Journal of Economic Psychology 31 (2010) 218–229

Contents lists available at ScienceDirect

Journal of Economic Psychology

journal homepage: www.elsevier.com/locate/joep

The effect of talent disparity on team productivity in soccer ☆

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ARTICLE INFO

Article history:
Received 31 July 2008
Received in revised form 3 December 2009
Accepted 23 December 2009
Available online 4 January 2010

JEL classification:
D23
D24
J44
L83

PsycINFO classification:
3620
3630
3720

Keywords:
Ability grouping
Ability level
Productivity

ABSTRACT

Theory predicts that the interaction type within a team moderates the impact of talent disparity on team productivity. Using panel data from professional German soccer teams, we test talent composition effects at different team levels characterized by different interaction types. At the match level, complementarities are expected due to the continuous interaction of the fielded players. If the entire squad is analyzed at the seasonal level, substitutability emerges from the fact that only a (varying) selection of players can prove their talent in the competition games. Holding average ability and unobserved team heterogeneity constant, we find that the players selected to play on the competition team should be rather homogeneous regarding their talent. However, if we relate talent differences within the entire squad to the team's league standing at the end of the season, talent disparity turns out to be beneficial.

1. Introduction

Team production is typically characterized by the fact that the total is more than the sum of its parts (Alchian & Demsetz, 1972). Thus, not only does the simple aggregation of members' task-relevant abilities matter, but the intra-team talent composition is likely to influence team productivity as well. Scholars both in social psychology (Steiner, 1972) and economics (Kremer, 1993; Prat, 2002) argue that the interaction type moderates the optimality of talent disparity. In the extreme case that production technology is strictly multiplicative, all conjunctive tasks must be completed successfully for the product to have full value. Hence, the optimal strategy is to combine workers of similar skill levels into a team. In the other extreme case of entirely disjunctive tasks, where individual inputs serve as substitutes for team production, team output depends on the most productive team member. Here, heterogeneous teams should have a clear advantage. In addition, talent disparity is beneficial whenever mutual learning is an important part of team collaboration, as it enables the less skillful team members to learn how to execute tasks more efficiently from their more talented teammates (Hamilton, Nicherson, & Owan, 2003).

☆ We are very grateful for the helpful comments of David Forrest, Ulrich Kaiser, Rob Simmons, Stefan Szymanski, Rainer Winkelmann, the guest editors Martin Kocher and Matthias Sutter, two anonymous referees, and the seminar participants at the conference "The Economics and Psychology in Football" 2008 in Innsbruck. Nicolai Grüter and Isabelle Linder provided excellent research assistance. The usual disclaimer applies.

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0167-4870/$ - see front matter
doi:10.1016/j.joep.2009.12.003

This paper empirically tests the effect of talent disparity on team productivity in a setting in which different interaction types are expected on different team levels within the same overall context, namely professional soccer. At the match level, only a (varying) selection of players competes in the single games that make up the championship race. The interaction type within the competition team is likely to be conjunctive: the team's outcome depends on the complementary skills and on the continuous interaction of all fielded players performing up to some standard. If the entire team is analyzed at a seasonal level, a clearly substitutive relationship between the reserve and the fielded players is introduced. The different team levels in soccer also represent different stages of team production with unequal importance of mutual learning: the preparatory stage and the competition stage. Whereas at the preparatory stage all players of the squad are involved in an ongoing process of exercising and training, only winning matters at the competition stage.

Using extensive panel data from German soccer teams, we proceed in two steps. On the one hand, we only analyze the fielded players and relate the talent composition of the competition team to the likelihood of winning the game. On the other hand, we examine the influence of talent disparity of the entire squad in a given season on the team's (inverted) league standing at the end of the season as the ultimate measure of long-term team effectiveness.

In this paper, we use productivity data to proxy a player's ability. Individual productivity, however, is affected by inborn talent as well as time-varying aspects, like physical fitness or injuries. Since we assume that player inputs combine in a non-additive manner to produce the team's output, productivity is also influenced by the playing ability of the other teammates. We therefore define a player's talent by his *permanent* productivity, purged of possible intra-team spillover effects. First, we compute individual productivity as a weighted sum of various detailed performance statistics that affect winning. Then we model individual productivity as a function of player fixed effects, reflecting the unobserved talent of a player, of the average productivity of the rest of the team to incorporate intra-team spillovers, and of an idiosyncratic error term that captures unexplained productivity variation beyond playing ability and spillovers. The fixed effects obtained by fitting this model serve as talent proxies. As a second approach to proxy individual talent, we rely on expert evaluations.

Using match-level data from all games in the German soccer league *Bundesliga* over a period of six seasons (i.e. 1836 games), we find evidence that homogeneous competition teams are more likely to win a game than heterogeneous teams, all else being equal. Talent disparity within the competition team decreases sportive performance. The empirical results of the second model including all team members at the seasonal level confirm that talent disparity improves a team's standing in the championship race, holding average playing ability and other confounding factors constant. Hence, although teamwork is usually characterized by complementarities – otherwise, team output would be less, not more, than the sum of the individual contributions – talent disparity may still be beneficial when necessary substitutes and the training activities are taken into account.

The remainder of this paper is structured as follows: Section 2 lays the theoretical foundations and presents related empirical papers. Subsequently, we explain team production in professional soccer and frame our hypotheses. In Section 4, we test our hypotheses. First, we explain how individual talent is measured. Then, the main features of our data, the estimation approaches and the results are illustrated. The last section presents the conclusions and general implications.

2. Theoretical foundations

It is beyond controversy that teams with more talented individual members outperform, ceteris paribus, teams with less talented members. However, due to the manifold interdependencies in team production settings, individual skill levels are likely to combine in a non-additive manner, implying that the team's output is also affected by the talent composition within the team (Tziner, 1985; Tziner & Eden, 1985).[1] Thus, we model team productivity (Y_{it}) as a function of the sum *and* the product of strictly positive individual playing abilities (x_{itp}), a vector of control variables (C'_{it}), unobserved team heterogeneity (δ_i) and an idiosyncratic error term (ε_{it}):

$$Y_{it} = \alpha + \beta_1 \sum_{p=1}^{p=n} x_{itp} + \beta_2 \prod_{p=1}^{p=n} x_{itp} + \beta C'_{it} + \delta_i + \varepsilon_{it}. \tag{1}$$

If individual talent combines in a strictly additive way to lead to team success, β_2 is 0, and team composition makes no difference. If player inputs are complements in team production, individual cross derivatives of productivity are positive, i.e., $\frac{\partial^2 Y_{it}}{\partial x_{itp1} \partial x_{itp2}} > 0, \quad p_1 \neq p_2$. In this case, the coefficient of the hyperbolic term is positive, and team performance is maximized when individual talent disparity is minimized. If player inputs are substitutes in team production, individual cross derivatives of productivity are negative. Here, β_2 is negative, which implies that team productivity is highest when talent differences are maximized.

Hamilton et al. (2003) argue that talent heterogeneity increases team performance by facilitating mutual learning and by forming a social norm of higher productivity. Mutual learning may increase team performance, as the less skillful team members learn from their more talented teammates how to execute tasks more efficiently. Hence, the wider the ability gaps within a team, the higher the learning potential. In addition, a positive link between talent heterogeneity and team performance could also result from peer pressure and social norms of teams. Hamilton et al. (2003) assume that group norms and resulting peer pressure emerge from a bargaining process in which workers negotiate over the common effort level. As a result of

[1] For a different perspective, see Jones (1974), who finds that individual performances combine in a strictly additive way to affect team performance.

having the best outside options, the most able team member has the strongest bargaining power and is, therefore, able to increase the team norm.[2] Indeed, in two studies of teams in a garment manufacturing facility, Hamilton et al. (2003) and Hamilton, Nicherson, and Owan (2004) find that teams that have a higher ratio of maximum to minimum average individual productivity level are more productive than teams with more homogeneous ability structures, controlling for the average ability within a team.

On the other hand, scholars both in social psychology (Steiner, 1972) and in economics (Kremer, 1993; Prat, 2002) argue that the optimal talent heterogeneity is strongly moderated by the task type. The two fields use different wordings to express the same idea: if complementary tasks must be successfully completed for the product to have full value, every input needs to perform at or above some threshold level of proficiency to attain high team productivity. Below threshold performance by a single team member ("weakest link") can dramatically endanger the whole team's output. On such conjunctive tasks, talent disparity decreases team performance, as individual cross derivatives of productivity are positive. In settings, however, where one member or a subgroup can "solve the problem", it is optimal to match the highest- and the lowest-skilled workers together. Kremer (1993) refers to the example of flying an airplane, with the co-pilot just serving as backup in case the captain fails to perform the task. Steiner (1972) speaks of disjunctive tasks in which team productivity depends – in the extreme case – only on the most talented team member. Such disjunctive tasks often require an "either-or" decision, which means that more talented team members receive more "weight" in determining the team's output. Here, talent heterogeneity increases team performance, as the cross derivatives of productivity within the team are negative.

Empirical papers referring to the theoretical arguments of Steiner (1972), Kremer (1993), and Prat (2002) test talent composition effects mostly in settings characterized by complementary tasks. It is, therefore, not surprising that they all find a negative impact of talent disparity on team outcome: Tziner and Eden (1985) analyze three-man military crews engaged in performing real tasks that demand a high level of interdependence. They manipulate crew composition based on ability and motivation and find that uniformly high-ability military tank crews impressively exceed the effectiveness anticipated on the basis of their individual abilities. Elberse (2007) shows that the marginal impact of a star actor on movies' expected revenues is higher the stronger the cast already is. These positive cross derivatives of productivity imply that all actors need to perform up to some level of proficiency for the film to have the highest quality. LePine, Hollenbeck, Ilgen, and Hedlund (1997) test the decision accuracy of teams whose members have unique expertise and information resources. Their results show that the best decisions are made when both the leader and staff are high on general cognitive ability and conscientiousness, supporting the "weakest link" hypothesis. What is missing, however, is a study that tests talent disparity effects in different settings characterized by different interaction types within the same overall context. We try to fill this gap using data from professional soccer teams.

3. Team production in soccer and testable hypotheses

Team production in soccer basically includes two stages: the preparatory stage and the competition stage. At the preparatory stage, the entire squad of players and trainers employed by a club is almost constantly involved in a process of practicing. The goal of this preparatory process is to improve the team's playing strength, which includes the improvement of the technical and tactical capabilities of the players as well as the cooperation between them. A professional soccer player invests up to 8 h a day in soccer-related preparatory activities, including physiotherapy, massage, and mental and physical strength training. Provided that he manages to fulfill certain eligibility criteria, he will be promoted to play on the competition team.

The competition team consists of a (varying) selection of players from the entire squad. It competes in the championship race against the teams of other clubs from the same league. Team production at the competition stage usually involves one 90 min match per week. The number of players eligible to play is defined by the rules of soccer. The competition team comprises eleven players on the field (one goalkeeper and ten field players) and three potential substitutes. Production at the contest stage has only one aim: to win the game and accumulate points to succeed in the championship race. Improving the technical and tactical abilities of players, which are important goals of preparatory team production, are at most by-products at the contest stage, where only winning matters. Regarding the question of how players' talent levels combine to affect team success, it seems plausible that the two stages of team production in soccer should exhibit different patterns.

Studying the contest stage of team production is tantamount to studying the relationship between the players on the field trying to win a championship game. It seems likely that the team's outcome depends on the complementary skills of all fielded players performing up to some standard, which implies positive cross derivatives of productivity. Even the best goalkeeper can hardly manage to impede the opposition's goal scoring if his team's defense is virtually nonexistent. Similarly, even outstanding attackers become "lame ducks" if they are not supported by offensive passes from midfielders or defenders. Soccer players continually interact, and coordination is achieved through constant mutual adjustment. Interaction among soccer players is even higher than in American Football, where each player's role is narrowly circumscribed (Katz, 2001). The degree of cooperation is similar to that of basketball teams and much higher than for baseball teams. It seems somewhat of an exaggeration to compare a soccer team to a rope team of mountain climbers who cannot move faster than

[2] Empirical studies examining *individual* effects of peer pressure show that low productivity workers react more sensitively to peer pressure than high-productivity workers (e.g. Bandiera, Barankay, & Rasul, 2009; Falk & Ichino, 2006; Mas & Moretti, 2009). Hence, they confirm that the mix of workers that maximizes productivity is the one that maximizes talent disparity.

the weakest team member. In soccer, a weak individual performance can at least partly be absorbed by the performance of others. However, these substitutive elements on the pitch are very limited. Since individual playing abilities are rather complementary at the contest stage of team production, weak individual performances can endanger the output of the entire team. A prime illustration is the "offside trap" tactic, which requires that all defenders display high levels of cohesion and discipline in moving up together in a relatively straight line to interrupt the opposition's offense. No defender can guarantee the successful functioning of the "offside trap" alone. However, each can trigger its failure all by himself. Thus, we conjecture that:

H1: Talent disparity of the competition team decreases the likelihood of winning, holding the average ability level constant.

At the preparatory stage of team production, where continuous improvements of technical and tactical abilities play an important role, the situation seems different. Here, talent heterogeneity should increase team performance, as it enables the less able players to learn from their more talented teammates.[3] Furthermore, talent disparity also affects the social norm of productivity and the resulting peer pressure during training activities. The question of whether potential shirking is plausible in professional soccer is controversial. However, it would certainly be of higher relevance at the preparatory stage than in competition games, where thousands of spectators are watching. In the process of forming a team norm, the more capable players have stronger bargaining power than the less talented team members (Hamilton et al., 2003). Therefore, talent heterogeneity is associated with a higher team norm of productivity during training activities, which promotes learning as well.

Unfortunately, we cannot assess the talent composition effects at the preparatory stage of team production directly, as our data are restricted to games played. Although there are two stages of team production in soccer, the only relevant measure of team success is defined at the competition stage: the performance of the club in the championship race. By analyzing the relationship between talent heterogeneity and team performance at a seasonal level, we are, however, able to define all the players of the club who played on the competition team at least once in the considered time frame as the entire team. In doing so, we also capture talent composition effects in the training activities since the so-called "benchwarmers" are included in the sample too. Of course, the complementarities among the players on the pitch still play a role, but they are supplemented by the clearly substitutive relationship between reserve players and fielded players as well as by the advantages of talent disparity at the preparatory stage of team production. We conjecture that the latter two effects dominate. The relationship between reserve and fielded players is highly disjunctive. Because teams in our sample have an average roster size of 26 players, only about half of the team members are allowed to play in a game. For obvious reasons, highly talented players tend to be more frequently nominated for the competition team and, therefore, exert a stronger influence on the team's league standing than their comparably less skilled teammates. This explains some of the benefits of talent disparity within the entire team. In addition, talent heterogeneity facilitates mutual learning and imposes social pressure on low performers to catch up in training (Hamilton et al., 2003). Even though both explanations postulate a positive impact of talent disparity on team performance, their effects are competing. If a coach draws a clear distinction between the competition team and the reserve players, the disjunctive element within the squad is very high, but the learning benefits of the reserve players cannot affect team performance because they are not nominated for the competition team. Conversely, if the number of appearances on the competition team is equally distributed among the squad members, all players receive the same "weight" in determining the team's output, but the improvement of the technical and tactical capabilities of newcomers becomes very important. A histogram of the number of seasonal appearances of the soccer players analyzed in the next section (see Fig. 2 in the Appendix) reveals that there is neither a clear distinction between the competition team and the reserve players nor do all squad members receive the same amount of playing time. Instead, the players cover the whole range of possible seasonal appearances, from 0 to 34. Hence, we expect that both explanations of a positive link between talent disparity of the entire team and seasonal team performance are relevant in our context.

H2: Talent disparity of the entire squad increases seasonal team performance, holding the average ability level constant.

4. Empirical framework

We test our hypotheses using professional German soccer as a labor market laboratory. We agree with Kahn (2000) that there is hardly any other research setting besides professional sports where we know the name, age and employment history of every production worker and supervisor in the industry. In addition, accurate performance statistics of individuals and teams are widely available. Unlike in many other industries, team performance is clearly defined by the rules of the game and identified by independent referees. The team that scores more goals than its opponent wins. If both sides score an equal

[3] Strictly speaking, talent disparity does not increase team performance through learning unless knowledge spillovers within the team are asymmetric in favor of less talented players, which means that the benefit from having highly talented peers is higher for less talented newcomers than for top performers. As individual training data are not available, we cannot explicitly test this conjecture. The assumption of asymmetric learning effects in favor of less skilled team members was confirmed, however, by the results of several empirical studies on heterogeneous peer effects in primary and secondary education (e.g. Levin, 2001; Sacerdote, 2001; Schneeweis & Winter-Ebmer, 2007).

number of goals, the game is counted as a draw. Whereas team performance is easily measurable, the determination of a team's talent composition is more complex. First, talent proxies of all players on a team are necessary. Then, we have to calculate team-level talent disparity measures for the competition team and for the entire squad.

4.1. Estimation of a player's talent

As talent is unobservable, we have to rely on productivity data to proxy playing ability.[4] Individual productivity, however, is not only affected by inborn and therefore time-constant talent, but also by time-varying aspects, like physical fitness or injuries. Since we assume significant cross derivatives of productivity, individual performance is also influenced by the productivity of the other teammates.[5] First, we explain how we measure individual productivity, and subsequently, how talent proxies are derived based on productivity.

Playing soccer involves various capabilities, such as passing the ball to free-standing teammates, retaining possession of the ball, running or dribbling with the ball, creating goal scoring chances, tackling opponents, blocking or intercepting the opposition's passes and shots, clearing the ball from pressure situations, and last but not least, goal scoring. A competition team consists of one goalkeeper plus ten outfield players, who can generally be categorized as defenders, midfielders and attackers. In order to test the team-level effects of talent disparity, we first need a productivity measure that is equally adaptable to defensive and offensive players. The number of goals or assists, for example, could suitably capture offensive quality but not defensive performance. We therefore measure individual productivity by making use of a large series of individual performance statistics provided by the *Opta Sports Data Company* that quantify and qualify every touch of the ball during the game by each player. The *Opta* performance statistics are available for all players appearing in the *Bundesliga* between 2001/02 and 2006/07 (1153 players and 2764 player-season observations). Before a player's performance index can be ascertained, the marginal contribution of each statistic to the team's winning percentage must be determined.[6] Analyzing the results of 1530 games of the *Bundesliga* using the same data, Franck and Nüesch (2007) showed that the following statistics significantly influence the final score of a match (coefficients as weights in parentheses): number of goals (1) and assists (1) scored[7]; pass success rate (1.082); cross success rate (0.676); dribbling success rate (0.419); shots on target (0.217); red cards (−0.287); yellow cards (−0.072); clearances, blocks, and interceptions (0.010); and the saves-to-shots ratio by the goalkeeper (3.791).[8] The productivity index of a player is measured by the sum of each player's seasonal statistics multiplied by the marginal value of the corresponding variable. All performance statistics not expressed as ratios are divided by the number of appearances in a season in order to obtain average values. As we assume that player excellence is equally distributed over the different tactical positions, we subsequently divide a player's performance index by the mean for the player's respective tactical position in a given season in order to eliminate potential bias stemming from the tactical position of a player.[9]

How can we derive talent from productivity data? Whereas productivity may change, for example, as a result of varying effort and discipline in the training activities, talent is typically considered time-constant. Thus, we define a player's talent by his *permanent* productivity, purged of possible spillovers within the team. Formally, the talent measures are derived by fitting a model that explains the individual performance index of player *i* in season *t* as a function of his time-constant talent π_i, of the average productivity of the rest of the team $P_{kt,-i}$ and of an idiosyncratic error term ε_{it} that incorporates unexplained shocks to individual productivity beyond talent and intra-team spillovers[10]:

$$P_{it} = \pi_i + \beta_1 P_{kt,-i} + \varepsilon_{it}. \tag{2}$$

Eq. (2) is estimated with least squares using panel data of all players appearing in the *Bundesliga* between 2001/02 and 2006/07 and receiving more than half an hour accumulated playing time at least in one season. We did not consider observations of players with a seasonal playing time of less than half an hour as the productivity level might not be representative given the short period under consideration.[11] Thus, our sample contains 1098 players and 2638 player-season observations.

[4] Alternatively, we could use salary data to proxy talent. However, we refused this approach as both a player's talent and his popularity influence salaries in German soccer (Franck & Nüesch, 2007).

[5] We are grateful to an anonymous referee for raising this issue.

[6] See also Berri (1999), who employs the same procedure to estimate the value of a basketball player.

[7] The numbers of goals scored and assists are by definition strongly related to the team's winning chances.

[8] Other performance statistics – like flick success rate, tackling success rate, shots off target, shots hitting the woodwork, blocked shots, fouls, hands, balls caught by the goalkeeper, or balls dropped by the goalkeeper – do not significantly affect the team's winning probability. For further information about the team production estimates, see Franck and Nüesch (2007).

[9] Summary statistics revealed that goalkeepers received higher average performance statistics than defenders, midfielders, or attackers, even though various studies show that they receive the lowest salaries on average (e.g. Frick, 2007).

[10] Eq. (2) is very similar to the equations in the papers of Kendall (2003) and Foster (2006), which estimate peer effects and spillovers in academia and professional baseball teams using individual panel data. However, whereas the focus of Kendall (2003) and Foster (2006) lies on β_1, we are primarily interested in π_i. We also experimented with further approaches to separate spillover effects from individual productivity proposed by Mas and Moretti (2009) and Arcidiacono, Foster, Goodpaster, and Kinsler (2007). Mas and Moretti (2009) regress individual productivity on worker fixed effects and on a set of dummy variables, one for every possible combination of co-worker composition. Arcidiacono et al. (2007) model individual productivity as a function of the student's fixed effect plus a linear combination of the fixed effects of all peers. However, given the high number of players (1098) and the high variability of team compositions, we would have to add more dummies than would be computationally feasible using the program STATA/SE 10.

[11] A more detailed analysis revealed that most of the outlying observations of the variable *performance index* were produced by players with very short playing time. Whereas in the short run productivity may easily deviate from ability, stochastic shocks even out in the long run. As we have a relatively short time dimension in the panel, the fixed effects in (2) might be biased if we included observations of players who played just a few minutes during a season.

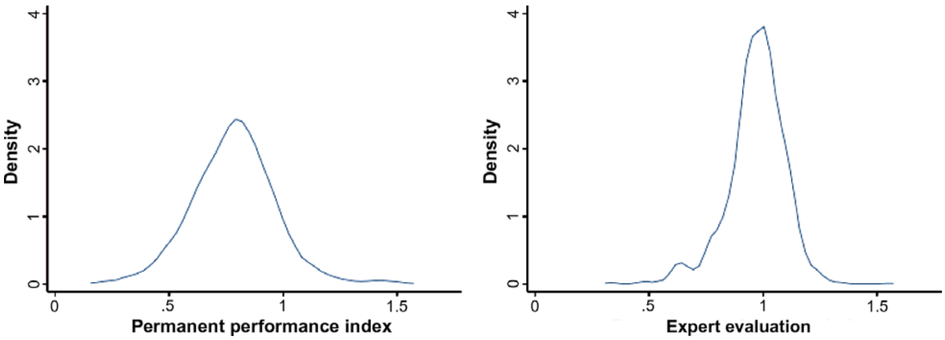

Fig. 1. Distribution of the players' talent levels.
Notes: The two figures show nonparametric kernel estimates of the distribution of the variable *permanent performance index* (the parameter π_i), obtained by fitting Eq. (2), and the variable *expert evaluation*. The sample size is 1098 players regarding the *permanent performance index* and 1641 regarding the variable *expert evaluation*. We used an Epanechnikov kernel and "optimal" bandwidth.

Whereas almost all player fixed effects are highly significant, the spillovers are positive but only weakly significant ($\beta_1 = 0.207$; $p = 0.07$).[12] As already mentioned, the player fixed effects (π_i) obtained by fitting Eq. (2) are interpreted as talent and labeled as *permanent performance index*.

Even though the *Opta* performance statistics are very precise, they reflect a quantitative rather than qualitative point of view, ignoring fuzzy talent aspects like creativity of play or key player attitudes. As a second talent indicator, we use expert appraisals of individual match performances. Reinstein and Snyder (2005) show that expert evaluations may be important "product" information revealing otherwise uncertain quality aspects. Unlike the quantitative *Opta* statistics, experts are likely to take intra-team spillover effects into account when drawing inferences about the contribution of a player.[13] In professional German soccer, every match performance of a player who plays more than half an hour is individually and consistently evaluated and rated by sports experts using the German grading scale that varies between 1.0 (excellent) and 6.0 (very bad). The individual match evaluations are available for all players appearing in the *Bundesliga* between 1995/96 and 2006/07 (1641 players and 4991 player-season observations) from a highly respected soccer magazine (*Kicker*). For ease of interpretation, we transform the original marks by subtracting the original mark from 7. Here again, we divide the expert evaluations by the means for the players' respective tactical positions in a given season in order to eliminate potential bias stemming from the tactical classification of a player. The second talent proxy, labeled *expert evaluation,* is then defined by the mean of centered expert evaluations he received.[14] In Fig. 1, we report the nonparametric kernel density estimates of the two talent proxies.

The correlation between the variables *permanent performance index* and *expert evaluation* is high (0.54) but not 1, which indicates that the talent proxies reflect the inherent playing ability in an imperfect way. Expert evaluations, for example, may suffer from a potential centrality bias of the evaluators (Murphy, 1992). Thus, the distribution of the variable *expert evaluation* could be too compressed. Indeed, the standard deviation of the variable *expert evaluation* is half the standard deviation of the variable *permanent performance index*. However, since we have two talent indicators, separate estimations may serve as a robustness test.

4.2. Talent disparity of the competition team

4.2.1. Data and dependent variable

We test the hypothesis that talent disparity of the competition team decreases the winning probability using all match results of the Bundesliga during six seasons (2001/02 to 2006/07). With 18 teams playing each other twice during the season, the full season includes 306 games, generating 612 team performance observations. Since the data set covers six seasons, we have 3672 team performances from 1836 games. Only half of the observations are used in order to avoid double counting. Each of the 1836 observations relates to a different fixture, and for each season the total is equally divided between home and away teams as well as between all participating teams in order to prevent selection bias.

Team performance as the dependent variable is measured in terms of the final score, expressed as the goal difference. Measuring output in this way reflects the team's primary purpose of winning a soccer match by scoring more goals than the opposition. This measure allows using ordinary least squares (OLS) estimates that are easier to interpret than an ordered probit or logit approach (win, draw, loss). In addition, unlike ordered probit or logit estimates, the consistency of OLS estimators does not crucially rely on the normality and homoskedasticity of the error term. The model used here is similar to

[12] β_1 denotes the average spillover effect of the sample. Since there may be substantial heterogeneity in how the productivity of a player responds to the average productivity of the rest of the team, the effect of talent disparity on team productivity is a priori unknown.

[13] We are grateful to an anonymous referee for making us aware of this point.

[14] In the match-level analysis of the competition team, we use seasonal averages as the squad compositions substantially change between, but not within, seasons. Within a season, the complementarities implicitly considered by the experts are comparable. In the seasonal level analysis we use career averages, however, because the reverse causality problem would otherwise be too severe.

Table 1
Descriptive statistics of the talent composition variables.

Variable	Aggregation level	Description	Obs.	Mean	SD
Talent composition of the competition team					
Mean performance index	Team-match	Average permanent performance index of the fielded players, aggregated from a player-match data set containing 25,089 obs.	1836	0.85	0.06
CV performance index	Team-match	Coefficient of variation of the permanent performance indexes of the fielded players, aggregated from a player-match data set containing 25,089 obs.	1836	0.17	0.05
Mean expert evaluation	Team-match	Average expert evaluation of the fielded players, aggregated from a player-match data set containing 25,053 obs.	1836	1.03	0.07
CV expert evaluation	Team-match	Coefficient of variation of the expert evaluations of the fielded players, aggregated from a player-match data set containing 25,053 obs.	1836	0.10	0.03
Talent composition of the entire squad					
Mean performance index	Team-season	Average permanent performance index of all team members, aggregated from a player-season data set containing 2638 obs.	108	0.81	0.05
CV performance index	Team-season	Coefficient of variation of the permanent performance indexes of all team members, aggregated from a player-season data set containing 2638 obs.	108	0.20	0.04
Mean expert evaluation	Team-season	Average expert evaluation of all team members, aggregated from a player-season data set containing 5547 obs.	216	1.00	0.04
CV expert evaluation	Team-season	Coefficient of variation of the expert evaluations of all team members, aggregated from a player-season data set containing 5547 obs.	216	0.09	0.02

that of Carmichael, Thomas, and Ward (2000) or Stefanie (1980), whose team production models are estimated with least squares techniques as well. In order to test the robustness of our results, we also ran an ordered probit estimation with the final result (win, draw, loss) as the dependent variable. The results, however, react insensitively to the alternative estimation procedure.

4.2.2. Talent composition variables

In order to analyze the determinants of team performance, team-level aggregates of individual talents are necessary. In Eq. (1), we modeled team performance as a function of the sum and the product of individual playing abilities, additional confounding variables and an error term. In our econometric models, we use the mean and the coefficient of variation (CV) of individual talents as measures of a team's talent composition. The mean characterizes the aggregated playing ability, whereas the CV represents a team's talent disparity. Harrison and Klein (2007) suggested using the CV in order to operationalize diversity whenever socially valued resources, such as pay, status, authority or social power, are involved. We regard talent as a socially valued asset of which more is generally better than less. The team-level talent composition variables are calculated using the talent measures of the fielded players in the considered match. Since individual talent does not change between games, a team's talent composition variables may change as a consequence of varying team selection only. Thus, we do not relate *current* individual playing strength to *current* team productivity, which could generate mechanical spurious correlations, as a transitory shock may simultaneously affect the current productivity of all players in a game. Table 1 illustrates the descriptive statistics of the talent composition variables of the competition team as well as of the second model analyzing the entire squad.

The fact that a team can substitute up to three players during a game introduces a disjunctive element, even at the competition stage of team production. The cross derivatives of productivity between the outgoing and the incoming players are clearly negative as only one of them is eligible to play on the pitch in a given minute. In order to eliminate any substitutional relationship between fielded and reserve players, we also run a model that considers the talent levels of only those players who played during the whole game.

4.2.3. Control variables

We control for potential home field advantage, the number of substitutions during a match, and the average tenure of the fielded players in order to eliminate alternative explanations of a team's sporting success. Carmichael and Thomas (2005) show that the effectiveness of home and away team performances is influenced by home-field factors related to crowd and stadium familiarity effects. We control for such factors by including a dummy variable, *home game*. The number of substitutions is also expected to exert a positive influence on the outcome of a game as fresh substitutes can replace exhausted players on the pitch. Average tenure of the fielded players may affect performance as a result of experience and socialization as well as by internalizing the team's playing style and strategy (Smith et al., 1994). Besides these match-specific controls, we also include team fixed effects to account for constant unobserved team heterogeneity that may bias the relationship between talent composition and team success. Some teams are, for example, more efficient when combining individual talents to win a game than others (Barros & Leach, 2006).

Table 2
Test of the effect of talent disparity of the competition team on match-level team productivity.

Variables	1 Coef.	Std. err.	Beta	2 Coef.	Std. err.	Beta	3 Coef.	Std. err.	Beta	4 Coef.	Std. err.	Beta
All fielded players												
Mean performance index	6.12***	1.15	0.20									
CV performance index	−2.74**	1.12	−0.07									
Mean expert evaluation				7.75***	0.92	0.28						
CV expert evaluation				−3.75**	1.51	−0.06						
Fielded players who played 90 min												
Mean performance index							−0.41	0.97	−0.01			
CV performance index							−1.93**	0.92	−0.06			
Mean expert evaluation										6.76***	0.86	0.25
CV expert evaluation										−5.80***	1.68	−0.08
Control variables												
Home game	0.86***	0.07	0.24	0.85***	0.07	0.23	0.88***	0.08	0.24	0.87***	0.07	0.24
Number of substitutions	0.42***	0.07	0.13	0.43***	0.07	0.12	0.39***	0.07	0.12	0.35***	0.07	0.10
Mean tenure of fielded players	−0.11	0.08	−0.05	−0.05	0.08	−0.05	−0.07	0.08	−0.03	−0.12	0.08	−0.05
Team fixed effects	Yes (F = 2.80; p < 0.01)			Yes (F = 1.64; p < 0.05)			Yes (F = 4.69; p < 0.01)			Yes (F = 1.90, p < 0.01)		
Opposition team seasonal fixed	Yes (F = 2.71; p < 0.01)			Yes (F = 2.82; p < 0.01)			Yes (F = 2.69; p < 0.01)			Yes (F = 2.74; p < 0.01)		
R^2	0.28			0.31			0.27			0.30		
Observations	1836			1836			1836			1836		

Notes: Ordinary least squares (OLS) estimation with White-robust standard errors. The dependent variable is the goal difference of a match. The reset test for non-linearity is insignificant in all models.
** Significance level (two-tailed): 5%.
*** Significance level (two-tailed): 1%.

Of course, the final result of a game is a relative outcome that reflects the playing quality of one team in comparison to the opposing team. We control for the playing strength of the opposing team by including 108 seasonal team fixed effects variables. Thus, we assume that the playing strength of the opposing team remains constant during one season but not between the seasons. By doing so, we take into account that a team's seasonal roster and budget can vary considerably. A team that qualified for the UEFA Champions League in the preceding season, for example, generated substantial extra income with which the team could buy excellent players for the current season.[15]

4.2.4. Results

Table 2 illustrates the coefficients, the levels of significance and the robust standard errors using OLS. Since the talent composition variables are measured on a scale that is difficult to interpret, we also list the standardized coefficients that indicate the change in the dependent variable if a regressor varies by one standard deviation.

The results of Table 2 show that talent disparity on the pitch is detrimental to winning. The negative coefficients of the CVs of individual talent levels are statistically significant, even after controlling for the mean ability, unobserved heterogeneity of both competing teams and other confounding factors like the home field advantage. Hypothesis 1 is confirmed. Thus, fielded players should have similar playing talent in order to attain the highest level of team productivity.

Analyzing the standardized coefficients of our talent composition variables, we see that the average talent of a fielded team exerts a stronger influence on winning than talent disparity (except in model 3). Moreover, models 2 and 4, in which individual playing ability is proxied by expert evaluations, better predict the team's sporting success than models 1 and 3 that use the *Opta* performance statistics. Third, the negative effect of talent disparity on winning remains more or less the same if we exclude outgoing and incoming players.

Additionally, we find evidence for a significant home field advantage. A team playing at home scores approximately 0.9 goals more than on the road, holding all other factors constant. Even though this effect is quite large, our point estimate is still smaller than that reported by Carmichael et al. (2000). One reason for the considerable home field advantage could be the widely documented tendency of referees to favor the home team when awarding penalties or extra-time at the end of a game (Garicano, Palacios-Huerta, & Prendergast, 2005; Sutter & Kocher, 2004). The relationship between the number of substitutions during a match and a game's result is also significantly positive, although the direction of causation is unclear. On one hand, substitutions allow the coach to replace temporarily bad performers or exhausted or injured players with fresh players sitting on the bench; on the other hand, it is also plausible that the team that is ahead substitutes in order to gain valuable seconds and to disturb the opponent's attempts to catch up. Unlike the variable *mean tenure*, unobserved hetero-

[15] The clubs that qualified for the UEFA Champions League in 2006/07 received in total € 530 million of additional broadcasting income and generated substantial extra match day turnover.

geneity of both competing teams significantly impacts a game's result. Fixed effects of the considered teams capture time-constant team aspects that influence winning beyond the analyzed variables. Not surprisingly, the 108 dummy variables for all possible opposition teams in a given season display high joint significance as well. The same fielded team that wins against a weak opponent may lose against a stronger team.

4.3. Talent disparity of the entire squad

4.3.1. Data and dependent variable

So far, we have used match-level data to test talent composition effects at the competition stage. In order to examine the influence of talent heterogeneity on team performance at the preparatory stage, we must also include the "benchwarmers". Since the team roster remains rather stable during a season,[16] it no longer makes sense to focus on single games. Instead, we use *seasonal* measures of talent composition and team performance. As already stated, we do not measure the effectiveness of the preparatory activities directly because the only relevant indicator of team success is defined at the competition stage, namely the performance of the club in the championship race. As the dependent variable we use the team's league standing at the end of the season, transformed by the formula $-\text{In}[\text{position}/(n+1-\text{position})]$, where n denotes the number of clubs in the league (in our case, 18).[17] The league standing variable varies between +2.89 (club winning the championship) and -2.89 (least successful club). At the seasonal level, we use panel data containing all teams that played in the *Bundesliga* over 12 seasons (1995/96 to 2006/07). Due to promotion and relegation in European soccer, we have an unbalanced panel, as some teams did not always play in the highest German soccer league. In total, our sample consists of 30 different teams and 216 team-season observations, at least if individual talent is measured by expert evaluations.

4.3.2. Talent composition variables

As in the match-level analysis, we use the mean and the CV as measures to represent the average talent and the talent disparity of a team. At the seasonal level, however, we consider all players, independently of how often they played on the competition team.[18] Thus, we relate the mean and the CV of individual talents of the entire squad to the team's final standing in the championship race. Since we use *permanent* talent indicators, a team's talent composition variables may change only by players joining or leaving the club, which facilitates the identification of the causal effect. If we measured both individual playing ability and team performance on a seasonal basis, we would not be able to determine if team productivity is shaped by individual excellence rather than vice versa. Our identification strategy is similar to the one employed by Mas and Moretti (2009), who also use *permanent* ability to explain *current* productivity.

4.3.3. Control variables

To eliminate alternative explanations of a team's sporting success, we control for mean tenure, the competition team's stability and roster size.[19] The variables *mean tenure* and *competition team's stability* capture the steadiness of the entire squad and the competition team, respectively. Team stability is expected to increase team performance as it fosters team collaboration and interaction on the field. In their study of National Basketball Association (NBA) teams, Berman, Down, and Hill (2002) showed that the more stable a team's membership is, the more likely it is that the team will win. The more often teammates play together, the more they are able to anticipate each other's passes, and the clearer their understanding of their own and others' roles becomes. The competition team's stability is measured by the mean number of appearances of the players appearing at least once on the competition team during a season. In an extreme example, if the same 11–14 players played all 34 games during a season, the value of this variable would be 34. However, this value is never achieved due to injuries, sickness, suspensions or varying playing strategies of the coach. The variable *roster size* controls for potential group size effects. Finally, we include season dummies to account for possible time effects.[20]

4.3.4. Estimation approach

We estimate a team fixed effects model since the reason why a team is promoted or relegated (causing sample attrition) is not random. Instead, it is likely to be correlated with unobserved team playing strength, which may cause biased estimators due to the resulting sample selection. This problem is moderated through our choice of a fixed effects model as fixed effects

[16] Between 1995/06 and 2006/07, around 2% of all players changed teams within a season.

[17] Szymanki (2000) suggested transforming the position into the log odds of position, as it gives a higher weight to progress further up the league. However, our results would not change in any significant way if the dependent variable was linearly specified, or if a team's winning percentage was employed as the measure of seasonal team success.

[18] Since suitable talent indicators are unavailable unless a player appeared at least once on the contest team during the considered time frame (i.e. 1995/96 until 2006/07 for *expert evaluations* and 2001/02 until 2006/07 for the *permanent performance index*), we cannot include "pure benchwarmers".

[19] We also tested whether a club's wage expenditures distort the talent composition effects. However, the club's financial power did not have a partial effect on team performance.

[20] As it is reasonable to assume that coaches may rest their star players in the national club games scheduled shortly before Champions League (CL) games, the conjectured positive effect of talent disparity may diminish for teams playing in the Champions League (winner and runner-up of the last season) or competing in the CL qualifying games (the third place club of the previous season). To test this hypothesis, we included a dummy variable coded 1 if the club played in the CL or in the CL qualifying round and an interaction term of the dummy with the talent disparity variables. The interaction term was insignificant, which indicates that the positive effect of talent disparity on team productivity is not diminished for clubs playing in the CL. We are grateful to an anonymous referee for raising this issue.

Table 3
Test of the effect of talent disparity of the entire squad on seasonal team productivity.

Variable	5			6		
	Coef.	Std. err.	Beta	Coef.	Std. err.	Beta
Mean performance index	9.948***	3.136	0.360			
CV performance index	4.804*	2.661	0.139			
Mean expert evaluation				19.858***	3.202	0.583
CV expert evaluation				6.503*	3.786	0.110
Mean tenure	−0.353	0.232	−0.155	−0.024	0.100	−0.011
Competition team's stability	0.225***	0.053	0.282	0.219***	0.050	0.287
Roster size	−0.067	0.043	−0.124	−0.031	0.029	−0.089
Season fixed effects	Yes			Yes		
Team fixed effects	Yes			Yes		
R^2		0.80			0.74	
Observations		108			216	

Notes: Team fixed effects estimation with White-robust standard errors clustered at the team-level to account for serial correlation of the disturbance within team observations. The dependent variable is the modified league standing at the end of the season determined by the formula $-\ln(\text{position}/(n+1-\text{position}))$. The reset test for non-linearity is insignificant in both models.
* Significance level (two-tailed): 10%.
*** Significance level (two-tailed): 1%.

analysis allows for the attrition to be correlated with the constant unobserved effect (Wooldridge, 2002).[21] Hausman (1978) specification tests support this choice.

The fixed effects approach consistently estimates partial effects in the presence of time-constant omitted variables as long as the explanatory variables are strictly exogenous, which implies that the regressors are uncorrelated with the idiosyncratic error at any point in time. A test outlined by Wooldridge (2002, 285) does not reject the null hypothesis of strict exogeneity of our explanatory variables. In order to obtain correct inference we calculate White-robust standard errors adjusted for potential heteroskedasticity and autocorrelation of the disturbance within team observations.

4.3.5. Results

The results of the team fixed effects estimation are illustrated in Table 3. They show that talent disparity of the entire squad improves a team's standing in the championship race, holding average ability, unobserved team heterogeneity and other confounding variables constant. Teams whose squad members are highly dispersed regarding their playing skill levels outperform rather homogeneous teams in the long run, ceteris paribus. Thus, our data support Hypothesis 2. Player inputs combine additively as well as multiplicatively to contribute to team success. Both average talent and talent disparity significantly increase team performance.

The empirical results are consistent with explanations emphasizing learning benefits at the preparatory stage of team production. They also concur with a further advantage of talent disparity within the entire team, namely the fact that playing time at the competition stage is influenced by a player's talent. More talented players typically appear more often in a contest than less able team members and, therefore, exert more influence on the team's outcome. Whereas mean tenure and roster size have no clear effect on the team's league standing at the end of the season, the competition team's stability significantly increases sporting success. The fact that teams benefit from having a stable competition team may have several explanations, such as increased shared experience, lack of injuries or lack of suspensions of core players.[22]

5. Concluding remarks

This paper analyzes the relationship between talent disparity and team productivity. Using panel data from professional soccer, the results show that talent disparity of the competition team decreases the likelihood of winning the game, whereas talent disparity of the entire squad improves the team's final standing in the championship race, ceteris paribus. Our findings confirm the moderating influence of the interaction type on the relationship between talent disparity and team performance. Due to the high interaction in soccer, player inputs of the fielded players can be considered as complements. Analyzing the entire squad, the complementarities among the players on the pitch are supplemented by the clearly substitutive relationship between reserve players and fielded players. In addition, our results are consistent with explanations emphasizing the varying importance of mutual learning at the two stages of team production. Whereas continuous improvements of technical and tactical abilities play an important role at the preparatory stage, only winning matters at the competition stage.

[21] In order to account for non-constant selection effects as well, see, e.g., Kyriazidou (1997).
[22] The causality of this relationship could also be reversed: if a fielded team plays well, the coach is unlikely to change the team (Berman et al., 2002).

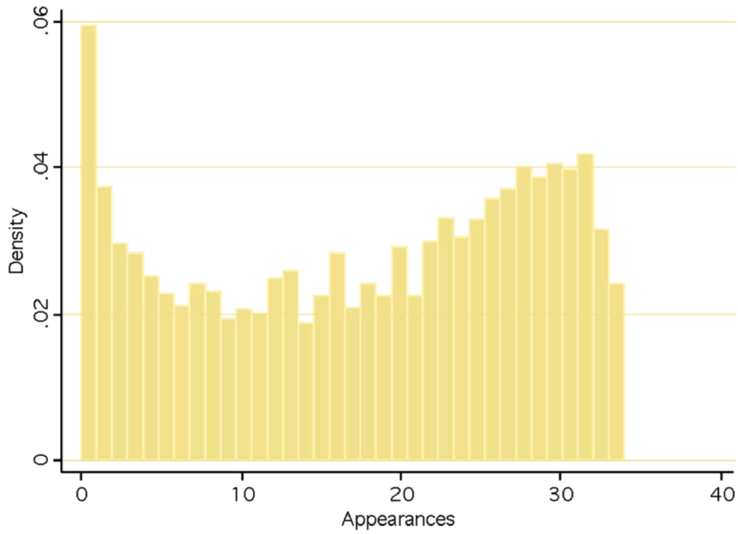

Fig. 2. Histogram of the number of match appearances during a season.

The main goal of this paper was to advance the knowledge on team production in soccer by applying theories and concepts from economics and psychology to soccer teams and by empirically testing their predictions. The generalizability of our findings to other contexts of team production raises the well-known concerns about external validity, as the same properties that make the sports context an advantageous area of research – accurate performance measures, a clear and simple institutional setting – also limit the transfer of results to other areas lacking these properties. However, on a rather abstract level of analysis, some general implications and wider lessons can be drawn nevertheless. What are these lessons?

First, before making any judgments about the advantage or disadvantage of talent disparity within teams, it is crucial to select an appropriate team definition. Our study suggests that the more broadly a team is defined, the more likely it is that talent disparity will turn out to be beneficial. Although in professional soccer the two team levels and the substitutive relationship between fielded and reserve players are rather clear, work teams in the business world also act in institutional settings that may affect the type of interaction involved in team production. Critical team members may, for example, have predetermined substitutes in case of vacations or illness. Support teams, which intervene in the case of a breakdown in standard operations, are common in many production processes, for example, in automobile assembly. Obviously the team definition matters as it determines the inclusion or exclusion of substitutive relationships. Second, this paper suggests securing sufficient talent diversity whenever learning is important. As the learning cycles are usually very short-lived during the production phase, organizations often set up special education and training programs to develop their workers. In analogy to the training activities in professional soccer, it may be essential to have outstanding senior team members from whom newcomers can learn in these preparatory stages of team production. Overall, our findings may deliver additional insights for many work environments in which a work team is embedded in a wider institutional setting that is likely to introduce manifold interdependencies.

Appendix. See Fig. 2.

References

Alchian, A. A., & Demsetz, H. (1972). Production, information costs, and economic organization. *American Economic Review, 62*, 777–795.

Arcidiacono, P., Foster, G., Goodpaster, N., & Kinsler, J. (2007). Estimating spillovers using panel data, with an application to the classroom. *Working paper.* University of Rochester.

Bandiera, O., Barankay, I., & Rasul, I. (2009). *Social incentives in the workplace*. IZA discussion paper series no. 4190.

Barros, C. P., & Leach, S. (2006). Analyzing the performance of the English F.A. premier league with an econometric frontier model. *Journal of Sports Economics, 7*, 391–407.

Berman, S. L., Down, J., & Hill, C. W. L. (2002). Tacit knowledge as a source of competitive advantage in the National Basketball Association. *Academy of Management Journal, 45*, 13–31.

Berri, D. J. (1999). Who is 'most valuable'? Measuring the player's production of wins in the National Basketball Association. *Managerial and Decision Economics, 20*, 422–427.

Carmichael, F., & Thomas, D. (2005). Home field effect and team performance. Evidence from English premiership football. *Journal of Sports Economics, 6*, 264–281.

Carmichael, F., Thomas, D., & Ward, R. (2000). Team performance. The case of English premiership football. *Managerial and Decision Economics, 21*, 31–45.

Elberse, A. (2007). The power of stars: Do star actors drive the success of movies? *Journal of Marketing, 71*, 102–120.

Falk, A., & Ichino, A. (2006). Clean evidence on peer effects. *Journal of Labor Economics, 24*, 39–57.

Foster, G. (2006). It's not your peers, and it's not your friends: Some progress toward understanding the educational peer effect mechanism. *Journal of Public Economics, 90*, 1455–1475.
Franck, E., & Nüesch, S. (2007). Talent and/or popularity – What does it take to be a superstar? *Working paper*. University of Zurich.
Frick, B. (2007). The football players' labor market: Empirical evidence from the major European leagues. *Scottish Journal of Political Economy, 54*, 422–446.
Garicano, L., Palacios-Huerta, I., & Prendergast, C. (2005). Favoritism under social pressure. *The Review of Economics and Statistics, 87*, 208–216.
Hamilton, B. H., Nicherson, J. A., & Owan, H. (2004). Diversity and productivity in production teams. *Working paper*. Washington University.
Hamilton, B. H., Nicherson, J. A., & Owan, H. (2003). Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *Journal of Political Economy, 111*, 465–497.
Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Journal, 32*, 1199–1228.
Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*, 1251–1271.
Jones, M. B. (1974). Regressing group on individual effectiveness. *Organizational Behavior and Human Performance, 11*, 426–451.
Kahn, M. L. (2000). The sports business as a labor market laboratory. *Journal of Economic Perspectives, 14*, 75–94.
Katz, N. (2001). Sports teams as a model for workplace teams: Lessons and liabilities. *Academy of Management Executive, 15*, 56–67.
Kendall, T. D. (2003). Spillovers, complementarities, and sorting in labor markets with an application to professional sports. *Southern Economic Journal, 70*, 389–402.
Kremer, M. (1993). The o-ring theory of economic development. *Quarterly Journal of Economics, 108*, 551–575.
Kyriazidou, E. (1997). Estimation of a panel data sample selection model. *Econometrica, 65*, 1335–1364.
LePine, J. A., Hollenbeck, J. R., Ilgen, D. R., & Hedlund, J. (1997). Effects of individual differences on the performance of hierarchical decision-making teams: Much more than g. *Journal of Applied Psychology, 82*, 803–811.
Levin, J. (2001). For whom the education count? A quantile regression analysis of class size and peer effects on scholastic achievement. *Empirical Economics, 26*, 221–246.
Mas, A., & Moretti, E. (2009). Peers at work. *American Economic Review, 99*, 112–145.
Murphy, K. J. (1992). Performance measurement and appraisal: Motivating managers to identify and reward performance. In W. J. Burns, Jr. (Ed.), *Performance measurement, evaluation, and incentives*. Boston: Harvard Business School Press.
Prat, A. (2002). Should a team be homogeneous? *European Economic Review, 46*, 1187–1207.
Reinstein, D. A., & Snyder, C. (2005). The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *The Journal of Industrial Economics, 53*, 27–51.
Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *Quarterly Journal of Economics, 116*, 681–704.
Schneeweis, N., & Winter-Ebmer, R. (2007). Peer effects in Austrian schools. *Empirical Economics, 32*, 387–409.
Smith, K. G., Smith, K. A., Olian, J. D., Sims, H. P., O'Bannon, D. P., & Scully, J. A. (1994). Top management team demography and process. The role of social integration and communication. *Administrative Science Quarterly, 39*, 412–438.
Stefanie, R. T. (1980). Improved least squares football, basketball, and soccer predictions. *IEEE Transactions on Systems, Man, and Cybernetics, 10*, 116–123.
Steiner, I. D. (1972). *Group process and productivity*. New York: Academic Press.
Sutter, M., & Kocher, M. G. (2004). Favoritism of agents – The case of referees' home bias. *Journal of Economic Psychology, 25*, 461–469.
Szymanki, S. (2000). A market test for discrimination in the English professional soccer leagues. *Journal of Political Economy, 18*, 590–603.
Tziner, A. (1985). How team composition affects task performance: Some theoretical insights. *Psychological Reports, 57*, 1111–1119.
Tziner, A., & Eden, D. (1985). Effects of crew composition on crew performance: Does the whole equal the sum of its part? *Journal of Applied Psychology, 70*, 85–93.
Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge/London: The MIT Press.