
Age squared			0.0000	0.0003			0.00003	0.0003
Instruments include:								
Birth Year Dummies?	yes	yes	yes	yes	yes	yes	yes	yes
Lagged Payroll?	no	no	no	no	yes	yes	yes	yes
Coach Height if Played in NBA?	no	no	no	no	yes	yes	yes	yes
Played Guard in NBA?	no	no	no	no	yes	yes	yes	yes
Played for Current Team?	no	no	no	no	yes	yes	yes	yes

Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Coach's Total Years as NBA Player	0.009	0.004	0.009	0.004	0.008	0.003	0.008	0.003
Team Relative Payroll	0.373	0.092	0.405	0.086	0.338	0.077	0.356	0.075
Age			0.016	0.018			0.014	0.019
Age squared			-0.0001	0.0002			-0.0001	0.0002
Instruments include:								
Birth Year Dummies?	yes	yes	yes	yes	yes	yes	yes	yes
Lagged Payroll?	no	no	no	no	yes	yes	yes	yes
Coach Height if Played in NBA?	no	no	no	no	yes	yes	yes	yes
Played Guard in NBA?	no	no	no	no	yes	yes	yes	yes
Played for Current Team?	no	no	no	no	yes	yes	yes	yes

Sample size is 219. Standard errors clustered by coach. All explanatory variables are measured as deviations from the season mean.
Team dummies not included.

Table A3: Further IV Ordered Logit Results for Team's Playoff Performance

Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Coach's Total Years as NBA Player	0.108	0.032	0.101	0.036	0.095	0.026	0.092	0.024
Age			-0.123	0.187			-0.122	0.190
Age squared			0.001	0.002			0.001	0.002
Cutoff: 1	0.034	0.127	0.034	0.132	0.033	0.150	0.034	0.143
Cutoff: 2	1.146	0.138	1.155	0.174	1.153	0.173	1.163	0.192
Cutoff: 3	1.993	0.184	2.005	0.244	2.003	0.226	2.017	0.247
Cutoff: 4	2.770	0.260	2.778	0.301	2.780	0.341	2.791	0.315
Cutoff: 5	3.505	0.481	3.512	0.409	3.512	0.521	3.522	0.352
Instruments include:								
Birth Year Dummies?	yes	yes	yes	yes	yes	yes	yes	yes
Lagged Payroll?	no	no	no	no	yes	yes	yes	yes
Coach Height if Played in NBA?	no	no	no	no	yes	yes	yes	yes
Played Guard in NBA?	no	no	no	no	yes	yes	yes	yes
Played for Current Team?	no	no	no	no	yes	yes	yes	yes

Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Coach's Total Years as NBA Player	0.107	0.034	0.103	0.038	0.094	0.020	0.093	0.026
Team Relative Payroll	4.604	0.837	4.705	1.142	3.826	1.007	3.889	0.942
Age			0.041	0.167			0.013	0.215
Age squared			-0.0003	0.002			0.000002	0.002
Cutoff: 1	0.012	0.173	0.005	0.139	0.014	0.157	0.010	0.145
Cutoff: 2	1.213	0.188	1.211	0.143	1.205	0.168	1.207	0.155
Cutoff: 3	2.135	0.248	2.135	0.247	2.113	0.224	2.117	0.194
Cutoff: 4	2.969	0.308	2.969	0.312	2.940	0.306	2.942	0.316
Cutoff: 5	3.732	0.460	3.733	0.465	3.705	0.556	3.709	0.397
Instruments include:								
Birth Year Dummies?	yes	yes	yes	yes	yes	yes	yes	yes
Lagged Payroll?	no	no	no	no	yes	yes	yes	yes
Coach Height if Played in NBA?	no	no	no	no	yes	yes	yes	yes
Played Guard in NBA?	no	no	no	no	yes	yes	yes	yes
Played for Current Team?	no	no	no	no	yes	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). All explanatory variables and instruments are measured as deviations from within-season mean. Team dummies not included.