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UZH Business Working Paper Series

Working Paper No. 386

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March 2020

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http://www.business.uzh.ch/forschung/wps.html

UZH Business Working Paper Series

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Are Workers Rewarded for Inconsistent Performance?

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Abstract

This paper examines whether workers are rewarded for inconsistent performances by salary premia. Some earlier research suggests that performance inconsistency leads to salary premia while other research finds premia for consistent performances. Using detailed salary and performance data, we find that inconsistency is rewarded for some dimensions of performance, specifically those where creativity is important and outcomes have higher variance. We find salary penalties for inconsistent performances in those dimensions that are basic requirements of successful team production.

JEL Classification: J31, M52, Z20

Keywords: salaries, performance, consistency

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1. Introduction

Following Lazear (1998), a body of personnel economics literature has considered whether workers who demonstrate greater performance inconsistency than comparable workers of similar average productivity are rewarded more highly. Lazear conjectured that there would be an 'upside potential to risky workers' so inconsistent performers would be more highly rewarded in salary due to their capability of providing extraordinarily high productivity albeit on a few occasions. Firms would consider this unusually high performance to be an option value and would reward workers more highly to reflect this.

In some cases, principals prefer consistent performances to volatile ones by their agents (Bodvarsson & Brastow, 1998; Deutscher, Gürtler, Prinz, & Weimar, 2017; Dickinson & Oaxaca, 2014), in other cases, researchers suggest that principals prefer inconsistent agents to consistent ones (Bollinger & Hotchkiss, 2003; Deutscher & Büschemann, 2016). Although existing literature finds evidence for either case, the question under which conditions inconsistency is penalized or rewarded remains ambiguous, especially because the necessary conditions are not identified. Beyond the aforementioned studies, Andersson, Freedman, Haltiwanger, Lane, and Shaw (2009) show that software firms that are active in areas with highly skewed positive returns (e.g., video game developers) pay higher upfront salaries and offer higher compensation growth. The analysis, however, does not consider inconsistency and salary differences are explained by firms' product payoff dispersions.

To solve the puzzle, one could try to compare two industries, one in which inconsistency is punished and one in which it is rewarded, and then identify the determinants of the differences. However, such an analysis is very difficult because industries differ by many factors and it would be impossible to identify the relevant factors. Another strategy could be to analyze such differences within a single industry. This approach would require an industry in which performance inconsistency is measured very precisely and in which there are some tasks in which workers are

penalized and some tasks in which workers are rewarded for performance inconsistency. Empirical testing for upside potential of risky workers is very difficult in most industries as individual workers' mean and variance of productivity cannot be cleanly derived (Ernst & Vitt, 2000; Garen, 1988). Self-reported survey data are unhelpful in this context and results from firm-specific data may not easily generalize (Barrett & O'Connell, 2001; Chapman & Southwick, 1991), because cross-firm comparisons are not possible. Instead, sports data offer good opportunities to study the relationship between worker salary and variations in productivity since we can extract performance data at individual worker (player) level for many different competing firms (clubs) over time (seasons) into a large data set. Kahn (2000) emphasizes that the sports industry presents a valuable laboratory setting to analyze labor markets. In recent years, many researchers have turned to sports data to analyze numerous research questions in management, economics, and other social science fields.

We exploit detailed European football performance data from the top division of one of the Top Five European football leagues, i.e., the Italian Serie A. We define performance inconsistency as performance variation and are particularly interested in the effects of performance variation on salary. Some players might be rewarded for consistency of performances (e.g., defenders) while others might be rewarded for performance variation as their roles require creativity which, in turn, generates inconsistency. Such features of heterogeneity may be important in a wider complex organizational setting. Especially in settings where creative workers combine with workers doing more mundane tasks in a repeated team production context, e.g., celebrity chefs and immediate co-workers in a restaurant, star actors and background artists in a theater production, or surgeons in the operating room and assisting nurses. Our data set facilitates testing of heterogeneous effects of performance on salary.

In contrast to Deutscher and Büschemann (2016), who use the same single performance proxy measure (journalist ratings for player performances) for all players regardless of field position in the team, we use actual salary data, which is clearly

superior to market values and other proxies. Deutscher and Büschemann's (2016) analysis of Bundesliga football lacks data on both direct salaries and player performances, so the authors use proxy measures. The salary proxy is a player valuation measure created by experts at *Kicker* sports magazine. The researchers argue that *Kicker* valuations are closely correlated with a subset of available salaries for Bundesliga players. The performance proxy is a set of subjective grade scores (journalists' ratings) recorded by *Kicker* ranging at match level from 1 (excellent) to 6 (very poor). Using market values as proxies for salary data (e.g., via Transfermarkt.de or *Kicker* ratings) raises several issues: (i) the algorithm to calculate market values is non-transparent, (ii) the algorithm does not update frequently, and (iii) crowd estimates cannot be verified or replicated (Müller, Simons, & Weinmann, 2017). Market values conflate transfer fees with salary payments. Thrane (2019) shows the limitations of market values as predictors of actual salary in Norwegian football.

Although expert ratings might have their merits, Gauriot and Page (2018) show that managers, journalists, and sports fans significantly overrate observed outcomes when they evaluate performance, i.e., they demonstrate outcome-bias. Specifically, journalists have a tendency to overrate players two-thirds of a standard deviation when a goal is scored compared to when no goal is scored (Gauriot & Page, 2018). Outcome bias occurs in settings where ex-post outcomes influence an individual's judgements of a given situation, although the ex-ante information was identical (Baron & Hershey, 1988; Lefgren, Platt, & Price, 2015).

Going beyond previous research, we show that salary premia in our setting are only offered for particular dimensions of performance. To the best of our knowledge, this is the first paper to empirically show that inconsistency is rewarded for some dimensions of performances, while it is penalized in others. The existing literature on the effect of performance inconsistency on worker salaries does not differentiate between differences of tasks within a team and therefore cannot capture the insights generated by our study. In short, performance inconsistency in defensive tasks is penalized while performance inconsistency in attacking and goal scoring is rewarded.

As in any other industry, workers need to provide various skillsets for different tasks. Some tasks are more repetitive or administrative and others require more creative skills, where effort, productivity, and salary returns have disproportionate relationships to performance attributes.

The remainder of this paper is organized as follows: section 2 provides the necessary theoretical background, section 3 presents our data and empirical model. In section 4, we analyze empirical results, ans we conclude the paper in section 5.

2. Background

A widely used regression model to explain earnings as a function of schooling and experience is Mincer's (1974) framework, a cornerstone of empirical labor economics, that has been replicated in many studies around the world (Ashenfelter & Alan, 1994; Bils & Klenow, 2000; Card & Krueger, 1992; Willis, 1987). More-educated workers earn higher salaries; additional years of work experience and age have a positive albeit diminishing effect on salaries (i.e., upward sloping and concave functional form). Within sports, researchers have focused largely on Mincer's wage equation to model salary outcomes, where age, experience, position, national team selection, team effects, country of origin, and performance have been used to determine salaries. Bryson, Frick, and Simmons (2013) find that age, height, goals per game, international appearances, and two-footedness increase salaries. In general, offensive players earn more (Lucifora & Simmons, 2003). Extraordinarily talented football players, i.e., superstars earn up to 34% more (Lucifora & Simmons, 2003) and according to Bryson, Rossi, and Simmons (2014), migrant players earn more than domestic ones, which is partly explained by superstar effects. Furthermore, evidence for superstar effects is offered by Carrieri, Principe, and Raitano (2018) using Google citations as a measure of player popularity.

Rosen's (1981) seminal paper formally analyzed the economics of superstars. He showed that marginal differences in talent can lead to huge differences in earnings.

When talent is highly valued by consumers, the most talented individuals earn disproportionately high incomes due to economies of scale in audience consumption of the performer's talent. In modern European football, audience consumption refers to global broadcast coverage of matches featuring superstar players. Even regular league games are broadcast worldwide live across all major continents.

Furthermore, Adler (1985) shows that equally talented individuals might have huge differences in earnings because consumers are more familiar with one talent compared than the other, suggesting that it might be an individual's celebrity status associated with accumulated reputation, rather than that individual's talent leading to higher earnings. Both Rosen's and Adler's explanations of superstar effects are complementary and not mutually exclusive: to qualify as a superstar, a player needs strong performances, high popularity, and the ability to reach a large audience (i.e., players like Messi and Ronaldo have all three attributes).

Superstar effects are most likely to occur in arts, entertainment, and sports but they are also observed in other fields. Researchers have focused on the earnings of CEOs (Malmendier & Tate, 2009), Wall Street analysts (Groysberg, Lee, & Nanda, 2008), scientists (Narin & Breitzman, 1995), actors (Ravid, 1999), and athletes (Carrieri et al., 2018; Lucifora & Simmons, 2003). Using several regression methods, including unconditional quantile regressions, and Italian salary data similar to ours, Carrieri et al. (2018) show that football players' popularity is the most important determinant of salary in the top decile of the player salary distribution, outweighing player performance and bargaining power, thereby supporting Adler's (1985) theory.

Some researchers have turned to sports data to find empirical evidence for Lazear's (1998) theory of upside potential of risky workers: Bodvarsson and Brastow (1998) show that managers prefer consistent over volatile performances by analyzing data from the National Basketball Association (NBA), i.e., inconsistent NBA players earn less because they need to be monitored, which is costly. Bollinger and Hotchkiss (2003) empirically test baseball player's salaries and performances and find that inconsistent baseball players earn a salary premium compared to their colleagues who

have the same average performance but do not offer larger upside potential. Deutscher and Büschemann (2016) and Deutscher et al. (2017) study the relationship between player salaries and performance variation in the German Bundesliga and in the NBA, respectively. For German football, the researchers offer evidence that players are more highly rewarded for more inconsistent performance. For the NBA, the results point in the opposite direction, where greater consistency is rewarded by a salary premium. Thus, these two papers deliver contradictory results from two different sports leagues.

Beyond sports industry related studies, Dickinson and Oaxaca (2014) use experimental settings to show that inconsistent workers are more likely to be hired but earn lower salaries. Andersson et al. (2009) argue that there is a strong connection between talent and product innovation in the software industry, a sector that has large economies of scale in production and is characterized by highly skewed payoffs for both firms and skilled workers. Indeed, some software products may generate extra-ordinary revenues while others might turn out to generate large losses. This is often a result of winner-take-all markets. The researchers define star employees as those project managers and engineers who have better abilities to pick projects with high positive returns. As such, they conjecture that star employees would increase project payoffs both in less risky industries and in high-risk industries. However, the project payoffs are much larger in markets that have high variance and high skewness. Using OLS and quantile regressions, the researchers show that firms with higher revenues pay higher salaries but they emphasize that product payoff dispersions have a significant positive effect on starting salaries and salary growth.

Similar to Andersson et al.'s (2009) arguments about the software industry, scoring and winning in European football are heavily dependent on athletes' talents. Here again, club managers need to pick the best talents that maximize their club's winning percentage, and therefore, revenues. European football is known as a low-scoring and low-numbers game. Given the nature of the game, the relationship between effort and payoffs (e.g., goals scored) can be highly skewed. Not only can an additional scored goal decide whether a team wins or loses, winning the league leads

to extraordinary prize money for the winning club but also to enormous additional revenues in subsequent seasons because winners qualify for prestigious tournaments, e.g., UEFA Champions League (UCL), with high prizes

[1]. On the other hand, losing teams at the bottom of the league face relegation. An additional goal that is conceded might lead to an extraordinary loss of revenues (e.g., from TV-rights, stadium attendance, and merchandising, etc.) because there is a steep drop in revenues between top divisions and subsequent lower divisions. According to Dietl, Franck, and Lang (2008), clubs overinvest in talents because of these unequal industry payoff structures. The structure of rewards in football competitions points to potential large returns to teams and players from success generated by high levels of player performance. The question we pose is whether player salary returns are increased or decreased by higher performance variation.

3. Data and Methods

In European football, two teams compete against each other with 11 players on each side; the team that scores more goals wins, hence, the objective team production function is to produce more goals. Players have different tasks, i.e., goal keepers guard the goal and are allowed to use their hands, defenders try to keep the ball as far away from their goals as possible, midfielders connect defense and attack (some have coordinating tasks, others have creative tasks), and strikers need to be creative to outplay the opponent's defenders in order to score goals. To oversimplify: attackers proactively seek to outplay defenders, while defenders react and try to minimize any mistakes.

To study the heterogeneous relationship between inconsistent worker performance and earnings, we require a detailed dataset with information on

[1] Juventus, Roma, and Napoli qualified for the UCL after ranking 1st, 2nd, and 3rd respectively in the 2016/17 Serie A season. In the subsequent 2017/18 UCL season, these teams generated additional revenues between 39m € and 83m €. For a detailed list of UCL revenue distributions, see: https://www.uefa.com/MultimediaFiles/Download/competitions/General/02/57/82/51/2578251_DOWNLOAD.pdf

numerous performance metrics and earnings. For this, we use player performance data from eight seasons (2009/10 to 2016/17) of the Italian Serie A. Our choice of Italy Serie A is motivated by availability of both player salary and player performance data. Italy is the only European country for which reliable and consistent football player salary data are published in a comprehensive manner over a long period (Bryson et al., 2014; Carrieri et al., 2018).

The rich player performance data set was purchased from *Panini Digital*, an official data provider for clubs of the Italian Serie A. In total, we count 84,499 player-match observations. The sample reduces to 78,302 player match observations because we exclude goalkeepers from our analysis. Assessing individual goalkeeper performances is very difficult compared to defenders, midfielders, and forwards. Our salary data come from the most popular sports newspaper *La Gazzetta dello sport* and are published in September of each year, since 2008. The salary data represent gross basic pay and exclude performance-related and other bonuses. In order to estimate salary models, we collapse our match-level performance statistics into season-level aggregates.

3.1 Performance Measures

We measure individual player performances by numerous on-field metrics (e.g., balls played, successful passes, recovered balls, shots on target). Players are assigned different positions by the data provider (e.g., defender, midfielder, forward) which require different sets of skills. We take the position categories as given by the data providers. Although some players might be more versatile and therefore are assigned to different positions in different games by the managers, they are usually playing the same position in a given season.

Thousands of actions (events) are measured by *Panini Digital*, of which some are more important for team match outcomes than others. For this reason, we proceed as follows: First, we use a single composite performance index called IVG that is

provided by *Panini Digital*. The measure is used by Italian Serie A clubs media outlets, and researchers (Fumarco & Rossi, 2018; Montanari, Silvestri, & Bof, 2008) for player performance evaluation.

The IVG measure is an index that is calculated by an algorithm that includes more than thousand in-game actions. The measure has been developed by researchers at the Department of Statistical Sciences of the University of Bologna, together with a team of football experts that are all current or past football coaches (e.g., Sacchi, Lippi, Zeman, Lucescu, Ancelotti). This index covers several situations (e.g., player in possession, player dictating the pass, player recovering the ball) and compares each player to a historical average, i.e., a benchmark that is specific to that role (Fumarco & Rossi, 2018). The IVG can take values from 1 (minimum) to 30 (maximum), and has a sample mean around 17. The index may increase for defenders that are able to contribute to attack (e.g., shots) or decrease for attackers that are caught offside or lose the ball; there are penalties and extra points for each role. Scoring is highly rewarded with additional extra points, the extra points for goals decrease with every additional goal scored in a match (e.g., 4 points for the first goal, 3 points for the second goal, 2 points for the third goal, 1 point for any additional goal above 3).

Second, we apply factor analysis to reduce the number of performance metrics to arrive at a more representative and smaller number of performance variables that can summarize more accurately different skillsets for different players. A very similar multivariate technique for data reduction is called Principal Component Analysis (PCA) (Jackson, 1991). Both methods reduce the dimensionality of the data into a smaller number of unobserved variables expressed as linear combinations of observed variables. Other than factor analysis, however, PCA assumes that there is no unique variance of the observed variables and that the total variance is equal to the common variances.

Factor Analysis (and PCA) is used in many fields, including social sciences (Cattell, 1978; Gorsuch, 1983), economics (Bai & Wang, 2016; Bhatti, Al-Shanfari, &

Hossain, 2006; Huang-Lachmann, Hannemann, & Guenther, 2018; Studer & Winkelmann, 2017), and biostatistics (Van Belle, Fisher, Haegerty, & Lumley, 2004).

We collected data for 26 on-field metrics (see Tables 1 and 2) to assess player performances. For example, a defender's performance is assessed by observing the number of interceptions, blocked shots, tackles, etc. he had, while an attacker's performance is assessed by the number of shots on target, dribblings, assists, etc. Using factor analysis, we reduce these observable and measurable variables (e.g., shots on target, tackles) into a set of fewer underlying latent variables, i.e., factors that explain the interrelationships among observed variables. At the center of the analysis is the covariance among the observed variables: variables that are highly correlated will share a lot of variance. The assumption is that the observed variables are linear combinations of the underlying and unobserved factors. The procedure reduces dimensionality because the factors that share common variance (communality) can explain more of the variance of an individual observed variable (Bhatti et al., 2006; Mueller & Kim, 1978).

Other than PCA, factor analysis assumes that there are latent factors that better explain the relationship between correlating observed variables. This supports our decision to apply factor analysis instead of PCA: Even if we can measure the number of passes, shots, etc., we do not know how these variables relate to ability and effort. Ability itself can be individual (a player's own skillset) and peer-related, that is, the ability to interact in a team. These are intangible factors. Nonetheless, we have also tested our models using PCA with results available on request. The resulting tables (eigenvalues, explained variance, factor loadings) are different due to the different procedure; however, the patterns of the extracted components and the interpretations thereof are very similar. Thus, the regression results using the two methods are not remarkably different. Indeed, previous researchers have shown that PCA and factor analysis show very similar results (Velicer & Jackson, 1990).

[Insert Table 1 here]

[Insert Table 2 here]

Usually the procedure takes several steps. (1) The factor analysis is run on a set of observed variables, in our case 26 (see Table 2), and factors are extracted. Table 3 shows the eigenvalues (i.e., the variance) of the factors. Following Kaiser (1960), we drop all factors that have eigenvalues lower than unity. This leaves us with three factors. Although there are multiple approaches to select the number of factors to retain, the Kaiser rule is the most commonly used. (2) Factors are rotated to achieve a simple structure that allows us to more easily interpret the results. Without factor rotation, most of the observed variables are loaded on the first factor so that the first factor explains most variance. Achieving a simple structure is helpful because each factor can define a distinct cluster of interrelated variables and the results are more easily interpretable (Cattell, 1978; Mueller & Kim, 1978). We use oblique rotation for our analysis, because the factors are correlated (i.e., a player can have strong playmaking skills and striking skills)[2]. Note that the underlying data does not change here. Results of the rotated factor analysis are shown in Tables 4 and 5.

[Insert Table 3 here]

After rotating the factors, we focus on interpreting the results. The factor pattern matrix in Table 5 shows the partial standardized regression coefficients of each observed variable (rows) with a specific factor (columns). For instance, 0.772 is the effect of factor 1 on the observed variable *balls played*, controlling for factors 2 and 3; while 0.450 is the effect of factor 2 on *balls played* controlling for factors 1 and 2.

[2] We run tests with orthogonal rotation, which assumes that the factors are uncorrelated and imposes that assumption on the data. The factor loadings lead to very similar interpretations of the factors and the results in our main econometric model are not remarkably different. Because oblique rotation does not impose orthogonality on the data, the approach is suitable for both uncorrelated and correlated factors.

Squaring the loadings, e.g., $0.772^2 = 0.60$, gives us factor 1's unique contribution of the variance in 'balls played', controlling for factors 2 and 3.

The uniqueness column presents the portion of variance that is not explained by the three factors. To calculate the communality of each observed variable, we subtract each uniqueness value from 1. For instance, *balls played* has a communality of 0.88, meaning that 0.88 of the variance of *balls played* is accounted for by the three factors. Variables with higher uniqueness (lower communality) are not as well explained by the three retained factors as those variables with lower uniqueness.

A closer look on Table 5 helps us to interpret the specific skillsets for players. For instance, the factor loadings for balls played (0.772), balls played in opposition half (0.818), successful passes (0.741), useful plays (0.851), useful plays in opposition half (0.904) are all very high for factor one: they describe playmaking skills. Players associated with high values of this factor have the ability to control and direct the ball. Moreover, they also contribute to creative attacking play, as the loadings for assists (0.520) and useful short passes in opposition half (0.494) indicate. It is not surprising that most midfielders score high on this factor. In contrast, factor two explains defensive skills, clearly visible by the high loadings of recovered balls (0.904), recovered balls in defensive area (0.946), anticipations (0.700), interceptions (0.578), and clearances (0.804). The third factor describes typical striker skills: loadings on shots (0.715), shots on target (0.828), goal chances (0.834), and goals (0.726) are all high. We can see that these three factors, i.e., skillsets, are well correlated with the player positions.

Having extracted the three factors (playmaking, defense, striker), we predict factor scores for every player-match observation to see how players have performed on a given skillset in a game. This step is important because include the predicted factor scores into our main regression analysis. Technically, statistical software packages use regression methods to predict factor scores. After predicting the factor score, we calculate the average factor score per season (e.g., average score over all

matches in a given season) and the standard deviation of factor score per season to include these newly generated performance variables in our salary regressions.

[Insert Table 4 here]

[Insert Table 5 here]

3.2 Econometric Strategy

Based on the Mincer wage equation and literature on salary determination in team sports (Bryson et al., 2014; Carrieri et al., 2018), we first model player salaries as a function of player productivity measures (mean and standard deviation of performance) and control covariates. This model faciliates testing of previous research findings on the effects of performance inconsistency on salaries. Because three teams are relegated from Serie A in each season and we do not observe Serie B earnings, some players in our unbalanced panel data set may appear in one season and disappear in the next. In addition, some players may move to other leagues or may retire. As salaries are outcomes of performances, we cannot regress salaries and performances in the same year due to endogeneity concerns. Therefore, salary levels at time t are regressed on performance levels and associated coefficient of variation from season t-1, where these performances may come from a different club if the player has switched teams. We calculate average performance (*MEAN IVG*) per season for each player and the standard deviation of performance (*SD IVG*) per season for each player. Hence, performance variation refers to dispersion of performances within a given season rather than across seasons.

We control for player age, career games, and national team selection before the beginning of the season. In addition, we use dummies for non-European players, for positions (defender, midfield, forward), and for teams. Along the lines of numerous papers that have used the Mincer wage regression, we expect age and the number of

career games to have a positive yet diminishing (i.e., concave) effect on salaries (Bryson et al., 2013). Appearance in the national team represents both a selection and signaling effect, which will also have a positive effect on salaries. While we expect foreign players (Bryson et al., 2014) to have higher salaries as well, reflecting unobserved ability and specialized skills. Moreover, we already see, from a descriptive analysis, that attacking players usually earn more than defending players, hence, midfielder and forward dummies should have a positive effect on salaries (Frick, 2007; Lucifora & Simmons, 2003).

$$LN(SALARY_t) = \alpha_0 + \alpha_1 MEAN\ IVG_{t-1} + \alpha_2 SD\ IVG_{t-1} + \alpha_3 AGE_t + \alpha_4 AGE_t^2 + \alpha_5 CAREER\ GAMES_t + \alpha_5 CAREER\ GAMES_t^2 + \alpha_6 NATIONALTEAM_t + \alpha_7 NONEU + Position + Team + \text{error} \quad (1)$$

Our focus is on the sign and size of α_2. A negative sign shows that performance inconsistency, i.e., standard deviation of performance, reduces player salary. A zero coefficient shows no effects, indicating perhaps that team managers regard performance inconsistency as a consequence of luck and so should play no role in assessing salary in contract negotiations. A positive coefficient indicates support for Lazear's hypothesis of upside potential of risky workers.

[Insert Table 6 here]

[Insert Table 7 here]

In our second and main model, we switch our productivity measure IVG with the three factors from our factor analysis that explain playmaking, defensive, and striker skills respectively. The control covariates do not change. Here, we are interested on the sign and sizes of α_2, α_4, and α_6 to see if inconsistent performances for different skillsets have different effects on salaries.

$$LN(SALARY_t) = \alpha_0 + \alpha_1 PLAYMAYKING_{t-1} + \alpha_2 SD\ PLAYMAKING_{t-1} + \alpha_3 DEFENSE_{t-1} + \alpha_4 SD\ DEFENSE_{t-1} + \alpha_5 STRIKER_{t-1} + \alpha_6 SD\ STRIKER_{t-1} + \alpha_7 AGE_t + \alpha_8 AGE_t^2 + \alpha_9 CAREER\ GAMES_t + \alpha_{10} CAREER\ GAMES_t^2 + \alpha_{11} NATIONALTEAM_t + \alpha_{12} NONEU + Position + Team + \text{error} \quad (2)$$

4. Regression Results

We run OLS regressions for 2,049 player observations over eight seasons. Our initial results (see Table 8, regressions 1 to 4) show that we can replicate previous findings from German football. Using more precise salary and performance measures (the *IVG* single composite measure), we find that inconsistent players earn more than consistent ones; similar to Deutscher and Büschemann (2016). The baseline regression (1) shows positive and significant coefficients of average performance (*MEAN IVG*) and performance inconsistency (*SD IVG*).

An increase of the average performance by one unit increases salaries by 7.4%, while increasing the average performance by one standard deviation would raise salaries by 11.3% in the OLS regression. If performance inconsistency increases by one unit, salaries increase by 7.9%. Our control covariates perform as expected. Age has a positive, yet diminishing effect on salaries. The turning point where the positive age effect diminishes is roughly 30 years in the OLS regression. Similarly, tenured players with a larger number of career games are paid higher salaries. Moreover, players that were selected into the national team squad are also paid higher salaries. In regression (2), we add player fixed effects and see that the results on player inconsistency persist. Naturally, the coefficients are smaller than in the OLS regression but they are positive and significant. Here, a one unit increase of performance inconsistency would lead to a salary increase of 0.4%.

As a robustness check, we have used 78,302 player-match observations and corrected the productivity scores (IVG) by additionally controlling for the rank difference between home and away teams, derby matches, last eight matches of the season and the opposition team. Regressions (3) and (4) show the results of the

corrected productivity scores. The results persist: inconsistency is rewarded by a salary premium.

[Insert Table 8 here]

Using quantile regressions (Table 9), we test whether our results are consistent at different points in the conditional distribution of our dependent variable. OLS focuses on the average relationship between the dependent and independent variables; while quantile regressions test this relationship on assigned percentiles and median, using least absolute deviation of observations from fitted regression line and still using all observations for any given quantile estimate. The median regression is especially more robust to outliers in comparison to OLS. We regress salaries on our performance (*MEAN IVG*, *SD IVG*) and control variables to yield coefficient estimates at the 10th, 25th, 50th, 75th, and 90th percentiles (see Table 9). Intriguingly, while the average performance on different percentiles of salaries has similar effects, performance inconsistency at the 75th and 90th percentile have stronger effects, i.e., inconsistent players that are earning above median incomes earn much higher salary premia than below median.

[Insert Table 9 here]

To this point, our regression results confirm earlier findings in European football (Deutscher & Büschemann, 2016) and basketball (Bodvarsson & Brastow, 1998). It seems that by using one single performance metric, inconsistent football players earn higher salaries than consistent ones. However, analyzing more detailed performance metrics, we show that inconsistency is not favored in all performance dimensions.

Table 10 shows the regression results using our three factors from the factor analysis. High scores of playmaking, defensive, and striking skills each lead to

increased salaries in the OLS regression (model 1). Interestingly, however, we observe that an increase in the standard deviation of defensive skills significantly decreases salaries, while an increase in the standard deviation of striking skills raises salaries. It seems that the coefficient on standard deviation of playmaking skills is insignificant for salary determination. A one unit increase in standard deviation of defensive skills decreases salaries by 24.7%, while a one unit increase in standard deviation of striker skills increases salaries by 16.6%.

We can see that inconsistency is not rewarded in every dimension, and in the defensive case, inconsistency is penalized. When we add player fixed effects to the regressions (model 2), inconsistency in these three different skills no longer plays a significant role. This could be due to unobserved heterogeneity that is captured by the player fixed effects in a panel structure where the number of players per group is rather small (less than three on average). Because of this feature of our data set, we prefer the OLS estimates over the player fixed effects estimates.

The positive effect of performance coefficient variation on player salaries for strikers fits Lazear's notion of 'upside potential of risky workers' but in our setting it is the more creative and more productive workers who gain from higher performance variation. Strikers are hired specifically to score goals. However, strikers' own abilities may be thwarted by bad luck (Gauriot & Page, 2018) and the efforts of opposing defenders. Hence, the variation of striker performances within a given team-season can be substantial. In contrast, inconsistent performances by defenders will be viewed by team management as a threat to team wins. A given team's defense needs to work together to prevent goals from being conceded to a team's opponent in a given match. Erratic performances by defenders in terms of our factor loadings may be compensated by other attributes so the player is still selected for the team (because mean performance is still viewed as reasonable). However, salary for an inconsistent defender will tend to be lower than for a more consistent defender, ceteris paribus, where that condition includes mean performance over the season.

[Insert Table 10 here]

In the quantile regressions (Table 11), we test the three factors for robustness. Similar to our OLS regressions, we can see that the key results persist. Greater inconsistency in defensive skills leads to significantly lower salaries at the 25th, 50th, and 75th percentile of the salary distribution, while inconsistency in striking skills has a positive and significant effect, although for the 10th, 75th, and 90th percentile but not at the median.

The striker 'upside potential' wage premium is apparent at both extremes of the salary distribution. The strikers at the 10th percentile tend to be young and inexperienced players whose full potential has yet to be realized. These players fit the characterization of rookie players identified by Bollinger and Hotchkiss (2003) as new arrivals from the baseball draft in North America. Team managers welcome the future prospects of such emerging talent, recognizing that high mean performance comes with high inconsistency, partly due to inexperience.

The 90th percentile is occupied by proven stars whose performance record is already known. Players at this level also deliver 'upside potential' but more in terms of winning key games that help a team towards winning championships and other trophies. Higher performance inconsistency, for the same mean level, is accompanied by the capability to win important games by a small margin, quite likely a single goal. That special match-winning and championship-winning capability is rewarded by higher salary.

[Insert Table 11 here]

Overall, our results are intriguing because they show (1) that only inconsistency in those actions that increase the chances of scoring are positively rewarded and (2) that single performance indicators, such as IVG or *Kicker* grades are highly skewed because of these scoring effects – an outcome bias that has been empirically

demonstrated by Gauriot and Page (2018). Attacking players need to be creative to improve their chances of scoring goals and this is what seems to be rewarded, both in mean and variance. In essence, similar to other industries with highly skewed positive returns (e.g., software), an additional goal scored (conceded) in one match can lead to extraordinary revenues (losses), i.e., returns of scoring are highly disproportional. This is one of the reasons offensive players that need to creatively outplay defenders to score goals are allowed to be inconsistent in comparison to defensive players.

For defensive players, being inconsistent might lead to goals conceded by the opponent team. Contrary to offensive players, inconsistency in defense is penalized in salary. Just as scoring generates disproportionate positive returns, so too do mistakes in defensive areas generate disproportionate risks of conceding goals, i.e., negative returns. The results are in line with previous research in the software industry, where positive outcomes are highly skewed and software developers in these industries experience faster salary growth (Andersson et al., 2009).

Moreover, the results indicate that inconsistency is rewarded for creative skills that have a high positive impact. Just as workers have different types of tasks where, for some, consistency in execution is preferred over creativity (e.g., highly repetitive and administrative tasks), there are other types of tasks where creativity and problem solving is much more important and therefore inconsistency might be highly rewarded.

5. Discussion and Conclusion

In this paper, we analyze whether inconsistent workers earn a salary premium. By analyzing 78,302 player-match observations over eight seasons (from 2009-10 to 2016-17) in the Italian Serie A, we show that inconsistent players earn a salary premium when only one performance indicator is used to assess overall match performance. Analyzing more detailed performance metrics from on-field actions of the same players, we show that inconsistency is only rewarded for some dimensions of

performance, while it is penalized in others. That is, players that are inconsistent in defense are penalized, while offensive players earn a salary premium for being inconsistent.

We confirm earlier results that used European football data to test whether performance inconsistency is rewarded. In contrast to previous research (Deutscher & Büschemann, 2016) we show that using single performance indicators for overall performances (e.g., expert ratings, grades, or single performance indices) is not sufficient to test this relationship, especially because single performance indicators cannot capture the complexity of different skillsets that are needed for different job roles. Here, we go further; we apply factor analysis and introduce three factors that capture the different skillsets that are needed on the field. These three factors correspond closely to player positions on the field. Using our three components, we show that greater inconsistency is rewarded in salary for players with high scores in attacking skillsets, but it is penalized in salary for defensive players. To the best of our knowledge, this is the first paper that can show these relationships in detail for subgroups of workers in team production. Our results suggest that a simple focus on performance variation in one metric is inadequate for consideration of salary determination.

Although we exploit a rich data set for our paper, there are also technical limitations regarding our performance metrics. Measuring individual performance in team competitions is not always conclusive. While an attacking player's performance can be measured in the number of dribbles, shots on target, assists, or goals, it is much more difficult to measure the individual performance of a defensive or midfield player. Because good defending is usually a team effort requiring considerable coordination among team members. Midfield players have both attacking and defensive responsibilities including regaining possession for their team and the effort provided in that task is hard to capture empirically.

Moreover, positional play in defense is an important skill that cannot be as easily measured compared to blocked shots or tackles. In some cases, a tackle might

even be an outcome of bad positional play. In that sense, the action and event statistics that are gathered for defensive players might not fully cover their actual performances. A tackle that has occurred can be both an outcome of good defending or bad defending depending on the situation in a game. This is a common problem in football: data providers can gather events and measure what is happening on the field, while they cannot gather what is not happening, e.g., a lost attacking chance because the defending team had extraordinary positional play or because of poor decision-making by the attackers. As sports analytics develops further, we expect better metrics for all players to emerge with explicit consideration of the context for player actions. Such improved measures will greatly facilitate analysis of salary determination in team sports.

Notwithstanding issues with performance evaluation in football, our results point to an interesting and important separation of effects of performance inconsistency on salary. Creative and star performers appear to be rewarded for inconsistent outcomes. Workers who perform more mundane but essential tasks, who are not primarily responsible for spectacular payoffs for their employers, appear to be rewarded for consistent outcomes. That polarity in our results merits further research in other labor market settings.

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Table 1: Definitions of observed variables for factor analysis.

Accurate crosses	Accurate passes from a wide position to a central attacking area.
Accurate long balls	Accurate passes of 22.83 meters or more.
Accurate through balls	Accurate passes between opposition players in their defensive line to find an onrushing teammate (running through on goal).
Aerial duels won	Winning a header in a direct contest with an opponent.
Anticipations	Preventing an opponent's pass from reaching their teammates.
Assists	Pass leading to scoring a goal.
Balls played	Total number of played balls.
Balls played in opp. half	Total number of played balls in the opposition half.
Blocked shot	An outfield player's prevention of an opponent's shot reaching the goal.
Clearances	Defending player that removes the attacking threat on their goal, effectively alleviating pressure on their goal.
Counterattack	An attack made in response to one by an opponent.
Fast breaks	Attempts to move the ball up the pitch and into scoring position as quickly as possible.
Goal chances	Players' opportunity to score a goal.
Goals	Scoring a goal.
Goals from inside goal area	Goal scored inside the box.
Interceptions	Preventing an opponent's pass from reaching their teammates leading to ball possession.
Recovered balls	Recovering the ball and keeping possession of the ball.
Recovered balls in def. area	Recovering the ball and keeping possession (defensive area).
Shots	Total number of player's shots.
Shots on target	Attempts to score which required intervention to stop it from resulting in a goal.
Successful passes	Passes from a player to a teammate.
Total tackles	Dispossessing an opponent, whether the tackling player comes away with the ball or not.
Useful dribbles	Dribbles that provide an advantage.
Useful plays	Plays that generate an advantage in favor of the team that possesses the ball.
Useful plays in opp.half	Plays that generate an advantage in favor of the team possessing of the ball (opposition's half).
Useful short passes in opp. half	Short passes that generate an advantage in favor of the team possessing the ball (opposition half).

Table 2: Descriptive statistics of on-field metrics (observed variables) used for factor analysis.

Variable	Obs.	Mean	SD	Min	Max
Balls played	78,302	40.572	22.428	0	196
Balls played in opp. half	78,302	19.634	14.603	0	131
Successful passes	78,302	25.844	17.405	0	176
Useful plays	78,302	6.830	5.723	0	76
Useful plays in opp. half	78,302	3.357	3.538	0	48
Recovered balls	78,302	10.446	7.627	0	50
Recovered balls in def. area	78,302	5.244	5.613	0	35
Anticipations	78,302	1.453	1.983	0	23
Counterattack	78,302	0.514	0.807	0	8
Fast breaks	78,302	1.933	1.944	0	18
Useful dribblings	78,302	0.595	1.029	0	14
Assists	78,302	0.644	0.979	0	10
Goal chances	78,302	0.350	0.714	0	8
Shots	78,302	0.973	1.328	0	13
Goal from inside goal area	78,302	0.019	0.138	0	3
Useful short passes in opp.	78,302	0.927	2.002	0	39
Shots on target	78,302	0.343	0.687	0	8
Aerials won	78,302	0.993	1.412	0	15
Total tackles	78,302	1.553	1.658	0	16
Interceptions	78,302	1.299	1.569	0	13
Clearances	78,302	2.135	3.027	0	29
Blocked shots	78,302	0.241	0.563	0	7
Accurate crosses	78,302	0.381	0.820	0	11
Accurate long balls	78,302	2.033	2.634	0	29
Accurate through balls	78,302	0.094	0.345	0	6
Goals	78,302	0.091	0.318	0	5

Table 3: Factor Analysis.

Factor	Eigenvalue	Differences	Proportion	Cumulative
Factor1	6.06159	1.53575	0.4287	0.4287
Factor2	4.52584	2.54691	0.3201	0.7488
Factor3	1.97894	1.34984	0.14	0.8888
Factor4	0.62909	0.0682	0.0445	0.9332
Factor5	0.56089	0.18724	0.0397	0.9729
Factor6	0.37364	0.05432	0.0264	0.9993
Factor7	0.31932	0.07022	0.0226	1.0219
Factor8	0.2491	0.05942	0.0176	1.0395
Factor9	0.18968	0.03235	0.0134	1.053
Factor10	0.15733	0.0447	0.0111	1.0641
Factor11	0.11263	0.05272	0.008	1.072
Factor12	0.05991	0.03381	0.0042	1.0763
Factor13	0.0261	0.00964	0.0018	1.0781
Factor14	0.01646	0.02975	0.0012	1.0793
Factor15	-0.01329	0.01194	-0.0009	1.0784
Factor16	-0.02524	0.00395	-0.0018	1.0766
Factor17	-0.02918	0.0386	-0.0021	1.0745
Factor18	-0.06778	0.0122	-0.0048	1.0697
Factor19	-0.07998	0.00193	-0.0057	1.0641
Factor20	-0.08191	0.00491	-0.0058	1.0583
Factor21	-0.08682	0.00161	-0.0061	1.0521
Factor22	-0.08843	0.02903	-0.0063	1.0459
Factor23	-0.11745	0.03034	-0.0083	1.0376
Factor24	-0.1478	0.04177	-0.0105	1.0271
Factor25	-0.18957	0.00413	-0.0134	1.0137
Factor26	-0.1937	.	-0.0137	1

Number of observations: 78,302 Retained factors: 3

Table 4: Factor Analysis – Rotated Factors (oblique promax).

Factor	**Variance**	**Proportion**	Rotated factors are correlated
Factor1	5.33453	0.3773	
Factor2	5.06215	0.358	
Factor3	3.22875	0.2284	
Number of observations: 78,302		Retained factors: 3	

Table 5: Rotated (oblique promax) factor loadings and pattern matrix.

Variable	**Factor1** Playmaking	**Factor2** Defense	**Factor3** Striker	**Uniqueness**
Balls played	0.772	0.450	0.057	0.118
Balls played in opp. half	0.818	-0.242	0.179	0.213
Successful passes	0.741	0.404	-0.050	0.215
Useful plays	0.851	0.229	-0.080	0.184
Useful plays in opp. half	0.904	-0.236	0.017	0.170
Recovered balls	0.220	0.904	0.016	0.095
Recovered balls in def. area	-0.069	0.946	0.005	0.120
Anticipations	0.030	0.700	0.005	0.506
Counterattack	0.182	0.181	0.017	0.927
Fast breaks	0.528	0.392	-0.086	0.508
Useful dribblings	0.375	-0.162	0.171	0.781
Assists	0.520	-0.236	0.103	0.661
Goal chances	-0.006	0.026	0.834	0.318
Shots	0.198	-0.085	0.715	0.364
Goal from inside goal area	-0.101	0.106	0.425	0.841
Useful short passes in opp. half	0.494	-0.048	-0.063	0.767
Shots on target	0.020	0.021	0.828	0.318
Aerials duels won	-0.041	0.409	0.163	0.849
Total tackles	0.261	0.363	-0.047	0.770
Interceptions	0.124	0.578	-0.021	0.627
Clearances	-0.167	0.804	0.047	0.379
Blocked shots	-0.068	0.413	0.011	0.835
Accurate crosses	0.462	-0.204	-0.016	0.771
Accurate long balls	0.413	0.350	-0.062	0.666
Accurate through balls	0.265	-0.119	0.066	0.908
Goals	-0.096	0.112	0.726	0.524

Table 6: List of dependent and independent variables and their descriptions.

Variable	Description
LN(SALARY$_t$)	Natural logarithm of salary in season t.
MEAN IVG$_{t-1}$	Average performance in season t-1.
SD IVG $_{t-1}$	Standard deviation of performance in season t-1.
PLAYMAKING $_{t-1}$	Average playmaking skills in season t-1.
SD PLAYMAKING $_{t-1}$	Standard deviation of playmaking skills in season t-1.
DEFENSE $_{t-1}$	Average defensive skills in season t-1.
SD DEFENSE $_{t-1}$	Standard deviation of defensive skills in season t-1.
STRIKER $_{t-1}$	Average striking/scoring skills in season t-1.
SD STRIKER $_{t-1}$	Standard striking/scoring skills in season t-1.
AGE$_t$	Age of player in season t.
AGE$_t^2$	Age squared of player in season t.
CAREERGAMES$_t$	Cumulative number of career games in the Serie A in season t.
CAREERGAMES $_t^2$	Cumulative number of career games sq. in the Serie A in season t.
NATIONALTEAM$_t$	Dummy = 1 if appeared in the national team squad in season t.
DEFENDER$_t$	Dummy = 1 if player is a defender.
MIDFIELDER$_t$	Dummy = 1 if player is a midfielder.
FORWARD$_t$	Dummy = 1 if player is a forward.
NONEU	Dummy = 1 if player is a non-European player.
Team dummies	Dummy variable for team.
Season dummies	Dummy variable for season.

Table 7: Descriptive statistics of dependent and independent variables.

Variable	Obs.	Mean	SD	Min	Max
LN(SALARY$_t$)	2,049	7.308	0.808	4.094	9.616
MEAN IVG$_{t-1}$	2,049	17.744	1.523	11.733	23.323
SD IVG $_{t-1}$	2,049	2.761	0.689	0.212	6.241
PLAYMAKING $_{t-1}$	2,049	0.074	0.645	-1.228	3.831
SD PLAYMAKING $_{t-1}$	2,049	0.684	0.251	0.019	2.055
DEFENSE $_{t-1}$	2,049	0.096	0.819	-1.268	2.242
SD DEFENSE $_{t-1}$	2,049	0.503	0.230	0.043	1.300
SRIKER $_{t-1}$	2,049	-0.016	0.565	-0.801	3.320
SD STRIKER $_{t-1}$	2,049	0.631	0.390	0.010	2.241
AGE$_t$	2,049	28.128	4.147	17.000	40.800
AGE$_t^2$	2,049	808.372	236.167	289.000	1,664.640
CAREERGAMES$_t$	2,049	138.226	100.027	5.000	619.0
CAREERGAMES $_t^2$	2,049	29,106.9	42,486	25.0	383,161
NATIONALTEAM$_t$	2,049	0.540	0.499	0	1.000
DEFENDER$_t$	2,049	0.368	0.482	0	1.000
MIDFIELDER$_t$	2,049	0.429	0.495	0	1.000
FORWARD$_t$	2,049	0.203	0.402	0	1.000
NONEU	2,049	0.424	0.494	0	1.000

Table 8: Estimation results for OLS and FE regressions (IVG).

Dependent variable: LN(SALARY$_t$)	**OLS** **(1)**	**FE** **(2)**	**OLS** **(corr. IVG)** **(3)**	**FE** **(corr. IVG)** **(4)**
MEAN IVG$_{t-1}$	0.074***	0.005	0.080***	0.017
	(0.008)	(0.010)	(0.012)	(0.012)
SD IVG$_{t-1}$	0.079***	0.040***	0.131***	0.056***
	(0.016)	(0.015)	(0.016)	(0.016)
AGE$_t$	0.374***	0.410***	0.372***	0.398***
	(0.038)	(0.073)	(0.038)	(0.072)
AGE$_t^2$	-0.006***	-0.009***	-0.006***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
CAREERGAMES$_t$	0.002***	0.007***	0.002***	0.007***
	(0.000)	(0.001)	(0.000)	(0.001)
CAREERGAMES$_t^2$	-0.000**	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
NATIONALTEAM$_t$	0.115***		0.095***	
	(0.023)		(0.023)	
MIDFIELD$_t$	0.062***		0.025	
	(0.024)		(0.022)	
FORWARD$_t$	0.259***		0.246***	
	(0.033)		(0.031)	
NONEU	0.100***		0.095***	
	(0.023)		(0.023)	
Constant	-0.339	1.841	-0.446	1.816
	(0.554)	(1.335)	(0.564)	(1.339)
Observations	2,049	2,049	2,049	2,049
Number of Players		725		725
R^2	0.723	0.526	0.731	0.533
Adj. R^2	0.716	0.516	0.724	0.522
Season Dummies	YES	YES	YES	YES
Team Dummies	YES	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimation results for quantile regressions (IVG).

Dependent variable: LN(SALARY$_t$)	**(1)** 10th pctile	**(2)** 25th pctile	**(3)** Median	**(4)** 75th pctile	**(5)** 90th pctile
MEAN IVG$_{t-1}$	0.088***	0.066***	0.072***	0.066***	0.067***
	(0.013)	(0.010)	(0.009)	(0.010)	(0.013)
SD IVG$_{t-1}$	0.056**	0.059***	0.063***	0.106***	0.106***
	(0.024)	(0.020)	(0.018)	(0.020)	(0.025)
Constant	-3.886***	-1.431**	-0.237	2.078***	2.175***
	(0.705)	(0.565)	(0.525)	(0.567)	(0.732)
Observations	2,049	2,049	2,049	2,049	2,049
Pseudo R^2	0.420	0.469	0.507	0.537	0.537
Controls	YES	YES	YES	YES	YES
Season Dummies	YES	YES	YES	YES	YES
Team Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05

Table 10: Estimation results for OLS and FE regressions (FA).

Dependent variable: LN(SALARY$_t$)	**OLS** **(1)**	**FE** **(2)**
PLAYMAKING$_{t-1}$	0.117***	0.083***
	(0.028)	(0.026)
SD PLAYMAKING$_{t-1}$	0.021	0.066
	(0.074)	(0.059)
DEFENSE$_{t-1}$	0.194***	-0.016
	(0.029)	(0.036)
SD DEFENSE$_{t-1}$	-0.247***	-0.045
	(0.087)	(0.068)
STRIKER$_{t-1}$	0.226***	0.060
	(0.049)	(0.054)
SD STRIKER$_{t-1}$	0.166***	0.069
	(0.059)	(0.052)
AGE$_t$	0.351***	0.389***
	(0.038)	(0.071)
AGE$_t^2$	-0.006***	-0.009***
	(0.001)	(0.001)
CAREERGAMES$_t$	0.002***	0.007***
	(0.000)	(0.001)
CAREERGAMES$_t^2$	-0.000	-0.000***
	(0.000)	(0.000)
NATIONALTEAM$_t$	0.080***	
	(0.023)	
MIDFIELD$_t$	0.084***	
	(0.031)	
FORWARD$_t$	0.266***	
	(0.053)	
NONEU	0.106***	
	(0.022)	
Constant	1.543***	2.265*
	(0.531)	(1.306)
Observations	2,049	2,049
R^2	0.739	0.538
Adj. R^2	0.732	0.526
Season Dummies	YES	YES
Team Dummies	YES	YES
Number of Players		725

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 11: Estimation results for quantile regressions with factor scores.

Dependent variable: LN(SALARY$_t$)	**(1)** 10th pctile	**(2)** 25th pctile	**(3)** Median	**(4)** 75th pctile	**(5)** 90th pctile
PLAYMAKING$_{t-1}$	0.114***	0.105***	0.142***	0.147***	0.132***
	(0.039)	(0.032)	(0.031)	(0.030)	(0.042)
SD PLAYMAKING$_{t-1}$	0.056	0.112	-0.077	-0.044	-0.075
	(0.098)	(0.080)	(0.078)	(0.076)	(0.104)
DEFENSE$_{t-1}$	0.180***	0.215***	0.177***	0.143***	0.135***
	(0.041)	(0.033)	(0.033)	(0.032)	(0.044)
SD DEFENSE$_{t-1}$	-0.178	-0.174*	-0.248***	-0.224**	-0.184
	(0.114)	(0.093)	(0.091)	(0.088)	(0.122)
STRIKER$_{t-1}$	0.178**	0.290***	0.295***	0.184***	0.166**
	(0.071)	(0.057)	(0.056)	(0.054)	(0.075)
SD STRIKER$_{t-1}$	0.220**	0.074	0.082	0.190***	0.221**
	(0.088)	(0.071)	(0.070)	(0.068)	(0.094)
Constant	-1.504**	0.946*	2.257***	3.532***	3.759***
	(0.649)	(0.526)	(0.514)	(0.501)	(0.690)
Observations	2,049	2,049	2,049	2,049	2,049
Pseudo R^2	0.434	0.486	0.527	0.555	0.550
Controls	YES	YES	YES	YES	YES
Season Dummies	YES	YES	YES	YES	YES
Team Dummies	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05