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New approaches of the effect of midseason coaching change on team performance in the history of the NBA

Nuevo enfoque sobre el efecto del cambio de entrenador durante la temporada sobre el rendimiento de los equipos en la historia de la NBA

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Resumen

This research overcomes some of the drawbacks of the study of Martínez & Caudill (2013) regarding mid-season coaching change in the National Basketball Association (NBA), adding new cases and achieving a disparate methodology. Changing a coach is an important managerial decision which does not guarantee improvement in the short term. Only about 12% of new coaches outperformed in a significantly way their predecessors. In order to maximize the probability of success, highly experienced coaches, with a long career as former professional players should be signed. In addition, change should be made before season advances, although it depends of the winning percentage of teams.

Key words: coaching change; NBA; sports management.

Abstract

Esta investigación supera varias de las limitaciones del estudio de Martínez y Caudill (2013) sobre el cambio de entrenador durante la temporada en la National Basketball Association (NBA), incluyendo nuevos casos y empleando una metodología diferente. La decisión de cambiar un entrenador es una importante cuestión para los gestores deportivos que no garantiza la mejora del rendimiento del equipo en el corto plazo. Sólo un 12% de los nuevos entrenadores mejoraron de manera significativa el rendimiento de sus predecesores. Con el fin de maximizar la probabilidad de éxito, entrenadores con gran experiencia y con una carrera previa y larga como jugadores profesionales deberían ser contratados. Además, el cambio debería hacerse antes de que avanzara demasiado la competición, aunque ello depende del porcentaje de victorias de los equipos.

Palabras clave: cambio de entrenador; NBA; gestión del deporte.

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Introduction

In their recent research, Martinez & Caudill (2013) analysed all of the midseason changes in the NBA from the 1949-50 season to the 2009-2010 season. These researchers concluded that midseason coaching change leads to improved team performance in approximately sixty-one percent of the cases examined. These researchers found that making a successful midseason coaching change is significantly related to hiring a new coach with previous experience as an NBA player. These authors also found that the earlier in the season the changes are made, the more likely improvements in performance will result. Finally, they found weak evidence that previous NBA experience as a coach is positively related to an improvement in performance.

This meritorious work, however, has several drawbacks that are important for the management viewpoint: (1) The authors do not present any statistical analysis to support the claim that team performance improved in approximately 61% of the cases; (2) They do not implement any model to analyse the determinant of successful changes, only the determinant of the changes in team performance (raw difference between the winning percentage after and before the change). This raw difference does not distinguish random changes in performance from real changes; (3) They do not exclude several cases of interim coaches who lead for a few games before the signing of a new coach; and (4) In some instances, they compared the performance of a new head coach with the sum of the performances of the 2 replaced coaches (first head coach + interim coach).

Given that midseason change of coach is a very important management dilemma for the owners and general managers of sports teams, as Martínez & Caudill (2013) explain, and given that this topic has been widely treated in the specialized literature in different sports (e.g., Audas, Dobson & Goddard, 1997; Barros, Frick & Passos, 2009; Brown, 1982; Etzen & Yetman, 1972; González-Gómez, Picazo-Tadeo & García-Rubio, 2011; Koning; 2003; Peñas, 2007; Pfeffer & Davis-Blake, 1986; Tena & Forrest, 2007; Wagner, 2010), a complementary vision of the data analysed by Martínez & Caudill (2013) is needed in order to obtain new evidence about the success of this decision for professional basketball teams.

Therefore, the aim of this research is to overcome several of the limitations of the study by Martínez & Caudill (2013) and expand their scope to the last six seasons, thereby providing a new approach to analysing the history of the NBA midseason change of coaches (from the 1949-50 season to the 2015-2016 season) and showing new evidence of the determinants of successful changes. After adding 19 new cases to the Martínez & Caudill (2013) database, and after dropping 30 cases that did not fulfil the inclusion criteria, results show that only a small number of changes - 23 of 192- can be considered successful (i.e., the winning percentage significantly increases). However, factors affecting the improving performance are in part congruent with the results obtained by Martínez & Caudill (2013), although with some relevant differences that deserve to be discussed.

Many of NBA coaches contracts are guaranteed. This means that coaches receive a compensation if they are fired. Therefore, firing a coach in the midseason is an important decision for managers becuase it increases the costs of the team by paying two coaches at time (the fired coach and the new coach). This is one of the reason this research is important for sports management, because it provides evidence about the determinants of success or failure of such decisions.

Methods

Data and measures

We collected data from Basketball-Reference employing the same raw data as Martínez y Caudill (2013), considering all mid-season coaching changes from the 1949-50 season to the 2009-10 season and expanding the scope to the 2015-2106 season. We also registered other measures: (1) experience and expertise of new coaches (winning percentage and games managed in the league at that moment), in addition to data for coaches who were former NBA players (number of seasons and minutes played); (2) number of games a team played at the moment of change, at the end of the season, and after new coaches were signed; (3) winning percentage of teams at the moment of change, at the end of the season, and obtained by new coaches.

Procedure to compare performance

We compared the winning percentage obtained by teams trained by old coaches with the winning percentage obtained by teams trained by new coaches We used the test for comparing two proportions coming from hypergeometric distibutions provided by Krishnamoorthy (2006). We considered *N* games of each season (number of games of the full season), of which *M* of them are wins and *N-M* are loses. A sample of *n* games is drawn without replacement for each coach (the wins and loses of the new and the replaced coach). Let *X* the number of wins observed in the sample. This random variable *X* is referred to as the hypergeometric random variable with parameters *N* and *M*. We denote *k* the wins observed for each particular sample.

The interest is to know if $p_1 = p_2$, where $\hat{p}_1 = k_1/n_1$ and $\hat{p}_2 = k_2/n_2$. If they are equal the performance of the new coach will be the same as the performance of the replaced coach. The alternative hypotesis is that $p_1 \neq p_2$, which means that the performance of the new coach was higher or lower than the performance of the replaced coach.

We employed the *E* test provided by Krishnamoorthy & Thomson (2002). The *E* test is computational demanding because is essentially equal to the one based on the parametric bootstrap approach, and has been computed using the StatCalc 3.0 program (Krishnamoorthy, 2014). The E test is partly based in the pivot statistic:

$$Z_{X1,X2} = \frac{(X_1/n_1) - (X_2/n_2)}{\sqrt{V_{X1,X2}}}$$

where $V_{X1,X2}$ is the variance estimate of $(X_1/n_1) - (X_2/n_2)$ under Ho: $p_1 = p_2$, and is given by:

$$V_{X1,X2} = \left(\frac{N_1 - n_1}{n_1(N_1 - 1)} + \frac{N_2 - n_{21}}{n_2(N_2 - 1)}\right)\left(\frac{X_1 + X_2}{n_1 + n_2}\right)\left(1 - \frac{X_1 + X_2}{n_1 + n_2}\right)$$

The *E* test is preferable to the *Z* test which is only based on the pivotal $Z_{X1,X2}$ statistic for practical use because it controls the Type I error rate much better than does the *Z* test. Both *E* and *Z* test rejects Ho when the *p* value is lees than or equal to α. For technical details see Krishnamoorthy & Thomson (2002).

This simplistic method has the advantage of considering uncertainty in the value of the winning percentage of teams. When a coach only leads a portion of all of the possible games of a season, it is highly desirable to depict the winning percentage obtained using an interval estimation because we are not sure if this punctual value at the moment of change reflects without error the strength of the team. This fact has not been addressed in past research on basketball, such as Fidel & D'itri (1999), Giambatista (2004) or McTeer, White & Persad (1995). This is also not considered in studies about other sports, such as soccer. For example, Wagner (2010) considered only the four prior and subsequent games after change in order to achieve the comparison. As we mentioned earlier, this was also not addressed by Martínez & Caudill (2013).

We consider this issue crucial for making comparisons among performance of different coaches when analysing midseason changes because we are comparing two samples of games from two hypothetical populations. Therefore, a statistical test is necessary to ascertain whether both populations are the same, i.e., if both winning percentages differ or are statistically the same. In addition, because the criteria to compare winning percentages is based on a probabilistic perspective, we believe that it outperforms the procedure presented by McTeer, White & Persad (1995), authors who subjectively considered 11 games played as a cut-off value for including cases in their study.

Statistical model

Once we determined which coaches improved team performance, we were interested in explaining successful changes. We created a new dichotomous variable y_i for all the i cases, with 0 for "no success" (including the cases of no difference in performance and worse performance of new coaches), and 1 for "success" (better performance of new coaches). In addition, in order to explain such variation in performance, we identified variables that could influence the probability of success. Following the principles of General Linear Modelling, we built a logit model with the following specification:

$$ln\left\{\frac{\Pr(y_i = 1|x_{ki})}{1 - \Pr(y_i = 1|x_{ki})}\right\} = \beta_0 + \sum_{1}^{k} \beta_k x_{ki}$$

where X_{ki} was a set of predictors, β_0 and β_k were the coefficients to be estimated.

We considered the following predictors: (1) the experience/expertise of new coaches reflected in games played in the NBA and the number of wins obtained; (2) the experience/expertise of new coaches as former NBA players; (3) the difference between the fraction of games played in a season before and after the coaching change; and (4) the winning percentage of teams at the moment of change. We explain the rationale for selecting those variables below:

Regarding the *experience/expertise* of new coaches, Salomo, Teichmann & Albrechts (2000) and Giambatista (2004) considered this variable as a good proxy for evaluating coaches' abilities. In addition, Barros, Frick & Passos (2009) found that the probability of being dismissed was negatively affected by head coaches' experience and their winning percentage. We consider a novel approach in this specific field to address this variable. We used a sigmoid function $\frac{1}{1+e^{-\lambda A_1}}$ (Schmueli, Patel & Bruce, 2007) in order to transform the distribution of the number of games played by a coach into a S-shaped curve. In this case A_1 refers to the number of NBA games played by a coach until the moment of signing with the new team, and λ is a parameter to adjust the curve to the desired rank of values. We hypothesised that this form of curve correctly reflects the effect of experience on performance, Therefore, increasing the number of games played yields a small effect of performance in the first steps of a coach's career and when a coach has played a great number of games.

In order to create an easily interpretable index after the sigmoid transformation, we took the following steps: First, we considered the distribution of the number of games played by all of the coaches. This distribution was highly asymmetrical with a high number of zeros (new coaches without any previous experience in the NBA). Taking the form of this distribution, we computed its median (280 games) and then the deviation of each value from that median. These values ranged from -280 (rookie coaches) to 2170 (Hall of Famer Lenny Wilkens). Second, we calibrated the sigmoid function using the λ parameter in order to obtain a normalized [0,1] function. This calibration process yielded a $\lambda=1/50$. We strongly believed that this S-shaped curve was a better model for characterizing coaching experience, rather than other forms of learning gains, such as the natural logarithm transformation achieved by Giambatista (2004). Logarithm yields a curve with increased diminishing returns to the extent that experience grows. However, we think that in the first steps of an NBA coach's career, gains in learning should be modelled using this type of exponential growth.

We followed exactly the same procedure with the number of wins by coaches because obviously playing many games and losing the majority of them is not the same as playing many games and winning a great percentage of them. Giambatista (2004) also used wins obtained by coaches, although with the natural logarithm transformation. We hypothesized that "winners" coaches should have a greater experience index (i.e., potential) than "losers". Median of the distribution was 115.5, and deviation from median ranged from -115.5 (rookie coaches) to 1177 of Lenny Wilkens. In this case, the calibration process yielded a $\lambda = 1/20$. Considering that the correlation between both measures of coaches experience (once transformed in a normalized form) was approximately 0.98, and in order to avoid multicollinearity problems, we aggregated both measures to finally obtain an index of *coach experience* ranged in a [0,2] interval[1]. Note the different parametrization with respect to the variables used by Martínez & Caudill (2013): number of previous games coached and the number of previous games won as a coach.

Recall that we speak about experience, expertise or ability of coaches in a similar way. We understand that they may be considered different concepts for some authors (e.g., Giambatista, 2004), but we only want to reflect the curriculum vitae of coaches defined by games managed and wins obtained, i.e., the a priori potential or quality of hired coaches.

Regarding *experience as former NBA players*, Goodall, Kahn & Oswald (2010) found that former star players make the best coaches. In addition, this expert knowledge effect was large. Therefore, we hypothesized that the experience of coaches as former players increased the probability of success. Goodall, Kahn & Oswald (2010) used several measures of experience. Following these authors, we also used measures such as the number of seasons played and the number of minutes played because we thought that this variable could measure the quality of experience of players in a more reliable way. Note that players could

[1] An important decision regarding the nature of this variable was about considering experience in the BAA (Basketball Association of America) and ABA (American Basketball Association) leagues. BAA league was a professional basketball league founded in 1946 and, together with ABL (American Basketball League) and NBL (National Basketball League), contributed to the expansion and promotion of basketball before NBA was created. Moreover, NBA was created from a merge of BAA and ABL. There are only BAA data available (from 1946/47 to 1948/49 seasons), so we decided to include the experience of coaches who trained BAA teams in the same form as if they had trained NBA teams. However, we do not have data regarding experience of coaches in the other professional leagues, such as NBL and ABL. A similar problem appeared with the ABA league, a professional competition founded in 1967. This league challenged the hegemony of NBA during several years, and finally merged with NBA in 1976. Four ABA teams joined to NBA, so we also decided to include the experience of coaches who trained ABA teams in the same way of NBA teams

play many NBA seasons but with a marginal presence in the roster rotation, so minutes played could overcome this limitation. Martínez & Caudill (2013) also employed minutes played.

Thus, we created a first variable, the *number of seasons played as NBA players*, and a second variable, the *minutes played/1000*, similar to Martínez & Caudill (2013). As we thought S-shaped curve was the best way to characterize ability and performance variables, then we transformed both variables using the procedure previously depicted for the coach experience. However, we also tested the alternative specification of considering the first two variables in the original scales, as Goodall, Kahn & Oswald (2010) did. Therefore, we ran several models using these variables.

Regarding the *difference between the fractions of games played in a season before and after the coaching change*, we wondered if the probability of success increases with the parity of games played by replaced and new coaches. In addition, this variable could provide information regarding a "time effect", i.e., if managing more games improves performance, as Martínez & Caudill (2013) explain.

Finally, we hypothesized that the *winning percentage of a team at the time of change* would be negatively associated with coach performance improvement. The rationale for this reasoning is straightforward: it will be easier to outperform a very bad winning percentage than a good winning percentage. Obviously, this association would be moderated for the intrinsic quality of each team considered because it would be easier for coaches of good teams to outperform a very bad winning percentage than for coaches of bad teams. However, as the proxy variable for evaluating team quality is the winning percentage at the end of the season, we did not consider using it as a predictor because the dependent variable was precisely measuring change in quality of teams due to the new coach effect.

Exclusion criteria

Not all of the changes should be considered. There are a considerable number of cases where a coach is fired and an assistant coach pilots a team during a few games. Often assistant coaches of the staff are chosen as temporary coaches for that purpose, i.e., they are interim coaches. After that, a new head coach is signed by that team. Consequently, we established as exclusion criteria to be an interim coach fulfilling some conditions because not all the interim coaches have to be excluded. Some of them manage teams until the end of the season, and others manage an important portion of games before a new head coach arrives. For example, in the 1994-95 season, Dan Issel resigned as the head coach of the Denver Nuggets with a win-loss record of (18-16). Gene Littles was the interim coach who led the team during 16 games before Bernie Bickerstaff signed as the new head coach. In such a case, we considered the performance of Gene Littles (3-13) in our analysis. Therefore, the record of Gene Littles (3-13) was compared with the performance of the replaced coach, Dan Issel (18-16), and the performance of the new head coach, Bernie Bickerstaff (20-12) was then compared with the replaced interim coach, Gene Littles (3-13).

Another important consideration stems from the number of games managed by a new coach. As we have explained, interim coaches occasionally coach several games during the transition between the time a coach resigns or is fired and the arrival of a new coach. However, there are occasions where the interim coach leads very few games at the end of the season. For example, in the 1980-81 season, Mike Fratello led only the 3 last games for the Atlanta Hawks as interim coach.

Another possibility is that teams fire a coach in the last games of a season and sign a new coach thinking primarily of the next season. This was the case with Donnie Butcher, who signed as a head coach of the Detroit Pistons in the 1966/67 season. Bucher only managed the last 8 games of that season, but he was the head coach for the following two seasons. Consequently, we established a minimum of 10 games as a threshold to include the performance of new coaches in our analysis.

In sum, we excluded temporary (interim) coaches who managed fewer than 10 games in the middle of the season or at the end of the season because the context of that change is not the same as signing a new coach to improve the team's performance. When a new coach manages fewer than 10 games, this is probably due to an extraordinary situation such as a transitional period between the fired/resigned coach and the arrival of the new head coach. Sometimes that arrival occurs in the same season, but other times it takes place in the following season. When an interim coach directs more than 10 games, that likely reflects the general manager's confidence in the interim's ability to lead the team, and in such cases, the interim's performance is compared with the replaced coach. This is an important contribution by our research compared to the study by Martínez & Caudill (2013).

Omitted variables

With regard to model specification, two important issues were not addressed: the home/away calendar and the strength of schedule. Both elements have been considered important to study the effect of firing a coach on team performance (Koning, 2003) because of the effect of home advantage (see Winston, 2009) and the effect of disparate winning percentages on the probability of win (see Huang, Weng & Lin, 2006).

However, there are important difficulties associated with considering these factors in our study. The main limitation arises from the practical impossibility of collecting data about the winning percentage of each team playing against all of the cases we have considered during more than 60 years of competition. Note that it would be necessary to "manually" register the winning percentage of rivals and if the game was played at home or away for the approximately 7500 games played by teams before changing a coach, and the approximately 8717 games played by the same teams after signing a new coach, i.e., a total of 16216 games. We say approximately because some games were played in a neutral venue. From 1950 to 1974, about 1461 games (13.77%) were played on a neutral court (Justin Kubatko from Basketball-Reference, personal communication).

In addition, there is interaction between the home/away variable and the winning percentage variable, so it was not been feasible to aggregate the winning percentage of teams played against the specified team that changed its coach in a season (this fact would have facilitated the task) because the home/away advantage acts in a different form for teams having better performance. As Koning (2003) claimed, the effect of the home advantage variable varies between teams. We made a small analysis in order to ascertain this in basketball. We obtained data from three seasons (from 2006/07 to 2008/09) and computed the number of total wins for each team and the percentage of home wins. The mean percentage of home wins was 0.61, indicating the influence of this factor for winning a game (11 points above the neutral value of 0.5). However, the distribution of values ranged from 0.46 to 0.73 in the 90 cases considered. Therefore, we correlated team wins with the percentage of home wins and we found a negative correlation of -0.33. This clearly indicated that, in the NBA, worse teams are relatively stronger in home than better teams.

Acknowledging the limitations of not accounting for the home/away variable and the strength of schedule, we made two simulations in order to study the possible bias in our results derived from omitting these variables. First, we analysed the effect of the disparity of calendar on the duality of home/away wins. Recall that all teams in the NBA play the same number of games at home vs. away (currently, 41 games). We used a database of team results from the 2006/07, 2007/08 and 2008/09 seasons, downloaded from NBAStuffer. This database is a user friendly Excel resource that allows users to program different procedures to analyse the home/field advantage and the strength of schedule. Unfortunately, data are only available from the 2006/07 season.

We registered the number of home and away games for each team, and we ordered data in function of each team schedule. To achieve simulations, we considered only data from game number 15 to game number 67, which encompasses from approximately 18 to 82% of season games because almost of 90% of changes of coaches in the history of NBA occurred within this interval of percentages. We compared the number of home games with the number of expected home games in each partition that would be necessary to maintain the parity of home vs. away games. Note that we considered the number of home games in 54 different partitions (from 15 to 67 games). Next, we computed the difference between the observed and the expected number of home games for the 30 teams, for the three seasons and for the 54 disparate partitions (30x3x54=4860 cases). Figure 1 shows the results of the simulation. The shaded area represents data between the percentiles 5 and 95. Thereby, 90% of data falls under approximately -3 and 3 home games of difference. It is true that there are cases within the 0-5 and 95-100 percentiles where this difference becomes approximately 6 games (see dashed line), but we may say, with considerable prudency, that the calendar disparity does not yield an ostensible difference in home vs. away parity, in particular when data move away from the middle of distribution.

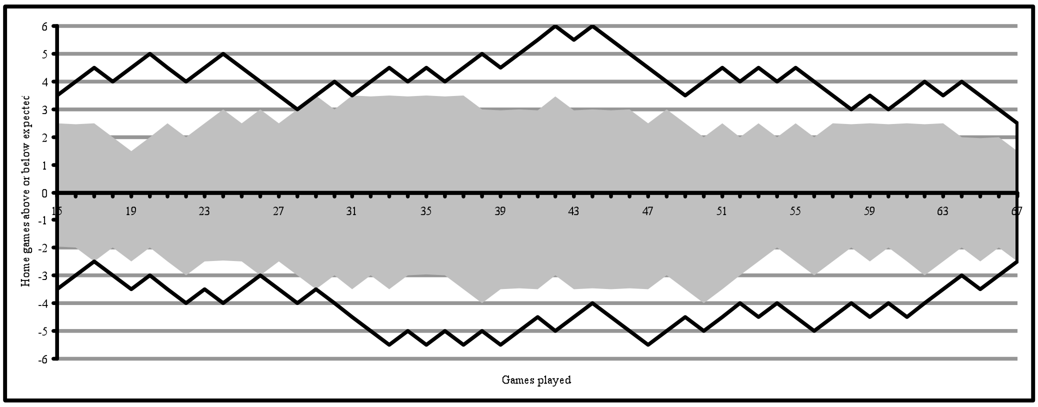

Figure 1. Simulation of the potential bias derived from omitting the disparity of home games played

Second, using the same database of three NBA regular season games, we analysed differences in strength of schedule in the same 54 partitions. For example, for the 15 games partition, we compared the mean of opponents' winning percentages at the end of the season (from game 1 to game 15) with the mean of the opponents' winning percentages at the end of the season for the 67 remaining games (from game 16 to game 82). In order to avoid scale problems and to count with dispersion of data, we also completed the same analysis using the coefficient of variation, i.e., the standard deviation divided by the mean. Figure 2 shows the results of the simulation. The shaded area represents data between the percentiles 5 and 95. Thereby, 90% of data falls under approximately (-0.05 and 0.05) units of difference. Considering the winning percentage is a [0,1] variable, this represents only between -5% and 5% of variation. It is true that this difference is a little higher for coefficient of variation (dashed line), which indicates that there is also a difference in the dispersion of distributions (some teams play with more homogeneous rivals than others, with respect to the quality of teams). Contrary to Figure 1, differences become larger in the tails of the graphic.

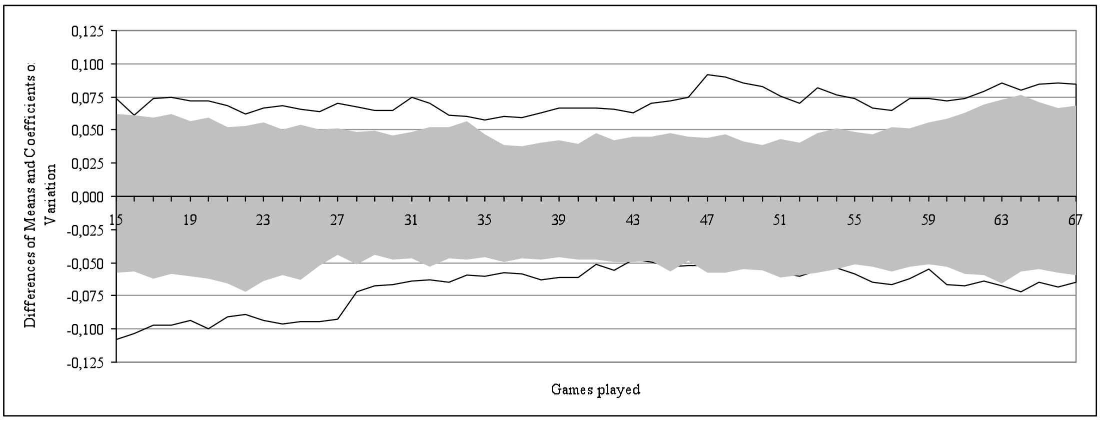

Figure 2. Simulation of the potential bias derived from omitting the strength of schedule

In sum, acknowledging the shortcoming of omitting variables such as home field advantage and strength of schedule, these simulations show that the potential omitted information should not have an important effect on the probability of success. The lack of an available database to facilitate the registration of this great amount of data has been an impossible barrier to overcome. However, after viewing these simulations, we are convinced that our results are still robust and they are not importantly biased.

Interpretation and generalization of results

A final commentary regarding our methodology deserves to be highlighted. We have studied all the population of NBA midseason changes in the history of the league. There is no sample of changes, consequently, from a theoretical viewpoint, there is no inference from the sample to the hypothetical population. Therefore, we do not need statistical tests to analyse results[2]. However, this philosophy of analysis excludes any potential extension of results to other populations, such as other leagues, for example. In addition, this excludes any predictive inference about future changes in the NBA. Therefore, we also report statistical tests and confidence intervals in the analysis made with all the population of coaches. Extension to a hypothetical infinite population of coaches' changes would require the following assumptions: (1) the changes of coaches analysed are a random sample of a population of changes in all the leagues of the world; (2) future conditions in the NBA will be the same (there will be no new systematic factors affecting change). The first assumption would be required to respond to the question: Does changing a coach within a season improve team performance in basketball (without restriction to the NBA)? And the second assumption would be necessary to make predictions. Taking into account the heterogeneity of basketball leagues in the world, placed in different countries with disparate sport cultures and systems of competition, the first assumption seems less plausible than the second. Therefore, we should be very cautious regarding the generalization of results. Nonetheless, these results are valuable by themselves because of the importance of the NBA league, and regardless any generalizations to other competitions.

[2] We are referring here to the inferential procedure from a sample of changes to the population of changes. We considered the population of changes, because we studied all of the midseason changes that occurred in the league's history. Therefore, we did not need statistical inference to explain the history of NBA coaching changes. Note that this is a different case from the procedure to compare the performance of coaches, depicted previously as a statistical comparison between two proportions. In this latter case, it is necessarily a statistical test because we compare two samples of games played by two distinct coaches.

Results

A total of 222 changes occurred during the period considered (from 1949-50 to 2015-2016). After applying the exclusion criteria, the total sample frame of coaches was 192 because 30 cases were dropped (Appendix 1).

We applied the *E* test to analyse whether the Win-Lose record (the winning percentage is computed as Wins/(Wins+Losses)) of new coaches was better, equal or worse than the Win-Lose record of the replaced coaches. The cut-off criteria for the *p*-value was 0.05. As Table 1 shows, 23 coaches outperformed the winning percentage of the replaced coaches. However, 10 new coaches performed significantly worse than the replaced ones (Table 2).

Table 1. New coaches who outperformed replaced coaches

New coach	Season	Team	*E* test (*p*-value)
Red Auerbach	1949-50	Blackhawks	0.046
Jack Smiley	1949-50	Waterloo Hawks	0.036
Red Holzman	1967-68	New York Knicks	0.006
Butch Van Breda Kolff	1974-75	New Orleans Jazz	0.012
Don Nelson	1976-77	Milwaukee Bucks	0.014
Billy Cunningham	1977-78	Philadelphia 76ers	0.002
Lenny Wilkens	1977-78	Seattle Supersonics	0.000
Dave Cowens	1978-79	Boston Celtics	0.031
Phil Johnson	1984-85	Kansas City Kings	0.039
Wes Unseld	1987-88	Washington Bullets	0.004
Bob Hill	1990-91	Indiana Pacers	0.031
Larry Brown	1991-92	L. A. Clippers	0.020
Bernie Bickerstaff	1994-95	Denver Nuggets	0.001
Danny Ainge	1996-97	Phoenix Suns	0.000
Don Casey	1998-99	New Jersey Nets	0.004
Paul Silas	1998-99	Charlotte Hornets	0.002
Hubie Brown	2002-03	Memphis Grizzlies	0.017
Avery Johnson	2004-05	Dallas Mavericks	0.019
George Karl	2004-05	Denver Nuggets	0.000
Scott Brooks	2008-09	Ocklahoma City	0.038
Kiki Vandeweghe	2009-10	New Jersey Nets	0.030
Mike Woodson	2011-12	New York Knicks	0.002
Randy Wittman	2011-12	Washington Wizards	0.000

Table 2. New coaches who performed worse than replaced coaches

New coach	Season	Team	*E* test (*p*-value)
Earl Lloyd	1971-72	Detroit Pistons	0.026
Gene Littles	1994-95	Denver Nuggets	0.007
Jim Todd	1999-00	L. A. Clippers	0.030
Don Chaney	2001-02	New York Knicks	0.004
Frank Hamblen	2004-05	L. A. Lakers	0.000
Kevin Pritchard	2004-05	Portland Trail Blazers	0.009
Randy Wittman	2006-07	Minnestota Timberwolves	0.005
Kim Hughes	2009-10	L. A. Clippers	0.018
Tyrone Corbin	2010-11	Utah Jazz	0.000
John Lover	2014-15	Detroit Pistons	0.031

The remaining changes (159) were not significantly different, i.e., in 159 of the 192 cases the winning percentage of new coaches was statistically equal to the winning percentage of the replaced coaches. Consequently, only 23 of the 192 coach changes improved the performance of teams, i.e., only 11.98% of cases (Table 3).

Table 3. Performance comparison between new and replaced coaches.

	Cases	%
Neutral effect	159	82.91
Worse performance	10	5.20
Better performance	23	11.98

Once we obtained the outperformed cases, we ran several logistic regression analyses employing Stata 13.0 using, as a dependent variable, the 23 successful cases as "ones" and the remaining unsuccessful cases (169) as "zeros". The independent variables were as follows: (1) *coaching experience*; (2) *experience as former players*; (3) *split* (the difference between the fraction of games played in a season before and after the coaching change); and (4) *winning percentage of teams at the time of change*. The different specifications of such variables were explained in the method section.

The best model presented an interaction between the *split* variable and the *winning percentage of teams at the time of change*. The parameter estimates are shown in Table 4 and compared with the results obtained by Martínez & Caudill (2013). The results of the disparate analyses supported the validity of the model as shown in Table 5.

Coaching experience and *former experience as NBA players* significantly increase the probability of a successful change. These results are similar to the results obtained by Martínez & Caudill (2013), but the evidence is stronger for coaching experience. Remember that we reparametrized both variables to be S-shaped. In addition, and similar again to Martínez & Caudill (2013), success is negatively related to the *fraction of games coached by the replaced coach* (*Split*). This implies that improvement in performance is more likely to take place as a larger number of games are played for the new coach.

However, and as a key divergence with respect to the study by Martínez & Caudill (2013), the *winning percentage of teams at the time of change* interacted with *Split*, which indicates a complex effect of both variables on the success of the change. For example, when *Split* diminishes, the probability of success increases, but only if the winning percentage at the time of change also decreases. If the winning percentage increases, it masks the negative effect of the reduction of *Split*. This indicates that *Split* has a more complex role in determining success than shown by Martínez & Caudill (2013) because its effects depend of the winning percentage of teams at the time of change.

Table 4. Estimation results compared with those obtained by Martínez & Caudill (2013).

	The present study	Martínez & Caudill (2013)
Method	Logistic regression	Linear regression
Period	1949-2016	1949-2010
Total cases	223	203
Valid cases	192	184
Dependent variable	*Succesfull changes/No succesfull changes*	*Difference in the team winning percentage after and before de change*
Intercept	-3.177**	-0.014
Coaching experience	0.816**	0.083*
Experience as former players	1.636**	0.002**
Split	-4.558**	-0.143**
WP% at the time of change	-1.625	Not measured
Split WP% at the time of change*	11.921**	Not measured
R^2	0.262	0.201

*p<0.10, **p<0.05

Table 5. Analyses supporting the model

Linktest (_hatsq)	0.020
Hosmer_Lemewhow test	7.060
Run test of residuals sign	-0.510
Cases correctly classified	80.21% (154 of 192)
Sensitivity	78.26% (18 of 23)

*p<0.10, **p<0.05

Linktest is a type of misspecification test in which the square of the linear predictor (_hatsq) has to be non-significant. The Hosmer-Lemeshow test compares observed and predicted values in different deciles of the distribution and has to be non-significant. Running a test of the residuals sign is employed to analyse the independence assumption and has to be non-significant

Discussion and Managerial Implications

In this research, we made a complete review of the mid-season coaching changes that have occurred in the NBA history. We statistically compared the winning percentage of each team at the moment of change with the winning percentage under a new coach, in order to obtain a reliable test considering performance achieved in a sample of all of the games in a season. In addition, we tested a model in order to explain the success cases, i.e., when a new coach achieved statistically better results than the coach he replaced. We considered the study of

Martínez & Caudill (2013) as a reference, but we complemented its results by overcoming some of its limitations, increasing the scope of the time and taking a different approach to data analysis.

Our study has the following four important differences from the research by Martínez & Caudill (2013): (1) We employ statistical analysis to analyse the success of the change; (2) We implement a model to analyse the determinant of successful changes in order to distinguish random changes in performance from real changes; (3) We exclude several cases of interim coaches who led for few matches before a new coach was signed, which would add noise to data; and (4) We compared the performance of a new head coach with the performance of the replaced coach and not with the sum of the performance of the replaced coach and interim coach.

Results show that changing a coach only improved performance in approximately 12% of cases, and instead decreased performance in approximately 5.20% of cases and had a neutral effect in the majority of cases (approximately 83%). This result indicates that NBA owners and general managers made bad decisions the vast majority of time given the financial costs associated with the change. These results are in some instance similar to the recent findings obtained by Ours & Tuijl (2016) regarding head coaches midseason changes in the Dutch professional football during 14 successive seasons; replacement of coaches does not improve team performance.

Given that coaches contracts are guaranteed (totally or partially), this result is noteworthy. For example, Mike Brown was fired from L.A. Lakers in the season 2012/2013, but he was still paid by the Lakers in the following season, where he was the head coach of the Cleveland Cavaliers. The Cavaliers also fired Brown at the end of the 2013/2014 season (Manfred, 2014).

Our results are restricted to the short-term, i.e., performance within a season. Recall that we did not consider play-off games, only regular season games. A new coach could achieve a great performance in the play-off series, but we excluded these types of games because we did not have a similar series of games managed by replaced coaches. Consequently, we acknowledge that these decisions might be successful in the long-term. Further research should explore this issue, along the same lines as Giambatista (2004). Nevertheless, it seems that owners followed a rational thinking with successful coaches because more than 75% of the coaches who obtained better results continued into the next season. In addition, because these coaching changes disrupt team stability, this result could partially support the findings of Montanari, Silvestre & Gallo (2008), who found that team stability and longevity of team relationships have a positive impact on performance.

The probability of success (i.e., the probability of new coaches improving performance) increased with the experience of new coaches (defined by the number of games managed and the number of wins achieved until the moment of change) as well as their experience as former NBA players (defined by the number of seasons played), but it was inversely related to the difference between games played by old and new coaches and moderated with the winning percentage of teams at the time of change.

It seems clear that if owners want to improve the probability of success when they fire a coach, then they have to hire a new coach with considerable experience as an NBA coach and as an NBA player. However, these types of coaches are typically the best paid, so owners and general managers have to make a difficult decision because of the trade-off between experience and salary.

Changing a coach in the earlier period of the season helps to improve performance. This indicates that when things go bad, it would be a wiser decision to fire a coach as soon as possible rather than to wait for more games to be played because there would not be enough time to redirect the situation. However, its effect depends of the winning percentage of the time at the moment of change. Among the teams that have a good Win-Lose record, the effect of the *Split* (time effect) vanishes. Therefore, changing a coach for the better teams of the NBA within a season is a very risky decision with a very low probability of success.

Limitations and Further Research

We recognize that all these conclusions are highly dependent of the procedure we used to compare the performance of coaches. We based our reasoning on the finite population approach for comparing proportions following a hypergeometric distribution. Note that this procedure requires the assumption that the number of games managed by coaches is a random sample of the hypothetical 82 games that they would play in the whole season. In addition, any sample realization (i.e., any result recorded) should be independent from the remaining games. Obviously, this is not exactly the reality. Games played by coaches could be considered a pseudo-random sample of games. In fact, they are not previously determined before a season starts. Although the schedule is known, it would be impossible to know how many games a fired coach and a hired coach would play, as well as the moment during the season when change would occur. Therefore, we believe the random sampling assumption is not severely problematic. Regarding independence, Arkes & Martínez (2011) found the existence of momentum in the NBA, i.e., the results of games partially depend on results from previous games, once several factors are considered. Although the marginal effect of momentum is small (approximately 3-4%), this nonetheless indicates that the independence assumption would be violated. We think that, considering the small impact of the momentum variable, our method is robust against this slight departure from independence of observations, but we acknowledge this fact as a limitation of our work.

Results also depend of the level of signification considered. We chose 0.05 (95% of confidence), as the vast majority of researchers do, but this is a subjective threshold, and results change if we increase alpha to 0.10 (90% of confidence). We have analysed results under this scenario, and the successful changes were 42 (21.87%) when alpha is 0.10 against 23 (11.97%) when alpha is 0.05. However, results of the determinants of the success after applying logistic regression are similar to the results obtained when alpha is 0.05, but with less explanatory power. Increasing the level of signification to 0.10 makes the results less reliable, so we think 0.05 is preferable.

Our research has another limitation derived from not considering resignation. Not all of the midseason changes are due to teams firing a coach because sometimes coaches resign. Future research should reanalyse data distinguishing both situations. Unfortunately, it is highly complicated in some cases to know if a coach resigned or was fired, so we decided not to consider this factor. Moreover, we collected reliable data approximately 75% of our cases, and only about 6% of cases were resignations.

We have also to acknowledge that in some occasions teams that changed a coach qualified for play-offs, and in some cases they did it well there. The most extreme case is the recent NBA champions, the Cleveland Cavaliers. David Blatt was fired after playing 41 games with a winning percentage of 0.73. Tyronn Lue was signed, and he led another 41 games with a winning percentage of 0.66. Therefore, this case is not a "successful" case because the winning percentage of the new coach was not significantly better than the winning percentage of the replaced coach, but obviously team owners were pleased with the final results of that change. However, it is impossible to know if the Cavs would have been won the championship if David Blatt had not been fired. In the 2005-06 season, another NBA Champion team, the Miami Heat, changed their coach. Stan Van Gundy resigned after a (11-10) record, and Pat Riley was signed (41-20). *E* test showed a non-significant increase in performance (p-value: 0.12), but Pat Riley won the championship. The same occurred in the 1981-82 season when again Pat Riley (50-21) was signed as coach of the Los Angeles Lakers. He did not outperform the winning percentage of Paul Westhead (7-4), but the Lakers won the championship. Similarly when Paul Westhead (50-18) replaced Jack McKinney (10-4) in the 1979-80 season, the Lakers won the NBA Championship. These were the only four cases when a team won the NBA Championship after a midseason change of coach.

An alternative form of interpreting the finite population approach would have been to compare the aggregated percentage of wins obtained by new coaches (0.41) against the aggregated percentage of wins earned by the coaches they replaced (0.38), i.e., to achieve a unique test of difference of proportions instead of the 192 tests achieved. Therefore, considering 15,309 games as the total population of games, with 8541 the number of games managed by new coaches and 6278 the number of games managed by old coaches, then 95% confidence interval around the two proportions would be (0.407; 0.421) and (0.367; 0.385). That is, in an aggregated form, new coaches significantly improved over the performance of their predecessors. This form of viewing the analysis would overcome the problem of the conservative individual tests but obviously does not allow for individual analysis of the success of change. However, we think it provides useful information regarding the trend of the change effect.

Nevertheless, a major limitation of our study arises from not controlling for midseason transactions. These types of transactions could improve (or decline) the quality of teams and could be a source of systematic noise in our analysis. Although data on transactions were available at Basketball-Reference, we think it would be highly complicated to analyse how these changes in rosters could influence results. Nevertheless, the most important changes in rosters are not usually achieved during midseason, but rather when a season ends. Therefore, the possible bias in our results would be of lesser importance that the potential bias of studies considering longitudinal approaches (e.g., Giambatista, 2004) or analysing the seasons before and after the coach were changed (McTeer, White & Persad, 1995). One of the possible solutions would be considering player talent as a proxy for the quality of the roster, as Fizel & D'itri (1999) did. However, how to measure the talent of players is a controversial issue in basketball (see Berri & Bradbury, 2010; Berri & Schmidt, 2010), and the way that Fizel & D'itri (1999) addressed this question is highly debatable. Consequently, it is a challenge for further research to try to account for this factor using the best measurement instrument.

Finally, the effect of a new coach on some variables related to performance could be reflected in the long term, not in the same season. Therefore, a positive or negative dynamic in several performance variables which have not a direct effect in the short term team performance are not considered in our study. Further research could achieve multifactorial studies to overcome this limitation.

Conclusion

In sum, and acknowledging the commented shortcommings, our research has advanced in the understanding of the effect of hiring new coaches on performance of NBA teams, when change is achieved in the middle of the season. Changing a coach is an important managerial decision which does not guarantee improvement in the short term, i.e. in the same season. Only about 12% of new coaches outperformed in a significantly way their predecessors. In order to maximize the probability of success, highly experienced coaches, with a long career as former NBA players should be signed. In addition, change should be made before season advances, although it depends of the winning percentage of teams at the moment of change. These results offer a complementary vision of Martínez & Caudill's (2013) study, overcoming some of its limitations, and after adding 19 new cases (coming from the 2010/11 to the 2015/16 seasons) to the analyisis.

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Appendix 1.

Dropped cases after applying exclusion criteria

New coach	Replaced coach	Season	Team	Exclusion
Ike Duffey (1-2)	Howie Schultz (21-14)	1949-50	Anderson Packers	A
John Logan (2-1)	Dave McMillan (9-14)	1950-51	Tri-Cities Blackhawks	A
Slater Martin (5-3)	Red Holzman (14-19)	1956-57	St. Louis Hawks	A
Bob Pettit (4-2)	Andrew Levane (20-40)	1961-62	St. Louis Hawks	A
Donnie Butcher (2-6)	Dave DeBusschere (28-45)	1966-67	Detroit Pistons	A
John McCarthy (22-59)	Dolph Schayes (0-1)	1971-72	Buffalo Braves	B
Terry Dischinger (0-2)	Butch Van Breda Kolff (6-4)	1971-72	Detroit Pistons	A
Draff Young (0-3)	Bob Cousy (6-14)	1973-74	Kansas City-Omaha Kings	A
Elgin Baylor (0-1)	Scotty Robertson (1-14)	1974-75	New Orleans Jazz	A
Gene Tormohlen (1-7)	Cotton Fitzsimmons (28-46)	1975-76	Atlanta Hawks	A
Bob Mackinnon (3-4)	Tates Locke (16-30)	1976-77	Buffalo Braves	A
Mike Fratello (0-3)	Hubie Brown (31-48	1980-81	Atlanta Hawks	A
Phil Johnson (0-1)	Jerry Sloan (19-32)	1981-82	Chicago Bulls	A
Bob Kloppenburg (0-3)	Don Delaney (4-11)	1981-82	Cleveland Cavaliers	A
Bill Blair (2-4)	Larry Brown (47-29)	1982-83	New Jersey Nets	A
Mel Daniels (0-2)	Jack Ramsay (0-7)	1988-89	Indiana Pacers	A
Mack Calvin (1-1)	Mike Schuler (21-24)	1991-92	L. A. Clippers	A
Bob Kloppenburg (2-2)	K.C. Jones (18-18)	1991-92	Seattle Supersonics	A
Rex Hughes (1-0)	Jerry Tarkanian (9-11)	1992-93	San Antonio Spurs	A
Bill Bertka (1-1)	Randy Pfund (27-37)	1993-94	L. A. Lakers	A
Bob Staak (0-1)	Jim Lynam (22-24)	1996-97	Washington Bullets	A
Bill Bertka (1-0)	Del Harris (6-6)	1998-99	Los Angeles Lakers	A
Bill Berry (0-2)	Tim Floyd (4-21)	2001-02	Chicago Bulls	A
Herb Williams (1-0)	Don Chaney (15-24)	2003-04	New York Knicks	A
Pete Myers (0-2)	Bill Cartwright (4-10)	2003-04	Chicago Bulls	A
Lionel Hollins (0-4)	Hubie Brown (5-7)	2004-05	Memphis Grizzlies	A
Pete Myers (0-1)	Scott Skiles (9-16)	2007-08	Chicago Bulls	A
Johnny Davis (0-2)	Marc Iavaroni (11-30)	2008-09	Memphis Grizzlies	A
Tom Barrise (0-2)	Lawrence Frank (0-16)	2009-10	New Jersey Nets	A
Bernie Bickerstaff (4-1)	Mike Brown (1-4)	2012-13	Los Angeles Lakers	A

Note: (W-L) Win-Lose record

A: New coach managed less than 10 games (interim coaches, or head coaches signed mainly for the next season)

B: Replaced coach managed only 1 game at the beginning of the season