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Summary

In this paper, football data from the 2007/2008 to 2016/2017 seasons of the Italian Serie A were used to identify the effects of replacing a coach mid-season due to poor team performance. We used an instrumental variable approach to correlate coach turnover within a season with player productivity and found a very low positive impact of the coach change in the short term but a significant negative impact in the long term. Our findings are also relevant to the literature on management replacement in small-size firms.

Keywords: Italian Football Data, Coach Changes, Team Performance, Models for Panel Data, Instrumental Variables

JEL Classification: C23, C36, M51, Z22

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Abstract

In this paper, football data from the 2007/2008 to 2016/2017 seasons of the Italian Serie A were used to identify the effects of replacing a coach mid-season due to poor team performance. We used an instrumental variable approach to correlate coach turnover within a season with player productivity and found a very low positive impact of the coach change in the short term but a significant negative impact in the long term. Our findings are also relevant to the literature on management replacement in small-size firms.

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I. INTRODUCTION AND LITERATURE

In this paper, we used football data from Italian Serie A to answer the following research question: Does changing a football team coach due to poor results improve the performance of the team? In addition to sports management, this question is also relevant for labour economics research, as it reflects possible mechanisms emerging in firms facing management turnover.

Sports data have been used in a large, and increasing, number of scientific studies. Due to the availability of detailed and reliable measures of team performance and of data on individual careers, they are mostly used to analyse issues related to incentives and labour market outcomes (Szymanski 2003, Kahn 2000). In this context, sports data can help in the evaluation of the effects of incentives on behaviour, through the observation of player performance when influenced by monetary incentive schemes.

The analysis of sports data also provides material for another issue, related to the tendency of firms and organisations to replace their managers to improve their economic results. Considering the importance of top managers, if a firm performs poorly, it is believed that the firing and replacement of the management board may lead to improved performance and financial results. Attempting to predict the outcome of replacing a manager before the expiration of his or her contract is a crucial element in business decision-making.

Football data have frequently been used to define the determinants and consequences of management changes, since the outcomes are measured weekly on a match-by-match basis (i.e. the results of the match) in an objective way and are not affected by measurement errors. In contrast, data on firm performance are usually collected on a yearly basis (i.e. financial reports), and the definition and measurement of manager productivity is influenced by external exogenous factors, such as macroeconomics or environmental contingencies, and lacks identifiable objective indicators of individual performance.

To avoid the problem of sparse data due to infrequent financial reports, some studies in the management field use stock prices, available on a daily basis, as a measure of firm performance. Stock prices, however, are strongly correlated with expectations and more influenced by market beliefs about the manager turnover than by the actual effect of the turnover on firm performance.

On the other hand, according to Pieper, Nuesch and Franck (2014), head coaches and top managers show similar characteristics: age (from 40 to 60), stress management capabilities, and well-honed media skills. Like a top manager in a firm, a coach is a fundamental representative of the owners and managers of football clubs, is given responsibilities in a variety of areas and makes a number of strategic and operational decisions which affect team performance. The roles of a coach may include motivating players, selecting the players for each match, selecting tactics and game strategies and determining which players to buy, sell or borrow during the market transfer season. Due to the crucial role of the coach, the replacement of one typically occurs in cases of poor team performance.

From a theoretical perspective, coach-firing might have conflicting effects on team performance. A new coach may provide motivation for the players by rearranging positions in team composition, resulting in the players making a greater effort in order to be selected for future games. On the other hand, coach change may be the result of pressure from fans and media, who generally do not take into account the fact that the replacement sacrifices the knowledge base and team skills developed by the fired coach (Hoffler & Sliwka, 2003).

There are two important econometric problems which need to be addressed when evaluating the consequences of coach turnover on team performance (De Paola, Scoppa 2011). First, coaches are not randomly fired. Dismissals are often decided after a streak of continuous negative results, and weaker teams tend to replace coaches more frequently within a season. Therefore, we found that coach turnover may influence team performance, but, in the same way, team performance may influence the decision of team managers on whether or not to change coach. This fact implies the possibility of an inverse causality relationship between team performance and coach turnover.

Second, in a stochastic environment such as a football competition, unusually strong or unusually poor results are statistically followed by outcomes that are closer to the mean. This phenomenon is known in econometrics as ‘regression to the mean’ or ‘Ashenfelter’s dip’, and it may influence team results during a football season.

Analyses and studies that do not take into account these aspects may incorrectly conclude that coach change has negative effects (i.e. negative correlation between coach change and team performance) or, alternatively, that the forced coach turnover leads to an improvement in team performance, even if its actual effects are negligible (because results tend naturally to improve after a string of bad matches). In statistical language, such misconceptions lead to inconsistent estimates. Similar problems occur when analysing firm performance and managerial turnover, and, probably because of these econometric problems, the literature on the effects of manager turnover on organisational performance fails to reach clear conclusions.

The business literature reports a range of results, even if it overall suggests small positive effects of management turnover on corporate performance. In the past, Bonnier and Bruner (1989) and Weisbach (1988) observed strong positive stock price reactions after a turnover-of-management announcement, while Khanna and Poulsen (1995) found the opposite result. In the same period, Reinganum (1985) and Warner, Watts and Wruck (1988) reported small, statistically insignificant price changes associated with turnover events.

Other studies have attempted to examine the relationship between management turnover and changes in operating performance using accounting information. Denis and Denis (1995) showed that forced resignations of top managers are followed by large improvements in firm performance. Similar results were found by Khurana and Nohria (2000). Later, Huson, Malatesta and Parino (2004) showed that turnover announcements were associated with significantly positive stock returns and positively related to accounting measures of performance.

As for management-specialised studies, research based on sports data has not been able to reach clear results regarding the effects of coach turnover on team performance. Several previous analyses on coach turnover are based on simple models which fail to consider the serious econometric issues discussed above. Some of them showed that a coach change improves team performance (Fabianic, 1994; McTeer, White & Persad, 1995), while others found a negative effect (Brown, 1982). Mixed results emerge also from studies carried out with more sophisticated econometric evaluations from 2000 to 2010. For example, Bruinshoofd and TerWeel (2004) showed that forced resignations were ineffective in improving team performance. Similar results appeared in Koning (2003), Maximiano (2006), Balduck and Buelens (2007) and Wirl and Sagmeister (2008). On the other hand, Salomo and Teichmann (2000), Audas, Dobson, and Goddard (2002) and Audas, Goddard and Rowe (2006) found a negative effect.

This work approaches the analysis from three different points of view. In particular, estimates are articulated in three different specifications, according to the choice of response variable, regressors and dataset dimension.

In each specification, team performance is the response variable of the regression analysis, although it is measured with three different indicators:

A. Player marks of each team
B. Number of points earned by a team by the end of each football season
C. Average score of teams during a football season.

In this study, only coach changes taking place within the season are considered, as replacement between years does not allow for distinguishing between effects caused by the coach change and those caused by other factors, such as different team composition, different quality of opponents and turnover of players.

II. Description of the dataset

All data used in the three specifications are collected from the records of *La Gazzetta dello Sport*, the most important Italian sports newspaper, and from Wikipedia, the well-known online encyclopaedia. Overall, 33 Serie A teams (over ten seasons) were examined, each of which having made at least one appearance in Serie A from 2007–2008 to 2016–2017. In a single season, Serie A is composed of 20 teams, which play against each other twice (once as the home team and once as the visiting one), for a total of 38 matches. Moreover, in each season, the composition of the league changes due to movements from Serie A to Serie B and vice versa.

A. Performance measure 1: player marks

For each team and match, player performances are recorded in the form of marks collected by *La Gazzetta dello Sport*. The newspaper gives each player participating in the match a mark from 1 to 10, with 1 indicating a poor performance and 10 indicating an outstanding one. From these marks, we calculated an average that can serve as an indicator for overall team performance in that match (the variable **average**). The players are then divided into sub-categories: strikers (**strikers**), midfielders (**midfielders**), defenders (**defenders**) and goalkeeper (**goalie**). For each of these categories, we calculated the average marks to give an indicator of performance for each player role. Table 1 contains a summary of these variables. It is notable that the marks are all within the range of 3 to 9 and that the averages for all categories are close to 6.

[TABLE 1 ABOUT HERE]

For each season, we recorded the teams that changed coach within that season and created from this record the discrete variable **counter**, with three values: 0, 1 and 2.

For all teams, the first match of each season always begins with a **counter** of 0. Since having more than two coach changes in one season is very rare, this event is categorised the same way as having two coach changes.[1]

Within the data collected, changing coach multiple times within a season was not found to be a rare occurrence in Serie A in the previous eight leagues. Out of the 30 teams presented in the dataset, 17 teams changed their coaches at least twice in one season during the reference period, and there are no seasons in which there is not at least one team changing its coach twice.

B. Performance measure 2: points made by a team in a season

For this analysis, we structured a panel dataset with a time-series dimension of 10 seasons (all seasons from 2007–2008 to 2016–2017) and a cross-section dimension of 33 teams. Since only 20 of the 33 teams compete during a season, the panel structure is unbalanced, and the number of observations is 20*10=200.

Given the panel structure of the data, alternative definitions of the dependent variable and the regressors are observed for each team and each year.

The dependent variable is now recorded with the total points obtained by teams at the end of each season. This variable, named **points**, shows exactly the outcome obtained by each team, reducing the reliability problem of the use of player marks.

The descriptive statistics of **points,** as with the other variables used in this section, are presented in Table 2. On average, teams earn about 52 points in a season, but a more significant insight is that the standard deviation within the groups/teams (9.4) is lower than the total standard deviation (16.2), so teams tend not to diverge significantly from their results from one year to the next.

[1] In fact, there are only three occurrencies of three coach changes in one season out of the 30 teams during this period.

[TABLE 2 ABOUT HERE]

We measured coach changes within a season using two types of variables, as a robustness check on our regression results:

- a dummy variable named **change**, which takes the value '1' if there is at least one turnover during a season and otherwise takes the value '0'
- a count variable named **changes_number**, which takes the values '0, 1, 2, 3, 4', based on the number of coach turnovers.

We included in the regression several controls, designed to capture other characteristics of a team that may influence its performance. We added, in particular, an economic variable, a performance indicator and a variable capturing the age structure of the team:

- **salary_cap**, which contains the aggregate net yearly wage of the players who played at least one match
- **drawn_matches**, which refers to the number of matches drawn by each team during each season
- **average_age**, which measures the average age of the players who played at least one match.

As mentioned earlier, we observed that a standard regression model may be affected by inconsistency of estimates. This problem concerns the coefficients of the two regressors for coach turnover. According to a well-known statistical theory, there is an endogeneity problem when the explanatory variable is correlated with the error term of a regression model, and this problem occurs when changes in the dependent variable cause changes in the explanatory variable.

This is, in fact, the case for our analysis, since the performance of a team during a season (dependent variable) influences the decision of a team's managers on whether or not to change coach (explanatory variable), and this effect is simultaneous, within the same league's season (time unit of the panel).
We then focused on the identification of the instrumental variables used to avoid the endogeneity problem. The aim is to find variables with two important characteristics: correlation with the endogenous regressors and a lack of correlation with the error term, so as not to suffer from the same problem as the original predicting variables.

We settled on the following three instrumental variables:

- **goal_scored**, which refers to the number of goals that each team scored in each season
- **goal_conceded**, which refers to the number of goals that each team concedes in each season
- **past_changes**, which counts the number of coaches that each team has hired during the previous ten seasons.

The first two variables are linked directly to the match and correlated with the decision of changing coaches, so they respect the first condition for eligible instruments. We argue that they are exogenous in the model because points gained by teams during a season do not influence player performance in terms of goals scored and conceded.

We analysed only three seasons and estimated six regression models, two for each season, with **goal_scored** and **goal_conceded** as dependent variables (see Table 3). The intent was to estimate the causal effect of the lagged points on team performance measured by goals, including also other regressors (number of goals scored by the team and number of goals scored against the team), which more accurately explains the number of goals during a match. Estimates show that the coefficients for the variables which refer to the lagged points gained in previous matches are not statistically significant, meaning that there is no significant causal effect between them and that the variables **goal_scored** and **goal_conceded** are exogenous with respect to points.

[TABLE 3 ABOUT HERE]

The variable **past_changes** attempts to capture the propensity of a team's CEO to fire the coach during the football season. It is a lagged variable with respect to the points gained in the league's season, so it is clearly exogenous in the model.

C. Performance measure 3: average score of teams during a football season

In this section, the purpose is to evaluate the effect of coach turnover in the short term, specifically on the match immediately following the coach change. The analysis was carried out on four leagues' seasons, from 2013/2014 to 2016/2017, although these do not represent the time dimension in the analysis. The datasets used in the empirical analysis are four in total, one for each season, with the same structure and variables, but different from the data described in subsections A and B of Section II. Here, the time-series dimension of the panel is represented by the 38 days of the league and the cross-section dimension by the 20 teams competing in a league.

These four datasets are very similar, as the only differences depend on the teams promoted in Serie A and on those relegated to Serie B. These characteristics allow for a comparison of the estimates, season by season, and for increasing the robustness of our results.

We used a new dependent variable to measure the performance of teams during a league: the cumulative average score of teams. This variable, named **mean_points**, varies after each match according to the points obtained, so it functions to capture the short-term effect of coach turnover.
Intuitively, we observed in the data a temporal evolution in the dependent variable. In fact, within a season, it is possible for the score gained in some close matches to follow a trend. Developing this intuition, we implemented a dynamic panel regression model, where the first lag of **mean_points** is included in the regressors (named **lag1_mean_points**).

As a preliminary descriptive analysis, we compared the mean of variable **mean_points** only for teams which had changed coach, calculated for the matches before and after changes. As shown in Table 5, we observed some conflicting results: during the 2013/2014 season, the average score increases after changes; during the 2015/2016 season, it decreases; and during the other two seasons, it remains stable.

The coach turnover is measured for each team during a season by a dummy step variable, named **1stchange**, that captures only the first coach's change (instances of further changes offer too few observations). It takes a value of 0 for every match as long as the coach is not changed and then takes value 1 from when a new coach takes over until the end of the season.

To reinforce the reliability of our estimates, we included two independent variables linked with player performance during a match:

- **shots_on_target**, which refers to the number of shots made by each team in each match, in the other team's goal
- **shots_suffered**, which refers to the number of shots suffered by each team in each match, in their own goal (i.e. goals conceded by the team).

III. Empirical results

In this section, we show the main results for each of the three types of analysis, having estimated the effect of changing coaches on team performance, when the latter is measured with the three indicators explained in the previous section.

A. Performance measure 1: player marks

We first performed a cross-section regression analysis in which the dependent variables are the different marks given to players, categorised according to player role, after each match. The coefficient of interest is associated with coach change within a season (data are for leagues from 2012/2013 to 2014/2015).

(1) $\textbf{Player performance}_i = \alpha + \beta_1\textbf{coach\_change1}_i + \beta_2\textbf{coach\_change2}_i + \varepsilon_i$,

i=1,…,N. The results of regression (1) are summarised in Table 5.

[TABLE 5 ABOUT HERE]

In general, coach change appears to have a negative effect on the team, as well as on the different sub-categories of players. All the coefficients are negative, which means that, compared to the performance of the first coach, on average, players perform slightly worse under the second and subsequent coaches. In addition, the magnitude of the second coefficients is larger than the first, which suggests that the second and subsequent coaches worsen player performance to a larger extent than the first coach change. The only exception to this trend is the case of the goalkeeper, upon whom the change of coach was found to have no effect.

Despite this clear trend, the magnitude of the coefficients indicates that the change in player performance due to the coach's influence is minimal. Considering an average mark of 6, a change of -0.1 represents a 2% decrease in performance.

We then controlled for teams and season in the regressions using the following equation:

(2) $\textbf{Player performance}_i = \alpha + \beta_1\textbf{coach\_change1}_i + \beta_2\textbf{coach\_change2}_i + \gamma_1\textbf{season1}_i + \gamma_2\textbf{season2}_i + \gamma_3\textbf{season3}_i + \theta_1\textbf{team1}_i + \ldots + \theta_{30}\textbf{team30}_i + \varepsilon_i$

i=1,…,N. The coefficients for coach change in regression (2) are shown in Table 6.

[TABLE 6 ABOUT HERE]

While seasons were not found to have any significant effect on player performance, the team effect is prominent for specific teams. Particularly in the case of the strikers, the coach change effect is insignificant. This may be because, like goalkeepers, but to a lesser extent, striker is a role depending less on coaching style or strategy and more on individual talent.

Looking at the team effect, our reference team is Juventus, and the coefficients represent how the other teams perform compare to this reference. In our case, as expected, the fact of being a player on a team different from Juventus produces a negative effect on the performance of the player.

Player performance data is based only on the marks given by *La Gazzetta dello Sport*, the most important Italian sport newspaper. Therefore, there is a possibility of bias in the evaluation process: players on stronger teams often face a higher expectations. For example, with the same match parameters, a midfielder who plays for Juventus will have a lower mark than a midfielder of Verona will.

B. Performance measure 2: points made by a team in a season

We estimated two types of regression: one using the regressor **change** to estimate the effect of changing at least one coach and another using the regressor **changes_number** to estimate the effect of multiple coach changes:

(3) $\textbf{ln\_points}_{it} = \alpha_i + \beta_1\textbf{change}_{it} + \beta_2\textbf{ln(salary\_cap)}_{it} + \beta_3\textbf{ln(matches\_drawn)}_{it} + \beta_4\textbf{ln(average\_age)}_{it} + u_{it}$

(4) $\textbf{ln\_points}_{it} = \alpha_i + \beta_1\textbf{number\_changes}_{it} + \beta_2\textbf{ln(salary\_cap)}_{it} + \beta_3\textbf{ln(matches\_drawn)}_{it} + \beta_4\textbf{ln(average\_age)}_{it} + u_{it}$

All the variables were previously transformed into logarithms to mitigate the presence of asymmetries in their empirical distributions. Since variables **change** and **changes_number** are endogenous, we implemented a two-stage instrumental variable estimation procedure. This procedure allowed us to instrument, in the first stage, the two endogenous variables, by regressing **change** and **changes_number** on a set of exogenous variables. We call the instrumented variables **change_fitted** and **changes_number_fitted**. It is worth noting that, given the nature of the variables **change** (binary) and **number_changes** (count), the first-stage regression models are Logit and Poisson regressions, respectively (see Tables 7 and 8). In the second stage, regressions (3) and (4) are estimated by replacing **change** and **number_changes** with **change_fit** and **number_changes_fit** and including different variables to collect information about many different aspects of the team's performance.

[TABLES 7 AND 8 ABOUT HERE]

The estimates of regression models (3) and (4) in Table 9 show that coach turnover generates a negative effect on the points obtained by the end of a league. In both the models, the estimate coefficient for the variable that captures coach change is negative and statistically significant, confirming the results presented in subsection A of Section III.

[TABLE 9 ABOUT HERE]

The magnitude of the two coefficients is similar: -0.34 for variable **change_fitted** and -0.3 for variable **changes_number_fitted**. This means that, after the first substitution, further changes are not influential.

Focusing on the other regressors, we noted that the average increase of salary cap significantly improves team performance (+0.17) in model (3), with the fitted dummy variable. The average age of teams was not found to be significant in either model.

Finally, we computed the Hausman's specification test, which was useful to demonstrate the stronger validity of the instrumental variable method over the simple least-squares regression without instruments. The test rejects the null hypothesis of superior efficiency of the simple least squares regression (p-value less than 0.001 in both models with dummy and count variable), supporting our choice of the instrumental variables method.

C. Performance measure 3: average score of teams during a football season

As already mentioned, this section concentrates on four seasons, but each of these is a panel dataset used to estimate a regression equation, based on the 38 matches of a league.

The estimation approach uses an instrumental variables estimator. Instruments are presented, jointly with the results, in Table 10, and they are the same in the four regressions.

[TABLE 10 ABOUT HERE]

The coefficients for variable **1stchange** are positive and statistically significant in the 2013/2014 and 2014/2015 seasons but not significant in the other two seasons. These findings are not coherent, both between seasons and compared with the previous regressions. That is, there are two seasons in which the effect of the first coach turnover is positive in the short term and the average score increases. However, the magnitude of these coefficients is very low (+0.04 and +0.02). In particular, it is lower than the trend-effect given by the lagged dependent variable (+0.77 and +0.78), which means that results of past seasons are sufficient to predict the performance of the team.

In 2015/2016 and 2016/2017, the values for coefficient **1stchange** are close to zero, and, together with that, the trend component is stronger than in the other two seasons. We can say that the more important the trend component, the less decisive the effect of coach substitution may be.

The variables measuring the number of goals made and suffered during a match are strongly significant. This gives more validity to the model and allows us to offer more accurate results, as the estimates for the variable **1stchange** are controlled by the two variables **shot_on_target** and **shot_suffered,** capturing player performance in a match.

Integrating these results with the comments made in subsection A and B of Section III, we can hypothesise that a coach change will provoke, on average in the short term, a positive reaction in player effort and motivation, but this response is temporary, and, in any case, with more time, the effect becomes negative.

In this paper, we have considered only coach changes within the same season. A possible further improvement of this research might include an analysis of the effects of such a change during the summer break between seasons. However, as already mentioned, it is important to note that analysing coach replacements between seasons does not allow for distinguishing between effects caused by the coach change and effects caused by other factors, such as different team composition and different quality of opponents.

IV. CONCLUSIONS

There is often said to be a close link between sports economics and labour economics. Using a highly original dataset from Italian Serie A in the seasons from 2007-2008 to 2016-2017 to analyse employee behaviour and morale after a management (coach) change, we have gained a few insights.

In our analysis, and consistent with the available literature, coach replacement was not found to be useful in influencing team performance and therefore does not have any significant effect on the team's results.

We used an instrumental variable approach to eliminate the problem of endogeneity between the progress of a team's performance within the season and the decision of changing a coach. Our estimates show no significant impact of coach changes in the long term.

When coach turnover was found to have an effect on team performance, it was only in the very short term and, we believe, mainly driven by increased motivation and effort of players, which probably contributed to a streak of wins. With more time, however, this effect disappears and, in fact, turns out to be negative.

How do these results translate to the corporate environment? We stressed in the introduction the usefulness of sports data due to their objectivity and the quasi-experimental nature of the sports environment, both of which help the researcher to objectively measure performance and productivity of workers—in this case, players.

We believe that the results found in this paper may of interest as potential insights, specifically for small companies, with regard to their industrial organisation and the possible effects of management turnover on economic performance.

The effects of a company management renewal would require an assessment period longer than one year, so it is necessary to be prudent in the generalisation of these results to a corporate environment. Nonetheless, we found a significant negative effect of coach change on individual performance of players and, due to the similarities between a football team and a corporate team as complex systems, our empirical analysis provides evidence for the importance of organisational strategy to employee morale.

Tables

Table 1. Descriptive statistics (I)

Variable	Obs	Mean	Std. Dev.	Min	Max
Goalie	2354	6.13	.62	3	9
Defenders	10169	5.84	.44	3.75	7.38
Middlefield players	11519	5.96	.43	4	7.5
Strikers	5673	5.97	.63	4	9
Average	7429	5.97	.39	4.4075	7.325

Source: Individual performances per role in Serie A (seasons 12/13, 13/14 and 14/15) from "La Gazzetta dello Sport".

Table 2. Descriptive statistics (II)

Variables			Mean	Std. Dev.	Min	Max	Observations
points	overall	51.945	16.29	18	102	N=	200
	between		13.935	20	80.1	n=	33
	within		9.414	26.845	76.833	T-bar=	6.06
change	overall	0. 435	0. 497	0	1	N=	200
	between		0. 315	0	1	n=	33
	within		0. 432	-0. 453	1. 335	T-bar=	6.06
number_changes	overall	0. 645	0. 873	0	4	N=	200
	between		0. 649	0	2	n=	33
	within		0. 722	-1.243	3.2	T-bar=	6.06
salary_cap	overall	41. 648	35. 566	8.3	160	N=	200
	between		29. 749	9.8	112.89	n=	33
	within		11.052	-0.051	88.898	T-bar=	6.06
matches_drawn	overall	10.005	2. 85	3	18	N=	200
	between		1. 502	6.5	13	n=	33
	within		2. 591	4.227	16. 755	T-bar=	6.06
average_age	overall	27. 178	1. 284	23.6	30.5	N=	200
	between		1.019	24.7	28.755	n=	33
	within		0. 949	23.368	29. 54	T-bar=	6.06
goal_scored	overall	50.045	14.022	18	94	N=	200
	between		11.173	32	69.6	n=	33
	within		8.639	19. 845	77.845	T-bar=	6.06
goal_conceded	overall	50.21	11.5	20	84	N=	200
	between		10. 081	31.5	82.5	n=	33
	within		7. 806	31.61	74.71	T-bar=	6.06
past_changes	overall	11.64	5.195	2	31	N=	200
	between		4.134	4	21.333	n=	33
	within		2.226	6.44	23.64	T-bar=	6.06

Note: The listed variables are observed for a Panel of 33 teams of Italian Serie A and 10 football seasons, from 2007/2008 to 2016/2017. In each season, only 20 of the 33 teams participated at the Serie A championship, because some of them are in Serie B. So, the panel structure is unbalanced, and number of observations is 20*10=200. For each variable, are calculated the “overall” mean and the “overall”, “between” and “within” standard deviation. Variable “points” observes the numbers of points that each team obtain in each season; variable “change” is a dummy variable that observes, for each team in each season, the change of at least one coach during the season; variable “number_changes” counts how many coaches have been changed during each season, by each team; variable “salary_cap” observes, for each season, the aggregate salary of the players in a team; variable “matchs_drawn” observes the number of matches that each team drew during each season; variable “average_age” observes the average age of the players that played at least one match during the season; variable “goal_scored” observes the number of goals that each team scored in each season; variable “goal_conceded” observes the number of goals that each teams conceded in each season; variable “past_changes” observes the number of coaches that each team has hired during the previous ten seasons.

Table 3. Analysis of endogeneity for variables goal_scored and goal_conceded

Football season	2013/2014	2014/2015	2015/2016
	(1)	(2)	(3)
Dependent variable: goal_scored			
shots_on_target	0.22***	0.164***	0221***
	(0.01)	(0.01)	(0.01)
lag1_points	-0.015	-0.031	-0.021
	(0.03)	(0.02)	(0.02)
lag2_points	-0.062	-0.008	0.03
	(0.03)	(0.03)	(0.03)
lag3_points	0.035	-0.041	0.03
	(0.02)	(0.02)	(0.03)
Wald chi-2(4)	217.6	249.22	269.2
(p-value)	(0.000)	(0.000)	(0.000)
	(4)	(5)	(6)
Dependent variable: goal_conceded			
shots_suffered	0.223***	0.161***	0.233***
	(0.01)	(0.01)	(0.01)
lag1_points	-0.004	0.003	0.006
	(0.02)	(0.02)	(0.02)
lag2_points	-0.011	-0.002	0.023
	(0.03)	(0.03)	(0.03)
lag3_points	-0.002	-0.001	0.029
	(0.02)	(0.03)	(0.029)
Wald chi-2(4)	403.4	178.8	364.19
(p-value)	(0.000)	(0.000)	(0.000)

Note: The models (1), (2), (3) are estimated using regression for panel data (fixed effects). Each model refers to one football season were cross-sectional dimension is N=20 teams, and time-series dimension in T=38 championship days. First three days are dropped because of lagged variables, so the number of observations is 700 (there are some missing values so the number of observation is 698 in models 1 and 2, 692 in models 4 and 5). Numbers in brackets, under estimated regression coefficients, are bootstrap standard errors. The t-test (*p<0.05;**p<0.01;***p<0.001) shows that in all the models only the variables “shots_on_target” and “shots_suffered” are significant to explicate respectively “goal_scored” and “goal_conceded”. Variables which refers to the lagged points made by teams, until the third lag, are not statistically significant in the models, so there isn’t a causality effect between the points gained in the previous matches and the numbers of goals scored and conceded in a match.

Table 4. Descriptive statistics (III)

			(1) 2013/2014	(2) 2014/2015	(3) 2015/2016	(4) 2016/2017
Variables						
mean_points						
before change	mean	overall	0.919	0.92	1.352	1.069
	std. dev.	overall	0.493	0.475	0.61	0.702
		between	0.39	0.362	0.643	0.542
		within	0.34	0.371	0.371	0.433
after change	mean	overall	1.029	0.934	1.077	1.081
	std. dev.	overall	0.277	0.294	0.374	0.521
		between	0.274	0.284	0.384	1.445
		within	0.091	0.123	0.108	0.101
shots_on_target						
before change	mean	overall	4.725	4.013	4.545	4.53
	std. dev.	overall	2.555	2.371	2.48	2.043
		between	0.878	1.182	0.883	0.906
		within	2.433	2.154	2.338	1.942
after change	mean	overall	4.787	5.606	4.497	4.99
	std. dev.	overall	2.748	2.87	2.516	2.643
		between	1.08	0.993	1.012	1.445
		within	2.612	2.714	2.338	2.26
shots_suffered						
before change	mean	overall	5.28	5.753	4.933	6.037
	std. dev.	overall	2.534	2.747	2.503	2.942
		between	0.904	0.632	0.702	0.872
		within	2.409	2.681	2.401	2.844
after change	mean	overall	5.435	6.478	5.124	5.577
	std. dev.	overall	3.001	2.981	2.693	3.074
		between	1.045	1.014	0.852	0.728
		within	2.864	2.858	2.578	3.005
N: Observations number						
before change			164	73	165	81
after change			216	117	177	109
n: Teams number			10	5	9	5
T: number of days						
before change			16.4	14.6	18.3	16.2
after change			21.6	23.4	19.6	21.8

Note: The descriptive statistics reported in the table are referred to teams that have changed coach. These variables are observed for four football seasons of Italian Serie A, from 2013/2014 to 2016/2017, each one is a panel consisting in 20 teams (cross-sectional dimension) and 38 championship days (time series dimension). The variable "mean_points" is the cumulative mean points, by championship days, for each team; the variable "shots_on _target" observe the number of shots done by each team in each championship day, in the opposite target; the variable "shot_suffered" observe the number of shots suffered by each team in each championship day, in their own target. In this table, for each variable, descriptive statistics are calculated only for teams that changed the coach during the season, and comparing between matches before the change and matches after the change.

Table 5. Estimation results of regression model (1): a summary

Dependent variables	**Coefficients of the first coach change (β_1)**	**P-values**	**Coefficients of the second and subsequent coach changes (β_2)**	**P-values**
average	-0.055	<0.001	-0.099	<0.001
strikers	-0.091	<0.001	-0.171	<0.001
middlefielders	-0.072	<0.001	-0.075	0.007
defenders	-0.066	<0.001	-0.113	<0.001
goalie	0.006	0.781	-0.027	0.497

Note: Main coefficients of a cross-section regression using as dependent variable average marks per role of individual performances and focusing on the effect of the coach change within season (2012/2013, 2013/2014, 2014/2015 leagues).

Table 6. Estimation results of regression model (2): a summary

Dependent variables	**Coefficients of the first coach change (β_1)**	**P-values**	**Coefficients of the second and subsequent coach changes (β_2)**	**P-values**
average	-0.283	0.038	-0.059	0.025
strikers	-0.371	0.093	-0.072	0.093
middlefielders	-0.483	0.002	-0.058	0.049
defenders	-0.391	0.012	-0.806	0.007
goalie	0.006	0.773	-0.020	0.640

Note: Main coefficients of a cross-section regression using as dependent variable average marks per role of individual performances and focusing on the effect of the coach change within season (2012/2013, 2013/2014, 2014/2015 leagues), controlling for season effects and specific teams effects.

Table 7. first step of IV regression for endogenous variable "change"

Dependent variable: change	(1)
Individual effects	fixed effects
ln(goal_scored)	-5.1
	(2.8)
ln(goal_conceded)	4.04***
	(1.09)
past_changes	-0.14
	(0.1)
ln(salary_cap)	0.47
	(0.65)
ln(matches_drawn)	1.73*
	(0.68)
ln(average_age)	-1.92
	(6.44)
Number of observations	188
Number of groups	25
Wald chi2(6)	25.83
(p-value)	(0.000)

Note: Model (1) is the first step, in the Instrumental Variable regression, for endogenous variable "change" (Table 2, model (1)). Estimates are made using a Logistical regression for panel data. Dataset includes observations for 33 teams of Italian Serie A and 9 seasons, from 2007/2008 to 2016/2017. Each season, only 20 of the 33 teams participate at the Serie A championship, because some of them are in Serie B, so the panel structure is unbalanced. Estimate uses only 25 of the total 33 groups, 8 groups (12 observations) are dropped because of all positive or all negative outcomes. Numbers in brackets, under estimated regression coefficients, are bootstrap standard errors. Dependent dummy variable is "change" (0,1). Instruments used in this first step are "ln(goal_scored)", "ln(goal_conceded)" and "past_changes". T-test (*p<0.05;** p<0.01;*** p<0.001) shows that only "ln(goal_conceded)" is significant between instruments. Fitted values from this model are called "change_fitted".

Table 8. First step of IV regression for endogenous variable "changes_number"

Dependent variable: number_changes	(1)
Individual effects	fixed effects
ln(goal_scored)	-1.99*
	(0.86)
ln(goal_conceded)	3.38***
	(0.57)
past_changes	-0.06
	(0.05)
ln(salary_cap)	-0.17
	(0.52)
ln(matches_drawn)	0.5
	(0.4)
ln(average_age)	-0.24
	(2.23)
Number of observations	195
Number of groups	28
Wald chi2(6)	35.9
(p-value)	(0.000)

Note: Model (1) is the first step, in the Instrumental Variable regression, for endogenous variable "number_changes" (Table 2, model (2)). Estimates are made using a Poisson regression for panel data. Dataset includes observations for 33 teams of Italian Serie A and 10 seasons, from 2007/2008 to 2016/2017. Each season, only 20 of the 32 teams participate at the Serie A championship, because some of them are in Serie B, so the panel structure is unbalanced. Estimate uses only 28 of the total 33 groups, 5 groups (5 obs.) are dropped because of only one observation per group. Numbers in brackets, under estimated regression coefficients, are bootstrap standard errors. Dependent count variable is "number_changes". Instruments used in this first step are "ln(goal_scored)", "ln(goal_conceded)" and "past_changes". T-test (* p<0.05; ** p<0.01; *** p<0.001) shows that "ln(goal_scored)" and "ln(goal_conceded)" are significant. Fitted values from this model are called "number_changes_fitted".

Table 9. Second step of IV regression for coach change effect on team's final results

Dependent variable: ln(points)	(1)	(2)
Individual effects	fixed effects	fixed effects
change_fitted	-0.34***	
	(0.07)	
changes_number_fitted		-0.3***
		(0.03)
ln(salary_cap)	0.17**	0.08
	(0.06)	(0.06)
ln(matches_drawn)	-0.1**	-0.09**
	(0.03)	(0.03)
ln(average_age)	0.09	0.16
	(0.36)	(0.34)
R^2 within	0.21	0.58
between	0.7	0.43
overall	0.61	0.58
Number of observations	200	200
Number of groups	33	33
Wald chi2(4)	40.31	112.82
(p-value)	(0.000)	(0.000)

Note: The models (1) and (2) are the second step of the Instrumental Variables regression. Hausman test proves that instrumental variables regression is better specified than standard regression without instruments (Tab.1). The explanatory variables "change_fitted" and "number_changes_fitted" are both predicted variables, at first step of IVregression. Estimates are made using unbalanced panel dataset of 33 teams of Italian Serie A, observed for 10 seasons, from 2007/2008 to 2016/2017. Each season, only 20 of the 33 teams participate at the Serie A championship, because some of them are in Serie B. So the panel structure is unbalanced, and number of observations is 20*10=200. Both estimates, in columns (1) and (2), are made with GLS method for linear model, with individual fixed effects and bootstrap standard errors. Numbers in brackets, under estimated regression coefficients, are robust standard errors. Model (1) uses fitted variable “change_fitted" to observe the predicted change of at least one coach. Model (2) uses fitted count variable “number_chages_fitted” to observe the predicted number of coach changes during the season. Estimated coefficients for these two variables are negative and t-tests (*p<0.05; **p<0.01; ***p<0.001) show the significance of results. Furthermore, in model (1), estimated coefficient for the salary cap of the teams, ln(salary_cap), is positive and statistically significant and estimated coefficient for the number of matches drawn, ln(matches_drawn), is negative and statistically significant. In model (2), only estimated coefficient for the number of matches drawn, ln(matches_drawn), is negative and statistically significant.

Table 10. Coach change effect on the single match result

Dependent variable: mean_points	(1)		(2)		(3)		(4)	
Football season	2013/2014		2014/2015		2015/2016		2016/2017	
lag1_mean_points	0.77***	(0.03)	0.78***	(0.03)	0.86***	(0.03)	0.81***	(0.02)
1st change	0.04**	(0.01)	0.02**	(0.01)	-0.002	(0.01)	-0.0002	(0.02)
shots_on_target	0.01***	(0.001)	0.01***	(0.001)	0.01***	(0.001)	0.01***	(0.001)
shots_suffered	-0.01***	(0.001)	-0.01***	(0.001)	-0.01***	(0.001)	-0.01***	(0.001)
R^2 within	0.76		0.78		0.82		0.76	
between	0.99		0.99		0.99		0.99	
overall	0.97		0.96		0.96		0.97	
Number of observations	676		666		680		680	
Wald chi-2(4) (p-value)	1780.04	(0.000)	627.93	(0.000)	715.53	(0.000)	1120.2	(0.000)
F-test that all u_i=0 (p-value)	5.66	(0.000)	5.54	(0.000)	2.66	(0.000)	4.01	(0.000)
Instrumented:	lag1_mean_points							
Insrtuments:	change, shots_on_target, shots_suffered, lag2(mean_points), lag3(mean_points), lag4(mean_points), lag1(shots_on_target), lag1(shots_suffered)							

Note: The models (1), (2), (3) and (4) are estimated using dynamic regression for panel data (fixed effects), with Anderson-Hsiao method. Each model refers to one football season were cross-sectional dimension is N=20 teams, and time-series dimension in T=38 championship days. The F-tests reject the null hypothesis that all individual fixed effects are equal to zero. First four days are dropped because of lagged variables, so the number of observations is 680 (there are some missing values in model 1 and 2 so the number of observation is 676 and 666). The instruments for "lag1_mean_points" are "lag2(mean_points)", "lag3(mean_points)", "lag4(mean_points)", "lag1(shots_on_target)" and "lag1(shots_suffered)". Variable "1st change" is a dummy variable, that observes only the first coach change (ulterior changes have only few observations). Numbers in brackets, under estimated regression coefficients, are bootstrap standard errors. The t-test (*p<0.05;**p<0.01;***p<0.001) shows that "lag1_mean_points" is always significant and with positive sign. Variable "1st change " is significant and positive in models (1) and (2), not significant in model (3) and (4). We can conclude that first coach change has a positive and statistically significant effect on the mean points of the following match in seasons (1) and (2), excluding the autocorrelation effect; it has null effect in seasons (3) and (4)

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