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Pay Dispersion and Work Performance

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Working Paper

12-075

February 27, 2012

PAY DISPERSION AND WORK PERFORMANCE*

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This version: February 27, 2012

The effect of intra-firm pay dispersion on work performance is controversial and the empirical evidence is mixed. High pay dispersion may act as an extra incentive for employees' effort or it may reduce motivation and team cohesiveness. These effects can also coexist and the prevalence of one effect over the other may depend on the use of different definitions of what constitutes a "team." For this paper we collected a unique dataset from the men's major soccer league in Italy. For each match we computed the exact pay dispersion of each work team and estimated its effect on team performance. Our results show that when the work team is considered to consist of only the players who contribute to the result, high pay dispersion has a detrimental impact on team performance. Several robustness checks confirm this result. In addition, we show that enlarging the definition of work team causes this effect to disappear or even become positive. Finally, we find that the detrimental effect of pay dispersion is due to worst individual performance, rather than a reduction of team cooperation.

Keywords: Team productivity, Incentives, Pay dispersion.

JEL codes: J31, J33, J44.

* We thank Alessio Occhi for skillful research assistance and Xiang Ao, Antonio Cabrales, Fabio Landini, Matthias Sutter, and Luca Zarri for useful comments. We are also grateful to Andrea Monti, Daniele Redaelli, and the editorial staff of the Italian newspaper *La Gazzetta dello Sport* for their kind cooperation in retrieving data. The usual disclaimers apply.

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1. Introduction

Does pay dispersion have a positive or negative effect on work performance? The literature does not provide a clear answer. On the one hand, pay dispersion can have a negative impact on team performance because it may undermine all the benefits of team cooperation (Milgrom and Roberts 1988; Akerlof and Yellen 1990; Lazear 1989). Because employees may experience feelings of relative deprivation if wages are unequal (Martin 1981), employers have to use narrow wage differentials to reduce dissonance among employees and favor team cohesiveness (Levine 1991). On the other hand, larger intra-firm pay dispersion can motivate employees around the bottom of the pay distribution scale to work harder for the future reward of a higher salary (Lazear and Rosen 1981). Pay dispersion may also be beneficial for attracting and keeping talent (Milgrom and Roberts 1992) or for avoiding the loss of workers who are crucial to the firm's output (Ramaswamy and Rowthorn 1991).

The empirical evidence on this issue is mixed and therefore inconclusive. Some studies support the idea that pay dispersion has a beneficial effect on team performance (Becker and Huselid 1992; Ehrenberg and Bognanno 1990; Marchand, Smeeding, and Torrey, 2006); other studies show that pay dispersion has a detrimental effect (Bloom 1999; Depken 2000; Wiseman and Chatterjee 2003; Jane 2010); further studies find no significant effect (Berri and Jewell 2004; Avrutin and Sommers 2007; Katayama and Nuch 2011). Our interpretation of these contradictory results is that these two effects coexist and that the prevalence of one effect over the other depends on the definition of *team* used.

In this paper we show that the estimates of the effect of pay dispersion vary when using different definitions of what constitutes a team. We think this is important because conflicting evidence does not help managers decide how to use pay dispersion optimally. Pfeffer and Langton (1993, 383) wrote that "one of the more useful avenues for research on pay systems may be precisely this task of determining not which pay scheme is best but, rather, under what conditions salary dispersion has positive effects and under what conditions it has negative effects." We provide evidence that the effect of pay dispersion can be positive, null, or negative depending on the precision of the definition of team. Our dataset in fact allows us to measure pay dispersion by distinguishing between "active" and "passive" players: both are part of the team, but only the former ones contribute to the team's performance.

Our dataset is drawn from two seasons of the men's major soccer league in Italy. Professional sports data represent a unique source of data for labor market research, and they are widely used because they provide detailed statistics about team performance, as well as the individual athletes' performances and salaries. Soccer is a particularly appropriate area of study for our research question for a number of reasons. First, it is a team sport where cooperation is crucial, although teams may also win (lose) because of extraordinarily good (bad) individual performance. Second, it is possible to identify each individual's participation (in terms of minutes played) and to obtain repeated measures of performance over time (multiple matches in one season). Third, these data are reliable, detailed, and reported with high precision. Our dataset contains information on the net salary of each team member, and statistics on each team, each team member, each head coach, and each match. Fourth, this sport is one of the most well known and popular in the world, particularly in Italy, where it generates revenues of about 1.5 billion euros (Deloitte 2011). Given this popularity, players' salaries are highly publicized in the media. This means that each player is aware of the pay of his teammates, at least until the opening of a new session of the players' transfer market (each January).

Another reason why we decided to use soccer data is that each team roster usually consists of around 25 to 30 athletes, but only 11 to 14 of them actually play a single match. Therefore, these data allow us to measure the effect of pay dispersion using various definitions of team and provide an explanation for why the previous literature has found mixed evidence. The existing literature cited above (for a recent review, see Kahn 2000) looks at end-of-season data, comparing the wins-to-matches ratio with the pay dispersion of the entire team roster, paying no attention to individual contributions to team performance. To the best of our knowledge, our study is the first to compare the outcome of a single task (a match) with the pay dispersion of only those who contributed to the task. We believe this improves the precision of the comparison and can shed new light on our understanding on the effect of pay dispersion on work performance.

Our findings are clear-cut. Using the narrowest definition of a team, that is, considering only those who played the match and how long they played for, pay dispersion has an overall negative impact on team performance; this result is consistent with different robustness checks. However, that effect changes—and it may even become significantly positive—when we enlarge the definition of team to include the entire team roster. We interpret this result as the consequence of taking an approximation of the correct pay dispersion where a less precise definition can bias the estimates.

Two different scenarios may explain the negative effect of pay dispersion on team performance: high pay dispersion can affect team performance through lack of cooperation among team members or through lack of individual effort. To understand which explanation is supported by data, we collected all (subjective) individual performance assessments for each match, for each team, and for each player reported by the three most popular Italian sports newspapers. Our results show that higher pay dispersion has a detrimental impact on individual performances, but has no significant effect on cooperation.

Finally, we want to point out that our analysis controls for pay size and we use indicators of pay dispersion that are dimensionless. For this reason, our results can be extended to other work contexts. This is crucial because one could object that we are considering a peculiar work environment, where workers usually earn much more than a typical worker. Our findings may be able to help employers determine which type of pay distribution will be more effective within a firm and make the right decisions about which employees to hire. This is not a trivial decision: should a firm hire one expensive superstar and two inexpensive employees, or three medium-priced players? This paper provides some numerical examples showing that managers should carefully take into account the hidden cost of hiring a superstar and its effect on team performance, while keeping constant the overall team quality.

The remainder of this paper is organized as follows. Section 2 briefly describes our data, discusses the methodology and reports some summary statistics on the key variables in our dataset. Section 3 shows our main results regarding team and individual performance. Finally, Section 4 presents conclusions. Two appendices provide more details on the data construction and further robustness checks.

2. Data and Estimation Methodology

In this section we discuss the environment and the variables we used in the analysis. Section 2.1 presents the environment and our dataset, Section 2.2 illustrates the estimation method and lists our variables, and Section 2.3 summarizes the statistics from the dataset.

2.1. Environment and Data

Our data cover the two seasons 2009–2010 and 2010–2011 of the men's major soccer league in Italy ("Serie A"). Every season 20 teams participate in the league, and each team plays against each other team twice (one time at the home stadium and one time away) for a total of 38 matches. After a match three points are assigned for a win, one point for a draw, and no points for a defeat. The ultimate goal of each team is to earn points and be classified as high as possible in the league's ranking in order to win it or at least be in the top six positions and in this way gain access to the European cups. Teams also want to avoid being placed in any of the bottom three positions, which would relegate them to the second division. In fact, at the end of each season, the three teams ranked last are replaced by the three teams ranked first in the second division.

Our dataset contains information on the outcome of each match (win, draw, or defeat), on who played every single match and for how many minutes, and his annual net pay, as well as other statistics on each player, on each team, on each head coach, and on each match. We collected this unique dataset by merging data from the three most popular Italian sports newspapers (*La Gazzetta dello Sport*, *Corriere dello Sport*, and *Tutto Sport*), and (for players' statistics) from the website www.tuttocalciatori.net.

In any season, each team consists of about 25 to 30 athletes (hereafter, the *team roster*) specializing in different roles (goalkeeper, defender, midfielder, forward). However, only 18 members are summoned for each match: 11 (starter players) start the game and the other 7 (substitutes) sit on the bench and can enter the match at any time after the beginning, replacing one of the starter players (who can no longer take further part in the match). During a match a maximum of three substitutions is allowed. Common reasons for substitutions include injury, tiredness, ineffectiveness, or a tactical switch. In the 2009–2010 season 462 players and in the 2010–2011 season 463 players played for at least one minute during our observation period. In most cases those who played in one season also played in the other one; however, from our perspective they are completely different players because they may earn different salaries in the two seasons. For this reason and for sake of simplicity and with a little abuse of terminology, we say that 925 team members have played overall. A similar argument can be made for teams: because those teams present in both seasons may have very different lists of team members, we treat them as different, and we say that our sample includes 40 teams. We know the salaries of only 874 of the 925 players (94.49%), while we impute the pay of the remaining 51 ones as specified in the Appendix, Section A.1. This imputation has a negligible impact on our statistics, because players for whom we needed to impute salaries have a marginal role in the team (on average they have played about 1% of the available time).

Our dataset includes the matches played between August 23, 2009, and December 20, 2009 (2009–2010 season), and between August 29, 2010, and December 19, 2010 (2010–2011 season), for a total of 666 observations.[1] To be conservative and have a clean dataset, we

[1] We observed 20 teams in season 2009–2010 and 20 teams in season 2010–2011 over a sequence of 17 matches for each team. In total we have 666 observations, 14 less than the expected 680 (= 40 × 17) because some

decided to use only the matches played before the opening of the January players' transfer market, during which every team is allowed to trade players with other teams. We then ignored the remaining matches, for which we cannot be sure about the exact salaries of players transferred, especially the ones coming from foreign leagues. On average these players account for around 12% of the team members after the January market (see the Appendix, Section A.2), and they usually take a relevant role in the team—playing most of the remaining matches. If we included these data, any guesses about the missing salaries would likely bias our estimates. However, there is relatively high correlation (0.589) between the number of points earned in the first 17 matches and the number of points earned in the remaining matches.

2.2. Variables and Estimation Method

Our unit of analysis is the team playing a match in a given season; in total we then have 40 teams, 20 for each season. Recall that the team may win, draw, or lose a match, earning respectively three, one, or no points. Our dependent variable, measuring team performance, is a dummy equal to 1 if the team wins the match (which happens in 37.24% of the cases); it is equal to 0 if the team draws or loses the match. We group draws and defeats together because the ultimate goal for a team is to win a match. In a robustness check, reported in the Appendix, Section B.1, we repeat the analysis treating first both wins and draws as a positive outcome, and then each outcome separately. Our main results were confirmed.

We perform a probit regression with panel-robust standard errors (clustered for each team in each season); this way we allow for possible correlation across observations referring to different matches of the same team. We opted for this model because our data show no evidence of team-specific panel effects (see the discussion at the end of Section 3.1); use of this model allows us to obtain more efficient estimates.

Our purpose is to obtain measures of pay dispersion, as well as other indicators, that are specific for each match of each team. For this purpose, the term *active team members* (ATMs) for a team in a given match refers to all team members who actually played at least one minute of the match. For such a match we then neglect all of the remaining members who did not contribute to the result of the match. As a consequence, the set of active team members for a team varies match by match.[2]

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matches were postponed to after the January transfer market due to bad weather conditions or schedule conflicts with international competitions.

[2] Consider that, in our data, on average 8.44 out of the 11 starter players also began the previous match. In addition, some number between 6 and 14 team members who played at least one minute in a match also played

The benchmark specification includes different variables that for clarity we group into six categories: *pay, team, coach, match*, *opponent*, and *time*. Our focus is on the first group of pay variables; the remaining ones serve as control variables. In the analysis, all of the variables concerning team composition are based solely on the ATMs, and the contribution of each member is weighted by the amount of time he actually played in the match. The variables in the *pay* and *team* categories thus refer to the ATMs of the team, whereas the variables in the *opponent* category refer to the ATMs of the opponent team. This means that *pay*, *team*, and *opponent* statistics differ match by match and that members who had no active role in the match are ignored. In what follows we discuss the variables used in the analysis.

Pay variables

We consider the logarithm of the average pay, and the logarithm of a dimensionless measure of pay dispersion. In all the cases we refer to annual salaries in thousands of euros net of taxes. Let us define $p_{i,x}$ as the pay of player $i, i = 1, \ldots, I$ in team $x, x = 1, \ldots, X$, where $m_{i,x,t} \in [0, 90]$ represents the minutes of the match actually played[3] by the same player in match $t, t = 1, \ldots, T$. We treat $m_{i,x,t}$ as a weight to compute the average pay for team x in match t:

$$\bar{p}_{x,t} = \frac{1}{\sum_{i=1}^{I} m_{i,x,t}} \sum_{i=1}^{I} m_{i,x,t} p_{i,x} .$$

As a pay dispersion measure, we take the Theil index. This indicator belongs to the class of entropy indexes and is frequently used to measure economic inequality. The index is defined as the mean of the products between individual pay relative to average pay, and its logarithm is as follows:

$$T_{x,t} = \frac{1}{\sum_{i=1}^{I} m_{i,x,t}} \sum_{i=1}^{I} m_{i,x,t} \frac{p_{i,x}}{\bar{p}_{x,t}} \ln\left(\frac{p_{i,x}}{\bar{p}_{x,t}}\right).$$

The index is equal to 0 for the case of no pay dispersion (i.e., all salaries are identical); a higher index denotes higher pay dispersion. Notice that the indicator is dimensionless, which means that what matters to us is only the individual pay *relative to the average pay*; this

at least one minute in the previous match. The set of active team members thus varies largely from one match to another.

[3] We do not consider the extra time played after the regular time (90 minutes), which is at the discretion of the referee and depends on various stoppages (e.g., substitutions, injuries) incurred during the match.

allows us to compare pay distributions across teams and matches, disregarding the average pay level, which varies markedly (from 213,808 euros to 4,356,061 euros). As a robustness check, we repeated the analysis using the popular Gini index rather than the Theil index. In this case our main findings were qualitatively confirmed, and quantitatively even emphasized (for details see the Appendix, Section B.2).

Team variables

We use weighted average values in a given match for players' ages, the fraction of new players on the team, and the number of years (even if not consecutive) on the team and in the Italian first division; the last two variables serve to proxy players' experience.

Coach variables

For the coach we use the same set of information as for the team, that is: coach age, a dummy variable equal to 1 if he is in his first season with the team, and the number of years (even if not consecutive) on the team and in the Italian first division. Head coaches in soccer are often fired from one season to another, and even during the same season. We then also include in the analysis a dummy variable equal to one if the head coach has been replaced during the season.

Match variables

We use a dummy variable equal to 1 if the team plays a domestic (home) match and also use the number of injured players and the number of disqualified players.[4] The last two variables are added because injuries and disqualifications may prevent a coach from using his preferred players during a match. However, we expect disqualifications to have a stronger effect because they usually involve team members who play more frequently.

Opponent variables

We consider the same variables as in the *pay* and *team* groups, but we base them on the ATMs of the opponent team. The purpose is to in this way capture the characteristics (in particular the strength) of the opposing team. An alternative would be to add as many dummy variables as the teams (40). Doing so, our main results would be confirmed. The shortcoming of such an approach, however, is the potential inefficiency of estimating many coefficients in a probit regression model; for this reason we prefer our benchmark specification.

[4] Soccer players may be sanctioned with a yellow or red card for a specific misconduct. Multiple yellow cards or one red card produces an automatic disqualification for at least one following match.

Time variables

We use a dummy variable equal to 1 if the match was played during the 2010–2011 season, and dummy variables for the month if the match was played from August to December.

2.3. Summary Statistics

Table 1 lists all variables used in the analysis and reports some summary statistics (median, mean, standard deviation, minimum, and maximum). All statistics are calculated for the ATMs in the 666 observations of our sample. The purpose of using all of these variables is to control for the physical, social, and other characteristics of the team members, the coach, and the match.

From the table we learn that, for the median observation, the ATMs' average pay is 584 thousand euros, the Theil index is 0.093 (ranging from 0.006 to 0.497), on average the ATMs are around 27 years old, they already have accumulated two years of experience in the team and five years in the first division, and around 26% of them are in their first year with the team. In addition, 57% of the coaches are new to the team, 14% of them started managing the team after the beginning of the season, and they have little experience with the team and the first division. Finally, disqualifications and especially injuries are frequent, and sometimes they may force the coach to reshape the starting team formation (in fact, we observe a maximum of 4 disqualified players and 11 injured players). In our analysis we account for this when measuring the effect of pay dispersion. Further statistics on pay dispersion are shown in the Appendix, Section A.3.

TABLE 1. Summary statistics (666 observations on 40 teams)

Variable	Median	Mean	Std. dev.	Minimum	Maximum
Pay					
Average pay (thousands of euros)	583.788	1039.801	998.699	213.808	4356.061
Theil index	0.093	0.114	0.077	0.006	0.497
Team					
Fraction of new players in the team	0.255	0.263	0.156	0	0.701
Years in the team	2.202	2.341	1.039	0.483	5.985
Years in first division	4.635	4.858	1.510	1.597	9.645
Average age	27.465	27.488	1.327	24.298	30.889
Coach					
New to the team	1	0.571	0.495	0	1
Replaced during season	0	0.144	0.351	0	1
Years in the team	0	0.685	0.982	0	4
Years in first division	3	4.372	3.686	0	14
Age	48	49.414	6.882	38	65
Match					
Injured players	3	3.081	1.798	0	11
Disqualified players	0	0.431	0.662	0	4
Home play	0.5	0.5	0.500	0	1

Note: For the "opponent" variables we consider the same variables as in the pay and team categories, but we base them on the ATM of the opposing team. We do not report summary statistics because they coincide with those in the pay and team categories.

Table 2 lists the teams in our dataset (20 for each season) and some average statistics (age, experience, fraction of new players) for their ATMs in each match. Teams are listed according to the ranking at the end of each season, where the first team listed is the winner of the championship and the last three teams are eventually relegated to the second division.

First of all, we notice that the 17 teams enrolled in both seasons show marked differences over the two years. From the table we also observe wide heterogeneity across teams within the same season, with no clear pattern going from bottom to top teams. The last column of Table 2 shows the fraction of players that in our sample played at least for one minute. This fraction is between 0.69 and 0.96; note that it is always below 1. This indicates that some team members never play; usually those excluded are injured and homegrown players. Ignoring this, and treating all team members equally, the analysis on the effect of pay dispersion may generate different results, as we will clarify in Section 3.2.

TABLE 2. Team statistics

A: 2009–2010 Season

Team	Fraction new to the team	Years on the team	Years in first division	Age	Fraction of players employed
FC Internazionale Milano	0.314	3.553	4.961	29.320	0.733
AS Roma	0.093	3.755	6.278	28.378	0.871
AC Milan	0.128	4.538	8.063	29.619	0.786
UC Sampdoria	0.265	1.862	5.751	26.639	0.778
US Città di Palermo	0.188	1.650	4.085	25.886	0.852
SSC Napoli	0.289	1.465	4.743	26.897	0.808
Juventus FC	0.239	3.056	5.838	28.460	0.929
Parma FC	0.535	0.847	6.160	27.604	0.808
Genoa CFC	0.359	1.527	4.421	27.760	0.786
AS Bari	0.435	1.507	2.836	26.267	0.774
ACF Fiorentina	0.110	2.695	7.519	27.818	0.750
SS Lazio	0.042	2.582	5.689	27.455	0.806
Catania Calcio	0.282	1.650	2.333	26.120	0.893
Cagliari Calcio	0.134	3.406	4.695	26.910	0.720
Udinese Calcio	0.131	2.370	4.312	25.502	0.733
AC Chievo Verona	0.199	2.647	4.622	29.198	0.852
Bologna FC	0.439	0.810	5.098	29.076	0.815
Atalanta Calcio	0.253	2.513	4.024	26.915	0.923
AS Siena	0.302	1.692	4.203	26.550	0.885
AS Livorno	0.310	1.552	3.689	27.437	0.800
AVERAGE	**0.252**	**2.280**	**4.962**	**27.491**	**0.834**

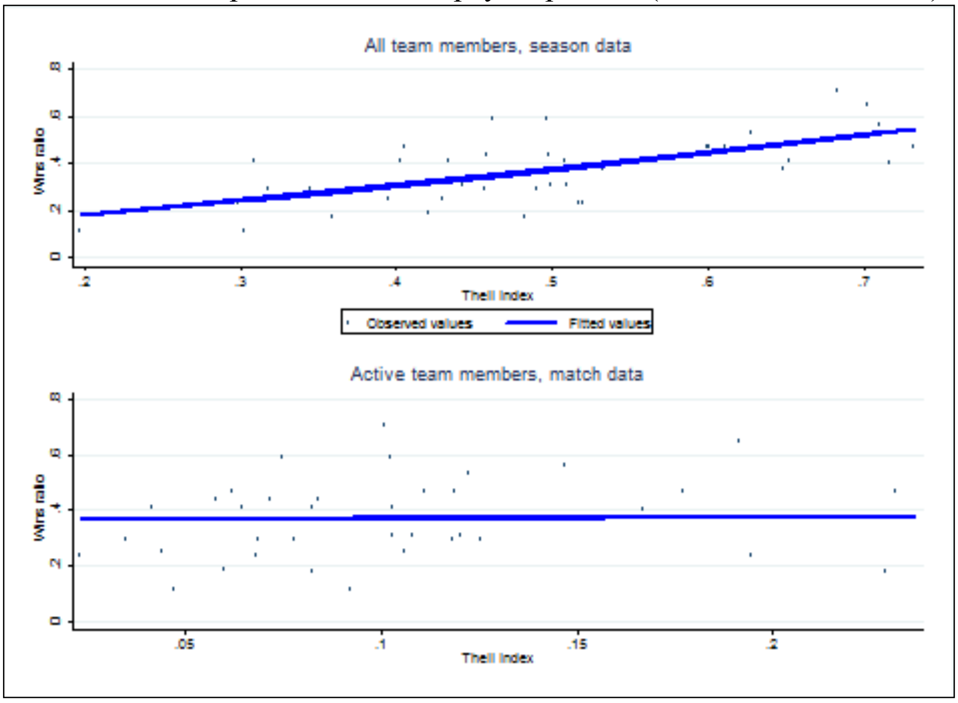
B: 2010–2011 Season

Team	Fraction new to the team	Years on the team	Years in first division	Age	Fraction of players employed
AC Milan	0.228	4.749	7.927	29.480	0.828
FC Internazionale Milano	0.108	3.786	5.430	29.308	0.862
SSC Napoli	0.166	1.766	5.393	27.573	0.917
Udinese Calcio	0.166	3.117	4.723	25.740	0.909
SS Lazio	0.196	2.130	4.479	27.918	0.846
AS Roma	0.188	4.001	7.135	29.506	0.963
Juventus FC	0.542	2.066	5.297	27.173	0.926
US Città di Palermo	0.308	1.555	3.299	24.939	0.692
ACF Fiorentina	0.124	2.960	7.440	27.659	0.929
Genoa CFC	0.499	1.550	4.310	27.718	0.846
AC Chievo Verona	0.434	2.065	3.594	27.916	0.880
Parma FC	0.311	1.358	5.315	27.914	0.769
Cagliari Calcio	0.077	3.281	4.391	26.090	0.760
Catania Calcio	0.083	2.255	2.887	27.144	0.889
Bologna FC	0.399	0.902	3.363	26.605	0.923
AC Cesena	0.494	1.703	4.168	28.302	0.852
US Lecce	0.401	2.446	2.529	27.306	0.926
UC Sampdoria	0.124	2.258	5.975	26.046	0.929
Brescia Calcio	0.383	2.446	4.015	28.541	0.960
AS Bari	0.236	2.322	3.679	27.012	0.929
AVERAGE	**0.274**	**2.401**	**4.755**	**27.484**	**0.873**

Note: Teams are listed according to their position at the end of the season; teams promoted from second division are highlighted. Averages for each team are based on the ATM of all of the matches (either 16 or 17) played by the team in a given season. Fraction of players employed: number of players employed at least for one minute over total number of players.

To stress this point, Figure 1 plots for each team the fraction of wins over the Theil index, using two different methods. In the top panel, the pay dispersion index is based on the whole team roster, disregarding players' involvement in the matches; this is the standard approach adopted in the literature. In the bottom panel, the index is the average over the matches, where for each match pay dispersion is based on the ATM; this approach is closer to the one followed in this paper. First of all, we notice that the index calculated in the top panel uses values that are on a higher scale than those of the index in the bottom panel; the reason is that this measure is inflated by the low pay of those members (usually the homegrown ones) who, although formal members of the team, do not contribute to the team's performance.

FIGURE 1. Team performance and pay dispersion (40 team observations)



The figure also shows a line indicating the predicted winning probability for a given level of the Theil index. The prediction is obtained from a simple probit regression over 666 observations, where the dependent variable is equal to 1 if the team wins the match, and 0 otherwise; the specification includes just the constant and the Theil index, based on either the whole team roster (top panel) or the ATM of each match (bottom panel). Comparing the two panels, we see that pay dispersion positively affects team performance when considering the whole team roster (top panel), whereas it has no impact when considering the ATMs (bottom panel). This suggests that results may change depending on how pay dispersion is measured. This finding warns us that findings may change depending on our definition of what constitutes a "team."

We conclude this section with an exploratory analysis of the effect of pay dispersion on performance, which is our ultimate goal. Overall in the data, pay dispersion shows no significant difference (t test: 0.37; p value: 0.712) when the match is won (average: 0.116) or when the match is drawn/lost (average: 0.114).[5] Table 3 then shows, separately for each team, the average pay, the average Theil index, and the wins ratio. Teams are listed as in Table 2, following their ranking at the end of the season. The first thing to note brings to mind the famous slogan "*The more you spend, the more you get.*" Indeed, teams that spend more (i.e., with a higher average pay) rank higher at the end of the season. In fact, our data exhibit a large Spearman's rank correlation (0.701) between average team pay and the wins ratio in the season. The data thus suggest that better players are also better paid, and for this reason we can interpret the average pay of a team as a proxy for the average skill in the team. In contrast, pay dispersion is much less highly correlated with the wins ratio (the rank correlation is 0.241), although the sign of this correlation is still positive.

A problem with this analysis is that it completely ignores the specific characteristics of each team. For this reason, we now compare, separately for each team, the wins ratio obtained in two groups of matches, where the Theil index is either below or above the median for the team. The last column of Table 3 shows that the wins ratio is higher in the matches with high pay dispersion in only 11 cases out of 40.

We have then found that, looking at the same data, one can interpret the relationship between team performance and pay dispersion as positive (considering all the team members: Figure 1, top panel), null (considering the ATMs: Figure 1, bottom panel), or negative (considering the ATMs separately for each team: Table 3). Our empirical exercise in the next section further analyzes the relationship considering the ATMs, each match separately, and controlling for the most relevant characteristics of the team, the coach, the match, and the opponent.

[5] Pay dispersion is not even affected by the team performance of the previous match (*t* test: 0.607; *p* value: 0.544; average after a match won: 0.117; average after a match drawn/lost: 0.113). This suggests that the coach does not adjust it to keep the team compact in case of performance problems.

TABLE 3. Pay and team performance

A: 2009–2010 Season

Team	Average pay	Theil index	Wins ratio: average by matches			(2) – (1) > 0
			All	Low disp. (1)	High disp. (2)	
FC Internazionale Milano	4115.021	0.101	0.706	0.875	0.556	NO
AS Roma	1718.652	0.232	0.471	0.375	0.556	YES
AC Milan	3250.733	0.147	0.563	0.750	0.375	NO
UC Sampdoria	724.647	0.393	0.412	0.750	0.111	NO
US Città di Palermo	658.497	0.083	0.412	0.500	0.333	NO
SSC Napoli	842.041	0.103	0.412	0.500	0.333	NO
Juventus FC	2673.181	0.123	0.529	0.625	0.444	NO
Parma FC	536.108	0.062	0.471	0.500	0.444	NO
Genoa CFC	817.235	0.058	0.438	0.500	0.375	NO
AS Bari	435.087	0.126	0.375	0.125	0.625	YES
ACF Fiorentina	1177.068	0.072	0.438	0.250	0.625	YES
SS Lazio	729.187	0.229	0.176	0.125	0.222	YES
Catania Calcio	413.871	0.048	0.118	0.125	0.111	NO
Cagliari Calcio	367.552	0.084	0.438	0.625	0.250	NO
Udinese Calcio	464.575	0.103	0.313	0.250	0.375	YES
AC Chievo Verona	380.442	0.042	0.412	0.500	0.333	NO
Bologna FC	523.939	0.106	0.250	0.375	0.125	NO
Atalanta Calcio	334.134	0.060	0.188	0.125	0.250	YES
AS Siena	436.847	0.083	0.176	0.250	0.111	NO
AS Livorno	358.900	0.125	0.294	0.500	0.111	NO

B: 2010–2011 Season

Team	Average pay	Theil index	Wins ratio: average by matches			(2) – (1) > 0
			All	Low disp. (1)	High disp. (2)	
AC Milan	3590.499	0.191	0.647	0.750	0.556	NO
FC Internazionale Milano	3250.635	0.167	0.400	0.429	0.375	NO
SSC Napoli	918.736	0.102	0.588	0.625	0.556	NO
Udinese Calcio	568.033	0.065	0.412	0.500	0.333	NO
SS Lazio	1099.115	0.075	0.588	0.750	0.444	NO
AS Roma	2049.492	0.177	0.471	0.625	0.333	NO
Juventus FC	2034.127	0.119	0.471	0.500	0.444	NO
US Città di Palermo	576.675	0.111	0.471	0.500	0.444	NO
ACF Fiorentina	1024.088	0.108	0.313	0.250	0.375	YES
Genoa CFC	1128.980	0.236	0.375	0.500	0.250	NO
AC Chievo Verona	316.556	0.035	0.294	0.375	0.222	NO
Parma FC	559.824	0.068	0.235	0.250	0.222	NO
Cagliari Calcio	403.838	0.078	0.294	0.250	0.333	YES
Catania Calcio	447.094	0.069	0.294	0.250	0.333	YES
Bologna FC	555.712	0.119	0.294	0.125	0.444	YES
AC Cesena	223.423	0.044	0.250	0.250	0.250	=
US Lecce	300.007	0.023	0.235	0.375	0.111	NO
UC Sampdoria	897.708	0.121	0.313	0.250	0.375	YES
Brescia Calcio	359.365	0.195	0.235	0.250	0.222	NO
AS Bari	482.681	0.093	0.118	0.250	0.000	NO

Note: See note to Table 2. Average pay is in thousand euros. For each team we split matches in two groups based on whether the Theil index was below (low) or not below (high) the median value for the team.

3. Empirical Analysis

In this section we summarize our main findings regarding the effect of pay dispersion on team performance (Section 3.1). We then discuss some robustness checks around the definition of team members (Section 3.2), and we report the results of a further analysis connecting pay dispersion with individual performance (Section 3.3).

3.1. Benchmark Analysis

The first column of Table 4 reports the average marginal effects from our benchmark probit regression analysis. The column shows that pay dispersion has a *negative impact* on team performance: doubling pay dispersion, the probability of winning a match would reduce on average by 0.06. Panel (a) of Figure 2 plots the predicted winning probability, conditional on pay dispersion and the other explanatory variables (fixed to their average), computed using this probit regression. It shows that probability falls, from 0.56 when there is no pay dispersion, to 0.24 when the Theil index is $T = 0.50$.

An example will help the reader understand this figure. Suppose you are the manager of a team, and you have to buy 11 new players who are expected to play all the next matches fully and on a regular basis. Your budget is limited, and you have to decide whether to buy (at the same total expenditure) either 1 top player and 10 average players, or instead 11 players with above-average skill. We assume their pays reflect their skill. Further, let us say that the average pay is 600 thousand euros (the actual pay size in our sample; however, this is irrelevant for the pay dispersion index) and that the manager can choose to pay all 11 players the same amount (600 thousand euros) or 1 top player much more (1.5 million euros as opposed to 510 thousand euros for the other ones). In the latter case the top player will earn 2.5 times the average pay, while each other player will earn 0.85 times the average pay; this pay distribution roughly corresponds to the median distribution in the sample. The resulting Theil index is $T = 0.083$, whereas it is $T = 0$ if all 11 players earn 600 thousand euros each. Hence, higher pay dispersion denotes higher variability of players' skills. Our estimates suggest that, everything else being equal, the differentiated pay distribution will make the probability of winning a match fall on average by 20%, from 0.56 to 0.36.

In our regression we also find significant evidence of a positive effect of average pay (doubling it would increase the probability of winning a match by around 0.15), replacing a coach during the season (the probability then increases by 0.12), and playing at home (0.25). In addition, we find significantly negative effects for the coach's experience with the team (one more year reduces the probability of winning a match by 0.03) and the opponent's average pay (doubling it would reduce the probability by 0.17). These results are not surprising: on average, the pay can be seen as a proxy for a player's skill (above we made an argument about this); replacement of a coach during the season may have a large psychological impact on the players; a team playing in its home stadium may benefit from the support of its fans; the longer a coach is on the team, the lower is the strength of his effort and the psychological impact on the players; and the opponent's average pay can also be seen as a proxy for its skill, which then lowers the winning probability of the team. No other explanatory variables—noticeably, those on the team characteristics and on the opponent's pay dispersion—are significantly different from 0, at least at a 5% significance level.[6]

The "rho" coefficient, shown in the bottom part of Table 4, is the proportion of the total variance contributed by the team-level variance. This is statistically equal to 0, indicating that there are no team-specific intrinsic characteristics; that is, if we moved all the team members from one team to another, their performance would be identical. "Team identity," or the environment in which they are trained and where they play, does not influence their performance. The consequence is that we could alternatively disregard the panel dimension of our data, and run our analysis with a probit regression on the pooled dataset. In what follows we then perform pooled probit regressions with team-clustered standard errors, because this approach is more efficient than using panel regression methods (fewer parameters have to be estimated).

Section B.1 of the Appendix repeats the analysis, also treating draws as a positive outcome, and confirms our benchmark results. Moreover, Section B.2 reports the results of some robustness checks on the specification, where we substitute the Theil index with the Gini index (which actually shows a stronger significant effect: –0.13 rather than –0.06), or where we add an indicator of the symmetry of the pay distribution (eventually not significant), a quadratic polynomial on pay dispersion, or the interaction between the index and a dummy variable equal to 1 if the team played a match in December. In the latter two cases, the purpose is to understand whether the effect of pay dispersion is non-monotonic or if it changes as team members get to know each other better. In neither case are the added variables significantly different from 0. In addition Section 3.3 discusses, among other things, the relationship between team performance and different technologies of production.

[6] One could expect the coefficients for the team and the opponent to be mirrored, because when a team wins, its opponent loses the match, and in the analysis we include one observation for the team and one for the opponent. This is not true, however, when a match ends up in a draw (this happens in 25.53% of the observations), in which case the dependent variable is equal to 0 for both.

TABLE 4. Team performance and pay dispersion (average marginal effects)

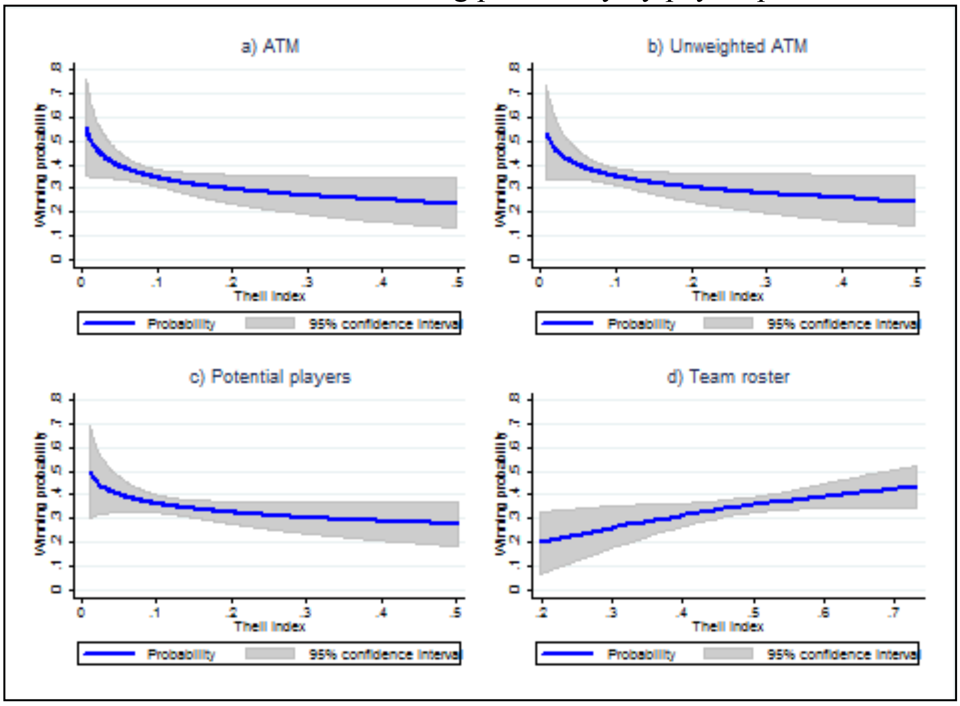
Members:		(1) ATM	(2) Unweighted	(3) Potential	(4) Roster
Pay:	Log(average pay)	0.146***	0.142***	0.147***	0.076**
		(0.027)	(0.028)	(0.032)	(0.039)
	Log(pay dispersion index)	-0.061**	-0.058*	-0.046	0.167**
		(0.030)	(0.032)	(0.031)	(0.082)
Team:	Fraction of new players on the team	0.095	0.040	0.059	0.044
		(0.143)	(0.148)	(0.144)	(0.141)
	Years on the team	0.015	0.011	0.020	0.006
		(0.026)	(0.029)	(0.030)	(0.037)
	Years in first division	0.002	-0.004	-0.006	0.006
		(0.016)	(0.018)	(0.018)	(0.022)
	Age	0.001	0.014	0.005*	0.009
		(0.017)	(0.016)	(0.002)	(0.017)
Coach:	New to the team	-0.091*	-0.086*	-0.089*	-0.116**
		(0.050)	(0.050)	(0.047)	(0.046)
	Replaced during the season	0.119**	0.115**	0.120**	0.108**
		(0.051)	(0.054)	(0.056)	(0.048)
	Years on the team	-0.034**	-0.033**	-0.032**	-0.033**
		(0.015)	(0.016)	(0.015)	(0.016)
	Years in first division	0.010*	0.011**	0.011**	0.009*
		(0.006)	(0.006)	(0.005)	(0.005)
	Age	0.000	-0.000	0.000	-0.000
		(0.004)	(0.004)	(0.004)	(0.003)
Match:	Injured players	-0.006	-0.005	-0.004	-0.007
		(0.010)	(0.010)	(0.010)	(0.010)
	Disqualified players	0.040*	0.040*	0.040*	0.024
		(0.023)	(0.023)	(0.023)	(0.022)
	Home play	0.253***	0.250***	0.248***	0.256***
		(0.034)	(0.035)	(0.033)	(0.034)
Opponent:	Log(average pay)	-0.169***	-0.160***	-0.183***	-0.125***
		(0.029)	(0.032)	(0.035)	(0.037)
	Log(pay dispersion index)	0.030	0.018	0.015	-0.083
		(0.025)	(0.026)	(0.033)	(0.095)
	Fraction of new players on the team	0.139	0.206*	0.088	0.183
		(0.105)	(0.119)	(0.120)	(0.153)
	Years on the team	0.044*	0.048*	0.045	0.084**
		(0.022)	(0.027)	(0.029)	(0.041)
	Years in first division	0.001	0.004	0.012	-0.014
		(0.015)	(0.016)	(0.017)	(0.025)
	Age	0.004	-0.007	-0.003**	-0.019
		(0.015)	(0.017)	(0.001)	(0.020)
+ time dummy variables on month and year of the match					
	Log-likelihood	-371.461	-371.522	-370.738	-371.522
	McFadden R^2	0.155	0.155	0.157	0.155
	Count R^2	0.689	0.688	0.700	0.688
	Rho coefficient	0.000			
	LR test rho =0	0.000			
		[0.496]			

Note: 666 observations on 40 teams (on average, 16.6 matches per team). The dependent variable is a dummy =1 in case of win. Pay and team statistics are based on ATM players (column 1); ATM players, not weighted by the amount of time they actually played (column 2); all potential players (starter players and substitute players; column 3); whole team roster (column 4). Team-clustered standard errors are given in parentheses; p *values in brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

3.2. Team Members

We repeat the analysis with the same regression specification as in the benchmark case, but this time we consider different definitions of team members. As we have already seen, the definition affects the computation of the variables on pay, team, and opponent statistics that are all match specific. The effect of pay dispersion on team performance may then change with the definition of group. The average marginal effects from the analysis are shown in columns (2), (3), and (4) of Table 4; the latest column is based on the broadest definition of team members.

FIGURE 2. Predicted winning probability by pay dispersion



Note: Predictions are based on the average explanatory variables and the parameter estimates from Table 4.

Unweighted ATM

We first consider the ATM, as in the benchmark, but disregarding the amount of time they actually played. For instance, if the match started with 11 players and then 3 substitutes also took part in the match, we derive our pay and players statistics from the characteristics of 14 team members, without weights.

Our results are reported in column (2) of Table 4, and they are close to the benchmark case of column (1). In particular, pay dispersion is still associated with a negative marginal effect of –0.06, although the effect is now significant at only 10%. This suggests that ignoring the amount of time spent in the field may create noise in the estimates.

Potential players

We then consider as team members all 18 athletes who were potentially able to play in the match because they were either starter players or substitute players. In this manner we exclude injured players, disqualified players, or players who are out of the match as a result of a decision made by the coach. All members are given the same weight, disregarding the number of minutes they actually played in the match. This definition of team members is less precise than our benchmark definition of ATMs, because at least four of these members in each match make no contribution to team performance, but they still affect the pay, team, and opponent statistics.

Our results are shown in column (3) of Table 4. Most variables show effects that are in line with the benchmark results; however, the pay dispersion index is now associated with a coefficient insignificantly different from zero.

Entire team roster

We conclude the analysis by considering as team members all athletes enrolled on the team, that is, the entire team roster, thus including injured, disqualified, and homegrown players. Hence, we consider the same team composition in each match, disregarding who actually played. This implies that, in our regression equation, the variables on pay and team statistics are constant for a given team (they are then fixed "team effects"), and the variables on opponent statistics are constant for a given opponent team. Such an approach is similar to that of some previous works in the literature, because it does not pay attention to whether and how much each team member contributed to team performance.

Our results are shown in column (4) of Table 4, and they are largely different from our benchmark analysis of column (1): we find a smaller effect of the team average pay (0.08 instead of 0.15), while the effect of pay dispersion is now even positive: according to these estimates, doubling pay dispersion would increase the probability of winning by 0.17. In contrast, the remaining variables, which have not changed relative to the benchmark case (they do not depend on the definition of team members), provide parameter estimates comparable with those of the benchmark case.

The results in Table 4 thus inform that, when broadening the definition of team (i.e., when going from column 1 to column 4), conclusions about the effects of pay dispersion change enormously: at a 5% level we may indeed find either a negative effect (column 1), a null effect (columns 2 and 3), or a positive one (column 4). Figure 2 plots the predicted winning probability, conditional on pay dispersion and the other explanatory variables (fixed to their average), computed separately from each of the four probit regressions in Table 4. From the figure it is clear that the direction of the effect goes from negative to positive as we use less information on the group definition, from panel (b) (where we ignore the amount of time actually played) to panel (c) (where we consider all starter and substitute players), and on to panel (d) (where we include the whole team roster).

This result warns that measurement of an effect can be biased if we do not consider a precise definition of what constitutes a "team." Notice in particular that we find a positive effect when we look at the most general definition (whole team roster). Those who play little or not at all usually earn less than those who play regularly (see the Appendix, Section A.4, for details). As a result, pay dispersion increases if we use a definition of team that incorporates them; in particular, considering the entire team roster, the index is on average 0.493, as opposed to 0.114 if we consider just the ATMs. Pay dispersion increases significantly more in the top 10 teams at the end of December of each season: the average difference between the pay dispersion index computed from the team roster and from the ATMs is on average 0.437 among the top teams, as opposed to 0.321 among the other teams (*t* test: 16.512; *p* value: 0.000). The pay dispersion index then captures part of the effect of the team skill; indeed, the correlation between average pay and pay dispersion is 0.722 using the whole team roster, whereas it is only 0.253 using the ATM. This correlation may explain why in column (4) of Table 4 the effect of pay dispersion is positive, and the effect of average pay is about half the effect found in the other three columns.

This suggests that our benchmark conclusions are not driven by a dataset with different features than others. Actually, our conclusions depend on the way we look at the data, and in particular on what we mean by "team members." This may explain why in the literature we observe different results, and it shows the importance of the precision of the definition of team to evaluate the effect of pay dispersion.

3.3. Individual Performance

So far the analysis has focused on objective indicators of team performance. Team performance, however, derives from individual performance and cooperation among team members. It is then possible that we observe poor team performance because there is *poor individual performance* or because there is *little cooperation*. For instance, in soccer, we can observe a poor team performance when each player tries to score without passing the ball to other players (lack of cooperation) or when each player prefers not to take the initiative but instead passes the ball to other players, thereby delegating to them the responsibility to score (the lack of effort). One may thus wonder what determines the detrimental effect of pay dispersion on team performance. Does pay dispersion work as a disincentive to individual effort? Alternatively, does pay dispersion merely decrease cooperation between players, leaving individual performance unchanged? These are the issues we want to address in this section.

Our data suggest that teams that win more often make significantly more passes during the match.[7] In Section B.1 of the Appendix we report the output of a within-group panel regression analysis of the number of passes over the same specification as in the benchmark. We find no significant effect of pay dispersion. If we see the number of passes as a proxy for team cooperation, we interpret this finding as an indication that team cooperation is not affected by pay dispersion. If our argument is correct, team performance should then be affected solely by individual performance.[8]

Obtaining an objective and thorough measurement of individual performance is impossible in our environment, because soccer is a team sport where few individual statistics are recorded compared to other sports such as baseball. (See, e.g., Scully [1974] for an analysis of the connection between individual performance and individual pay.) In addition, those few existing individual statistics record rare events (e.g., goals, assists, yellow cards) and are highly role specific (e.g., a forward player is more likely to score a goal than any other player). It would be difficult to use these statistics as measures of individual performance.

In Italy, however, it is quite common for journalists, when writing a newspaper report about a match, to assign a "mark" to each single player's performance. The mark is a number based on a scale from 0 to 10; a mark of 6 denotes fair performance and higher marks indicate good or excellent performance. This mark represents a *subjective individual performance assessment* (SIPA), because it is based only on the arbitrary opinion and taste of the journalist who attended the match. Still, it is a rough indicator of the individual performance of each team member and can be used to look at the effect of pay dispersion on individual team members. In this regard we collected all of the SIPAs for the players involved in the 333 matches considered in the main analysis, using the three major sport newspapers in Italy: *La Gazzetta dello Sport*, *Corriere dello Sport*, and *Tutto Sport*. To make SIPAs less heavily affected by the personal opinion of the journalists, we took an average SIPA from the three newspapers (the SIPAs from the three sources show a correlation of around 0.7). Overall we have 8,226 observations on 876 players (434 in the 2009–2010 season and 442 in the 2010–

[7] We split the 40 teams in two groups, depending on their wins ratio. The 20 teams winning more frequently on average make 410.47 passes, significantly more than the other teams making on average 383.52 passes (t test: 1.876; p value: 0.034).

[8] Contrary to team performance, this result is robust to any definition of team. In contrast Pfeffer and Langton (1993) find a negative effect of pay dispersion on collaboration in academic research. The academic environment, however, is not appropriate to assess team effort: researchers may keep working with no cooperation, or they may cooperate with researchers in other universities. This situation is hard to find in most jobs, and certainly not in soccer.

2011 season)[9], who then played an average of 9.39 matches each. In a separate analysis, available in the Appendix, Section B.3, we take the SIPAs from the major sport newspaper, *La Gazzetta dello Sport*, and add in the specification dummy variables on the journalist who made the SIPA. Our main conclusions are confirmed, both qualitatively and quantitatively.

Figure 3 plots the distribution of SIPAs in our sample. We see that SIPAs are concentrated between 4 and 9, with a peak around 6 (fair performance).

FIGURE 3. Distribution of individual SIPAs (8,226 observations)

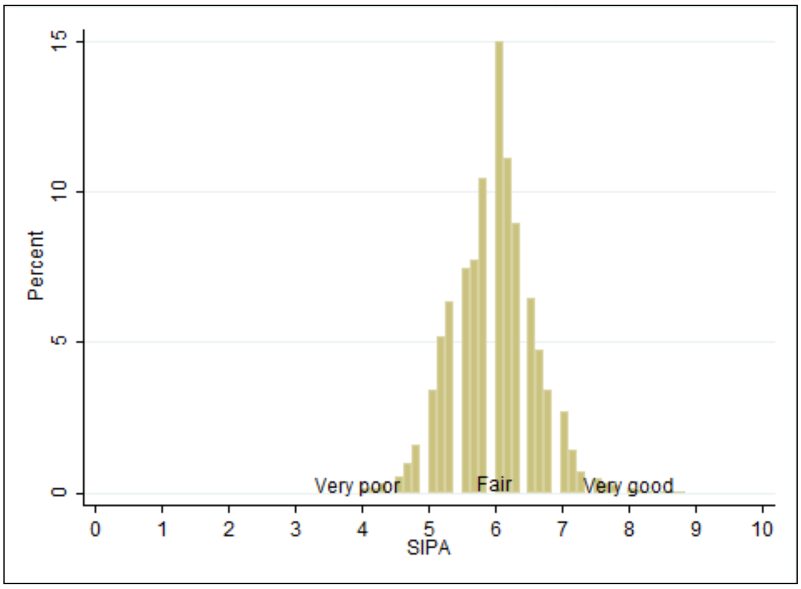


Table 5 reports some summary statistics at the player level. First of all, we notice that SIPAs are generally higher when the team wins a match (see the Appendix, Section A.4, for more details). However, low SIPAs are possible also in this case: players may indeed receive a SIPA of 4 even if their team wins the match. Moreover, the table lists some statistics about the main player's characteristics: his pay, his age, his past experience with the team and the first division, and his role (midfielder, forward, as opposed to goalkeeper or defender). We observe wide heterogeneity on these variables.

SIPAs show a weakly positive correlation with individual salaries (0.09) and team average pay (0.05), and a weakly negative correlation with pay dispersion (–0.05). It is also interesting to understand which "technology of production"—meant as a combination of individual SIPAs—determines team performance. If we regressed team performance over the minimum, mean, and maximum SIPAs of the team in the match (controlling for team, coach, match, opponent, and time characteristics), we would find all coefficients to be significant at 1%,

[9] This number is smaller than that for the players who played at least for one minute, 925, because marks are given only to those who play a significant portion of the match. The decision on what is a "significant portion of the match" is subjective, and different journalists may have different opinions.

suggesting that different technologies coexist. However, the average marginal effect of the mean SIPA is quantitatively much higher: 0.717, as opposed to –0.069 for the minimum SIPA and 0.129 for the maximum SIPA. This suggests that team performance depends on the individual effort of *all* players, more than on the effort of the best/worst ones.

TABLE 5. Summary statistics, individual players (8,226 observations on 876 players)

Variable	Median	Mean	Std. dev.	Minimum	Maximum
SIPA					
If win	6.333	6.308	0.563	4	8.833
If draw	6	5.968	0.504	4	7.833
If defeat	5.667	5.631	0.531	4	7.833
OVERALL	6	5.966	0.611	4	8.833
Individual variables					
Pay (thousands of euros)	600	1029.200	1255.642	30	10500
Pay/average pay	0.920	0.997	0.496	0.010	4.348
New to the team	0	0.271	0.445	0	1
Years on the team	1	2.287	2.679	0	18
Years in first division	4	4.789	3.807	0	18
Age	27	27.429	3.954	17	41
Midfield role	0	0.399	0.490	0	1
Forward role	0	0.191	0.393	0	1

The analysis in this section is meant to help us understand the link between individual performance and pay dispersion using an approach similar to that of our benchmark analysis. For this purpose we run a regression analysis, where the dependent variable is the individual SIPA, and the specification includes variables on the player (pay relative to the average pay, age, experience, and role), as well as the same variables used in Table 4. We consider ATMs as team members to construct our statistics. Table 6 shows the output from this regression, where we estimate the coefficients using a pooled ordinary least squares (OLS) method with player-clustered standard errors (column 1), a random-effect (RE) panel GLS method (column 2), or a fixed-effect (FE) panel OLS method (column 3); the latter method does not allow us to separate the effect of match-invariant variables from the player-specific effect. The "rho" coefficient reported in the bottom part of the table suggests that, in this context, it is important to consider player-specific effects. Moreover, the statistical tests comparing the three models, reported at the end of the table, suggest that it is advisable to use a panel method.

TABLE 6. Individual performance and pay dispersion (average marginal effects)

Method:		**(1)** **Pooled OLS**	**(2)** **RE GLS**	**(3)** **FE OLS**
Player:	Pay/average pay	0.105***	0.110***	-0.220
		(0.021)	(0.020)	(0.172)
	New to the team	-0.002	-0.004	
		(0.026)	(0.023)	
	Years on the team	0.014***	0.015***	
		(0.005)	(0.005)	
	Years in first division	-0.005	-0.005	
		(0.004)	(0.004)	
	Age	0.001	0.000	
		(0.003)	(0.003)	
	Midfield role	0.047**	0.050***	
		(0.019)	(0.019)	
	Forward role	-0.015	-0.014	
		(0.028)	(0.026)	
Pay:	Log(average pay)	0.082***	0.080***	-0.253
		(0.019)	(0.017)	(0.196)
	Log(pay dispersion index)	-0.064***	-0.080***	-0.139***
		(0.016)	(0.014)	(0.024)
Team:	Fraction of new players on the team	0.053	0.023	-0.007
		(0.073)	(0.071)	(0.115)
	Years on the team	-0.006	-0.012	-0.026
		(0.014)	(0.013)	(0.025)
	Years in first division	0.001	0.002	-0.007
		(0.010)	(0.010)	(0.018)
	Age	-0.009	-0.003	0.014
		(0.010)	(0.009)	(0.016)
Coach:	New to the team	-0.008	0.003	0.094
		(0.028)	(0.027)	(0.098)
	Replaced during the season	-0.016	0.012	0.134**
		(0.027)	(0.027)	(0.059)
	Years on the team	-0.011	-0.009	0.055*
		(0.014)	(0.013)	(0.033)
	Years in first division	0.007**	0.007**	-0.001
		(0.003)	(0.003)	(0.011)
	Age	0.001	0.002	0.004
		(0.002)	(0.002)	(0.007)
Match:	Injured players	-0.010**	-0.006	-0.000
		(0.005)	(0.004)	(0.005)
	Disqualified players	0.048***	0.056***	0.072***
		(0.011)	(0.011)	(0.012)
	Home play	0.144***	0.144***	0.140***
		(0.013)	(0.013)	(0.013)
Opponent:	Log(average pay)	-0.042***	-0.043***	-0.048***
		(0.014)	(0.013)	(0.013)
	Log(pay dispersion index)	0.055***	0.053***	0.053***
		(0.012)	(0.011)	(0.012)
	Fraction of new players on the team	0.035	0.058	0.120**
		(0.056)	(0.057)	(0.058)
	Years on the team	-0.001	0.003	0.011
		(0.010)	(0.010)	(0.010)
	Years in first division	0.004	0.005	0.009
		(0.006)	(0.006)	(0.007)
	Age	0.007	0.007	0.003
		(0.006)	(0.006)	(0.007)
	Constant	5.443***	5.217***	7.126***
		(0.308)	(0.276)	(1.521)
+ time dummy variables on month and year of the match				
	R^2	0.041	0.040	0.000
	Rho coefficient		0.063	0.380
	Test pooled vs. panel		276.810	1.930
			[0.000]	[0.000]

Note: 8,226 observations on 876 players (on average, 9.39 matches per player). The dependent variable is the average SIPA from three newspapers. Standard errors are given in parentheses; p *values in brackets. In column 1 we report player-clustered standard errors. * p < 0.1; ** p < 0.05; *** p < 0.01.*

Our main findings are as follows. In columns (1) and (2), where we can estimate the effects of match-invariant variables, we find positive effects for individual pay, years of experience with the team, and the midfield role of the player (a core role in soccer). The direction of all of these effects is intuitive. Notice in particular that a high relative pay seems to work as an incentive on individual performance; this result is in line, for instance, with the results of Pfeffer and Langton (1993). However, giving a disproportionately high pay to some is not necessarily an effective strategy. In fact, it may give rise to high pay dispersion, and in Table 6 we consistently find a negative effect for the team pay dispersion. In addition, we find positive effects for playing at home, number of disqualified players, and the opponent's pay dispersion, and a negative effect for the opponent's average pay.

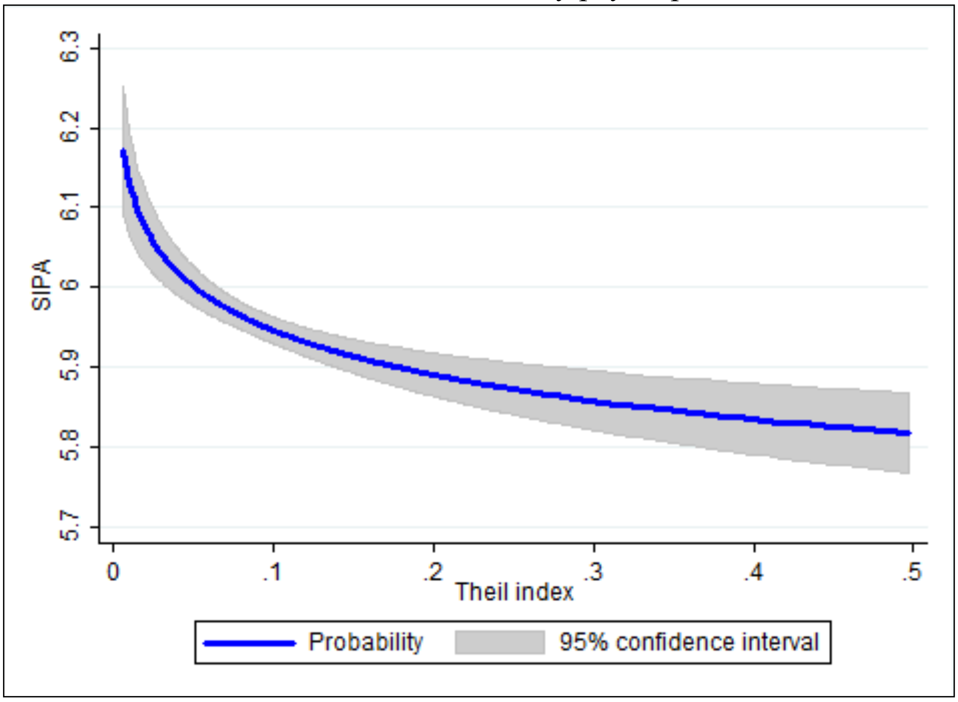
In the Appendix, Section B.4, we repeat the same analysis, adding into the specification variables that consider whether the player is a "superstar" (when he earns at least two times the average pay in the team) or a "regular player" (one of the 11 most frequent players in the first month of the season), alone and interacting with pay dispersion. Interestingly, we find that SIPA increases with regular players, and responds more negatively to pay dispersion among superstars. In particular the first result suggests that infrequent players, when they have "all eyes on them" during the match, are not able to perform as well as the regular players for whom they substitute.

Figure 4 reports the predicted SIPA conditional on pay dispersion and the average explanatory variables, using the estimates from column (2) of Table 6. We focus on this column, rather than column (3), because it shows a lower effect of pay dispersion (–0.08 instead of –0.14), and overall it provides more convincing estimates—in particular, because it shows significant effects as a result of the players' and team salaries. As its counterpart for team performance (panel [a] of Figure 2), the figure shows that the SIPA is the highest when there is no pay dispersion at all. This suggests that pay dispersion has a detrimental effect not just on team performance, but that it also negatively impacts individual performance. To interpret this figure, we return to our previous example with the team manager.

Let us say that the manager has to choose whether to increase or decrease the current pay dispersion (where 1 player earns 2.5 times the average income, and each of the 10 remaining players earns 0.85 times the average income). The outcome of this choice is not trivial, because varying the distribution of pays affects not only pay dispersion, but also the average pay and the players' pay, which in turn have different implications on individual performance. To keep the situation simple, let us say that the manager has a budget balance and he considers two alternatives that do not alter average pay: in plan A, the top player earns three times the average pay, and each remaining player earns 0.8 times the average pay; in plan B, the top player earns two times the average pay, and each remaining player earns 0.9 times the average pay. The corresponding Theil index goes from an initial level of $T = 0.083$ to either $T = 0.137$ in plan A or $T = 0.040$ in plan B.

We know from Table 6 that an increase in player's pay has a positive effect on individual performance, while an increase in pay dispersion has a negative effect. As a result, the direction of the effect on the top player is unclear *a priori*, while we already know that in plan A the performance of the lower-paid players will fall, and in plan B their performance will rise. With these numbers we find that, in plan A the SIPA of the top player will rise by 0.015 points, whereas the SIPA of each other player will fall by 0.046 points. In plan B, the SIPA of the top player will rise by 0.003 points (notwithstanding a reduction of his pay), while the SIPA of each other player will rise by 0.064 points. All in all, the effect on the top player is lower than that on the other players. This, together with the fact that there is just one top player, but 10 other players suggests that plan B is preferable, because it increases the average SIPA by 0.058 points; in contrast, plan A reduces the average SIPA by 0.04 points.

FIGURE 4. Predicted SIPA, by pay dispersion



Note: Predictions are based on the average explanatory variables and the parameter estimates from Table 6, column (3).

4. Conclusions

A team organization is common in the workplace, and the use of teamwork has been increasing over time (Lazear and Shaw 2007). For this reason, studying the impact of incentives on team performance is an important field of research. However, previous literature on the effect of pay dispersion is controversial: some authors think that pay dispersion may provide an extra incentive for employees' increased efforts, whereas other authors think that it may reduce motivation and team cohesiveness. The two effects may even coexist. Unfortunately, previous evidence does not provide a clear message; it suggests that the estimated effect on team performance can be positive, null, or negative.

In this paper we collect a unique dataset of matches played during two seasons of the men's major soccer league in Italy. This unique dataset allows us to measure the effect of pay dispersion according to different definitions of *team*. This peculiarity of our dataset is the crucial element that can explain the conflicting evidence. Indeed, we also find positive, null, and negative effects of pay dispersion on team performance, using the *same data* but *different definitions of team*. However, when we take the narrowest definition of a team—considering only the members who actually took part in the task and how long they played—pay dispersion has a detrimental impact on team performance: doubling pay dispersion decreases by 6% the probability of winning a match. This result is consistent with several robustness checks.

This negative effect of pay dispersion on team performance may be the reason why salaries are usually kept secret within a firm (see Lawler 1990, 238–42). Employees do not like to earn less than their coworkers; as a result, pay dispersion can decrease cooperation within the team and it may affect individual performance. We investigate this issue in our environment by looking at the number of passes within a match and the (subjective) individual performance assessments reported by the three most important Italian sports newspapers. Our results show that higher pay dispersion has a detrimental impact on individual evaluations, whereas it does not have a significant effect on cooperation.

Our results hold for any level of pay given the dimensionless nature of our pay dispersion index. Therefore, the external validity of our analysis goes beyond this specific sports environment. Actually, the fact that in the sport environment salaries can be high is a nice feature of our dataset, because it allows use to study a large variety of pay dispersions.

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Appendix A: Data and Environment

A.1. Salary and Salary Imputation

Each soccer player receives a salary that is defined through an individual agreement with the team, usually negotiated on a yearly basis at the end of the season. A salary is made of a fixed component and (sometimes) a variable component. The variable component, more frequent with top players, is linked to the performance of the team (e.g., winning a competition) or the *ad hoc* performance of the single player (e.g., number of goals scored, number of assists made). Further revenue, also more frequent with top players, may be generated by doing advertising endorsements for sports and non–sports-related firms. In our analysis we consider only the fixed component of the pay, which is the only amount known to us and the team members. Ignoring the variable component of a salary, as well as revenues generated from advertising endorsements, probably underestimates pay dispersion (because it more likely occurs in players who already earn high salaries).

In our sample 925 players have played at least one match for one minute or more. We are aware of the salaries of 874 of them (94.49%); for the remaining 51 players, pay imputation is necessary. Imputation applies to two categories of players (33 reserve players and 18 homegrown players) having a marginal role in the team, because they are employed in case of an emergency (injury or disqualification of the main players) to get the legal number of 18 players (11 starter players and 7 substitute players) in a match. These players have played on average 1.66 matches in the sample, and for roughly 1 minute out of 90; hence, imputation has a negligible impact on our statistics.

We impute the salary of reserve players as follows: we assign them the pay they earned in the other season in our dataset, when applicable; otherwise, we assign them the lowest pay in the team. The reason is that the salaries of these players are not likely to be negotiated every year, and they are comparable to those of (low-skill) regular players.

We adopt a different imputation rule for homegrown players. These are players ages 20 or younger who regularly play for the team, but in another league specifically devoted to them (*campionato primavera*). The salaries of these players are typically much lower than those of other players, and they are renegotiated on a yearly or longer basis. This means that a homegrown player, even if he becomes important for the team and plays a large number of matches during the season, will still earn a very low wage up to the end of the season. In our sample we set this type of player’s net annual pay uniformly to the level of 30 thousand euros per year[1]; this is very low, compared to the median pay of 582,879 euros we observe in our sample, but still well above the average wage in the country (17 thousand euros for a full-time male employee; source: Istat 2011).

A.2. January Players' Transfer Market

In Italy as well as in the other European countries, the players' transfer market takes place twice a year: the main market arises between July and August, when no league is active, while the second one is held in January, when the league is going on. This second (winter) transfer market is often exploited to repair mistakes made during the summer market, or to recover from unexpectedly poor rankings in the league. For this reason, the number of transferred players is usually large: during the January markets of 2010 and 2011, a total of 150 players were bought and 159 players were sold in *Serie A*, generating overall expenses of 182 million euros and revenues for 122 million euros. These transfer movements are relatively large compared to the summer market: in the two seasons under investigation, the *Serie A* teams had summer market expenditures of 739 million euros and revenues of 795 million euros (source: www.transfermarkt.it).

Table A1 lists the number of January transfers made by each team in each season (data are taken from www.fullsoccer.eu) and the resulting changes in team composition. We observe largely different behavior, even for the same team in different seasons (e.g., in 2011 Bologna FC bought and sold six new players, while in 2010 it just bought one new player). The last column reports the ratio of new players in each team at the end of the January market. Again, we observe large variety, with the number of new players going from 3.13% to 27.59% of the team members; on average, roughly 12% of the players enrolled in *Serie A* came to their team through the January transfer market. This proportion is not negligible, and certainly these new players contribute to the subsequent team performance in a significant manner.

[1] The minimum pay for soccer players ages 19 or older is set to 20,000 EUR gross of taxes. We take a higher pay because some bargaining is allowed to the teams.

TABLE A1. Players' transfer market statistics

A: 2009–2010 Season

Team	Bought players	Sold players	Initial no. of players	Final no. of players	Fraction new players
FC Internazionale Milano	3	4	35	34	0.088
AS Roma	1	7	33	27	0.037
AC Milan	3	2	35	36	0.083
UC Sampdoria	5	4	26	27	0.185
US Città di Palermo	3	4	33	32	0.094
SSC Napoli	1	3	29	27	0.037
Juventus FC	3	3	33	33	0.091
Parma FC	6	5	28	29	0.207
Genoa CFC	6	7	33	32	0.188
AS Bari	5	5	38	38	0.132
ACF Fiorentina	4	3	29	30	0.133
SS Lazio	5	3	33	35	0.143
Catania Calcio	2	1	29	30	0.067
Cagliari Calcio	3	2	33	34	0.088
Udinese Calcio	4	3	36	37	0.108
AC Chievo Verona	2	1	29	30	0.067
Bologna FC	6	6	30	30	0.200
Atalanta Calcio	4	4	30	30	0.133
AS Siena	5	4	30	31	0.161
AS Livorno	6	3	30	33	0.182
TOTAL	**77**	**74**	**632**	**635**	**0.121**

B: 2010–2011 Season

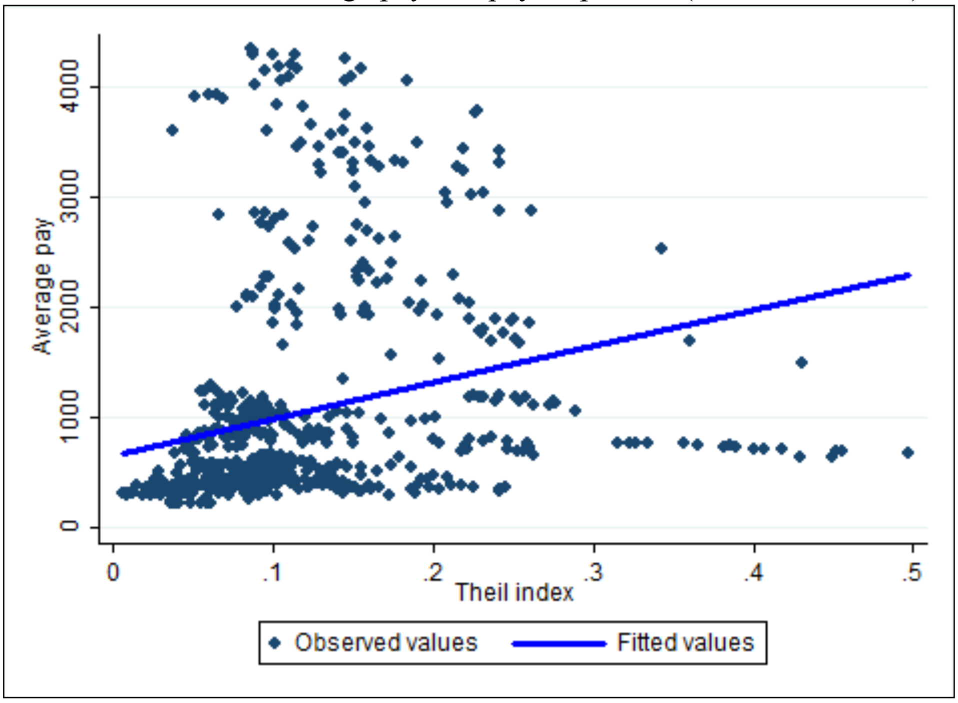
Team	Bought players	Sold players	Initial no. of players	Final no. of players	Fraction new players
AC Milan	5	2	31	34	0.147
FC Internazionale Milano	4	6	33	31	0.129
SSC Napoli	2	2	28	28	0.071
Udinese Calcio	1	5	32	28	0.036
SS Lazio	1	2	32	31	0.032
AS Roma	1	3	33	31	0.032
Juventus FC	3	4	38	37	0.081
US Città di Palermo	3	4	33	32	0.094
ACF Fiorentina	3	3	32	32	0.094
Genoa CFC	7	9	33	31	0.226
AC Chievo Verona	4	7	29	26	0.154
Parma FC	5	5	30	30	0.167
Cagliari Calcio	3	3	30	30	0.100
Catania Calcio	3	5	33	31	0.097
Bologna FC	1	0	30	31	0.032
AC Cesena	7	5	30	32	0.219
US Lecce	1	2	29	28	0.036
UC Sampdoria	8	8	29	29	0.276
Brescia Calcio	4	5	34	33	0.121
AS Bari	7	5	32	34	0.206
TOTAL	**73**	**85**	**631**	**619**	**0.118**

Note: Teams are listed according to their position at the end of the season; teams promoted from second division are highlighted. Players' market for the 2009–2010 season started on January 7, 2010, and ended on February 1, 2010; players' market for the 2010–2011 season started on January 2, 2011, and ended on January 31, 2011.

A.3. Pay Dispersion, Pay, and Skewness

Figure A1 plots the average pay against pay dispersion (Theil index) in our 666 observations. Both measures vary enormously: the average pay varies between 200 thousand euros and more than 4 million euros, while the pay dispersion index ranges between 0 and 0.5 (the theoretical maximum is $\ln(11) = 2.4$ in the hypothetical case where the team pays only one athlete, who plays the whole match). The correlation between pay and pay dispersion, however, is not strong (0.389); this is the consequence of having the pay dispersion index normalized by the pay level.

FIGURE A1. Team average pay and pay dispersion (666 observations)



In addition, pay dispersion has a relatively stronger correlation (0.477) with the usual skewness index. Using the notation in Section 2.2, the index is defined for team x in match t as follows:

$$A_{x,t} = \frac{\sum_{i=1}^{I} m_{i,x,t} \left(p_{i,x} - \bar{p}_{x,t} \right)^3}{\left(\sum_{i=1}^{I} m_{i,x,t} \left(p_{i,x} - \bar{p}_{x,t} \right)^2 \right)^3} .$$

More importantly, in 567 out of 666 cases the asymmetry index $A_{x,t}$ is positive. This indicates that pay dispersion usually arises when one or a few players are earning *less* than the others, rather than when one or a few players are earning *more* than the others.

A.4. Individual Performance

Figure A2 shows an example of the SIPA ratings (*pagelle* in Italian) taken from the main Italian sport newspaper, *La Gazzetta dello Sport*. The example is for the 12th match of the 2010–2011 season between FC Internazionale Milano and AC Milan. The match was eventually won by AC Milan.

FIGURE A2. An example of SIPA

PAGELLE INTER MILITO PRIGIONIERO, COUTINHO TROPPO TENERO

di SEBASTIANO VERNAZZA

5

Impotenza continua, anche in superiorità numerica. Squadra sgonfia.

Le modifiche dell'attacco
Fuori Obi, Inter con il 4-2-3-1. Fuori Milito, Eto'o al centro con Coutinho e Pandev ai lati. Poi si cambia ancora

ETO'O
PANDEV SNEIJDER COUTINHO
GDS

4,5 Benitez
Fare paragoni non è giusto, ciascuno ha il suo modo di vedere e interpretare il calcio, però non c'è interista che al fischio finale non abbia pensato a qualcuno dalle parti di Madrid. Inter scollata, senza nerbo e con gioco approssimativo.

6 Eto'o
Migliore di bandiera, perché stavolta è dura trovare nell'Inter qualcuno che spicchi. Eto'o parte forte a sinistra, dà l'impressione di sfondare, ma Abate e Gattuso gli cesellano le caviglie. Poi passa al centro e combatte. Meglio di niente.

6 Castellazzi
Parate zero. Il Milan tira in porta su rigore e stop. E' il gran paradosso della serata. Si fatica ad assegnare il voto al portiere dei perdenti. Alcune tempestive uscite gli valgono il sei.

5,5 Cordoba
Vice-Maicon d'emergenza, la fascia non è il suo pane. Ci mette una mezz'ora buona ad assestarsi. Qualche giro a vuoto, compensato da una bella discesa, ma il Milan dalla sua parte entra senza sforzi.

6 Lucio
Capisce che con Materazzi sono c... (vabbé, la rima fatela voi) e si auto-nomina angelo custode del «caro» Ibra. Con mestiere gli rifila botte invisibili e limita i danni di Piedone lo Zingaro.

5 Materazzi
Accecato dall'ira – meglio, dall'Ibra – molla un calcio al gran traditore, peccato che lo sgambetto costi il rigore. Nella ripresa RockIbra lo «spiezza» in due. K.o. fisico, tecnico e psicologico. **(Biabiany 5)**

5,5 Chivu
Pronti via, prende una girata da Abate (avessi detto Cristiano Ronaldo) e si capisce che Cristian Caschetto è destinato a un'altra notte di sofferenze. Troppi passaggi sbagliati.

5,5 Zanetti
I muscoli del Capitano non bastano più. Senza un ammiraglio che studi la giusta strategia, la nave procede senza rotta e finisce preda dei pirati milanisti. Gente spietata, con la bandana e l'occhio bendato.

5,5 Stankovic
Si veda sopra. Stankovic prova a fare argine, con tanto orgoglio, ma la testa non è lucida. L'Inter viaggia a fari spenti e neppure Dejan riesce ad accendere la luce. Si procede a tentoni, senza razionalità.

5,5 Obi
Da Oba Oba (Martins) a Obi Obi, la velocità ne risente. Ruoli differenti, certo. Timido e forse intimorito da Gattuso, non piglia iniziative e fa troppe marce all'indietro. Poi si infortuna.

6 Sneijder
Abbiamo visto Sneijder migliori. Tanto migliori, sia chiaro. E sia chiaro: avanti così il Pallone d'oro sarebbe immeritato. Però l'olandese è l'unico che tiri in porta con pericolosità.

5 Milito
Lo cercano poco e male, però lui non fa nulla per farsi trovare all'indirizzo giusto. Poi si fa male ancora. Il Principe resta prigioniero dell'incantesi-mo della Maga Mou(ghella).

5 Coutinho
Buttato dentro al posto di Obi, conferma di essere troppo tenero per un derby così cattivo. I suoi arzigogoli restano tali. Non è una bocciatura, il ragazzo ha mezzi notevoli, però va dosato.

5 Pandev
Largo a sinistra, nel tentativo di aprire la scatola milanista. La missione fallisce, non si ricorda uno spunto di Pandev che produca qualcosa di memorabile. Spaesato.

PAGELLE MILAN ABATE AIUTA L'INTER, BENTORNATO SEEDORF

7

Lezione di derby all'Inter: bisogna metterci anima e corpo.

Seedorf è mobile
Seedorf trequartista, ma con mobilità. Spesso compie una specie di virgola, dal centro a sinistra

IBRAHIMOVIC ROBINHO
SEEDORF
GDS

7 Allegri
Terza vittoria di fila con i tre mediani (e tanti saluti ai tre tenori). Ha trovato l'equilibrio, alla faccia di chi pensa che i gol arrivino sommando gli attaccanti. Sarà interessante vedere come se la caverà con Pirlo: e se lo rimettesse trenta metri avanti?

7,5 Ibrahimovic
Il delitto perfetto. Costringe Materazzi al rigore, poi lo manda all'ospedale e alle interviste dice di non averlo fatto apposta. Che simpatica canaglia e che mostruosa partita. Forte con i forti, stavolta.

6 Abbiati
Più che altro deve concentrarsi su innocui traversoni dalla trequarti. Sneijder gli scalda le mani, ma sono tiri centrali. Abbiati è la prova vivente della pochezza interista.

4,5 Abate
L'unico che faccia qualcosa di concreto per l'Inter. Già ammonito, si fa espellere per una stupida reazione su Pandev. Buon per lui che il risultato non ne risenta, altrimenti Allegri...

6,5 Nesta
Milito gli fa il solletico, qualche fastidio glielo crea il movimentismo di Eto'o, ma sono dettagli. Nesta è padrone della sua area e l'Inter nei sedici metri non è mai pericolosa.

6,5 Thiago Silva
Degno assistente di Nesta. Nel disbrigo delle marcature non commette gravi errori, qualche imprecisione in certi lanci, ma in una notte così sono cose che si possono perdonare.

6,5 Zambrotta
A sinistra, dedica molta attenzione alla fase difensiva. Sceglie di attaccare col contagocce e fa bene perché il nuovo Milan ha capito che la sostanza viene prima dell'apparenza.

6 Gattuso
Allegri fa quel che avrebbe dovuto fare Tagliavento: manda Gattuso a farsi la doccia. Falloso e nervoso, il «Gatto» brilla per lavoro sporco. Poiché si vince, si guarda il bicchiere mezzo pieno.

6,5 Ambrosini
Con autorevolezza, davanti alla difesa, finché non entra Pirlo. A quel punto «Ambro» si sposta un filo più in là, ma il rendimento non cambia. Si è capito che Ambrosini è indispensabile.

6 Flamini
Dei tre mediani è il meno visibile, quello che meno canta e più porta la croce. Gran corridore, è il tipico centrocampista che rende felici gli allenatori. Una specie di «cerottone» ambulante.

7 Seedorf
Riportato nel suo alveo, sulla trequarti, riscopre il gusto di giocare senza lo stress di rientri e coperture. Si muove, tocca tanti palloni e tira. E' un piacere riapplaudire Seedorf. **(Boateng 6)**

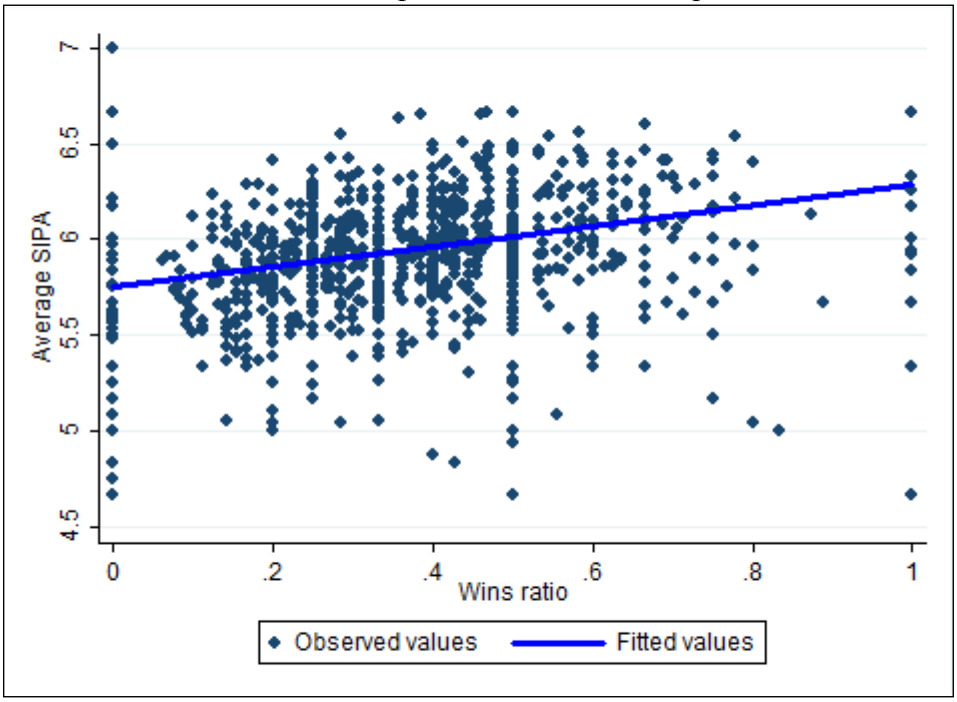
6 Robinho
Sufficienza stiracchiata, il Milan ha vinto e i pagellisti sono più buoni con i vincitori. Diciamo che il voto giusto sarebbe il vecchio 5/6. Non si è visto Robinho brillare.

6 Pirlo
Nella ripresa, al posto del cattivo Gattuso. Infuria la bufera, ma Pirlo tiene l'auto in strada. Domanda: con i tre mediani che cosa ne sarà di Pirlo? Se tornasse trequartista?

6 Antonini
Mezz'ora a remare, senza andare per il sottile. Contributo di corsa e di ripartenze. Non è facile entrare in una partita del genere, ma Antonini ci riesce.

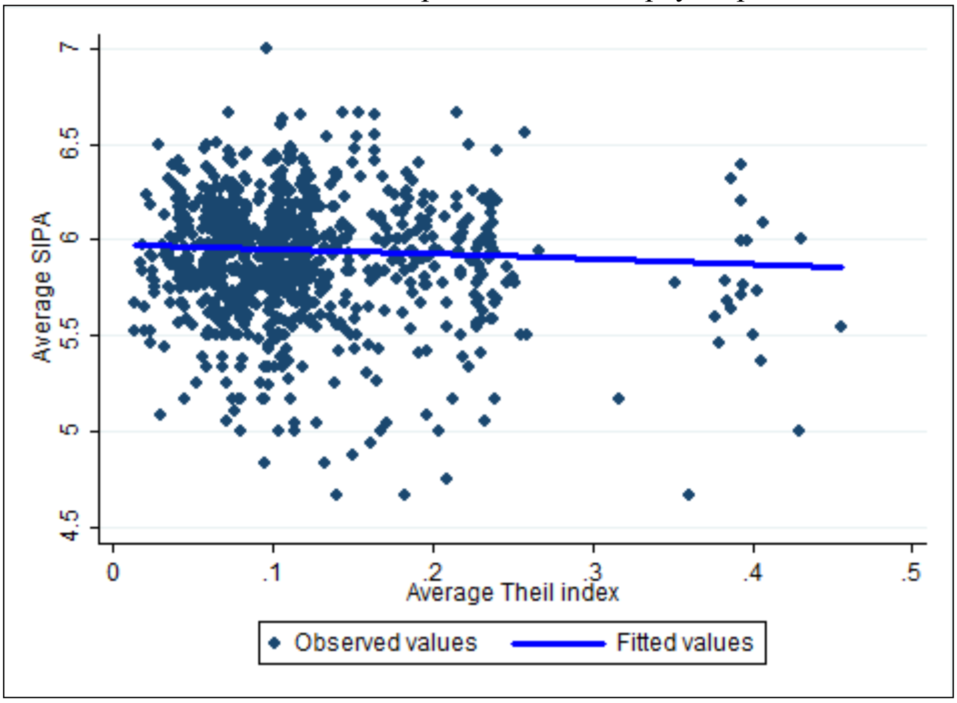
Figure A3 connects individual performance with team performance, by plotting the average SIPA of each player against the wins ratio over all matches he played. The figure suggests that the two measures of performance are positively correlated. However, the correlation is not strong (0.327 in the sample), which indicates that individual performance may still vary enormously conditional on team performance.

FIGURE A3. Individual performance and team performance



In our sample, SIPAs and Theil indexes show a –0.05 correlation. Figure A4 plots this graphically, by comparing the average SIPA of each player with the average Theil index over all matches he played.

FIGURE A4. Individual performance and pay dispersion



Individual performance is also generally higher in those players who play more frequently. To show this, we rank players in terms of the total amount of time they played in the 17 matches of the season. The 11 members who played most of the time in each team received an average SIPA of 6.014, against an average SIPA of 5.842 for the others. This difference is statistically significant to a *t* test (11.546; *p* value: 0). More frequent players also earn higher salaries on average: their average pay is 1,096 thousand euros, significantly higher (*t* test: 4.619; *p* value: 0) than the average pay (750 thousand euros) of all the other team members who played for at least one minute during the 17 matches.

In the analysis of the Appendix, Section B.4, we include a dummy variable that considers whether the player is a "regular" player. The purpose of this is to detect if the player is one of the 11 who are expected to play on the team more than all of the other teammates. We define as regular players the 11 who, in each team, played most of the time during the first month of the season (i.e., in the 5 matches up to the end of September). We rank players according to 5 rather than 17 matches to avoid potential endogeneity issues: after many matches, team members playing more often are likely doing so because their individual performance is higher, while after the first few matches team members playing often are more likely doing so because they are just *supposed* to be better players.

Other "behavioral" reasons may explain the exclusion of some players from the team. Let us give a concrete example from the Italian soccer league. In 2007 a small team, UC Sampdoria, hired Antonio Cassano, at that time considered one of the best Italian soccer players. His salary was 5.64 times higher than the average salary of the other players in the team and, as a result, his impact on pay dispersion was huge. In the 2010–2011 season Cassano regularly played the first matches, until a conflict with the team president excluded him from the team roster. Cassano was eventually sold to another team in January 2011; at the end of the season UC Sampdoria was relegated to the second division. However, these cases are rare: it turns out that 362 of the 440 team members (82.27%) who played more frequently in the first 17 matches are also among the most frequent players after the first 5 matches.

Appendix B: Robustness Checks

B.1. Team Performance: Dependent Variable

Wins and draws

Our analysis concentrates solely on the probability of winning a match. However, in soccer a draw is also a valuable outcome, because it returns one point (compared to three points for a win and no points for a defeat) that is useful for the final ranking for the season. In some circumstances (for instance, when weak teams play against strong teams) teams may play to conclude a match with a draw.

We consider this case using three models. First, we run a probit regression model with the same specification as in the benchmark analysis, but where the dependent variable is now equal to 1 if the team either *wins or draws* the match. Our findings are shown in column (1) of Table B1. The main results are preserved, and doubling pay dispersion now makes the probability of winning or drawing a match decrease by 0.05.

Second, we consider an ordered probit regression, treating separately each outcome (win, draw, and defeat) in the dependent variable. Column (2) of Table B1 reports the average marginal effects for the outcome "win." We still find a significant effect of the variables that are significant in the benchmark analysis. In particular, doubling the average pay would increase by 16% the probability of winning a match, while doubling pay dispersion would decrease it by 5.7%.

Third, we consider an OLS regression of the number of points on the same specification (column 3 of Table B1). Again, the main conclusions are confirmed. In particular, we find that doubling the average pay would generate an average increase of 0.48 points, while doubling pay dispersion would generate an average reduction of 0.17 points earned.

Team cooperation

Pay dispersion may affect team performance in two ways: through individual performance and through team cooperation. In Section 3.3 of the main text, we look at individual performance; here we focus on team cooperation. We measure team cooperation in terms of the number of passes made during the match. The idea is that the higher this number, the higher the level of cooperation within the team.

Column (4) of Table B1 shows the results of a fixed-effect (FE) panel OLS regression where the dependent variable is the logarithm of the number of passes, and the specification is the same as in the benchmark analysis. In this case, a panel model with fixed effects seems preferable to both a panel model with random effects and a pooled OLS model (see the tests listed at the bottom of the table). The reason is probably that different teams have different playing styles that influence the number of passes. Using this model we are then able to measure the effect of pay dispersion net of the playing style (captured in the fixed effect).

We find a strong effect of the average pay for both the team (+0.207) and the opponent (–0.091): doubling the average pay increases the number of passes by 20.7%, while doubling the opponent's average pay reduces the number of passes by 9.1%. In contrast, we find no significant effect of pay dispersion. This suggests that pay dispersion has no implications on team cooperation.

TABLE B1. Team performance: dependent variable (average marginal effects)

		(1)	(2)	(3)	(4)
Dependent variable:		**Pr(win /draw)**	**Pr(win)**	**Points**	**Log(passes)**
Method:		**Probit**	**Ord. probit**	**OLS**	**FE OLS**
Pay:	Log(average pay)	0.181***	0.160***	0.484***	0.207**
		(0.024)	(0.022)	(0.076)	(0.086)
	Log(pay dispersion index)	-0.053**	-0.057**	-0.173**	0.002
		(0.021)	(0.023)	(0.075)	(0.022)
Team:	Fraction of new players on the team	-0.085	-0.018	0.094	0.010
		(0.116)	(0.119)	(0.382)	(0.100)
	Years on the team	-0.030	-0.010	-0.003	-0.002
		(0.022)	(0.023)	(0.071)	(0.022)
	Years in first division	0.002	0.002	0.005	-0.010
		(0.021)	(0.016)	(0.049)	(0.016)
	Age	-0.004	0.001	-0.002	-0.004
		(0.017)	(0.015)	(0.048)	(0.014)
Coach:	New to the team	0.003	-0.034	-0.180	-0.087
		(0.040)	(0.041)	(0.132)	(0.086)
	Replaced during the season	0.040	0.074*	0.254*	-0.050
		(0.048)	(0.040)	(0.126)	(0.053)
	Years on the team	-0.046***	-0.039***	-0.118***	-0.032
		(0.015)	(0.014)	(0.041)	(0.029)
	Years in first division	0.000	0.005	0.021	0.011
		(0.006)	(0.005)	(0.016)	(0.010)
	Age	0.004	0.002	0.005	0.004
		(0.003)	(0.003)	(0.011)	(0.006)
Match:	Injured players	-0.009	-0.007	-0.021	-0.005
		(0.010)	(0.009)	(0.027)	(0.004)
	Disqualified players	0.059**	0.051**	0.145**	0.003
		(0.025)	(0.020)	(0.063)	(0.010)
	Home play	0.244***	0.245***	0.745***	0.009
		(0.034)	(0.030)	(0.094)	(0.012)
Opponent:	Log(average pay)	-0.141***	-0.154***	-0.485***	-0.091***
		(0.029)	(0.024)	(0.078)	(0.012)
	Log(pay dispersion index)	0.049*	0.038	0.108	0.011
		(0.027)	(0.023)	(0.072)	(0.011)
	Fraction of new players on the team	-0.053	0.058	0.254	-0.013
		(0.143)	(0.098)	(0.295)	(0.053)
	Years on the team	0.001	0.024	0.096	-0.009
		(0.029)	(0.021)	(0.063)	(0.009)
	Years in first division	0.000	0.000	0.001	0.002
		(0.014)	(0.012)	(0.039)	(0.006)
	Age	0.000	0.000	0.008	0.013**
		(0.017)	(0.013)	(0.041)	(0.006)
	Constant			0.190	4.878***
				(1.953)	(0.684)
+ time dummy variables on month and year of the match					
	Log-likelihood	-373.435	-641.663		
	McFadden R^2	0.151	0.111		
	Count R^2	0.701			
	R^2			0.215	0.211
	Rho coefficient			0.148	0.433
	Test pooled vs. panel			0.980	4.320
				[0.507]	[0.000]

Note: 666 observations on 40 teams (on average, 16.6 matches per team). Dependent variable: a dummy variable =1 in case of a win or draw (column 1); variable = 0 in case of a defeat, = 1 in case of a draw, and =2 in case of a win (column 2, showing marginal effects in case of a win); the number of points (column 3); the logarithm of the number of assists in the match (column 4). Team-clustered standard errors are given in parentheses; p *values in brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

B.2. Team Performance: Specification

Pay dispersion index

A popular statistic to measure (salary) inequality is the Gini index, defined as half the average absolute difference between any two salaries, divided by the average pay. Using the notation of Section 2.2 in the main text, the formula is:

$$G_{x,t} = \frac{1}{2\bar{p}_{x,t}\left(\sum_{j=1}^{I} m_{i,x,t}\right)^2} \sum_{i=1}^{I} \sum_{j=1}^{I} m_{i,x,t} m_{j,x,t} \left| p_{i,x,t} - p_{j,x,t} \right|.$$

This statistic is bounded between 0 and 1, with a value of 0 showing perfect equality (with every team member having equal pay), and a value of 1 showing maximum inequality (where only one team member is paid).

Despite its popularity, this index has a major shortcoming that makes us prefer a different dispersion index, the Theil index, in our benchmark analysis. The shortcoming is that two different pay distributions can have the same Gini index. For instance, consider a distribution where eight individuals earn 1 and two individuals earn 4 (the average pay is then 1.6), and another pay distribution where five individuals earn 1 and five earn 4 (the average is then 2.5). The Gini index is worth 0.33 in both cases, even though the two distributions are different and pay dispersion looks higher in the latter case.

In column (1) of Table B2, however, we report the results of a regression analysis using this index instead of the Theil index. Our results are largely confirmed, and actually the marginal effect of the pay dispersion index is quantitatively larger than in the benchmark analysis (it is now –0.126 instead of –0.061). This suggests that by doubling pay dispersion, the probability of winning a match would be reduced by 0.13 rather than by 0.06. Hence, our benchmark analysis actually seems conservative in terms of the size of the effect.

Skewness

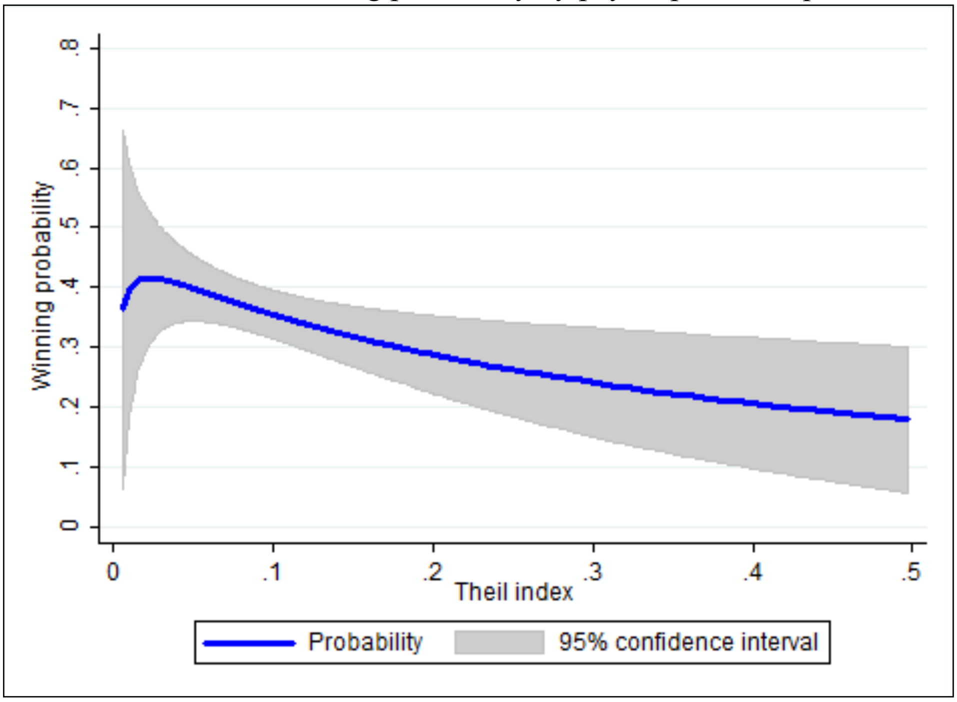
Pay dispersion may arise when most salaries are concentrated in the lowest end of the distribution (negative skewness; left asymmetry) or when most salaries are concentrated in the highest end of the distribution (positive skewness; right asymmetry); in the Appendix, Section A.3, we showed that the latter situation is more frequent in our data. One may thus wonder whether the direction of the asymmetry in the distribution also affects team performance. For this purpose we repeat the benchmark analysis adding into the specification a dummy variable that is equal to 1 if the pay distribution is skewed positively, and 0 otherwise. The former case denotes a situation in which most salaries are relatively high, and few salaries are relatively small.

Findings from this analysis are reported in column (2) of Table B2. The newly added variable is not significant, suggesting that skewness does not affect performance, while all the other variables remain virtually unchanged with respect to the benchmark case.

Nonlinear effect of pay dispersion

So far we have assumed a linear relationship between team performance and pay dispersion. This may be too restrictive. For this reason we now consider a quadratic specification for (log) pay dispersion. Our results are reported in column (3) of Table B2. The findings are in line with our benchmark analysis; regarding the dispersion index, its logarithm is now significantly negative only at the 10% significance level, while its squared value turns out to be insignificantly different from zero. A chi-squared test rejects the null hypothesis of joint significance of the two parameters only at a 10% level (test: 5.35; p value: 0.069). This suggests that a quadratic polynomial does not provide a good fit to the data. In fact, Figure B1 shows the predicted probability of winning a match for an average team, conditional on the level of the pay dispersion index. We see that the prediction is very close to the benchmark one in panel (a) of Figure 2 in the main text. The only difference arises at very small pay dispersion indexes; in fact, using the specification with the quadratic polynomial, the probability of winning a match is maximized when pay dispersion is set to 0.023. However, similar pay dispersion rarely occurred in our dataset: in fact, only 16 observations out of 666 show a lower index. In our dataset a similar pay dispersion index was found for AC Chievo Verona in the first match of the 2010–2011 season, where the ATMs were earning 500 (1 player), 380 (2), 350 (4), 300 (4), 250 (1), and 230 (2) thousand euros, for a weighted average pay of 321.35 thousand euros.

FIGURE B1. Predicted winning probability by pay dispersion: squared effect



Note: Predictions are based on the average explanatory variables and the parameter estimates from Table B2, column (3).

Effect of pay dispersion over time

Everything else being equal, the effect of pay dispersion may depend on how much team members know each other. In each season, several new players usually enter the team, often just a few days before the season starts. For a player, knowledge of other team members and their salaries may take time. It may then be that pay dispersion has a stronger effect in the latest matches we consider. For this reason we consider a specification where we add the interaction between the pay dispersion index and a dummy variable equal to 1 in the latest month of matches (those played in December, as opposed to the August–November period).

Our findings are reported in column (4) of Table B2. The interaction is not significant, suggesting that pay dispersion has an instantaneous effect on team members. Again, the other variables show an effect similar to that of the benchmark case.

TABLE B2. Team performance: specification (average marginal effects)

Model:		(1) Gini index	(2) Skewness	(3) Square	(4) Late
Pay:	Log(average pay)	0.145***	0.144***	0.140***	0.146***
		(0.026)	(0.027)	(0.027)	(0.027)
	Log(pay dispersion index)	-0.126**	-0.065**	-0.177*	-0.056*
		(0.064)	(0.029)	(0.091)	(0.031)
	Log(pay dispersion index)^2			-0.023	
				(0.017)	
	Log(pay dispersion index) × (matches held in Dec.)				-0.039
					(0.068)
	Right skewness		-0.023		
			(0.045)		
Team:	Fraction of new players on the team	0.090	0.107	0.121	0.098
		(0.144)	(0.154)	(0.142)	(0.143)
	Years on the team	0.013	0.016	0.022	0.015
		(0.026)	(0.026)	(0.027)	(0.026)
	Years in first division	0.003	0.002	-0.001	0.002
		(0.016)	(0.016)	(0.016)	(0.016)
	Age	0.000	0.001	0.003	0.001
		(0.017)	(0.017)	(0.016)	(0.017)
Coach:	New to the team	-0.093*	-0.090*	-0.080	-0.090*
		(0.049)	(0.050)	(0.049)	(0.050)
	Replaced during the season	0.120**	0.120**	0.112**	0.118**
		(0.051)	(0.051)	(0.051)	(0.051)
	Years on the team	-0.035**	-0.034**	-0.030**	-0.034**
		(0.015)	(0.015)	(0.015)	(0.015)
	Years in first division	0.010*	0.009	0.010*	0.009*
		(0.006)	(0.006)	(0.006)	(0.006)
	Age	0.000	0.000	0.001	0.001
		(0.004)	(0.004)	(0.004)	(0.004)
Match:	Injured players	-0.006	-0.006	-0.007	-0.007
		(0.010)	(0.010)	(0.010)	(0.010)
	Disqualified players	0.040*	0.041*	0.041*	0.041*
		(0.023)	(0.023)	(0.023)	(0.024)
	Home play	0.255***	0.253***	0.253***	0.254***
		(0.034)	(0.034)	(0.034)	(0.034)
Opponent:	Log(average pay)	-0.171***	-0.168***	-0.168***	-0.169***
		(0.029)	(0.029)	(0.029)	(0.029)
	Log(pay dispersion index)	0.071	0.029	0.030	0.030
		(0.048)	(0.025)	(0.025)	(0.025)
	Fraction of new players on the team	0.144	0.136	0.137	0.136
		(0.105)	(0.106)	(0.105)	(0.106)
	Years in the team	0.045**	0.044*	0.043*	0.044*
		(0.022)	(0.022)	(0.023)	(0.022)
	Years in first division	0.000	0.002	0.001	0.001
		(0.015)	(0.015)	(0.015)	(0.015)
	Age	0.005	0.004	0.005	0.004
		(0.015)	(0.016)	(0.016)	(0.015)
+ time dummy variables on month and year of the match					
	Log-likelihood	-371.072	-371.378	-370.997	-371.461
	McFadden R^2	0.156	0.155	0.156	0.155
	Count R^2	0.689	0.691	0.692	0.689

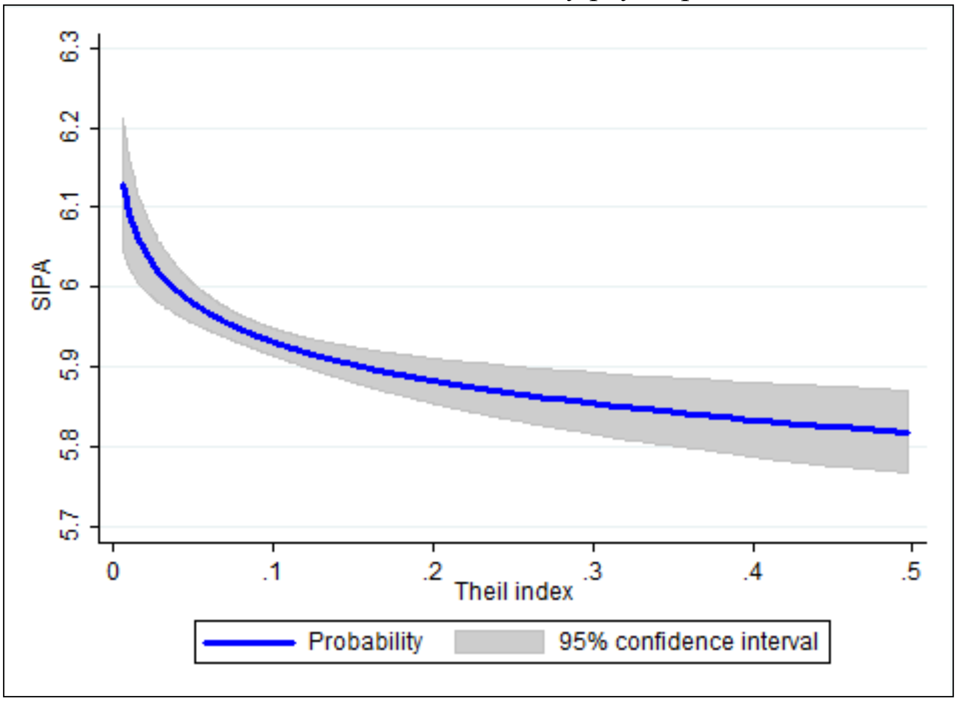
Note: 666 observations on 40 teams (on average, 16.6 matches per team). The dependent variable is a dummy =1 in case of a win. The pay dispersion index is the Gini index in column (1), and the Theil index in columns (2), (3), and (4). Team-clustered standard errors are given in parentheses; p *values in brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

B.3. Individual Performance: Accounting for SIPA's Authors

Table B3 replicates the analysis in Table 6 of the main text, using as SIPAs those reported from the main sport newspaper, *La Gazzetta dello Sport*, rather than the average from three newspapers (*La Gazzetta dello Sport*, *Corriere dello Sport*, and *Tutto Sport*). In this case we have 381 more observations, because journalists for *La Gazzetta dello Sport* also assigned SIPAs to athletes who played for just few minutes; they did so more frequently than did journalists in the other two newspapers.

To control for the subjectivity in this measure, the regression includes 34 dummy variables, each one indicating the journalist who made the SIPA. In most—but not all—cases we find no journalist effect. Figure B2 plots the SIPA predicted from column (2) of Table B3. This is the counterpart to Figure 4 in the main text.

FIGURE B2. Predicted SIPA, by pay dispersion



Note: Predictions are based on the average explanatory variables and the parameter estimates from Table B3, column (2).

TABLE B3. Individual performance: journalist effect (average marginal effects)

Method:		**(1) Pooled OLS**	**(2) RE GLS**	**(3) FE OLS**
Player:	Pay/average pay	0.105***	0.108***	-0.146
		(0.023)	(0.020)	(0.183)
	New to the team	0.009	0.008	
		(0.027)	(0.023)	
	Years on the team	0.012**	0.013***	
		(0.005)	(0.004)	
	Years in first division	-0.003	-0.003	
		(0.004)	(0.004)	
	Age	0.000	0.000	
		(0.003)	(0.003)	
	Midfield role	0.045**	0.048**	
		(0.020)	(0.019)	
	Forward role	-0.028	-0.027	
		(0.028)	(0.025)	
Pay:	Log(average pay)	0.076***	0.079***	-0.146
		(0.022)	(0.019)	(0.208)
	Log(pay dispersion index)	-0.050***	-0.062***	-0.140***
		(0.017)	(0.015)	(0.027)
Team:	Fraction of new players on the team	0.107	0.075	-0.089
		(0.083)	(0.078)	(0.127)
	Years on the team	0.003	-0.005	-0.040
		(0.016)	(0.015)	(0.027)
	Years in first division	0.006	0.008	0.007
		(0.011)	(0.010)	(0.020)
	Age	-0.003	-0.000	0.007
		(0.011)	(0.010)	(0.017)
Coach:	New to the team	-0.024	-0.018	0.022
		(0.031)	(0.028)	(0.108)
	Replaced during the season	-0.026	-0.009	0.153**
		(0.028)	(0.028)	(0.065)
	Years on the team	-0.011	-0.011	0.047
		(0.016)	(0.013)	(0.036)
	Years in first division	0.007**	0.007**	-0.007
		(0.004)	(0.004)	(0.012)
	Age	0.001	0.001	0.005
		(0.002)	(0.002)	(0.008)
Match:	Injured players	-0.011**	-0.010**	-0.004
		(0.005)	(0.005)	(0.005)
	Disqualified players	0.034***	0.039***	0.057***
		(0.012)	(0.012)	(0.013)
	Home play	0.152***	0.152***	0.149***
		(0.014)	(0.014)	(0.014)
Opponent:	Log(average pay)	-0.033*	-0.034**	-0.041**
		(0.017)	(0.016)	(0.017)
	Log(pay dispersion index)	0.061***	0.060***	0.062***
		(0.013)	(0.013)	(0.013)
	Fraction of new players on the team	-0.038	-0.023	0.075
		(0.071)	(0.067)	(0.069)
	Years on the team	0.007	0.008	0.018
		(0.012)	(0.012)	(0.012)
	Years in first division	-0.001	0.001	0.007
		(0.008)	(0.008)	(0.008)
	Age	0.009	0.008	0.002
		(0.007)	(0.007)	(0.008)
	Constant	5.243***	5.130***	6.649***
		(0.361)	(0.323)	(1.609)
+ time dummy variables on month and year of the match and dummy variables on the journalist giving the SIPAs				
	R^2	0.047	0.046	0.000
	Rho coefficient		0.039	0.307
	Test pooled vs. panel		223.700	1.840
			[0.000]	[0.000]

Note: 8,609 observations on 891 players (on average, 9.66 matches per player). The dependent variable is the SIPA from La Gazzetta dello Sport*. Standard errors are given in parentheses;* p *values in brackets. In column 1 (pooled OLS) we report player-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

B.4. Individual Performance: Regular and Superstar Players

We replicate the analysis shown in Table 6, including in the specification further variables on the player. Specifically, we include a dummy variable equal to 1 if the player earns at least twice the average pay in the team roster ("superstar") and another dummy variable equal to 1 if the player is one of the 11 team members who played most of the first five matches ("regular"). The output of this analysis, based on pooled OLS and random-effect (RE) panel GLS regressions, is shown respectively in columns (1) and (2) of Table B4. We then also add the interactions between the two dummy variables and the pay dispersion index. The purpose is to understand whether the effect of pay dispersion on individual performance persists after accounting for individual skills, and whether its effect is different among top players. In this case the output is shown in columns (3) and (4) of Table B4, respectively using pooled OLS and random-effect panel GLS regressions.

TABLE B4. Individual performance: specification (average marginal effects)

		(1)	(2)	(1)	(2)
Method:		**Pooled OLS**	**RE GLS**	**Pooled OLS**	**RE GLS**
Player:	Pay/average pay	0.065**	0.064**	0.075***	0.075***
		(0.025)	(0.025)	(0.027)	(0.026)
	New to the team	0.009	0.009	0.007	0.007
		(0.026)	(0.023)	(0.026)	(0.023)
	Years on the team	0.013***	0.014***	0.013***	0.014***
		(0.005)	(0.004)	(0.005)	(0.004)
	Years in first division	-0.005	-0.005	-0.005	-0.005
		(0.004)	(0.003)	(0.004)	(0.003)
	Age	0.001	0.001	0.000	0.000
		(0.003)	(0.003)	(0.003)	(0.003)
	Midfield role	0.058***	0.060***	0.058***	0.060***
		(0.019)	(0.019)	(0.019)	(0.019)
	Forward role	0.010	0.011	0.008	0.009
		(0.029)	(0.026)	(0.029)	(0.026)
	Regular	0.088***	0.090***	0.165**	0.143**
		(0.019)	(0.018)	(0.067)	(0.062)
	Superstar	0.040	0.051	-0.176	-0.216*
		(0.043)	(0.040)	(0.132)	(0.125)
Pay:	Log(average pay)	0.080***	0.078***	0.078***	0.076***
		(0.019)	(0.016)	(0.019)	(0.016)
	Log(pay dispersion index)	-0.065***	-0.078***	-0.080***	-0.085***
		(0.015)	(0.014)	(0.022)	(0.022)
	Log(pay dispersion index)			0.033	0.023
	× regular			(0.027)	(0.025)
	Log(pay dispersion index)			-0.096*	-0.120**
	× superstar			(0.055)	(0.053)
Team:	Fraction of new players on the team	0.054	0.029	0.063	0.037
		(0.073)	(0.070)	(0.072)	(0.070)
	Years on the team	-0.004	-0.009	-0.003	-0.008
		(0.014)	(0.013)	(0.014)	(0.013)
	Years in first division	0.001	0.001	0.000	0.001
		(0.010)	(0.010)	(0.010)	(0.010)
	Age	-0.008	-0.003	-0.007	-0.002
		(0.010)	(0.009)	(0.010)	(0.009)

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Coach:	New to the team	-0.006	0.003	-0.003	0.006
		(0.028)	(0.026)	(0.028)	(0.026)
	Replaced during the season	-0.016	0.009	-0.020	0.004
		(0.027)	(0.026)	(0.027)	(0.026)
	Years on the team	-0.009	-0.008	-0.010	-0.009
		(0.013)	(0.012)	(0.013)	(0.012)
	Years in first division	0.007**	0.007**	0.007**	0.007**
		(0.003)	(0.003)	(0.003)	(0.003)
	Age	0.001	0.001	0.001	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Match:	Injured players	-0.008*	-0.005	-0.009*	-0.006
		(0.005)	(0.004)	(0.005)	(0.004)
	Disqualified players	0.051***	0.058***	0.051***	0.057***
		(0.011)	(0.011)	(0.011)	(0.011)
	Home play	0.143***	0.143***	0.143***	0.143***
		(0.013)	(0.013)	(0.013)	(0.013)
Opponent:	Log(average pay)	-0.043***	-0.044***	-0.043***	-0.044***
		(0.014)	(0.013)	(0.014)	(0.013)
	Log(pay dispersion index)	0.054***	0.053***	0.054***	0.053***
		(0.012)	(0.012)	(0.012)	(0.012)
	Fraction of new players on the team	0.040	0.060	0.038	0.057
		(0.056)	(0.057)	(0.056)	(0.057)
	Years on the team	-0.001	0.003	-0.001	0.002
		(0.010)	(0.010)	(0.010)	(0.010)
	Years in first division	0.004	0.005	0.004	0.005
		(0.006)	(0.007)	(0.006)	(0.007)
	Age	0.007	0.007	0.008	0.007
		(0.006)	(0.007)	(0.006)	(0.007)
	Constant	5.365***	5.189***	5.304***	5.149***
		(0.305)	(0.272)	(0.310)	(0.276)
+ time dummy variables on month and year of the match					
	R^2	0.045	0.044	0.045	0.045
	Rho coefficient		0.051		0.051
	Test pooled vs. panel		256.120		253.810
			[0.000]		[0.000]

Note: 8,226 observations on 876 players (on average, 9.39 matches per player). The dependent variable is the SIPA from the three newspapers. Standard errors are given in parentheses; p *values in brackets. In columns 1 and 3 we report player-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

Our benchmark results of Section 3.3 are confirmed; in addition, we find a positive effect on individual performance of being a regular player (who receives on average a SIPA that is 0.09 points higher than a non-regular player) and a larger negative effect of pay dispersion among superstars: doubling pay dispersion gives rise to a SIPA reduction of 0.09 points for a generic player, and 0.20 points for a superstar.

We repeated this analysis using alternative definitions of regular players, based on those who played most of the first 9 or 17 matches. The results are qualitatively confirmed, essentially because in most cases we identify the same players as regular (of those who played most of the first 5 matches, 89.09% also played most of the first 9 matches and 82.27% also played most of the first 17 matches). Marginal effects are, however, quantitatively larger than what we find with the definition discussed here.