Why Do Leaders Matter? A Study of Expert Knowledge in a Superstar Setting

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Abstract

This paper provides evidence of the importance of what might be termed 'expert leaders'. Although it is widely assumed that leaders affect the performance of their organizations, the complexity of this social-science research area has meant that comparatively little empirical progress has been made. We deliberately choose a narrow focus. We examine a high-skill setting in which there are accurate data on performance. We argue that an influential role is played by a leader's expert knowledge. A strong predictor of a leader's success in year T is that person's level of technical attainment, in the underlying activity, in approximately year T-20. Our data are on U.S. professional basketball. The paper documents a correlation between brilliance as a player and the (much later) winning percentage and playoff success of that person as a team coach. The results reveal that leaders' effects on performance are substantial and are visible in the data within the first 12 months of a coach being hired.

Key words: Organizational performance, firms, expert leaders, expert knowledge, fixed-effects, productivity.

JEL Codes: J24, M51.

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1. Introduction

Comparatively little is known about why some people make successful leaders while others do not. This paper offers longitudinal evidence that leaders draw upon their technical ability in, and acquired expert knowledge of, the core business of their organization. It focuses on a work environment in which there are small teams of highly-paid professionals. In this 'superstar' setting, it is possible to measure individuals' productivity and performance more precisely than in many other kinds of workplaces. The paper documents evidence that how well an organization performs in year T can be traced back in part to the level of attainment -- in the underlying activity -- of its leader approximately 20 years earlier. The focus is highly skilled professional sportsmen (elite basketball players).

There remains a shortage of persuasive evidence about which characteristics of leaders are correlated with later organizational performance. Bertrand and Schoar (2003) demonstrate that CEO identities matter; they show that leader fixed-effects are correlated with firms' profitability. Their study is important because it shows 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, the Jones and Olken paper also leaves open the intellectual question: what is it about leaders that makes them effective? Bennedsen, Perez-Gonzalez and Wolfenzon (2007) spans these papers by establishing, in Danish data, that the death of a CEO, or a close family member, is correlated with a later decline in firm profitability[1].[2] While these studies demonstrate that leadership plays a role, they do not provide evidence on how.

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

[2] There are also theoretical analyses of leadership. They 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 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

Bennis and Nanus (1985) suggest that one requirement of a leader is to generate trust. Using data on basketball teams, Dirks (2000) argues that there is evidence of the role of trust in enhancing group productivity. Although he does not extend the argument to how trust might itself be produced, one possible channel would be by the leader demonstrating to team members that he or she, the leader, has an instinctive level of good judgment that comes from a deep technical understanding. Complementary evidence for such a view comes from Becker and Wrisberg (2008). They record 3296 actions by Pat Summitt, one of the most successful coaches in NCAA basketball Division 1 history. The authors find that the single most common action (happening 48% of the time in their sample) was ‘instruction’ and then ‘praise’ (14% of the time); while praise can be endogenous to success, the majority of the coach’s actions involved instruction, which is arguably a clear indicator of expert leadership. This study thus suggests a way that deep technical experience might run from a leader on to the group’s performance.

Kuhn and Weinberger (2005) are able to document evidence that certain leadership abilities seem correlated with their later remuneration. These characteristics include “directness” (“analyzing, criticizing, directing, judging, instructing, and resisting,” as discussed by Borghans, ter Weel, and Weinberg 2008, p. 819) and executive function ability (skills such as “working memory, attention” and an ability to “orchestrate lower-level processes,” as discussed by Borghans, Duckworth, Heckman and ter Weel 2008. p. 980). It is also likely that the nature of the good or service being produced, the environment in which it is produced, and the decision-making process/culture in the firm or organization may all have a significant impact on the necessary attributes of an effective leader. Hence, across industries, different particular (leader) qualities may carry different weights.

There has been a small amount of work on the impact of a leader’s technical ability upon organizational success. First, Goodall (2006, 2009a,b) finds a positive correlation between the scholarly quality of presidents and the academic excellence of their institutions, and also some longitudinal evidence, for a panel of British universities, that those institutions led by highly

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innovation; and by Dai, Lewis and Lopomo (2006), whose theoretical model stresses the superior information held by expert managers. There are also studies in the sports industry that suggest managers can make a difference, including Porter and Scully (1982), Kahn (1993), Ruggiero, Hadley and Gustafson (1996), and Dawson, Dobson and Gerrard (2000), and Dawson and Dobson (2002).

cited scholars perform the best over the ensuing decade. Second, Kaplan, Klebanov and Sorensen (2008) study the impact of CEO characteristics on the success of firms in leveraged buyout situations or where venture capital plays a prominent role. They establish that company success is related to both the leader's general execution skills and his/her interpersonal skills. Third, Dvir, Eden, Avolio and Shamir (2002) examine the results of a field experiment in which a treatment group of military officers was given "transformational" leadership training, a type of training in which the leaders are taught how to enhance the development of their followers. The authors find that this training had the intended, positive effect on follower military performance in physical fitness and weapons use, relative to a control group of leaders who did not receive such training. Leaders with more knowledge about motivation performed better. Dawson and Dobson (2002) study British football from 1992 to 1998 and find that having played internationally or having previously played or coached for the current team significantly raises a manager's productivity.

In settings where leaders command thousands or even millions of people, it will be analytically difficult to discern the reasons for leaders' effects. The remainder of this paper therefore takes a deliberately simple, narrow approach. It draws on data for an industry in which team size is small and objective data are plentiful. The 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 take data on a sample of games that provides 219 coach-season observations; we compute winning percentages; we also study post-season playoffs. Our work is complementary to a recent study by Frick and Simmons (2008), which, for the case of soccer, also explored the influence of managerial quality. Kahn (1993) found 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 in-depth the possible mechanisms through which successful coaches raise player performance.

This approach makes it possible to exploit data on coaches, some of whom serve on multiple teams through time, with three kinds of backgrounds:

(i) those who never themselves played NBA basketball

(ii) ones who played NBA basketball but were not 'all-star' players

(iii) ones who played NBA basketball and became 'all-star' players.

The paper tests whether, decades later, these attainment levels have any effect. Teams seem to perform better if led by a coach who was, in his day, an outstanding player -- a result previously debated, and sometimes doubted[3], in anecdotal discussions about team sports around the world.

The paper attempts to document a correlation between brilliance as a player and the (much later) winning percentage or playoff success of that person as a coach. Nevertheless, such a correlation might be an artefact. When we probe the data, however, there seem grounds to believe in more than a spurious correlation. First, the correlation appears to be robust to the inclusion of team fixed-effects and other (time-varying) inputs that affect a team's success. Second, once we isolate the exact years in a team's history in which a new coach arrives, we find evidence consistent with an immediate effect. As is required by the hypothesis, the extent of improvement in a team over the ensuing 12 months is correlated with whether the new appointee had himself once been a top player. Moreover, the size of the effect seems fairly substantial. For the performance of a team, the difference between having a coach who never played NBA basketball and the typical coach who played NBA all-star basketball is perhaps six extra places up in the rankings of NBA team winning percentages. This is a considerable effect (the league's size was 29 teams in the period). Third, we make efforts to adjust for the possible endogeneity of coaching and playing quality by using an instrumental variables strategy, since factors of production, including the quality of leadership, are chosen by the firm. This potentially leads to endogeneity bias in the estimation of production functions, and our results are robust to using instrumental variables.

Conceptual Framework

We next sketch a model that offers potential guidance on how expert coaches match with teams -- an issue that later influences our instrumental variables (IV) strategy.

[3] We thank Stefan Szymanski for this point.

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 also 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 wish to win, but do not like paying the costs of team and coach[4]. Players who play 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; these preferences might be due to nostalgia for a particular area. In many cases the value of τ will be zero, meaning that coaches are indifferent across such teams. Coaches as a whole may be a relatively 'thin' market, so individual $n(..)$ preferences may matter. [5] 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.

[4] This approach has the advantage that it does not impose profit maximization (although that case would follow from the assumption that r(p) is revenue). Here the function r(.) might weight winning beyond its implications for sheer revenue.

[5] Although some coaches may move between pro and college ranks (for example, Rick Pitino), the number of high profile college jobs may be small enough for us to still consider the coaches' market to be thin.

While leagues control the number of teams that are allowed to enter (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 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.[6] 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.[7]

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 $n(\tau, i)$ 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

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

[6] 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.

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

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

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 four first-order conditions:

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

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

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

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

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 as follows. 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).[8]

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.

2. Data and Empirical Procedures

To study the impact of playing ability on coaching success, the paper uses data drawn from *The Sporting News Official NBA Guide* and *The Sporting News Official NBA Register*, 1996-7 through 2003-4 editions for performance data covering the 1996-7 through 2002-3 seasons, 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.

[8] 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.

A. Basic Approach

The empirical setup is a production-function approach:

$$wpct_{\tau t}=a_0+a_1 playerpay_{\tau t}+a_2 coachexpert_{\tau t}+b_\tau+u_{\tau t}, \qquad \underline{\text{Team-performance equation}} \qquad (7)$$

where for each team τ and year t, we have: *wpct* is the team's regular season winning percentage, *playerpay* is a measure of the team's overall player quality given by the log of the team's salary payroll for players minus the log of the mean team salary payroll for all teams for that season, *coachexpert* is a dummy variable indicating the coach's own playing experience such as whether he was, say, an all-star player in the NBA minus the mean value for that variable across teams for the year, *b* is a team fixed effect, and *u* a disturbance term.

In equation (7), the team's regular season winning percentage is a measure of team success (our 'output' in this production function). However, as will be 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 0.5. In each season, exactly sixteen teams make the playoffs – which make up 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 express the inputs in a similarly relative way by defining them as the raw value minus the league average for the year. For example, in some years, many of the coaches who happen to be in the league that year may have had all-star playing careers, while in other years, only a few may have been all-stars. But there is exactly one champion in each year. What counts, therefore, is one coach's ability relative to the others, leading us to define the inputs relative to within-season averages.[9]

The paper aims to test whether ability as a player leads to greater success for a coach after controlling for other inputs. As was the case for the dependent variable, we also experimented

[9] We also estimated some models with raw values of log team payroll and the coach's playing expertise, as well as some models with ratios of these variables and the league within-season means. In these alternative specifications, the results, which are discussed below, were very similar to those of the basic specification described here.

with various measures of the coach's playing expertise, including the number of times the coach was named to an NBA all-star team as a player, 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 in that season. The incidence or total of all-star team appearances is one 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.

We control for player inputs available to the coach by using the team's relative payroll (compared to other teams) for the given season. Our maintained hypothesis is that better quality players earn higher salaries, which can then be used as an indicator of playing skill.[10] Szymanski (2003) provides evidence for all major team sports in North America as well as European football that team relative payroll is significantly positively correlated with team success, and the relationship is particularly strong for the NBA.[11] Specifically, for each of the four major team sports in North America (baseball, basketball, football and hockey) and European football, team payroll relative to the league average had a positive coefficient in a winning percentage equation that was significant at the 1% level; moreover, the size of the effect was largest for North American football (0.31) and the NBA (0.29) but ranged from 0.07 (Spanish football) to 0.19 (English Premier League football) for the other sports (Szymanski 2003, p. 1154). Thus, player payroll does appear to be a good indicator of playing skill in the NBA, despite the existence of a (soft) team salary cap, team minimum salary, and, since 1999, a team luxury tax on excess

[10] 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).

[11] See Szymanski (2000) and Hall, Szymanski and Zimbalist (2002) for further evidence finding a positive correlation between team payroll and performance in sports. There is some question in the literature as to whether causality runs from payroll to team success or vice-versa. Hall, Szymanski and Zimbalist (2002) address this issue by performing Granger causality tests for baseball and English soccer. The authors in fact find (positive) causality from payroll to performance for soccer for 1974-1999 and for baseball from 1995 to 2000. As discussed below, we address the causality issue by using past team payroll as an instrument for current team payroll.

payrolls and a maximum individual player salary.[12] The league implemented these constraints on team and individual salaries presumably to improve competitive balance. Even with limits on team salary, there is still room for considerable inequality across teams in payroll, and an individual team's relative salary will still reflect its relative player talent level. Our method uses team payroll rather than measures of player performance such as the scoring, rebounding, steals and turnover statistics used in studies that attempt to measure the output of individual players (see Lee and Berri 2008, for example). We follow this procedure because these performance measures are potentially affected by the coach, through teaching as well as motivating player performance, and through the coach's substitution patterns, which influence players' opportunities to accumulate playing statistics and also their propensities to be injured. For example, since coaches may decide to rest certain players in order to avoid injuries, we do not control for injuries during the season or playing time of star players. In this way we estimate the full effects of coaching expertise on team success.

While player payroll is a proxy for the talent the coach has at his disposal, by including the value of player payroll, we may in fact be understating the impact of the coach. This is the case since current payroll is a function of past performance, which could have been affected by the coach. As discussed further below, we will also estimate equations that exclude payroll, thereby providing arguably an upper bound estimate of the full effects of the coach's expertise, and we also estimate some models on a subsample of coaches in their first year with a team. In these latter analyses, the coach presumably has not affected the players' past performance levels.

Equation (7) includes also a vector of 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 the influence of the front office in selecting players, trainers, etc. In addition, team dummies serve to control for the theoretical model's common locational preferences τ and thus help sharpen the interpretation of the player payroll variable.

[12] See, for example, *NBA Collective Bargaining Agreement, September 1995*, Article VII (pp. 40-94) and *NBA Collective Bargaining Agreement January 1999,* Article II (p. 22) and Article VII (pp. 52-136). A new agreement was negotiated in 2005 (*NBA Collective Bargaining Agreement December 2005*), but this took effect after our sample period. For discussion of individual players' negotiation rights under the 1995 and 1999 NBA agreements, see Kahn and Shah (2005). Although we would have preferred to use coach's salary while he played as an additional indicator of playing skill, these data are not available.

Team dummies also absorb the effects of the underlying fan demand for winning, which, as argued below may affect both the level of output chosen, as well as the inputs necessary to achieve that level.[13]

As in basic production function analyses, all inputs are endogenous. The firm chooses them, and the output level, and, as suggested in the equilibrium model outlined earlier, there may be nonrandom matching between coaches and teams. In addition, our measure of the coach's playing ability could contain errors. Therefore, in some of the later sections, 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 (see also Table A1). 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. Player height and court position together may influence a player's career length or chance of being named to the all-star game and thus serve to correct measurement errors in relating all-star status or career length to true underlying playing ability. Having been born in, or attended college in, the current team's state may be one indicator of willingness to supply coaching talent in that particular state. For these locational variables to be good instruments, this supply effect must be stronger for either the all-stars or the nonall-stars. One possible reason why the effect of the location of college attendance might be stronger for all-stars is that they are especially likely to have experienced success at the college level and to have developed ties, and emotional attachment, to the area. An equivalent emotional-attachment effect might operate directly for the geographical area in which an all-star was born. The theoretical model presented above sketches how such preferences can shape an

[13] As discussed below in reviewing the results of alternative specifications, we also experimented with an intermediate specification in which the team dummies were replaced with the area population level and dummies for New York and Los Angeles, the two largest and most glamorous markets. The results were similar to those with team dummies.

equilibrium allocation of coaches across locations in the NBA.[14] These instruments are designed to reflect locational preferences of coaches that are not directly related to team success and therefore are justifiably excluded from the second stage equation. Coaches may also prefer to go to teams with a higher anticipated likelihood of success: for the example, the Los Angeles Lakers have been a much more successful team than the Los Angeles Clippers, despite being in a similar location. The existence of such preferences would pose no problem if they were equally held by all coaches, controlling for locational preferences. But if former all-stars have a stronger taste for success than non-all-stars, then team success and the coach's playing ability would be confounded in an OLS framework. However, in principle our instrumental variable design accounts for such a confounding, by removing the asymptotic correlation between unmeasured factors influencing team success and a coach's locational and team preferences; moreover, the direct inclusion of team dummies in both stages and past payroll as an instrument is likely to help control for differences in anticipated success.

As an extra robustness check, we report in the Appendix (Tables A2 and A3) 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 all-star appearances than on NBA career length, since the size of the all-star 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 all-star); on the other hand, a larger league size reduces the likelihood of being selected to the all-star team in any

[14] Although we adjust for the endogeneity of the coach's characteristics, we take the current set of coaches as given. That is, we do not model the decision to become a coach. For some recent experimental research on the decision to become a leader, see Arbak and Villeval (2007).

given year (reducing one's chances of being an all-star). Therefore, these birth-year instruments are more conceptually appropriate for the NBA playing career length specification of the coach's playing expertise. As discussed below, the results were similar with this alternative set of instruments. Our regression design uses multiple observations on the same coach, where the data are available.

The key explanatory variable in our study is the measure of the coach's playing ability, which of course does not vary for a coach. We therefore cluster the standard errors by coach. This procedure allows the data to determine the degree to which multiple observations on each coach represent truly independent observations. As noted below, we have 219 coach-year observations on 68 coaches. Thus, we have in effect something between 68 and 219 independent observations, and clustering will adjust the standard errors for the likely correlation across years for a given coach.

B. Alternative Specifications

As earlier noted, regular season winning percentage is our main measure of a team's success (or 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 that a team survives.[15] 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.

[15] An additional reason for analyzing playoffs in addition to winning percentage is that teams eliminated from playoff contention may "tank" at the end of a regular season in order to increase their chances of obtaining a good draft pick for the next season. Such strategic behaviour is less likely to affect our playoff success variable.

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, the predicted values of team relative payroll and coach's playing expertise are calculated. 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. On the other hand, to the extent that such measures of pre-NBA coaching experience are exogenous, then their exclusion may lead to biased estimates of the impact of the coach's playing ability. Therefore, we present our results with both types of specification. 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.

We also experimented with alternative specifications of the explanatory variables in the winning percentage equations including using the raw variables rather than deviations from the mean, as well as ratios to the mean instead of deviations. Further, in addition to replacing in some specifications the team dummies with a more parsimonious set of team controls (1997 population and dummies for New York and Los Angeles),[16] we also deleted observations on some key coaches who were either long time all-stars or highly successful coaches, in order to see whether the results were being driven by potentially influential observations. We also experimented with alternative corrections of the standard errors in the winning percentage equations. These results are discussed below, and in all cases, our basic conclusions hold up. Finally, we also estimate some models on the subsample of coaches in their first year with the team. One might view such analyses as a study of the short run effects of hiring an expert leader. As discussed below, our results hold for this subsample as well, suggesting that the effect of a former great player is felt relatively soon after he is hired.

3. Empirical Results

As noted, our data consist of 219 coach-season observations on 68 NBA coaches over the 1996-7 to 2002-3 seasons. We include partial seasons in part because a coach leaving after an unsuccessful partial season is still an observation on coaching success (as discussed below, results were robust to weighting by the number of games coached in a given year). Table 1 shows descriptive statistics for regular season and postseason coaching success by coach's playing ability. The latter is summarized in three categories: never played in the NBA; played in the NBA but was never an all-star; was an NBA all-star player. Twenty six of the coaches never played NBA basketball, and these accounted for 75 (34%) of the observations; another 26 played at less than an all-star level, accounting for 87 (36%) of the observations, while there were 16 former NBA all-star players coaching in the NBA in our sample, comprising 30% of the coach-season cases. For the full sample, Table 1 shows higher mean winning percentages the more skilled the coach was as a player: former all-stars' teams won 53.3% of their games, compared to 48.8% for teams coached by former NBA players who were not all-stars, and only 44.5% for teams coached by those who never played in the NBA.[17] The difference in the mean winning percentage of the former all-stars and former nonplayers (0.088) is slightly more than half of a standard deviation (0.17). Average playoff success is roughly comparable for the two

[16] Population data were taken from United States Department of Commerce (1998) and the Statistics Canada web site: http://www12.statcan.ca, accessed April 15, 2010. Population is measured as of 1997 for US metropolitan areas and, due to Census data availability, 1996 for Canadian metropolitan areas.
[17] The minimum values of zero for some winning percentages reflect partial seasons.

categories of former NBA players and much higher than that of nonplayers. The difference in playoff success between former players (the former all-stars and nonall-stars averaged together) and nonplayers is about 0.4 rounds in the playoffs, or almost one extra round every two years.

When we study coaches in their first year with the team, the differences in success across different levels of the coach's playing ability are even more striking than for the sample as a whole (panel B of Table 1). Former NBA all-stars have much average higher winning percentages and more playoff success than the other groups, and nonplayers have the least success of the three groups. In particular, the nonplayers never made the playoffs in their first year in our data, averaging 0.6 fewer rounds in the playoffs than former all-stars, and the difference in their mean winning percentages is 0.141.[18]

Table 2 shows some detailed information on the evolution of team success before and after hiring a new coach, disaggregated by the same three categories of the coach's playing ability used in Table 1.[19] While the year-to-year patterns can be volatile in some instances, particularly for a discrete outcome such as playoff success, the overall patterns are similar in most respects to the averages shown in Table 1. Specifically, on average, winning percentage declines 2.2 percentage points for teams taken over by nonplayers, with increases of 3.0-3.5 percentage points for teams taken over by former NBA players. Playoff success falls by roughly 0.3 rounds for teams with new coaches who were not NBA players, with an increase of 0.4 rounds for teams taken over by former players who were not all-stars and stability for teams taken over by former all-stars.

Finally, Figures 1 and 2 contrast team winning percentage (Figure 1) and playoff success (Figure 2) before and after the arrival of a new coach by the coach's playing experience by comparing teams taken over by nonplayers with those taken over by former NBA players. In order to smooth out the annual data, which were shown in their entirety in Table 2, we present two-year

[18] The sample sizes of coaches in their first year are slightly smaller than the total number of coaches because in some cases, we are unable to construct a full set of explanatory variables for the first year of a coach's tenure (because it occurred relatively long ago).

[19] Table 2 shows 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 because the coach's future tenure with the new team is endogenous to the team's success.

moving averages in Figures 1 and 2. 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 1 shows that before the new coach arrived, the team winning percentage was similar for teams that were about to hire non-players (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. While one might expect some regression to the mean if teams with poor records seek out high profile coaches, Figure 1 suggests that past records among teams that were about to hire experienced former players were similar to those about to hire non-players.

Figure 2 provides further complementary evidence. It shows that before the coach's arrival, the teams that were about to hire non-players 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 1 and 2, 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 Tables 1-2 and Figures 1-2 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 3 sets out ordinary least squares (OLS) results for team winning percentage. 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 all-star player, and the last panel uses a dummy variable indicating that he was ever an NBA all-star player. For each of these definitions of playing ability, there are five models shown: one model with only the coach's playing ability and four including this variable and team relative payroll for players -- 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 all-star 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 all-star player, raises team winning percentage by 5.9 to 11.4 percentage points. To provide a rough idea of the magnitude of these effects, we analyzed gate revenue (including that from club seats) data from 2003-4, the first year not in our sample of coaches, which we collected from Professor Rodney Fort's web site: http://www.rodneyfort.com/SportsData/BizFrame.htm (data were originally taken from *Forbes Magazine*). We then 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).[20] According to this estimate, hiring a coach who was an all-star 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 all-star. This estimate of the marginal revenue product of the coach's playing ability of course does not control for other potential influences on revenue such as arena size (which may of course be endogenous in the long run) and other aspects of the local market for NBA basketball. 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, which as noted is 17 percentage points. In our data, the raw differential in winning percentage between all-stars and non-all-stars (i.e. nonplayers plus former NBA players who never made an all-star team as players) is about seven percentage points. The 5.9-11.4 range of regression estimates in Table 3 implies that the raw differential is not caused by spurious correlation with other variables.

[20] We used gate revenue only (i.e., we excluded media and other revenues) on the idea that this portion of revenue would be the most responsive to how a team does relative to other teams, in contrast to shared national television revenues.

In the specifications in Table 3 using total years as an NBA all-star player, the effects range from 0.7 to 2.3 percentage points and, as mentioned, are usually statistically significant. Compared to hiring a coach who was never an NBA all-star player, hiring a coach who was an NBA all-star player for the average number years among all-stars (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 all-star player for the average number of all-star appearances among this group are $1.6 million to $5.3 million, relative to a non-all-star.

Finally, using total years as an NBA player, we find coefficient estimates in Table 3 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 10.5 years. Thus, Table 1 implies that hiring a former player with average playing experience raises winning percentage by 3.15 to 9.4 percentage points relative to hiring a non-player.

In other results in Table 3, 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 3, 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 all-star 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. On the other hand, as mentioned, the coach can affect team payroll by influencing the past performance of the players, implying that controlling for team payroll may lead to an understatement of the coach's influence. The first column of each model in Table 3 shows what happens when we exclude team payroll, allowing such indirect effects to be observed. The results are similar to those controlling for team payroll, suggesting that these effects are small.

In our basic setup, we enter only one measure of the coach's playing ability at a time. Attempts to distinguish both playing time and number of all-star appearances in the same regression were unsuccessful, presumably because the two variables are highly related. Nonetheless, in Table 3, the impact of all star appearances seems stronger than the impact of playing experience, suggesting that excellence as a player counts more than mere longevity as a player. Below, we summarize the results of all of the various specifications and conclude that indeed, overall, the number of all star appearances performs the best, a pattern that supports the idea that playing excellence rather than playing experience is what counts.[21] In addition, the results with the additional controls in the last two models shown in Table 3 are stronger than when we do not control for these additional factors (age, race, experience, etc.). In supplementary regressions (available on request), we found that number of years as an all-star player was significantly positively related to a coach's age and significantly negatively related to his NBA coaching experience all else equal. Table 3 shows that age generally lowers success, while experience raises it. Thus, failure to control for these factors leads to a smaller effect of all star appearances, for example. A similar analysis applies to the other two measures of the coach's playing ability. As noted above, it is not obvious that variables such as coaching experience should be controlled for, if we are interested in the full effects of playing expertise. For this reason, we treat the array of estimates in Table 3 as bounds on the true effect of the coach's playing expertise.[22]

Table 4 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

[21] As noted earlier, playing experience itself is likely to be positively correlated with playing excellence, since only the best players are asked to sign new contracts.

[22] Table 3 also shows that white coaches have better winning percentages, all else equal, and supplementary regressions show that former all-stars or former NBA players were less likely to be white than black, although these differences were not always significant. Nonetheless, the combination of these correlations also implies a larger effect of the coach's playing expertise controlling for race than not controlling for race. For a detailed analysis of racial productivity differences among NBA coaches, see Kahn (2006).

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 all-star player, in which case the coefficient is about the same size as its asymptotic standard error. Overall, Table 4 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.[23]

Table 5 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 All-star 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 all-star 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 all-star 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 5 are qualitatively similar to this one: adding a coach who was an all-star player (or one who has the average number of all-star appearances among the all-stars) 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.

[23] 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.

Table 6 shows IV results for the determinants of playoff success. The point estimates are considerably larger than Table 5's ordered logit results. Moreover, the effects are statistically significant whether or not we include team dummy variables. Overall, the point estimates in Table 6 show that adding an all-star 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, with larger effects for former all-stars than former players. Thus, in comparing the effects of playing excellence and playing longevity for playoff success, the IV results show larger effects for former all-stars than former players, while the non-instrumented results (Table 5) show the opposite. In contrast, for winning percentage, the effects of having been an all-star were larger than that of being of former NBA player in both the OLS and IV estimates.

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, although the average effects of playing experience are comparable to those of being an all-star.

While Tables 3-6 enter the coach expert and player payroll variables separately, it is possible that they interact in affecting team success. For example, more expert coaches may have a larger effect on better players by commanding their respect; alternatively, more expert coaches may help lesser players more by teaching them skills. We examined these issues by estimating models with interactions between the coach expert indicators and the team's relative payroll. The results did not suggest the presence of interaction effects. Specifically, adding these to the specifications in Tables 1 and 3, we found positive interaction effects 12 times and negative effects 12 times, with only one of the 24 estimates significant.[24] It is possible that more expert coaches help players at all parts of the salary distribution, given the strong overall positive effects that expert coaches have.

The results in Tables 3-6 use the entire sample of coach-year observations and therefore estimate the average effects over a coach's current, uncompleted tenure of having been a great player. It is also of interest to determine whether this effect is felt immediately, and to this end, we present in Tables 7 and 8 analyses of team success in the first year of a coach's tenure. In our data, we have 56 coach-season observations on coaches who are in their first year with the team (Table 1). 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. We show the results of regression models for team regular season winning percentage (Table 7) and playoff success (Table 8) 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 for the coach's playing ability (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. In addition, controlling for the previous season's winning percentage to some degree controls for a possible regression to the mean. Specifically, teams which temporarily perform badly may hire expert leaders and then revert to their normal winning patterns. The previous year's winning percentage helps control for this possibility under some circumstances, as discussed in more detail below.

Table 7 shows that adding coaches who were all-stars seems immediately to improve the winning percentage over what the team had accomplished in the previous year, whether or not

[24] The 24 estimates come from the fact that there are two dependent variables, three measures of the coach's playing skill, models with and without team fixed effects, and models with and without the additional controls for coaching characteristics (race, experience, etc.). This breakdown yields 2 x 3 x 2 x 2=24 possible interaction coefficients.

we control for current payroll.[25] Adding a former player as the coach also has a positive effect, although it is only slightly larger than its standard error. Finally, Table 8 reveals that adding a coach who was an all-star 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 all-star.[26] Tables 7 and 8 together provide evidence that adding a coach who was an expert player is correlated with improved team performance in the first year, all else equal, as also suggested in the raw data shown in Figures 1 and 2.

An alternative interpretation of the results in Tables 7 and 8 is that teams having temporarily bad results deliberately hire a former all-star player as their next coach, even controlling for the previous year's winning percentage. 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 all-star 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. Moreover, even this scenario in which the correlation in Tables 7 and 8 is spurious requires that the team believes that hiring an expert will rectify the team's poor performance.[27]

The models shown in Tables 3-8, A2 and A3 test our basic hypothesis about expert leadership under a variety of alternative specifications, including: two dependent variables, three measures of the coach's playing ability, alternative sets of controls, individual team fixed effects, instrumental variables with alternative sets of instruments, and the use of the first year subsample. We also implemented several other robustness checks on the basic winning percentage model, as shown in Table A4, although results for playoff success were similar. Table A4 uses the fully specified model with all controls and team dummies and reproduces the results from Table 3 to facilitate comparisons. The alternative specifications include the use of

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[25] Estimating the basic regression models in Tables 3 and 5 but excluding the current payroll variable yields very similar results.

[26] 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.

[27] It is also possible that differences in the owner's desire for a winning team can lead to alternative choices of a coach. But even under such a scenario, the coefficient on the coach's playing ability is a valid indicator of the effect of expert leadership unless the owner directly enhances the players' performance in ways not measured by payroll.

raw values of the explanatory variables instead of deviations from the within season mean (plus year dummies), using ratios to the within season mean rather than deviations, dropping some potentially influential observations on long time all-stars Larry Bird and Isiah Thomas or singularly successful coaches such as Phil Jackson, using area population and New York and Los Angeles dummy variables instead of team dummies, using bootstrapped standard errors instead of clustering, and weighting the observations by the number of games the coach was on the job in a given season.[28]

The results appear to be robust to these alternatives, particularly for the all star specifications. Specifically, for the "Ever an NBA All Star Player" and "Total Years as NBA All Star Player" specifications, the results are all positive and of comparable magnitude to the basic model's results.[29] Moreover, the findings for these two variables in Table A4 are highly statistically significant: of the 16 alternatives to the basic model for the all star measures of coach's expertise, 15 range in significance level from 0.3-4.8%, and the sixteenth is significant at the 7.5% level, all on two tailed tests. The results for the playing experience specification are qualitatively similar to those in the basic specification, but they are weaker than those in the all star specifications, reaching significance twice in the 4.9-5.5% range.

Considering all of the results in Tables 3-8 and A2-A4, the most consistent findings are the positively, large and statistically significant effects of the number of all-star teams the coach was named to as an NBA player. Of the 29 coefficients for this variable reported in Tables 3-8 and A2-A4, its effects were significantly different from zero at better than the 5% level 24 times and the 10% level 27 times on two tailed tests. Thus, this variable yields some consistently strong results. Corresponding figures for the "ever an all-star" variable were 19 (5% significance level) and 23 (10% significance level), while those for the playing longevity variable were 11 (5% significance level) and 15 (10% significance level). The superior performance of the number of

[28] Using bootstrapped standard errors addresses the possibility that there are multiple causes of correlations across observations in our sample, as our discussion of matching coaches and teams might suggest.

[29] To assess the magnitude of the coefficients in the "ratios to mean" specification, for the average all-star, we multiply the ratio of the conditional value of the all-star variable (1 for "ever an all-star" and 4.9 years as an all-star) to the unconditional values for these variables (0.30 for ever an all-star and 1.5 for years as an all-star) by the associated coefficient. We obtain effects of 0.14 for the ever an all-star specification and 0.13 for the years as an all star specification. These are of comparable magnitude to the effects we reported in discussing Table 3's results, which were both 0.11.

all-star teams variable suggests that this is the best measure of the coach's playing expertise and that playing excellence matters more than playing longevity.

4. Conclusion

The paper provides evidence of the importance of what might be termed 'expert leaders'. Our analysis finds that one predictor of a leader's success in year T is that person's level of attainment (their 'expert knowledge'), in the underlying activity, in approximately year T-15 to T-20.[30] Our study draws on data from a high-skill setting in which there are small teams of employees and clear measures of leaders' characteristics and organizational performance. It is found that leader fixed-effects are influential. The principal contribution of the paper, however, is to try to look behind these fixed effects. Ceteris paribus, in the professional basketball industry it is top players who go on to make the best coaches. According to the paper's estimation, the 'expert knowledge' effect appears to be fairly large. Moreover, it is visible in the data within the first year of a new coach arriving. For the typical team, the difference between having a coach who never played NBA basketball, and one who himself played 5 years of all-star basketball (approximately the average among coaches who were former all-star players), is estimated to be six extra places up the league table.[31]

It might be argued that the level of a coach's acquired knowledge is not 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. This remains a possibility. Nevertheless, there are reasons to be cautious of such a claim. One is that it is hard to see why mystery personality factor X should not be found equally often among those particular coaches -- all extraordinarily energetic individuals -- who did not achieve such heights as players. A second is that most

[30] In our data, coaches who were NBA all-star players averaged 51 years of age in the current season of observation and played for an average of 12 years in the NBA. Assuming the coach left school at age 22 (a likely overestimate for coaches, such as former all-star Isiah Thomas, who left college early), this would imply an average of at least 17 years' elapsed time between the end of a former all-star's playing days and the present.

[31] The conclusion is based on the following computation. From Table 1, a team with a coach who was an all-star player 5 times has a winning percentage that is up to 11.5 percentage points than with a non-all-star coach, all else equal (i.e. the point estimate 0.023 times 5). At the mean winning percentage, this gain is approximately 20 percentile points up the distribution, or about 6 places out of 29.

social-science discoveries are subject to some version of this -- almost unfalsifiable -- claim. A third is that it seems, 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.

If the coach's skill as a player is the driving force behind our finding, there are different routes through which this effect could 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.[32] 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. Having a coach who was a great player may make it easier to recruit great players from other teams.

These general mechanisms are not specific to basketball. It may be that this paper's ideas and results -- although explored here for only one special sector -- will prove to be relevant to a range of high-skill work settings.

[32] See, for the example the *USA Today* salaries database at: http://content.usatoday.com/sports/basketball/nba/salaries/default.aspx , accessed April 19, 2010.

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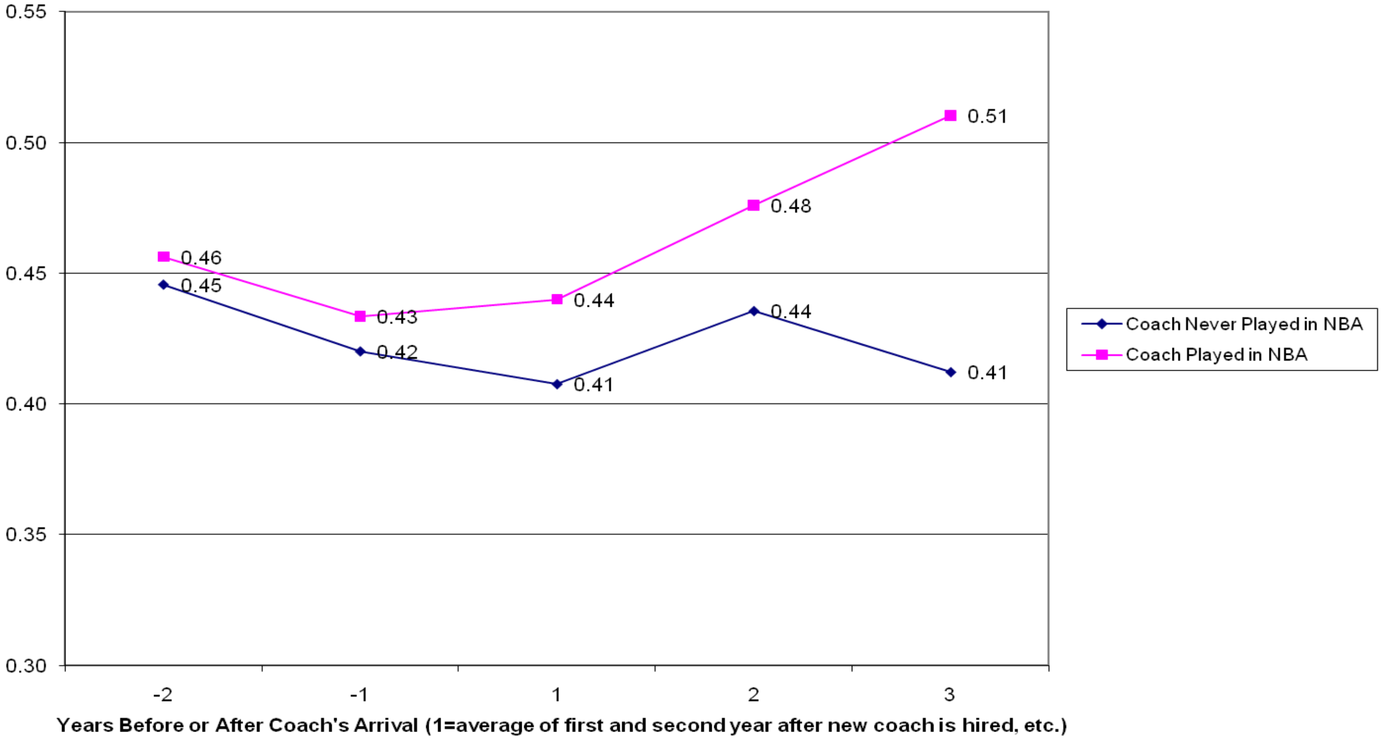
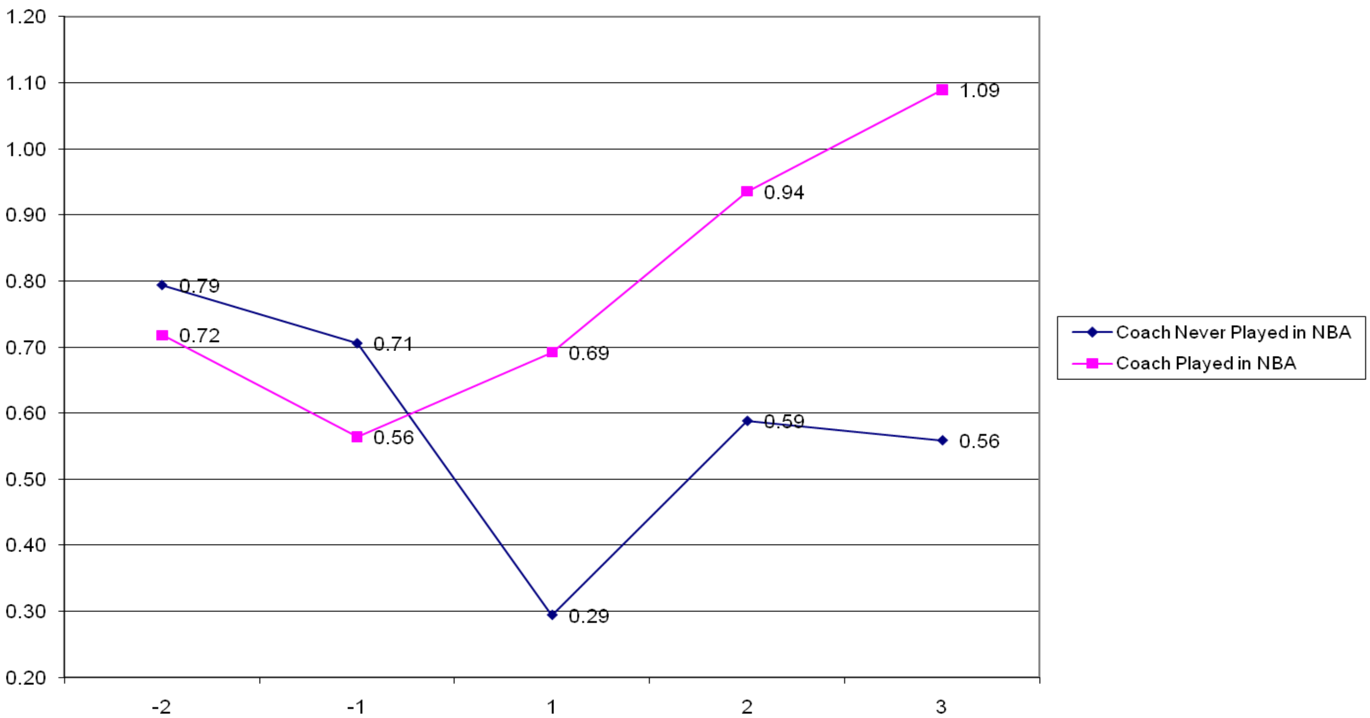
Figure 1: Team Winning Percentage (WPCT) Before and After Arrival of New Coach (2 year moving average)



Note to Figure 1: 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 2: Team Playoff Success Before and After Arrival of New Coach (2 year moving average)



Years Before or After Coach's Arrival (1=average of first and second year after new coach is hired, etc.)

Notes to Figure 2: 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: Regular Season Winning Percentage and Playoff Success by Coach Playing Expertise

	Regular Season Winning Percentage			Playoff Success		
	Never Played in NBA	Played in NBA, Never an All Star	Was NBA All Star	Never Played in NBA	Played in NBA, Never an All Star	Was NBA All Star
A. Full Sample						
Mean	0.445	0.488	0.533	0.707	1.141	1.061
Minimum	0.000	0.000	0.186	0	0	0
Maximum	0.744	0.841	0.780	5	5	4
Number of Coaches	26	26	16	26	26	16
Number of Coach-Year Observations	75	78	66	75	78	66
B. Coaches in Their First Year with Team						
Mean	0.354	0.391	0.495	0.000	0.500	0.615
Minimum	0.207	0.134	0.207	0	0	0
Maximum	0.500	0.817	0.707	0	5	3
Number of Coaches	17	26	13	17	26	13

Note: 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.

Table 2: Regular Season Winning Percentage and Playoff Success by Coach Playing Expertise, Before and After Arrival of New Coach

	Never Played in NBA	Played in NBA, Never an All Star	Was NBA All Star
A. Regular Season Winning Percentage			
Year t-3	0.455	0.458	0.459
Year t-2	0.436	0.439	0.482
Year t-1	0.404	0.387	0.464
Year t (Coach's first year)	0.354	0.391	0.495
Year t+1	0.462	0.423	0.516
Year t+2	0.410	0.509	0.476
Year t+3	0.415	0.529	0.510
Average Before Coach's Arrival	0.432	0.428	0.469
Average After Coach's Arrival	0.410	0.463	0.499
B. Playoff Success			
Year t-3	0.765	0.692	1.077
Year t-2	0.824	0.500	0.846
Year t-1	0.588	0.346	0.846
Year t (Coach's first year)	0.000	0.500	0.615
Year t+1	0.588	0.769	1.000
Year t+2	0.588	1.154	0.769
Year t+3	0.529	1.115	1.231
Average Before Coach's Arrival	0.725	0.513	0.923
Average After Coach's Arrival	0.426	0.885	0.904

Note: 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.

Table 3: 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 4: 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 5: 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	
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 5 (2): 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 6: 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 7: 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 8: 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.

Table A4: OLS Winning Percentage Results for Alternative Specifications, Fully Specified Model

Specification	**Coach Playing Expertise Measure**					
	Ever an NBA All Star Player		Total Years as NBA All Star Player		Total NBA Seasons Played	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Basic Specification from Table 3	0.1144	0.0468	0.0226	0.0091	0.0075	0.0053
Use raw explanatory variables instead of deviations from mean (plus year dummies)	0.1169	0.0463	0.0229	0.0089	0.0076	0.0054
Use ratios to mean rather than deviations from mean for explanatory variables	0.0408	0.0132	0.0390	0.0111	0.0587	0.0293
Drop Larry Bird (3 obs)	0.1204	0.0468	0.0215	0.0091	0.0073	0.0053
Drop Coaches with > 9 NBA All Star Teams (6 obs)	0.1234	0.0469	0.0219	0.0121	0.0068	0.0054
Drop Phil Jackson (6 obs)	0.1040	0.0475	0.0181	0.0090	0.0049	0.0059
Use metro area population and dummies for LA, NY instead of team dummies	0.0886	0.0312	0.0098	0.0038	0.0092	0.0047
Use bootstrapped standard errors (50 reps)	0.1144	0.0539	0.0226	0.0097	0.0075	0.0063
Weight observations by number of games coached in given season	0.0852	0.0345	0.0243	0.0072	0.0016	0.0037

Note: each measure of playing expertise is used in a separate regression that includes the full set of controls in Table 3 except where indicated. Larry Bird and Isiah Thomas both made more than 9 NBA All Star teams as players.