Impact and efficiency ranking of football managers in the Italian Serie A: sport and financial performance

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Abstract

The contribution of managers to the performance of football teams in the Italian Serie A is investigated. Previous results are extended by analyzing two measures of performance: the awarded points from winning matches (sport performance) and the growth of the market value of players (financial performance). Several empirical methods are employed: OLS regressions, Shorrocks-Shapley decompositions of R-squared and Data Envelopment Analysis. Our findings suggest that managers exert a significant influence on both sport and financial performances with differences between top and worst coaches. However, most of the observable characteristics in a manager's curriculum are not significantly related to team performance.

Keywords

Football Manager; sport performance; financial performance; DEA; fixed effects

1 Introduction

The ability of top managers is likely to strongly affect the performance of the organization and the equilibrium sorting of persons with different skills along control positions in firms has been the object of research interest for decades (Rosen, 1982). The impact of managerial traits and behavior on firm performance has been addressed by the scientific literature over years. However, the understanding of how bosses affect workers' productivity is limited (Lazear, Shaw & Stanton, 2015). Data availability and control of the research setting make the empirical assessment of the impact of managers on the productivity of the team of workers they coordinate a challenging exercise. Recent contributions in the literature (e.g. Graham, Li & Qiu, 2012; Bertrand & Schoar, 2013; Bandiera et al., 2020) propose innovative methods to measure and interpret managerial behavior, highlighting underexplored dimensions of managerial activities.

A traditional approach for measuring the contribution of individual managers to organizations consists of analyzing the business performance in correspondence to a managerial change. Grusky (1963) first argued that the empirical evidence of improved performance after dismissals would signal a significant role of the manager and the possibility to add value to the businesses by selecting higher managerial ability. This common-sense theory suggests that managers are expected to be replaced by more productive ones, thus increasing the performance of the business, and is tested against opposite theories associated with a negligible role of the manager (Kuper and Szymanski, 2009).

The empirical approach in Grusky's work (1963) focused on a sample of managerial changes in baseball professional teams. The sports sector offers opportunities for robust analyses on the effects of managers on performance: unlike companies in most of the other industrial sectors, teams are very similar in size, goals, and governance structure. Moreover, this research framework is provided with plenty of unambiguous disclosed data (Kahn, 2000; Garcia-del-

Barrio and Szymanski, 2009). Even though team performance largely depends on players' abilities, sport managers have a role that can be compared to the one of top managers in a business company.

In this vein, our work addresses the topic by exploiting the role of managers in the Italian football industry (more specifically, the Serie A Championship).[1] Following the recent study of Muehlheusser et al. (2018), we assess the contribution of a head coach to team performance leveraging on the possibility to observe him managing different teams. This observational study is made possible by the higher turnover of football managers compared to that observed in other business activities. Indeed, managers usually lead several teams in a few years and the same championship.

Our approach first replicates the analyses of Muehlheusser et al. (2018) using a novel dataset based on the Italian Serie A, with information from season 1998-1999 to season 2018-2019. In this regard, the study has been conducted to allow a direct comparison with the results of Muehlheusser et al. and confirms the presence of a significant role of managers. Second, in addition to being the first study of this kind focused on football managers in Italy, this contribution extends the existing literature by introducing an empirical setting with new characteristics. Such setting builds on the longstanding debate on whether teams are profit- or win-maximizers.[2] Indeed, our measures are not limited to sport performance (i.e. earned points), but focus also on asset valorization. The latter is evaluated by considering the growth of the market value of the players as an additional dimension of performance (an increased value is expected to generate future capital gains and, thus, improve the economic sustainability of business). Our empirical approach considers that football clubs can ask coaches to contribute in maximizing a payoff determined by sport and financial performances, and that different teams are interested in pursuing different combinations of the two variables. To this aim, in addition to the fixed effects OLS regressions, Shorrocks-Shapley decompositions are computed to further assess the results of OLS regressions, and Data Envelopment Analyses are introduced (as in Frick and Simmons, 2008).

Finally, we investigate whether a selection of observable characteristics of a manager's career (e.g. age, starting the career as manager in lower leagues, nationality, being a former professional player or a star) is correlated to performance. Our findings suggest that most of them are not associated with improved performance, neither sport nor financial ones. A slightly significant positive correlation is found for managers with an experience in abroad leagues. Previous experience as a midfielder reports a slightly significant positive correlation with improved sport performance. Several robustness checks were implemented to support the findings and alternative measures of the value of players were considered.

The paper is organized as follows: in Section 2 the existing literature is analyzed and research hypotheses are developed; Section 3 describes the sources of data and the operationalization of variables alongside with some descriptive evidences from the sample; in Section 4 we describe the employed methods of analysis and show the results; Section 5 summarizes and discusses the results, stating limitations and indicating future grounds of research.

2 Research Framework

2.1 Role of managers on sport and economic performance

The literature on the role of sport managers has shown mixed results. On one side, some studies (Frick and Simmons, 2008; Muehlheusser et al., 2018) have confirmed the presence of a significant effect of managers on team performance. On the opposite side, some other studies argued that the role of manager is "vastly overestimated" (Kuper and Szymanski, 2009) and with a small impact on performance, as in the findings of Bradbury (2017) concerning major-league baseball players performance under different managers.

Considering the studies that focus on football, the consensus has not been reached yet. Audas et al. (2002) noted a negative contribution of managers in the first months after replacement; Flepp and Franck (2020) found evidence of an improved performance when dismissals are a consequence of poor performance on the pitch and of no improvement when the reason for replacement is bad luck. Muehlheusser et al. (2018) identified a non-negligible impact of managers on sport performance with significant differences across managers in the German Bundesliga.

Our first research objective is to contribute to the literature by providing evidence on the presence of an impact of managers on team performance in the Italian first tier football league, Serie A. Following the approach in Muehlheusser et al. (2018), sport performance is measured as average points per game.

On a further level of analysis, the literature on sport economics suggests that football clubs can pursue multiple goals along profit or win (utility) maximization strategies (Sloane, 1971; Dietl et al., 2011). Focusing on the role of managers, there is evidence that they pursue only utility maximization goals (Sloane, 1971; Garcia-del-Barrio & Szymanski, 2009), and can jointly aim at profit and win goals (Romer, 2006; Vrooman, 2000). Club ownership can require the hired managers to align to the preferred goal whenever a tradeoff between win and profit emerges. The two objectives could be in conflict in some cases, for example when deciding to limit the on-field time of an older experienced player in favor of a younger novice with the aim to increase her/his market value.

Consequently, in line with the existing literature, it is reasonable to assume that clubs maximize a utility function where profits and wins are differently weighted and managers are expected to adopt their strategies accordingly. Given that the main sources of revenues for football teams are: i) broadcast rights[3]; ii) brand licensing, iii) sponsorship, iv) event day revenues (tickets and other home match related incomes),[4] and v) player trading, we recognize that managers can contribute to future revenues by increasing the market value of the assets-players they train[5].

Managers are expected to directly impact on sport performance and thus indirectly contribute to all the sources of revenues. However, with respect to player trading, the effect of managers could be more relevant since their decisions and their leadership could directly determine changes in the market value of players, even when the bargaining process that leads to a transfer is excluded from the analysis. The managers can impact on expected asset valorization by improving players' on-field performance through training methods that improve skills and tactics, finding the best role for a player on the pitch, and making young players debut. Managers decide the starting eleven and the timing of substitutions, hence determining each player's field-time and visibility. Under this perspective, the impact on player trading is not examined in terms of direct involvement in the scouting or bargaining activities, even though sometimes coaches take part to such tasks (e.g. there are players that follow their coach when s/he move to anothr team)[6]. Managers that facilitate the increase of players' market value could support a team's economic performance from player trading, which represents a substantial part of the profits (from capital gain) and may generate vital cash flows.

This aspect suggests that the impact of managers might not be limited to sport performance but affect also an additional dimension, that is the growth of the players' market value. To the best of our knowledge, previous literature has not sufficiently focused on the presence of multiple areas of impact for a football manager and the introduction of an additional dimension of analysis would contribute to improve the assessment of a manager's role.

Our study will thus introduce two dimensions of analysis to understand whether managers have a significant role in team performance measured as points earned and as a variation in players' market value.

This study provides analyses that test the two dimensions independently and departs from those findings to explore whether different types of managers exist along the two axes that measure performance: coaches are expected to be relatively more able to reach financial and/or sport results. Indeed, anecdotal evidence suggests that managers might be more likely to pursue one of the two objectives in accordance with her/his managing style, in line with the different approaches on what aspect football clubs aim to maximize, profit or win (Sloane, 1971). Football clubs might be more oriented toward a win-maximization strategy or a profit-maximization strategy and dictate their priority goal to the hired manager. As mentioned, the revenues from player trading could be particularly relevant both for those teams with a smaller fan base and for those with a larger pool of supporters when the other sources of revenues are not sufficient to cover operating costs. Furthermore, clubs competing in the richest tournaments at the European level are subject to the UEFA financial fair play, which aims to make sure that the operating costs of professional football clubs are in line with their earnings (Ghio et al., 2018), although the benefits of its introduction are still debated (Franck, 2018; Ahtiainen and Jarva, 2020). In this framework, the ability to recognize and hire managers that are able to increase players' value may be the best choice in line with a profit-maximization strategy.

Given that both sport and financial performance could be pursued, a football club does not necessarily have an ex-ante preference for one of the two objectives or may simply be interested in hiring the most efficient manager on the job market. Efficient managers maximize a predetermined (and unknown) combination of the two objectives. The multidimensional nature of performance requires a specific method of analysis that we identified in the DEA. The method will provide a ranking of managers based on an efficiency score and provide a practical implication for football teams and their preferences when hiring managers. In adopting this kind of approach, we extend the previous literature, which focused mainly on clubs and their management as a whole (e.g., Haas, 2003a, 2003b; Barros and Leach, 2006; Barros and Garcia-del-Barrio, 2010) and/or focused only on one performance dimension at a time, as in Delice and Gercek (2018) and Dawson and Dobson (2002), who analyzed financial and sport performance respectively[7].

2.2 Characteristics of managers that impact on performance

If football managers provide heterogeneous contributions to sport and economic performance, it is possible to investigate which individual characteristics are more likely to be correlated to higher levels of performance.

The existing literature (e.g., Dawson and Dobson, 2002; Muehlheusser et al., 2018) is scarce and suggests that some aspects of a manager's past experience can be associated with better performance. The limitations derive from both data availability and the presence of an expected sorting mechanism in the allocation of the best managers to the subsample of the richest and best performing teams. Concerning the former, some of the characteristics that are expected to be related to better managers are not disclosed nor immediately measurable, such as the relational abilities in dealing with the players or collaborating with the rest of the managing staff (e.g., medical doctors, trainers, and financial officers)[8]. Concerning the sorting mechanism, in a competition where coach allocation is efficient (i.e. the richest teams provide the highest salaries and hire the best managers), selection and sorting should lead to a general framework where the characteristics (especially the disclosed ones) that are expected to be correlated to higher performance are incorporated in salaries, with the result that the relevant element would be only to be hired in top or bottom clubs (Frick and Simmons, 2008). However, previous studies found that some of the managers' observable characteristics are correlated to sport performance and this suggests the presence of allocative inefficiency in the market for head coaches (Bertrand and Schoar, 2003; Frick and Simmons, 2008).

Boto-Garcia et al. (2020) provided a novel contribution analyzing the impact of managerial beliefs, which is observable from tactical choices, on team performance showing that selfconfidence in a specific playing style is related with higher winning probabilities, as well as adopting a higher risky behavior.

In Spanish basketball, de Corral et al. (2017) found that foreign coaches are more efficient. The evidence could be related to the presence of a selection mechanism that screens the best managers from abroad. Concerning the English Football Association, Dawson and Dobson (2002) found that foreign managers perform better in terms of sport results.

Focusing on Bundesliga, the German football top league, Muehlheusser et al. (2018) showed that there is a negative correlation between being a former professional player and the points earned. The authors argued that several hypotheses can explain the results: i) being a former professional player allows to skip experiences and directly start from top leagues; ii) in football there may be potential overrating in the hiring process of manager; iii) managers who have not been professional players have more incentives to perform better in order to secure a job. By contrast, in the U.S. basketball top league, former top players have more chances to become better coaches (Goodall, Kahn & Oswald, 2011), and, in the English Football Association, the prior experience of managers as a football player is more significant than their curricula as coaches in explaining their performance (Dawson and Dobson, 2002).

Among former professionals, Muehlheusser et al. (2018) found that former midfielders are more likely to perform better with respect to forwards, defenders or goalkeepers. On the other hand, Dawson and Dobson (2002) found that former strikers prove to be as efficient as former defenders or midfielders, suggesting that managers may have innate abilities.

Finally, Muehlheusser et al. (2018) found no significant link between performance and the following observable characteristics: age and having played in the national team (as a proxy for having been a “star” player).

Following the leads of the previous works, we introduced an additional variable that identifies those managers having their career starting in lower leagues[9]. In the presence of market inefficiencies, they are expected to perform better since they worked their way up the ladder.

This study thus aims to investigate the presence of a correlation between some of the observable characteristics of managers (age, nationality, abroad experience, participation in lower leagues, former professional player and role, having played in the national team) and (i) their sport/economic performance and (ii) global efficiency, after controlling for clubs and half seasons effects. The presence of correlations would suggest that the market is not completely efficient.

3 Data Collection and Sample

The analysis focuses on the Italian top division, namely the Serie A. 20 football clubs play against one another twice, in two half seasons of 19 matches per team[10]. The winning team in each match gains three points while the losing side zero; in case of a draw, both teams gain one point[11]. Our dataset considers Serie A seasons from 1998-1999 to the first half of the season 2019-2020 (22.5 seasons in total)[12].

Data on points earned from winning matches are available for all the years and were gathered from online resources (e.g. https://www.worldfootball.net).

Information on the value of football players has been retrieved from TransferMarkt (TM) (https://www.transfermarkt.it). Although the value of the athlete is known with certainty only when the transaction is completed, TM provides a measure based on press releases, comparisons with similar players and the discussions that take place on the website forum within the large community of users. It is relevant to highlight that TM market value incorporates not only the recent on-field performance of the player but also additional characteristics that are expected to influence the transaction value: it accounts for the player's age, injuries, and the remaining years of contracts. TM measure has been previously employed in studies dealing with players' market values, such as Majewski (2016) and Rohde and Breuer (2017) since it provides a more accurate assessment of players' quality than general characteristics such as age, appearances and scored goals (effective only for some types of players). Data on players' market value were collected in four different moments, right before and after the opening and closing of the two annual market sessions. The collected data are available for the seasons from 2010-2011 to 2019-2020 and represent the aggregate market value of team players at the beginning and at the end of each half season. This approach is useful to exclude the variation in team value in the half season due to the completed transactions on the market for players (i.e. arrivals and departures). The employed measure captures the change in value due to the on-field performance in the season, when the managers can leave their mark: this technical and/or tactical improvement indirectly might turn into an increase in the asset valorization of the football club when the market session opens.

Economic data from financial statements have been collected from the AIDA repository[13] for most of the examined teams in the seasons from 2007-2008 to 2018-2019. In particular, team level yearly operating costs will be employed as a proxy of the players' value since they include salaries and the depreciation of the players' asset value[14]. This variable would provide additional robustness checks since literature found significant evidence of a correlation between players' salaries and success/revenues (see, e.g., Szymanski and Smith, 1997; Hall et al., 2002; Garcia-del-Barrio and Szymanski, 2009; Carmichael et al., 2011).

At the manager level, data on age and career were collected from several public sources[15].

The final database is built at the level of manager and team in each half seasons. The unit of analysis is determined by the manager *j* on the bench of team *k* in the half season *t*. The operationalization of the dimension "half season" was carried out in several ways to tackle different issues and increase robustness.

A complete half-season would include matches against all the other participants in the Serie A, thus equally distributing the difficulty of matches in the sample. However, managers are replaced all along the season and sometimes they work only for a limited number of matches of the half season, against challenging or weaker opponents[16]. To cope with this issue, we follow the approach of Muehlheusser et al. (2018) and consider only those managers who meet what they call *Footprint Condition* (*FC*), namely those managers with a sufficiently long *spell*, i.e. a continuous number of matches, to leave their mark on the trained team. The continuous spell is not necessarily completely overlapping to the half seasons. In our study we employed two diverse FCs in accordance with the different types of data employed in the analyses. When the aim is to investigate the impact of managers on sport performance (i.e. the average points per game), the examined managers are those with a continuous spell of at least 19 consecutive matches in the same team[17]. We label this FC as "*FC:spell*". Since managers are fired and hired within the whole season, there are cases of managers with at least 19 consecutive appearances on the same bench but covering a fraction of the half season (the spell can start on any match day and last in two or more consecutive tournaments). These cases are not discarded but their contribution to performance (in this case the average number of points gained in the matches of the half season) is weighted accordingly in the econometric models. For example, Stefano Pioli managed Fiorentina in season 2018-19 from the first match to the 31st: his second half season is kept in the sample with weights that adjust the impact of the manager to the fraction of covered half season. This approach is coherent with the one of Muehlheusser et al. (2018) and the results can be compared.

When we considered the financial performance in terms of growth of the value of players, we had to take into consideration that there are two moments in the year when football players can be traded, hence changing the asset value of the squad due to transfers and not because of a player's valorization. These two moments are at the beginning of the season and around the end of the first half season, usually in January. Hence, we collected the value of teams at the beginning of the season, before and after the January market and at the end of the season. The FC has to be defined more strictly and aligned to the half season (occurring between two market sessions): the examined managers are those with at least 12 matches (63%) on the same bench in the half season between the two market sessions[18]. We label this FC as "*FC:share*. The spell is not necessarily starting on day 1 and the econometric models will consider the contribution to performance (i.e. the growth of players' value in this case) of any observation as weighted by the number of matches on the bench in the half season.

A second condition to select managers is introduced: we kept in the dataset only those observed in more than one team. This condition is consistent with the *Mover Condition* (*MC*) of Muehlheusser et al. (2018) and is necessary to estimate manager fixed effects as distinguished from team fixed effects.

Table 1 provides a summary of the different samples employed in the analyses, according to the application of the FCs and the MC.

Table 1 Observations as half seasons-manager-team combinations in each sample from the application of different filtering conditions and number of different examined entities (half seasons, managers, teams).

Sample ID	Sample	# of obs.	# of half seasons	# of managers	# of teams
1	Full sample (data on points per game)	1077	43	170	46
2	Sample after FC:spell	729	43	107	44
3	Sample after FC:spell and MC	597	43	57	40
4	Sample having data on team value (from TM)	492	19	98	34
5	Sample having data on team value with FC:share	351	19	76	34
6	Sample having data on team value with FC:share and MC	261	19	37	30

Table 2 Summary statistics on the main variables of performance: average points per match in the half season (PPM) and growth of players' market value in the half season (GMV).

Variable	Sample ID	# of Obs.	Mean	St.Dev	Min	Max
Average points per match earned by the manager in the considered half season (***PPM***)	1	1077	1.258	0.584	0.000	3.000
	3	597	1.402	0.508	0.000	2.789
	6	261	1.428	0.501	0.400	2.789
Growth of players' market value from the beginning to the end of half season (***GMV***)	6	261	0.073	0.184	-0.326	1.521

Table 2 provides summary statistics of the main variables examined in this study with respect to the main subsamples employed in the analyses. Further information at the manager- and team-level are reported in the Appendix (Table 15 and Table 16). Data show the presence of a large difference between the best and the worst manager along both the examined dimensions of performance. In terms of average points per game calculated in sample 3, the top performer is Antonio Conte (2,398 along seven half seasons, Table 15) and the worst Massimo Oddo (0,291 along three half seasons). The maximum average growth of the team market value is reported for Davide Nicola (+41.7% as average in four half seasons), while the minimum for Filippo Inzaghi (-4.6% as average in four half seasons).

Table 3 provides details on the variables that have been collected as observable characteristics of each manager (additional statistics on the distribution across the playing role for those managers with a previous career as a football player are reported in Table 17 in the Appendix).

Table 3 Descriptive statistics and definitions of managers' observed characteristics (at the manager level)

Variable	Description	Sample	# of managers	Mean	St.Dev.	Min	Max
Age (AGE)	Managers' age in logarithm	3 6	57 37	3.892 3.920	0.130 0.155	3.611 3.611	4.167 4.210
Italian (ITA)	Dummy variable equal to one if the manager is Italian.	3 6	57 37	0.930 0.892	0.258 0.315	0 0	1 1
Abroad Experience (AEX)	Dummy variable equal to one if the manager has coached teams in foreign leagues.	3 6	57 37	0.281 0.324	0.453 0.475	0 0	1 1
Former Professional (PRO)	Dummy variable equal to one if the manager has formerly played in top football leagues.	3 6	57 37	0.807 0.784	0.398 0.417	0 0	1 1
Career start in lower leagues (LLE)	Dummy variable equal to one if the manager has formerly coached in lower championships (e.g. Italian Lega Pro).	3 6	57 37	0.719 0.703	0.453 0.463	0 0	1 1
Former Star (STA)	Dummy variable equal to one if the manager has at least one presence in his national team.	3 6	57 37	0.263 0.270	0.444 0.450	0 0	1 1

Notes: the age in logarithm is considered as the average age in all the observed half seasons; the abroad experience is time dependent and the reported statistics considers it as equal to 1 if the manager worked abroad at least once in the selected time frame

4 Empirical Analysis

This section aims to provide empirical evidence about the individual contribution of managers to sport and financial performance of teams in the Italian Serie A, measured in terms of average points per game and players’ market value respectively. The first set of analyses applies OLS regressions and Shorrocks-Shapley decompositions. Then, the multidimensional impact of managers on team performance is further explored with the aim to rank their contribution according to a single comprehensive efficiency score determined by applying DEA. Finally, in the third sub-section, managers’ observable characteristics are investigated in search of correlations with performance measures.

4.1 The impact of managers on team performances

The first part of the analyses focuses on the contribution of managers on two measures of performance. The model is represented by the following equation:

$$Y_{jkt} = \alpha \quad + \beta X_j + \delta W_k + \gamma Z_t + \varepsilon_{jkt}$$

where the dependent variable Y_{jkt} is the measure of performance: the average points per game earned by manager *j* in team *k* during the half season *t* for the first batch of models; the growth of the market value of players in team *k* managed by *j* in the half season *t* for the second set of models. As anticipated, each manager might contribute to each observation with a different number of matches depending on the length of his spell in the same team and half season. Hence each value of Y_{jkt} is weighted by the number of matches managed by coach *j* on the bench of team *k* in the half season *t* by using the Stata command *aweights* as in the work by Muehlheusser et al. (2018). X, W and Z are the sets of dummy variables representing the managers, the teams and the half seasons respectively[19].

4.1.1 The impact of managers on sport performances

With the aim of testing the impact of managers on sport performances, we considered the average points per match (PPM) as the dependent variable. Table 4 reports the results of the OLS models. Models 1, 2 and 3 considered the full sample (sample 1). Models from 4 to 6 focus on the sample resulting from the application of the FC:spell and the MC at the same time (sample 3)[20]. Models 7 and 8 replace the team dummies with a variable that describes the team starting value: the aggregate TM market value of all the players at the beginning of each half season (PMV, in logarithm); these two models are tested on the smaller sample 6, where data from TM are limited to recent years.

We find evidence of increasing explanatory power in the model as teams and manager fixed effects have been included. In line with the results of Muehlheusser et al. (2018), the R^2 considerably increases when including manager dummies. More specifically, when comparing the full models on each sample (i.e. models 3 6 and 8) with those excluding managers' dummies (i.e. models 2, 5 and 7), the R^2 increases by 0.133, 0.096 and 0.121 respectively, suggesting the presence of a non-negligible impact of managers on team performances. Moreover, in models 3, 6 and 8 the F-Test is highly significant. As an additional expected result, the team value shows a statistically significant positive effect on the average PPM.

Table 4 Results of OLS regression models. Dependent variable is average points per match in the half season. Models 7 and 8 includes the independent variable: players' market value at the beginning of the half seasons in million euro (PMV, in logarithm).

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
		Sample 1			Sample 3		Sample 6	
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummies		Yes	Yes		Yes	Yes		
Manager dummies			Yes			Yes		Yes
PMV							0.486***	0.347***
							(0.026)	(0.041)
Constant	1.333***	0.314	-0.080	1.316***	0.896**	1.269**	-0.840***	0.181***
	(0.113)	(0.272)	(0.506)	(0.149)	(0.376)	(0.511)	(0.149)	(0.263)
F-Test			5.15			5.21		9.32
Prob > F			0.000			0.000		0.000
Observations	1077	1077	1077	597	597	597	261	261
R^2	0.003	0.482	0.615	0.030	0.513	0.609	0.593	0.714

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

To further understand the magnitude of the contribution of managers, we computed the Shorrocks-Shapley decomposition of the R^2 term of OLS regressions. The analysis provides an additive decomposition of the statistic and highlights the relative contribution of the regressors. In our case, we grouped the variables related to the half seasons, the teams and the managers respectively. Table 5 shows that the group of managers' dummies account for more than 45% of the R^2 resulting from model 6 of Table 4 (around 51-54% when considering the full sample and the sample 6 with TM data).

Table 5 Shorrocks-Shapley decompositions of the R2 relative to the previous OLS regressions (models 3 6 and 8 of Table 4 respectively) where the dependent variable is the average point per match.

Group of variables	Shapley Value (Estimate)	Percent (Estimate)	Shapley Value (Estimate)	Percent (Estimate)	Shapley Value (Estimate)	Percent (Estimate)
	Sample 1		Sample 3		Sample 6	
Half Season dummies	0.015	2.49%	0.030	4.98%	0.024	3.34%
Team Dummies	0.230	37.35%	0.260	42.72%		
PMV					0.318	44.52%
Manager dummies	0.333	54.09%	0.276	45.36%	0.368	51.53%
R^2	0.616	100.00%	0.609	100.00%	0.714	100.00%

We further investigated the coefficients of each manager dummy from the OLS regression models reported in previous Table 4. The aim of this analysis is to provide a relative ranking of each manager's contribution to earned points, controlling for half season and team dummies (Table 10, column II, based on sample 6): the approach is the same of Muehlheusser et al. (2018)[21]. We considered the median manager ("Domenico DiCarlo") as reference for the ranking. The highest coefficient is associated with "Massimiliano Allegri" (0.473), which is statistically different from the median manager: *ceteris paribus*, his teams have won on average 0.473 points per match more than a team guided by a manager of median ability. Departing from these statistics, the best manager would contribute on average with an additional 19x0.473=8.987 points per half season, or 17.974 points per season[22]. Although this calculation should be considered with caution and with respect to the examined data, the amount of additional points is significant: for example, in season 2018-19 it would have led a team from relegation to safety and a team from rank 9th to 3rd, which would have granted access to the UEFA Champions League. These results are in line with those in Muehlheusser et al. (2018).

As an additional robustness test, we replaced the variable PMV with the logarithm of the yearly operating costs of each team (they include depreciation of players as assets and their gross salaries). Although this variable presents some issues (limited availability across the examined teams; the same amount of costs is associated with the first and the second half season in each year), it provides an alternative time-dependent measure. The results of the corresponding OLS regressions are reported in Table 6 and confirm the presence of a large contribution of managers' dummies to the increase of the R^2 of the models even when considering the different resources available. In line with expectations, yearly operating costs (OPC, in logarithm) have a statistically significant positive relation to PPM. The corresponding Shorrocks-Shapley decomposition shows a relative contribution of managers of 52% (details available on request), in line with the previous findings.

Table 6 Robustness tests: results of OLS regressions. The dependent variable is the average points per match. Note: models are tested on a subset of the sample 3 for those teams with available data from financial statements. Independent variables: operating costs in logarithm (OPC).

Model	**(1)**	**(2)**
OPC	0.471***	0.363***
	(0.032)	(0.055)
Half Season Dummies	Yes	Yes
Manager dummies		Yes
Constant	-7.134***	-5.245***
	(0.585)	(0.970)
Observations	322	322
R^2	0.396	0.597

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

This set of analyses provides support for the hypothesis of managers having a significant role in team performance measured as points earned.

4.1.2 The impact of managers on financial performances

With the aim of testing the impact of managers on financial performances, the next analyses consider the increase in the market value of the team, through the TM indicator, as the dependent variable. Table 7 reports the results of the OLS models. Models 1, 2 and 3 are tested on the sample having teams with available data about the market value of players (sample 4). Models from 4 to 6 focus on the sample resulting from the application of the FC:share and the MC at the same time (sample 6). Models 7 and 8 control for the starting value of the team at the beginning of the half season (PMV, in logarithm). As for the previous results on earned points, Table 7 suggests the presence of a relevant contribution of managers on the growth of team market value. Indeed, the R^2 of the model increases when including managers' dummies (+0.184 from model 2 to model 3; +0.095 from model 5 to model 6; +0.232 from model 7 to model 8).

Interestingly, the result on the starting value of the team is negatively related to its growth, contrary to the result of the previous regressions about the earned points. This indicates that it is more frequent to observe the growth when the starting market value is lower. This evidence suggests the presence of potential differences in the two types of performance examined (i.e. the output) and the starting conditions (i.e. the input) which will be tackled in the next section.

Table 7 Results of OLS regression models. Dependent variable is the growth of the players' market value in the half season.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
		Sample 4			Sample 6		Sample 6	
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummies		Yes	Yes		Yes	Yes		
Manager dummies			Yes			Yes		Yes
PMV							-0.085***	-0.144***
							(0.013)	(0.021)
Constant	0.041	0.088*	0.067	0.032	0.097*	0.157	0.430*	0.833***
	(0.035)	(0.051)	(0.113)	(0.047)	(0.058)	(0.149)	(0.076)	(0.133)
F-Test			1.76			2.10		3.20
Prob > F			0.000			0.000		0.000
Observations	492	492	492	261	261	261	261	261
R^2	0.086	0.243	0.427	0.099	0.401	0.496	0.229	0.461

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

We computed the Shorrocks-Shapley decomposition of the R^2 from the OLS regressions. Table 8 shows that the group of managers' dummies account for more than 34% of the R^2 resulting from model 6 of Table 7 (40% when considering sample 4, and 52% when including PMV).

Table 8 Shorrocks-Shapley decompositions of the R2 relative to the previous OLS regressions (models 3 6 and 8 of Table 7 respectively) where the dependent variable the growth of the players' market value in the half season.

Group of variables	Shapley Value (Estimate)	Percent (Estimate)	Shapley Value (Estimate)	Percent (Estimate)	Shapley Value (Estimate)	Percent (Estimate)
	Sample 4		Sample 6		Sample 6	
Half Season dummies	0.078	18.31%	0.078	15.69%	0.098	21.31%
Team Dummies	0.168	39.34%	0.246	49.56%		
PMV					0.113	24.41%
Manager dummies	0.171	40.07%	0.172	34.69%	0.241	52.28%
R^2	0.427	100.00%	0.496	100.00%	0.461	100.00%

We performed an analysis of the coefficients similar to the previous one, to provide a relative ranking of each manager's contribution to the growth of players' market value (GMV) points, controlling for half season and team dummies (Table 10, column III, based on sample 6). The median reference manager is now "Rolando Maran". The highest coefficient is associated with "Davide Nicola" (0.307) although not statistically different from the median manager, *ceteris paribus.* Considering that the average GMV is +7.3% in a single half season, the best manager would contribute with an additional +30.7% in the half season. On the contrary, at the bottom of the ranking "Stefano Colantuono" reports for the considered sample a negative coefficient (-0.147), totaling an average decrease of -7.4% of market valuations.

As an additional robustness test, we replaced the PMV with the yearly operating costs (OPC, in logarithm), similarly to the previous section. The coefficients are negatively related to the increase in players' market value: the result is consistent with the finding in Table 7. Table 9 confirms the presence of a non-negligible contribution of managers' dummies to the increase of the R^2 of the models. The corresponding Shorrocks-Shapley decompositions indicate that the group of managers' dummies account for more than 60% of the R^2.

Table 9 Robustness tests: results of OLS regressions. The dependent variable is the growth of players' market value. Note: models are tested on a subset of the sample 4 for those teams with available data from financial statements. Independent variables: operating costs in logarithm (OPC).

Model	**(1)**	**(2)**
OPC	-0.069***	-0.111***
	(0.016)	(0.028)
Half Season Dummies	Yes	Yes
Manager dummies		Yes
Constant	1.297***	1.997***
	(0.294)	(0.508)
Observations	232	232
R^2	0.175	0.381

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Our results suggest that managers significantly impact on team performance measured as an increase in players' market value.

4.2 The role of managers: multidimensional impact and efficiency

Table 10 shows the relative ranking of managers with respect to their impact on the scored points and the growth of the team value respectively. Interestingly, the best managers to improve sport performance (earned points) are not necessarily the best in improving the team market value. Indeed, the correlation coefficient between the values of column II and III is 0.192[23].

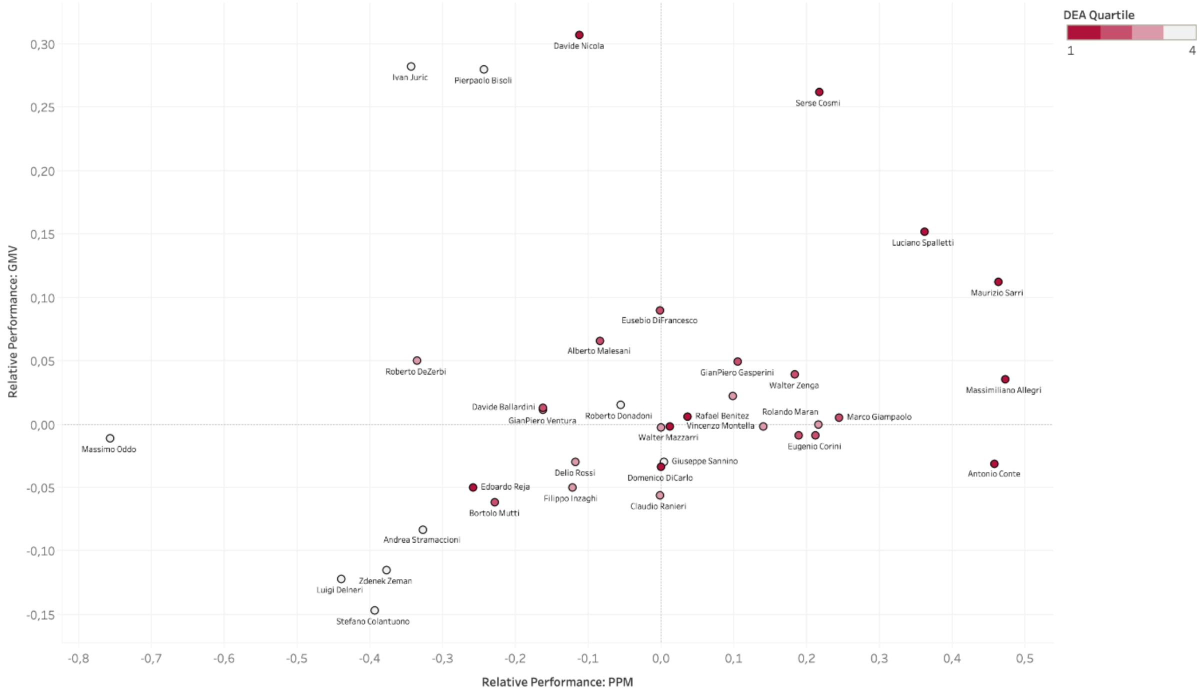
Table 10 Relative contribution of managers to performance. Column I shows the average points per match (PPM) in the half seasons. Column II and III show the coefficients of OLS models for manager dummies when the dependent variable is the average PPM and the growth of players' market value (GMV), respectively (sample 6). Column IV shows the average DEA score as distance from the efficient frontier (sample 6). Rows ordered by column IV. Top three managers in each column are *in bold text. OLS models for columns II and III have "Domenico Di Carlo"and Rolando Maran" as reference manager respectively (median manager).*

	I	II	III	IV
Manager	**Average PPM**	**Sport performance [OLS Coeff. - PPM]**	**Financial performance [OLS Coeff. - GMV]**	**Avg. distance from efficiency [DEA Score]**
Antonio Conte	**2.398**	**0.459***	-0.031	**1**
Serse Cosmi	1.111	0.218	0.262	**1**
Davide Nicola	0.819	-0.112	**0.307**	**1**
Massimiliano Allegri	**2.198**	**0.473*****	0.035	1.001
Maurizio Sarri	2.041	**0.464***	0.112	1.002
Rafael Benitez	1.802	0.037	0.006	1.014
Luciano Spalletti	**2.060**	0.362	0.152	1.038
Walter Mazzarri	1.702	0.012	-0.002	1.043
Edoardo Reja	1.500	-0.258	-0.050	1.048
Domenico DiCarlo	1.018	0	-0.034	1.050
Alberto Malesani	1.226	-0.084	0.066	1.054
Eusebio DiFrancesco	1.426	-0.001	0.090	1.060
Davide Ballardini	1.110	-0.162	0.013	1.064
Giuseppe Iachini	1.248	0.190	-0.009	1.065
Bortolo Mutti	0.879	-0.228	-0.062	1.067
Walter Zenga	1.161	0.184	0.039	1.071
Eugenio Corini	1.119	0.213	-0.009	1.072
Marco Giampaolo	1.298	0.245	0.005	1.074
GianPiero Gasperini	1.537	0.106	0.049	1.075
Claudio Ranieri	1.741	-0.002	-0.056	1.077
Sinisa Mihajlovic	1.433	0.099	0.022	1.090
GianPiero Ventura	1.228	-0.162	0.011	1.094
Delio Rossi	1.200	-0.117	-0.030	1.105
Roberto DeZerbi	0.944	-0.335	0.050	1.106
Vincenzo Montella	1.495	0.140	-0.002	1.115
Stefano Pioli	1.378	-0.0003	-0.003	1.115
Rolando Maran	1.184	0.217	0	1.120
Filippo Inzaghi	1.158	-0.122	-0.050	1.129
Andrea Stramaccioni	1.250	-0.327	-0.083	1.139
Stefano Colantuono	1.237	-0.394	-0.147	1.142
Pierpaolo Bisoli	0.731	-0.243	**0.280**	1.158
Massimo Oddo	0.441	-0.757	-0.011	1.161
Roberto Donadoni	1.166	-0.056	0.015	1.165
Luigi Delneri	1.267	-0.440	-0.122	1.205
Ivan Juric	1.100	-0.344	**0.282***	1.211
Zdenek Zeman	1.020	-0.377	-0.115	1.282
Giuseppe Sannino	1.000	0.004	-0.030	1.317

****** p<0.01, ** p<0.05, * p<0.1*

Figure 1 plots the coefficients reported in columns II and III of Table 10 on two axes where the zeroes represent the reference median managers ("Domenico Di Carlo" for sport performance, "Rolando Maran" for growth of team value) for the examined sample 6. Nine managers (24% of sample 6) are in the top right quadrant: they have been able to increase both sport and financial performance better than the median references; the ten managers (27%) in the lower left corner are those showing a relatively lower impact on both the dimensions.

Figure 1 Relative contribution of managers in terms of sport performance (average points per match – PPM: x axis) and of financial performance (growth of players' market value – GMV: y axis). Colors are based on the distribution of efficiency scores from DEA.



The analysis provides support to the hypothesis of managers impacting on performance in terms of multiple dimensions that are only mildly correlated. As discussed in Section 2, football clubs might be more oriented toward a win- or a profit-maximization strategy, hence they are expected to search for the best available manager in line with that goal. However, since the performance of managers under one strategy or the other are intertwined, a coach's efficiency cannot be exhaustively evaluated along one single dimension, disregarding the nature of the objective function they were submitted to. To improve the identification of the best managers and consider the two types of performance at the same time, we will rely on the DEA method and compute the efficiency of managers in a single score that accounts for both sport and financial performance of teams[24].

In the context of this analysis, DEA provides several advantages (Bogetoft and Otto, 2011). First, it offers a more system-oriented approach overcoming the limitations of partial evaluations (e.g., good players' value maximizers vs good win maximizers). In addition, the implicit assumption that performance outcome can be scaled in a linear way along each dimension is relaxed (e.g., the performance of a coach in a small club may not necessarily be directly comparable to the one of a top club colleague). Finally, in this empirical setting, the examined managers can achieve efficiency through different approaches since the examined types of performance are weighted in the objective function with respect to the neighboring managers (e.g., there can be efficient win- and efficient value-maximizers or managers with an efficient combination of the two goals).

When applying DEA, the first step is the definition of the *production process* and the selection of the key input and output variables. In the case of football managers, according to the evidence of the previous analyses, we select the value of the team at the beginning of each examined period as input, and two measures are considered as output: the average PPM and the final team value, representing sport and financial performance respectively[25]. As a result, managers are evaluated in terms of both types of performance.

Once that the input/output variables have been defined, the DEA model is selected according to the assumptions on the production possibility set. The frontier is the boundary of such a set and the relative efficiency is the distance of a given entity to the frontier. Two assumptions are common to most DEA models, namely free disposability and convexity (Bogetoft and Otto, 2011). Free disposability means that firms can produce less (outputs) with more (inputs), i.e. inefficiency is admitted. Convexity implies the practicability of any weighted average of feasible input/output combinations, thus extending the frontier beyond the limited set of real observations and including possible interpolations of efficient performances.

DEA requires additional hypotheses on the frontier about the orientation and the returns to scale (RTS) of the production process. In terms of orientation, it is reasonable to choose an output orientation implying that managers are required to obtain the maximum in terms of points and value given the level of the team put at their disposal at the beginning of each period of analysis, which depends mainly on the resources of the club and on the ability of all the company financial staff. The RTS refers to the allowed rescaling of production. We assume here that no rescaling is possible (i.e., input and output are not scaled linearly, meaning that variable returns to scale are assumed). As a result, the shape of the frontier changes with the scale of production so that, along each dimension, the manager under evaluation is compared only to those colleagues that are under the same portion of the frontier[26].

Given our assumptions, DEA identifies for each manager a specific “reference manager”, operating at a similar scale of production, as projection on the frontier of the manager himself. Such reference can be either an existing (efficient) manager or a weighted average of existing managers (peers) spanning the portion of the frontier where the reference itself (the projection) lays (Bogetoft and Otto, 2011). As a result, each manager is not compared with a single reference manager, but with what is feasible at a certain level of production.

DEA is performed on the sample of managers that satisfies both the MC and the FC:share (sample 6). A single DEA is estimated for each half season because, by definition, it would be misleading to compare performance of managers belonging to different periods. In fact, a base assumption in DEA is that the same “technology” (i.e. tools and techniques) is available to all the managers. This may not be the case of observations originated in different time periods (Henningsen, 2014)[27]. The results for each manager in different half seasons are then averaged in a single score. Column IV in Table 10 shows the average DEA score: the most efficient managers are “Antonio Conte”, “Serse Cosmi” and “Davide Nicola”[28].

Since DEA does not compare each manager with all the sample, but only with the part of the efficiency frontier where comparable peers are located, the results are only partially overlapping to those from previous OLS regressions. Some of the managers found excellent in at least one of the dimensions examined in the previous section are also the most efficient (e.g.”Antonio Conte”, “Serse Cosmi”, and “Massimiliano Allegri”). However, DEA score is relatively low, i.e. the managers are quite efficient, also for some managers who were not ranked among the top positions in any of the two dimensions (e.g. "Rafael Benitez", "Walter Mazzarri", "Domenico DiCarlo" and "Eusebio Di Francesco). All these managers performed well on average, when considering both sport and financial performance and with respect to their peers having a similar starting endowment.

As a robustness test, bias-corrected DEA scores are computed (Bogetoft and Otto, 2011; Simar and Wilson, 1998). The bias is due to the fact that DEA measures efficiency according to a frontier built on a subset of the real technology – i.e., the one determined by the available observations. As a result, the probability to be deemed as efficient may be higher in such a subset, as compared to the one in the real (but unfortunately unknown) technology set. It is not possible to measure directly this bias because the distribution of the true efficiency is not known. A bootstrap estimate of the bias is therefore performed in order to get bias-corrected efficiency measures. The results are shown in the appendix in Table 19. However, despite some differences in the scores and in the ranking, we find (i) high correlation (0.93) with traditional DEA scores and (ii) similar second stage results. Hence, we prefer to rely on traditional DEA scores to be able to identify managers defining the frontier that is one of our main objectives.

4.3 Characteristics of best performing managers

In this section we test if some of the observable characteristics of managers are correlated to an increase in the performance of the teams.

The first group of analyses replicate the OLS models and exclude the managers' dummies while introducing the examined characteristics. Table 11 shows the results for the case of average PPM as dependent variable. The reference sample is the dataset resulting from the application of the criteria movers (MC) and FC:spell (sample 3). A robustness analysis is reported in the appendix (Table 18) where team dummies are replaced by the market value of players at the beginning of the half season.

No observed characteristic results significantly related to the sport performance. Concerning the nationality of the managers, we highlight that the number of foreign coaches is very small in the examined sample (4 out of 57) and thus the interpretation should be considered with caution, also in light of the previous findings. Of course, the evidence is expected to depend on the internationalization and the allocative efficiency of the specific market for managerial services: de Corral et al. (2017) for basketball and Dawson and Dobson (2002) for English football suggested the presence of a positive relation between foreign managers and sport performance. Frick and Simmons (2008) found evidence of allocation inefficiencies in the market for football managers in Germany, related to the limited inbound and outbound mobility.

Concerning the variables on the former experience as a football player (models 5 and 7), no one is significantly related to PPM, partially in contrast with the findings of Dawson and Dobson (2002). In particular, neither being a former professional player nor a former star player report a significant coefficient: an opposite finding to those in Goodall et al. (2011) for the U.S. National Basketball Association and in Muehlheusser et al. (2018) for German football. Among the subset of managers with a past as professional player, midfielders are associated with higher sport performance than forwards and defenders (model 6), confirming the results in Muehlheusser et al. (2018).

Table 11 Results of OLS regression models with managers' characteristics. Dependent variable is average points per match in the half season. Sample of reference: 3.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE	-0.004						
	(0.134)						
ITA		0.103					
		(0.080)					
AEX			0.050				
			(0.052)				
LLE				-0.016			
				(0.044)			
PRO					0.043		
					(0.045)		
ROLE: Forward						-0.285***	
						(0.084)	
ROLE: Defender						-0.175***	
						(0.045)	
ROLE: Goalkeeper						-0.099	
						(0.233)	
STA							0.018
							(0.041)
Constant	0.913	0.807**	0.901**	0.911**	0.865**	1.141***	0.900**
	(0.674)	(0.382)	(0.376)	(0.378)	(0.377)	(0.388)	(0.376)
Observations	597	597	597	597	597	493	597
R^2	0.513	0.515	0.514	0.513	0.514	0.561	0.513

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 12 shows the results for the case of GMV as dependent variable. The reference sample is the dataset resulting from the application of the criteria movers (MC) and FC:share (sample 6). In this setting the observed characteristics are never significant predictors for the ability of increasing team market value. In addition, no specific former role as a football player is associated with improved performance with respect to the others. The same results are found in the robustness test with the players' market value included in the models (Table 19 in the appendix).

Table 12 Results of OLS regression models with managers' characteristics. Dependent variable is the growth of the players' market value in the half season. Sample of reference: 6

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE	-0.065 (0.088)						
ITA		-0.010 (0.039)					
AEX			-0.007 (0.031)				
LLE				-0.021 (0.027)			
PRO					-0.019 (0.032)		
ROLE: Forward						-0.065 (0.047)	
ROLE: Defender						-0.032 (0.028)	
ROLE: Goalkeeper						-0.130 (0.133)	
STA							-0.001 (0.027)
Constant	0.361 (0.360)	0.107 (0.069)	0.099* (0.059)	0.111* (0.061)	0.114* (0.065)	0.086 (0.060)	0.097* (0.059)
Observations	261	261	261	261	261	217	261
R^2	0.403	0.402	0.402	0.403	0.402	0.411	0.401

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

With the aim to consider the two dimensions at the same time and identify potential correlations between the efficiency of managers and their curricula, we regress the pooled DEA scores on the examined variables. We use truncated regressions that, as suggested by Simar and Wilson (2007), are preferable to both OLS and Tobit models. Table 13 shows the results of this second stage analysis. The reference sample is the dataset resulting from the application of the criteria movers (MC) and FC:share (sample 6). Note that a negative sign means a positive impact on efficiency since DEA scores range between 1 (lower bound of the truncated regression), for the efficient managers, and infinite. According to Table 13, the majority of the variables do not report significant coefficients confirming most of the evidence of Tables 11-12. However, differently from previous analysis, a past managerial experience in a foreign league is significantly related to an improvement in the average efficiency score.

Table 13 DEA second stage. Dependent variable is the efficiency score from DEA carried out on half seasons. Truncated regression with a lower bound equal to 1.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE	0.111						
	(0.155)						
ITA		0.061					
		(0.077)					
AEX			-0.150**				
			(0.069)				
LLE				0.070			
				(0.056)			
PRO					0.005		
					(0.066)		
ROLE: Forward						-0.058	
						(0.094)	
ROLE: Defender						-0.022	
						(0.061)	
ROLE: Goalkeeper						-0.003	
						(0.330)	
STA							0.009
							(0.053)
Constant	0.519	0.898***	0.968***	0.893***	0.944***	0.878***	0.947***
	(0.625)	(0.155)	(0.125)	(0.147)	(0.146)	(0.194)	(0.138)
sigma	0.176***	0.175***	0.168***	0.174***	0.177***	0.182***	0.177***
	(0.025)	(0.025)	(0.023)	(0.025)	(0.026)	(0.030)	(0.026)
Observations	159	159	159	159	159	134	159
Truncated observations	102	102	102	102	102	102	102

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

5 Conclusions

This study contributes to the empirical literature aimed at assessing managers' impact on the performance of the organizations they are working for. More specifically, we focus on the framework of professional football in Italy, which allows to access several types of relevant data. We extend the existing literature in several ways. First, a manager's performance is measured in terms of both sports results and contribution to financial growth as measured by the players' market value. Second, the techniques of analysis are enriched by employing Shorrocks-Shapley decompositions and DEA. In particular, DEA provides a useful setting for the analyses: the two performance outputs are jointly considered with respect to the available input (players' market value) and the activities of peer managers, with the aim to identify the most efficient ones. The study provides practical applications by reporting rankings of managers to support the identification of the top performers.

The analysis builds upon the previous mixed evidence about managers' effect on performance, also in football (Audas et al., 2002; Dawson and Dobson, 2002; Frick and Simmons, 2008; Muehlheusser et al., 2018; Flepp and Franck, 2020). We start by replicating the approach in Muehlheusser et al. (2018) and expand their analysis by introducing a new proxy of performance, further control variables for robustness tests and techniques of analyses (Shorrocks-Shapley decompositions and DEA).

In addition to sport performance (measured by a manager's earned points), we analyze team-level financial performance by focusing on the revenue source where managers are more directly expected to impact, namely the growth of the market value of players. This approach makes it possible to consider managers in line with the different goals pursued by football clubs as profit- or win-maximizers (Sloane, 1971; Dietl et al., 2011).

Our empirical framework considers more than 22 Serie A seasons from 1998-1999 to the first half of the season 2019-2020. OLS Regression results and Shorrocks-Shapley decompositions confirm the presence of a significant role of managers, both on sport and financial performance. In particular, the best manager would contribute with an additional amount of points that could notably change the final ranking of the managed team, from relegation to safety or from a middle position to those granting access to European level competitions in the following year (the results are in line with the findings of Muehlheusser et al., 2018). Our findings also suggest the presence of an impact on asset valorization (i.e. value of team players), which in the case of the best performer amounts to an average increase of 37% in the half season. However, the best managers in improving sport performance are not necessarily the best in asset valorization. Single-performance analysis could reveal only a limited portion of a manager's efficiency. To improve the identification of the best managers and consider the two types of performance at the same time, we applied a DEA analysis to compute a unique efficiency score for managers. This approach can also be useful for football clubs who are looking for the most efficient manager, jointly considering a win- or a profit-maximization strategy (Vrooman 2000; Romer, 2006;). Compared to the rankings on each of the two performance metrics (sport and financial), the one generated by DEA exhibits some similarities, but also non negligible differences. Such differences are not only due to the multi-output nature of DEA, but also to the different base assumptions of the two methodologies.

The third set of analyses deals with the observable characteristics of managers in terms of prior career as coach or former football player and their correlation with sport and financial performance. The results suggest that there is no evidence of correlations with improved performance or increase in efficiency, with two exceptions. First, in line with previous results, among the managers that were professional players, those having played as midfielders are associated with higher sport performance than the other on-field roles. Second, a previous experience in a foreign league is associated with an average better efficiency but the correlation is significant only in the DEA-second stage analysis.

Age, starting the career in lower leagues, being a former professional player or having played in the national team do not report significant coefficients associated to performance or efficiency. The lack of significant and robust correlations can be considered as an indication of the presence of a quite efficient market of managers, who are selected and sorted across teams in the Italian Serie A, or at least more efficient than the German one as the findings of Frick and Simmons (2008) suggested. However, other characteristics that are not easily available might have an impact, such as relational abilities with players or staff members.

Our work has several limitations. Data availability determined an unbalanced number of observations for managers (and teams). We tried to balance data availability and hypothetical streaks of un/lucky half seasons by considering footprint and mover conditions in Serie A: future research could expand the framework of analyses to lower leagues and/or competitions in other countries. Under this perspective, exogenous events in the half season might impact team performance and efficiency, such as financial distress, changes in ownership, or an abnormal rate of injuries among players. Future research could address the economic measurement on a more fine-grained level and disentangle the effects on revenues from those on profits. Concerning the empirical approach, the application of SUR regressions could lead to a better identification of managers fixed effects by modelling simultaneously both measures of performance, while DEA analysis could be enriched with further variables (e.g., inputs and/or environmental factors). For example, the average age of the team or the share of foreign players might capture further aspects exerting an influence on team performance such as, respectively, the players' potential and the possible communication barriers between players and managers.

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7 Appendix

Table 14 Number of Manager Replacements in each season

Season	First Half season	Second Half season	Total
1998-99	2	8	10
1999-00	5	1	6
2000-01	5	5	10
2001-02	8	2	10
2002-03	4	4	8
2003-04	5	2	7
2004-05	7	4	11
2005-06	5	8	13
2006-07	3	9	12
2007-08	7	8	15
2008-09	5	6	11
2009-10	9	6	15
2010-11	5	7	12
2011-12	9	8	17
2012-13	7	6	13
2013-14	6	6	12
2014-15	4	3	7
2015-16	5	7	12
2016-17	4	6	10
2017-18	7	2	9
2018-19	7	5	12
2019-20	8	/	/
Total	127	113	240
Average number of replacements in seasons with 20 participants (from 2003-04)	6.1	5.8	11.8

Table 15 Descriptive statistics at the manager level. On the left part of the table, the statistics calculated on the sample 3 report the number of observed half seasons, the average Points Per Match (PPM) earned and the rank by PPM. On the right

side of the table, the statistics calculated on the sample 6 report the rank by average growth of the players' market value (GMV), the average GMV and the number of observed half seasons.

Obs.Half S. [Sample 3]	Avg PPM [Sample 3]	Rank by PPM	Manager	Rank by GMV	Avg GMV [Sample 6]	Obs.Half S. [Sample 6]
7	2.398	1	Antonio Conte	28	-0.003	7
9	2.041	2	Maurizio Sarri	4	0.207	9
21	2.024	3	Massimiliano Allegri	19	0.037	17
14	2.006	4	Fabio Capello		excl.	excl.
22	1.982	5	Carlo Ancelotti		excl.	excl.
3	1.947	6	Nascimento Leonardo		excl.	excl.
16	1.869	7	Roberto Mancini		excl.	excl.
22	1.779	8	Luciano Spalletti	7	0.15	7
8	1.723	9	Claudio Ranieri	30	-0.017	4
11	1.663	10	Marcello Lippi		excl.	excl.
17	1.614	11	Cesare Prandelli		excl.	excl.
24	1.499	12	Walter Mazzarri	22	0.026	12
11	1.474	13	Vincenzo Montella	24	0.02	12
20	1.472	14	GianPiero Gasperini	11	0.124	14
23	1.44	15	Francesco Guidolin		excl.	excl.
10	1.429	16	Alberto Zaccheroni		excl.	excl.
12	1.408	17	Eusebio DiFrancesco	10	0.139	12
13	1.377	18	Edoardo Reja	23	0.02	8
13	1.367	19	Sinisa Mihajlovic	15	0.059	11
7	1.344	20	Giuseppe Iachini	16	0.05	9
21	1.343	21	Luigi Delneri	31	-0.02	6
9	1.319	22	Pasquale Marino		excl.	excl.
19	1.314	23	Delio Rossi	18	0.044	5
17	1.301	24	Stefano Pioli	21	0.027	17
6	1.279	25	Zdenek Zeman	26	0.012	3
12	1.272	26	Alberto Malesani	13	0.075	3
14	1.265	27	Walter Novellino		excl.	excl.
4	1.25	28	Andrea Stramaccioni	32	-0.032	4
3	1.216	29	Renzo Ulivieri		excl.	excl.
14	1.213	30	Carlo Mazzone		excl.	excl.
8	1.204	31	Davide Ballardini	25	0.017	4
10	1.196	32	Luigi DeCanio		excl.	excl.
16	1.182	33	Roberto Donadoni	27	0.002	13
13	1.169	34	Rolando Maran	17	0.05	14
14	1.165	35	Marco Giampaolo	5	0.175	9
15	1.148	36	GianPiero Ventura	14	0.068	9
12	1.136	37	Stefano Colantuono	20	0.027	8
3	1.105	38	Walter Zenga	9	0.142	2
2	1.105	39	Nedo Sonetti		excl.	excl.
3	1.078	40	Emiliano Mondonico		excl.	excl.
6	1.074	41	Bortolo Mutti	29	-0.016	2
9	1.071	42	Mario Beretta		excl.	excl.
12	1.066	43	Serse Cosmi	3	0.238	2
4	1.063	44	Daniele Arrigoni		excl.	excl.
3	1.059	45	Attilio Perotti		excl.	excl.
4	1.039	46	Roberto DeZerbi	8	0.147	5
3	1.035	47	Giuseppe Papadopulo		excl.	excl.
7	1.033	48	Franco Colomba		excl.	excl.
5	1.026	49	Filippo Inzaghi	33	-0.046	4
7	1.015	50	Eugenio Fascetti		excl.	excl.
4	0.994	51	Silvio Baldini		excl.	excl.
12	0.977	52	Domenico DiCarlo	12	0.103	6
7	0.948	53	Gianni DeBiasi		excl.	excl.
5	0.906	54	Giancarlo Camolese		excl.	excl.
4	0.853	55	Ivan Juric	2	0.415	3
4	0.818	56	Davide Nicola	1	0.417	4
3	0.291	57	Massimo Oddo	6	0.167	2

Table 16 Descriptive statistics at the team level for the yearly operating costs from available financial statements in logarithm (OPC) and for the players' market value at the beginning of each half season (PMV).

Variable	Sample ID	# of Obs.	Mean	St.Dev	Min	Max
Operating Costs in logarithm (***OPC***)	3	322	18.404	0.663	16.903	20.040
	6	232	18.458	0.665	16.903	20.040
Team Value at the beginning of the half seasons in million euro, in logarithm (***PMV***)	4	492	4.546	0.813	2.634	6.767

Table 17 Descriptive statistics on the distribution of roles as former professional players.

Sample ID	Managers with previous career as a professional player	Forwards	Midfielders	Defenders	Goalkeepers
3	46	10.9%	58.7%	28.3%	2.2%
6	29	10.3%	58.6%	27.6%	3.5%

Table 18 Results of OLS regression models with managers' characteristics. Dependent variable is average points per match in the half season. Sample of reference: 6.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Half Season d.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE	0.175						
	(0.201)						
ITA		0.125					
		(0.094)					
AEX			0.065				
			(0.064)				
LLE				0.092			
				(0.063)			
PRO					-0.011		
					(0.072)		
ROLE: Forward						-0.248**	
						(0.109)	
ROLE: Defend.						-0.200***	
						(0.070)	
ROLE: Goalk.						-0.019	
						(0.394)	
STA							-0.027
							(0.055)
PMV	0.552***	0.548***	0.538***	0.556***	0.545***	0.506***	0.544***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.119)	(0.102)
Constant	-1.680*	-1.079**	-0.930**	-1.058**	-0.937**	-0.726	-0.949**
	(0.962)	(0.465)	(0.454)	(0.460)	(0.457)	(0.530)	(0.455)
Observations	260	260	260	260	260	218	260
R^2	0.647	0.649	0.648	0.650	0.646	0.665	0.646

Table 19 Results of OLS regression models with managers' characteristics. Dependent variable is the growth of the players' market value in the half season. Sample of reference: 6

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Half Season dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE	-0.102						
	(0.082)						
ITA		-0.021					
		(0.036)					
AEX			-0.004				
			(0.028)				
LLE				-0.037			
				(0.025)			
PRO					-0.006		
					(0.030)		
ROLE: Forward						-0.076*	
						(0.045)	
ROLE: Defender						-0.036	
						(0.027)	
ROLE: Goalkeeper						-0.091	
						(0.128)	
STA							-0.003
							(0.025)
PMV	-0.270***	-0.267***	-0.266***	-0.273***	-0.265***	-0.198***	-0.266***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.051)	(0.045)
Constant	1.658***	1.252***	1.228***	1.284***	1.229***	0.926***	1.227***
	(0.397)	(0.203)	(0.198)	(0.201)	(0.198)	(0.224)	(0.198)
Observations	261	261	261	261	261	217	261
R^2	0.491	0.488	0.487	0.492	0.487	0.460	0.487

Table 19 Average bias-corrected DEA scores of each manager in sample 6 (ordered descending).

Manager	Average Bias Corrected DEA Score
Antonio Conte	1.075
Rafael Benitez	1.078
Bortolo Mutti	1.085
Serse Cosmi	1.091
Edoardo Reja	1.099
Massimiliano Allegri	1.101
Walter Mazzarri	1.102
Davide Ballardini	1.117
Maurizio Sarri	1.118
Alberto Malesani	1.123
Domenico Dicarlo	1.128
Giuseppe Iachini	1.137
Davide Nicola	1.138
Eugenio Corini	1.145
Luciano Spalletti	1.149
Eusebio Di francesco	1.149
Walter Zenga	1.159
Gianpiero Gasperini	1.159
Delio Rossi	1.163
Claudio Ranieri	1.174
Sinisa Mihajlovic	1.174
Roberto De zerbi	1.175
Marco Giampaolo	1.179
Vincenzo Montella	1.189
Gianpiero Ventura	1.192
Andrea Stramaccioni	1.195
Stefano Pioli	1.195
Filippo Inzaghi	1.201
Massimo Oddo	1.206
Stefano Colantuono	1.211
Rolando Maran	1.215
Roberto Donadoni	1.243
Pierpaolo Bisoli	1.274
Luigi Delneri	1.313
Ivan Juric	1.334
Giuseppe Sannino	1.388
Zdenek Zeman	1.412
Sannino Giuseppe	1.422

8 Notes

[1] Football industry has risen to prominence as one of the main industries both in terms of followers (the 2014 World Cup final has been watched by 3.2 Billion people; FIFA 2015) and real contribution to the economy, especially in Italy. Indeed, the economic impact of football in Italy has been estimated at about 3.01 Billion Euros in 2018, representing 0.17% of the national GDP (AREL, PwC, 2019).

[2] See the survey in Garcia-del-Barrio and Szymanski (2009).

[3] For Italian Serie-A, sales of broadcast rights are bargained by the League Association with the broadcasters and then revenues are allocated to teams considering parameters and weights that changed through years (e.g. estimated number of supporters and recent results).

[4] Stadium profits are very limited for the majority of clubs which have started only recently to build their own structures. Currently, only four football clubs that played in the Serie-A in recent years own the home stadium (Frosinone, Juventus, Sassuolo, Udinese).

[5] We acknowledge that Italian head coaches, unlike for example English Premier League, provide only an indirect contribute to clubs' potential financial goals, since they are not used to directly participate to player trade activities.

[6] Our method focuses on the valorization of the players outside the market windows. This is meant to exclude other effects related to team level staff (e.g. scouts, management of youth squads, personnel dedicated to trading) and country specificities (e.g. the involvement of managers in player trading decisions seem larger in the UK than in Italy).

[7] The study of Dawson and Dobson (2002) is the most similar to ours: it focused on football managers and applied a SFA while we will rely on DEA. Our study extends their contribution by considering a multi-output approach (both sport and financial performance are examined) and by measuring players' value through the market value indicator.

[8] Those pieces of information are not easily available to external observers and would require ad-hoc surveys among staff and players. The employers might have a better access to this type of knowledge than an external observer and incorporate it in the hiring processes.

[9] Manager's career started in minor championships (not in one of the two top leagues, Serie A or Serie B). We also analyzed a variable tracing those managers that debuted as head coach of a "primavera" team. "Primavera"

is the B-squad made of usually under 19 players that compete in championships parallel to main ones. Primavera players sometimes train with main teams and can be appointed for A squad matches.

[10] Before Season 2003-04, 18 teams were taking part in Serie A. Half of the matches are played in the home stadium and half away.

[11] At the end of the season the Italian Champion (first in rank) and the following three teams are awarded with the participation to the UEFA Champions League, the most important European competition per clubs, that secures high visibility and high revenues to participants; the fifth and the sixth teams get access to the UEFA Europa League (the rules to access European level competitions changed in the examined time frame but this is not relevant to our framework). The last three clubs are relegated to the Italian second level league: Serie B.

[12] The second half season of 2019-20 campaign was severely impacted by the health emergency due to the Covid19 pandemic and we preferred to exclude it from the analyses. Note that the seasons 2004-2005 and 2005-2006 were affected by a partial revision of the final ranking due to the scandal called "Calciopoli". The main consequences were the attribution of penalty points to some of the involved teams for season 2006-07 and Juventus lost *de iure* both titles in 2004-05 and 2005-06. Our empirical models have also been tested excluding those two seasons with no significant changes in the results.

[13] Aida is maintained by Bureau Van Dijk (https://www.bvdinfo.com/en-gb/our-products/data/national/aida).

[14] Note that this value includes the manager's gross salary which however accounts for a small fraction of the total costs (our estimates: around 2-4%).

[15] Data collected and validated from multiple online sources, such as World Football (https://www.worldfootball.net) and Wikipedia (https://it.wikipedia.org). Missing data points are a negligible share.

[16] For instance, a manager hired in a middle level club for the last three matches of the season could play against the top three clubs in the league, thus the contribution could be underestimated; or against the bottom three and the impact could be overestimated. See Table 16 in the Appendix for an overview on the number of replacements per half-season on the full sample.

[17] 17 matches for the seasons from 1998-99 to 2003-04 when the number of participants was 18.

[18] We performed several tests with other thresholds. The results are very similar, and we opted for the number of matches that is the best trade-off between sample size and expected likelihood for a manager to leave his/her mark on the players' market value.

[19] The correlation matrix of dummy variables reports 12 cases out of more than 10 thousand pairs with the correlation value higher (lower) than 0.5 (-0.5). The regression models were tested also excluding these cases: the results are fully coherent with those reported.

[20] The results from the application of the same model specifications on different subsamples built by applying other filtering criteria (e.g., FC:share, MC only, etc.) are very similar and are available on request. We highlight that the potential minimum and maximum amount of average earned points are 0 and 3: we performed the tests by using a truncated regression and found very similar results.

[21] We have not considered the variable measuring the players' market value at the beginning of the half season to allow comparison with the results of the reference study and at the same we selected the same sample 6 that grants the maximum coverage also for the analyses on the growth of team value in the next section.

[22] The coefficients calculated on different subsamples are similar. Managers' relative ranking is coherent across the subsamples with slight changes in the order. For example, when considering the full sample, the top two positions are inverted.

[23] Focusing on the observed half seasons of sample 6, the correlation coefficient between the two measures of performance is -0.106.

[24] DEA and Stochastic Frontier Analysis (SFA) are the two most used techniques in benchmarking analysis. We chose DEA because it provides an estimate of the frontier and does not require assumptions that are currently too uncertain in the examined framework, i.e. (i) on the functional form of the production function and (ii) on the distribution of the inefficiency term. Furthermore, DEA is simple from the computational point of view.

[25] The choice of the final team value as output implies that the performance is measured in terms of final/initial values ratio (i.e., output/input ratio). This is in line with the growth value used in Section 4.1.2 and consistent with our assumption on the production possibility set. We point out that it would be instead misleading to choose the percentage growth directly as the "financial output". Indeed, growth is already a partial performance measure and not an output. In other words, while performance being equal, a higher initial value requires a higher final value, this does not necessarily work with the percentage growth. The latter is, in fact, a relative (with respect to the input) measure of performance that may be disconnected from the input size.

[26] It implies that, for example, the manager of a club having a low market value of players at the beginning of the half season (e.g. aiming at avoiding relegation) would be considered "efficient" with different terms of

output/input ratio with respect to the colleagues managing teams aiming at the championship thanks to a high market value of players.

[27] The set of feasible input/output combinations may be affected by the so-called “technological change” (e.g., a change in the training methodologies, in the organization and/or specializations of the training staff, etc.). Notice that such change may occur even between two consecutive half seasons. Furthermore, the winter transfer market session may change significantly the input endowment of many clubs (and therefore the balance of power among clubs). Even if this does not necessarily affect the shape of the frontier and the technology set, we notice that this may however happen in some cases. In this regard, we anyway believe that it is reasonable that the same performance in terms of input/output may not necessarily have the same value in different halves of the same season when the level of the competitors is not constant.

[28] Average scores are often used in the benchmarking literature to sum up the obtained results. Note that the average value alone conveys a useful even if limited measure since the number of half seasons is different across managers: the higher the number of observed half seasons for a manager, the higher the consistency of the efficiency score. A complementary information is the relative number of times that a manager defines the frontier (i.e., he is identified as the best practice). The upper half of managers in the DEA ranking shown in Table 10 are on the efficient frontier on average in 54% of the half seasons (63% for the top-ten managers), compared to 19% for the managers in the lower half-ranking (14% for the lowest ten). This suggests that our results exhibit a certain level of consistency.