Do high wage footballers play for high wage teams? The case of Major League Soccer

by Rachel Scarfe, Carl Singleton and Paul Telemo

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Department of Economics
University of Reading
Whiteknights
Reading
RG6 6AA
United Kingdom

www.reading.ac.uk
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Rachel Scarfe       Carl Singleton       Paul Telemo*

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Abstract

Intuition and sports knowledge suggest the most talented professional footballers play for the best teams, i.e. positive assortative matching based on productivity. We consider Major League Soccer between 2007 and 2017. We estimate a wage equation, finding that player and team fixed wage premiums are negatively correlated. This is a puzzle, especially because our estimates of players’ wage premiums do correlate strongly with measures of their performance on the pitch, and there is evidence of teammate sorting. One potential solution to this puzzle would be that players match to teams according to some sort of compensating wage differential, for example from their desire to play for successful or well-supported teams; the estimated wage premiums of MLS teams are highly and negatively correlated with their success in the league and their home game attendances.

Keywords: firm-specific wages, AKM wage equation, matching, superstar pay

JEL codes: J31, J49, Z22
1 Introduction

The question of whether high productivity workers are matched to high productivity firms is of considerable interest, not least because it sheds light on the matching process taking place between workers and firms (e.g. Becker, 1973; Shimer and Smith, 2000). To address this, studies have used longitudinal linked employer-employee data to estimate AKM (Abowd, Kramarz and Margolis, 1999) wage equations, which admit both worker and firm fixed effects: if the fixed effects are indicative of worker and firm productivity, then the sign and magnitude of the correlation between these two sets of estimated effects may indicate whether a labour market features assortative matching of worker and firm productivity types (e.g. Andrews et al., 2012; see Lopes de Melo, 2018, for a summary of the evidence on assortative matching in labour markets using the AKM methodology).

Association football, or soccer, has been extensively studied by labour and sports economists (Frick, 2007). Due to the global popularity of football and the nature of the game, there is extensive data on measures of worker (player) and firm (team) productivity. Data on player wages is rarer, but where it exists it has been combined with the readily available productivity data to attempt to draw insights about labour markets in general. Because the market for football talent features high levels and variance of earnings, much of this literature has focused on the impact of superstars and what determines their wages (e.g. Lucifora and Simmons, 2003; Coates et al., 2016), and the related migrant wage premium (e.g. Bryson et al., 2014). Other studies have more generally asked what determines the pay of football players (e.g. Kuethe and Motamed, 2010; Thrane, 2019).

The fact that the market for professional football players is generally closed off from the rest of the labour market, with very little mobility in or out during the typical career span of a footballer, makes this an appropriate context to study the assortative matching of workers and firms. To investigate this, we estimate an AKM wage equation using data on the earnings of professional football players in US Major League Soccer (MLS) between 2007 and 2017. Despite the very particular nature of this labour market, including its rules and regulations, which we elaborate on further in Section 2, there are some advantages from studying it, reflected in the number of previous studies which have done so (e.g. Kuethe and Motamed, 2010; Coates et al., 2016; Jewell, 2017). First, we observe the salaries of almost all players rather than a limited sample. Second, our data includes worker and firm productivity measures (e.g. minutes played and league performance), which means we can sense check the interpretation of the results from applying the AKM methodology to this question. We would be naïve to think that our estimates from an AKM wage equation in this context provide conclusive evidence on the presence or not of assortative matching. Nonetheless, we can answer
the question of whether high wage footballers play for high wage teams, as fundamentally, despite the peculiarities, this is a market where players and teams negotiate pay, where players receive and reject offers from teams, and where teams search for and match with talent.

We find that the correlation between estimated player and team fixed wage effects is small and negative. This result is robust to varying the sample selection, including excluding the superstar designated players of Major League Soccer (e.g. David Beckham). High wage footballers do not appear to play for high wage teams in this talent market. Yet intuitively, and based on sports knowledge, we would expect that the most talented footballers do in fact play for the most successful teams. As suggestive evidence that this might nonetheless be the case in MLS, there is evidence of player segregation across teams, as players earning high wage premiums tend to have teammates with similarly high wage premiums.

This is not the first study to consider the issue of assortative matching in football, or sport more generally. Gandelman (2008) showed that positive assortative matching exists in football, in terms of players’ performances on the pitch being correlated with the nature of their mobility across teams, with good performances leading to promotion to a better team and poor performance leading to demotion. Outside of football, Filippin and van Ours (2015) find similar patterns by studying the performance and mobility of elite long-distance runners across teams in Italy. Returning to football, Drut and Duhautois (2017) use player and team performance data from five seasons of Italian professional football, along with wages, to find substantial evidence of positive assortative matching using an AKM approach. They estimate a correlation between player and team fixed wage premiums of 0.46. Because their data features a high degree of mobility and approximately the universe of players over their sample period, they argue that the AKM-type wage models are appropriate for detecting assortative matching when the amount of mobility observed is not limited. In our study, we apply a similar approach to Drut and Duhautois (2017), but we study a longer sample period of eleven seasons. This ought to allow more precise and robust estimates of the AKM wage equation, as well as featuring greater mobility of players between clubs with which to identify relative team wage premiums. Furthermore, the MLS is a very different institution when compared with Italian professional football, not least in terms of competitive balance: in Italy, the same team, Juventus F.C., have been the champions in each of the past 8 seasons between 2011/12 and 2018/19, whereas over the same period only one team won the MLS Cup more than once.

There are potential ways to reconcile the particular differences between our results for MLS compared with the findings from Drut and Duhautois (2017) for Italy. The first is negative ‘limited mobility bias’ in the estimated correlation of the player and team fixed effects (Andrews et al., 2008). However, like Drut and Duhautois (2017), the data we use are approximately a universe of players and teams, and we show this source of bias is not an
issue. Second, it may be difficult to identify assortative matching using wage data alone, and in fact a small or negative correlation estimate from an AKM wage equation does not rule out that in fact high productivity workers move to and match with high productivity firms (e.g. Eeckhout and Kircher, 2011; Lopes de Melo, 2018; Bartolucci et al., 2018). There are specific reasons why this might be the case in a football talent market. First, salary regulation could affect hiring decisions and the distribution of surplus when a player and team match. Second, there are well-known examples throughout football of players who turn down lucrative wage offers from more successful teams to instead play for teams they have some personal affinity for, such as their home-town team.  

Closely related, footballers perhaps have some preference to play for successful (productive) and well-supported teams, and their decisions might not be just about the money offered directly by teams. In other words, players who switch to more successful teams may be willing to accept relatively low wages. We find evidence to suggest that this is a plausible explanation for MLS. Like Drut and Duhautois (2017) show for Italy, we find that the players’ estimated wage premiums do correlate strongly with measures of their productivity for teams on the football pitch. However, unlike in Drut and Duhautois (2017), this is not the case for the estimated team wage premiums: more successful teams, both in terms of winning football matches and attracting supporters, and thus revenue, pay significantly lower wages in MLS.

The remainder of the paper proceeds as follows: Section 2 introduces our data and briefly discusses the context of MLS, given this has been widely covered elsewhere in the literature; Section 3 describes the Mincerian AKM wage equation which we estimate; Section 4 presents our results; and Section 5 concludes.

2 Data

The data on player wages and team affiliations come from the MLS Players’ Association (MLSPA), the collective bargaining representative of players during the negotiation of league-wide salary rules. These data refer to midway through each MLS season in August of each year, after the secondary transfer window when players can be signed from abroad. The wage measure is the guaranteed annualised compensation or salary, henceforth referred to as wages. This includes payments for signing with a team or related to marketing.  

1For example, Francesco Totti played for his home-town team AS Roma for his whole career, despite reported huge offers from Spain for his services; https://www.marca.com/en/football/real-madrid/2018/11/27.html

2It does not include team- or individual-level performance payments. However, according to the league’s annual bargaining agreements, team-level performance payments are a tiny fraction of overall salary payments. Individual performance payments that are considered “achievable are” included in the team’s total salary figure, which is subject to a cap. We have compared total team salaries to the salary cap and found that reported total team salaries are close to, or exceed, the cap, suggesting that individual performance payments are not large.
Figure 1 tracks percentiles of player log wages between 2007 and 2017. This was a period of rapid pay growth in MLS, with nominal wages more than doubling across the distribution, and an increase in the median of 160%. This coincided with the growing popularity of the league, higher revenues and more foreign players choosing to play in the US (Brownlee and Lorgnier, 2017). The league expanded in this period, from 13 teams in 2007 to 22 in 2017.\footnote{The analysis covers 23 teams, since one was dissolved in 2014; 2007: 13, 2008: 14, 2009: 15, 2010: 16, 2011: 18, 2012-2014: 19, 2015-2016: 20, 2017: 22.}

FIGURE 1: Percentiles of MLS player log (guaranteed) wages, 2007-2017

![Figure 1: Percentiles of MLS player log (guaranteed) wages, 2007-2017](image)

Notes.- author calculations using MLSPA data.

MLS is unique when compared with other professional football leagues. The league itself is closed, with no promotion or relegation, and the only change in membership is through franchise expansion or dissolution. There are detailed regulations concerning pay and the mobility of players in MLS (see Kuethe and Motamed, 2010 or Coates et al., 2016 for a comprehensive discussion). Like other US sports leagues there is a salary cap, but this only covers the first 18-20 of up to 30 players registered on a team’s roster for the season.\footnote{For example, the salary cap does not cover young “homegrown” players from the USA.} Players in MLS are technically not paid by their team, but by the League itself, with whom they have a contract. Despite this, each team negotiates with each player on their roster to determine their salaries, which is the measure of the wage we use in this analysis. The teams’ overall budgets affecting these wage negotiations, besides what appears in some sense to be a nominal salary cap, are determined by their revenues, mostly from attendance at home games (Brownlee and
Lorgnier, 2017). Teams can also hire so-called designated players, between one and three each season over the period we study, whose wages are in effect mostly outside the salary cap. In most cases these are the highest paid players in a team. Each designated player contributes to the salary cap up to a fixed percentage of the overall cap level. Teams also pay a lump sum tax to the League for each designated player.

To level the playing field, the League also makes not insignificant monetary allocations to some teams each season, typically those that do not make the end of season playoffs through their performances on the pitch, effectively raising their salary caps (Coates et al., 2016). Similarly, if the teams fill their third designated player slot, which the higher revenue teams are most likely to do, the tax to the league from doing so is redistributed to the others above the cap, raising their purchasing power in the market.

Despite these and other regulations, in reality it appears that teams in MLS are operating to a salary budget rather than an effective league-wide cap. For example, Figure 2 shows the guaranteed salary totals for teams in the 2017 season. There is substantial variation across teams, ranging from $5million for the lowest budget teams to over $20million for the highest, whereas the salary cap for roster spots 1-20 that year was just $3.85million.

**FIGURE 2: Team guaranteed salary totals for the 2017 MLS season**

Due to the peculiar contracting situation in this talent market, player mobility between teams is to an extent controlled by the league, under the roster regulations mentioned above. That said, players and teams are not forced upon one another. Players can reject moves and
any offers made by other teams. They also have outside options. Similarly, teams search for, evaluate and choose the players which make up their rosters. Combined with the fact that players and teams negotiate pay, the question of what the general sorting and matching patterns are between employer and employee in this labour market are just as relevant in any other. Though the peculiarities of MLS make it not a priori obvious that these patterns will be similar to those found elsewhere.

We obtain information on a player’s age, the number of games they started, minutes played during a season, designated player status, assists, goals and shots at goal, and team-level performance data, including season average attendances, from the MLS official website. A handful of player observations are dropped from the dataset, where we could not reliably match a record in the salary data with the information on player characteristics. In our preferred specification and results, we exclude any observations where the player did not play for their team in that season, thus ignoring any players who were either continuously injured or just making up the numbers on a team’s roster. This leaves 4,213 player-year observations, covering 1,410 different players. The minimum, median and maximum ages of players in the analysis are 15, 25 and 42, respectively. Almost 7% of player-year observations are designated players. The median number of teams played for over player-year observations is 2, implying a significant amount of mobility between teams. Just under 30% of the players represented in the main results played for more than one team in 2007-2017.

### 3 Method

To decompose wages into components associated with players and with teams, we use an AKM wage equation with player and team fixed effects. Let there be \( i = 1, \ldots, P \) players, \( j = 1, \ldots, J \) teams, \( t = 1, \ldots, T \) years, \( T_i \) years per player and \( N = \sum_i T_i \) total observations. The standard Mincerian AKM-type wage equation is given by:

\[
    w_{it} = \alpha_i + \phi_{J(it)} + x_{it}' \beta + \epsilon_{it},
\]

where \( w_{it} \) is the log wage for player \( i \) in year \( t \) and \( \alpha_i \) is the player fixed effect. Team fixed effects with mean zero are given by \( \phi_{J(it)} \), where \( J(it) = j \) indicates the team employing player \( i \) in year \( t \). In this specification, the player and team fixed effects capture constant unobserved heterogeneity in players and teams respectively. \( x_{it} \) is a vector of time-varying observable characteristics: a dummy variable indicating designated players; player age minus 15, to roughly represent football career experience; this value squared and cubed, all to address

5https://www.mlssoccer.com/stats
football-life-cycle wage growth; and year effects, accounting for average annual wage growth in MLS. The remaining heterogeneity in wages is in the residual, $\varepsilon_{it}$.

Equation (1) can be estimated using least squares with a strict exogeneity assumption: $E[\varepsilon_{it} | x_{it}, \alpha_i, \phi_{J(it)}] = 0$. In words, the estimated team fixed effects will be biased if players change teams due to some component of $\varepsilon_{it}$, such as transitory shocks to team-wide or player-team match-specific wage effects. This is equivalent to assuming that players are assigned randomly to teams, conditional on the observable characteristics $x_{it}$ and the unobservable time-invariant heterogeneity captured by $\alpha_i$ and $\phi_{J(it)}$. Most applications have found that labour market data appear to support this exogenous mobility assumption (see Card et al. (2018), for a general discussion of this assumption in reality and practice). As a rough test for one implication of this assumption, we look at the year-to-year changes in residual wages for players at their original clubs prior to moves within MLS. We obtain measures of residual wages by estimating the equivalent of Equation (1) without the player or team fixed effects; i.e. we estimate using least squares the equation:

$$w_{it} = x_{it}'\tilde{\beta} + \eta_{it},$$

where $\eta_{it} = \alpha_i + \phi_{J(it)} + \varepsilon_{it}$ is a residual measure of a player’s wages, after controlling for their experience in MLS and average annual wage growth. If players move between teams exogenously, then on average we should not observe any growth or decline in their residual wages prior to a player move. For the 321 player moves in our main analysis sample where that player had played for their previous club for at least two years, we find no significant evidence that mobility is related to a change in wages at the previous club. On average, these players experienced annual residual wage growth of 2.6% between the two seasons before their moves, with a median value of 0.8%. The mean residual wage growth is significantly different from zero and non-negative, providing some evidence that mobility is not related to depressed wage growth at the previous team.

The player fixed effects are constant and transferable, affecting wages wherever and whenever a player features in MLS, throughout their career in the league. The team fixed effects are wage premiums received by all players within a team, identified by players who switch teams. Therefore, estimates of these premiums are only comparable within connected sets of players and teams (Abowd et al., 2002). As we observe the salaries of almost all players during their time in MLS, in our main results all of the players and the 23 teams are connected in a single set, meaning our estimates will be fully representative of this particular labour market in this period. It is worth noting that we are only estimating the wage premiums for these individuals in their particular occupation as footballers in MLS, and for a portion of their
working lives. For instance, the model is completely silent on what wage premiums these particular workers gain from playing football in MLS as opposed to some other occupation, or even how the wage premiums in MLS compare to other football leagues where these players may also find themselves during their careers. For robustness we later vary the dependent variable of the wage regression, for example considering the log of wages per minute played. We also estimate Equation (1) excluding some players, such as designated players, who do not contribute fully to the teams’ salary caps.

To assess whether high wage players generally play for high wage teams in MLS, we consider the correlation between the estimated player and team fixed effects from Equation (1), $\text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_j(it))$. This measure is negatively biased because the fixed effects are estimated with errors (Andrews et al., 2008). This ‘limited mobility bias’ is large in small sample settings and related to the amount of observed mobility between teams. Andrews et al. (2008, 2012) predict and demonstrate empirically that the estimated value of $\text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_j(it))$ will be increasing and concave in the number of observed movers per team, asymptoting towards its true value as this mobility increases.

4 Results

Column (1) of Table 1 shows our preferred estimates of Equation (1). The fit of the wage equation is high with $R^2 = 0.91$. This fit increases only slightly to 0.95 when we estimate a version with player-team (match-specific) fixed effects rather than separate player and team effects, suggesting the assumed additive separability in Equation (1) is a workable assumption. In other words, the extent to which synergies between players and teams are reflected in players’ wages is small. Unsurprisingly, the designated player premium is large and significant at 65 log points, which is identified by players who switch between being a designated player or a standard roster player. The estimated coefficients on the age terms imply that on average a player’s wages fall up to age 20, then increase and peak at a 2.5% premium by age 27, thereafter declining rapidly, with a player aged 35 earning just 55% of what he would have earned when aged 29.

The estimated team fixed effects, $\hat{\phi}_j$, are shown in Figure 3. Relative to the average player-year wage, these team wage premiums range from -23 log points to 18 log points. Despite what might appear to be sizeable premiums, these are dwarfed by the overall wage variation in MLS. Individually, these wage premiums are not significantly different from zero at the 95% level. However, pair-wise, there are significant differences, implying that this talent

\footnote{This is illustrated by Figure 1. In 2017, for example, a player at the 90th wage percentile earned over 11 times more than a player at the 10th percentile.}
TABLE 1: AKM-style Regression model estimation results for log player wages, 2007-2017

<table>
<thead>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td>Designated player</td>
<td>0.652***</td>
<td>0.658***</td>
<td>0.655***</td>
<td>0.536***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.108)</td>
<td>(0.112)</td>
<td>(0.108)</td>
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<tr>
<td>Age (years)</td>
<td>-0.070</td>
<td>-0.124***</td>
<td>-0.073</td>
<td>0.093</td>
<td>-0.411***</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.041)</td>
<td>(0.052)</td>
<td>(0.059)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Age squared</td>
<td>0.012**</td>
<td>0.016***</td>
<td>0.012**</td>
<td>0.013**</td>
<td>0.030***</td>
</tr>
<tr>
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<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
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<td>(0.007)</td>
</tr>
<tr>
<td>Age cubed</td>
<td>-0.0006***</td>
<td>-0.0006***</td>
<td>-0.0005***</td>
<td>-0.0005***</td>
<td>-0.0008***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
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Player, team & year effects Yes Yes Yes Yes Yes

$R^2$                      | 0.913         | 0.922         | 0.862         | 0.849         | 0.685         |
RMSE                      | 0.349         | 0.342         | 0.341         | 0.361         | 0.732         |

St. dev. of log wages - $\text{Std}(\ln w_{it})$ | 0.959         | 0.981         | 0.743         | 0.929         | 1.057         |
St. dev. player effects - $\text{Std}(\hat{\alpha}_i)$ | 0.893         | 0.909         | 0.765         | 0.723         | 0.965         |
St. dev. team effects - $\text{Std}(\hat{\phi}_J)$ | 0.092         | 0.091         | 0.089         | 0.097         | 0.146         |
St. dev. observables - $\text{Std}(\hat{\beta})$ | 0.601         | 0.591         | 0.551         | 0.673         | 0.728         |

Correlation - $\text{Corr}(\hat{\alpha}_i, \hat{\phi}_J)$ | -0.102        | -0.097        | -0.084        | -0.110        | -0.121        |

| $N$: player-years | 4,213         | 5,195         | 3,906         | 3,138         | 4,213         |
| $P$: players     | 1,410         | 1,820         | 1,320         | 606           | 1,140         |
| $J$: teams       | 23            | 23            | 23            | 23            | 23            |
| $M/J$: mobility  | 27            | 30            | 26            | 25            | 27            |

Notes.- ***,**,* indicate significance from one at 1%, 5% and 10% levels, respectively, two-sided tests. Values in parentheses give standard errors robust to player-level clusters. Dependent variable is the log of guaranteed salary ($).
whom a suitable measure of their productivity would reflect their creativity, such as the number of goal assists they generate per 90 minutes. This is positively correlated with the player wage effects, with a correlation coefficient of 0.26, which would likely be higher if we were able to filter out more defensive-minded midfield players. The primary aim of a forward in football is to score goals. Therefore, panels (E) & (F) focus on forward players and show that the number of goals they score and the number of shots at goal they take per 90 minutes played are strongly positively correlated with their estimated fixed wage effects.

The evidence above suggests that the estimates of $\alpha_i$ do reflect individual player productivity. Similarly, the team fixed effects are often thought of as reflecting some type of team level productivity, that is not related to individual players’ productivity. This could be the team’s support structure for players, for example, facilities, or the management. Both elements contribute to the overall productivity of the team. We consider two possible measures of this overall productivity: the number of regular season points achieved per game and the average home attendance.\(^7\) There is a substantial literature which relates the two measures in sport, as well as in MLS specifically (e.g. Jewell, 2017; Wooten, 2018), but home attendance will also capture the purchasing power of teams, as this is their major source of revenue.\(^8\) We are able to

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\(^7\)In MLS, a win earns 3 points, a draw 1 point and a defeat no points. Cumulative points determine final league standings and qualification for playoffs.

FIGURE 4: Correlation of estimated player fixed wage effects with their teams’ performance and average attendance, and selected player performance statistics

(A) Team points per game

(B) Average home attendance

(C) Percent of team minutes played

(D) Midfielders: assists per 90 mins

(E) Forwards: goals per 90 mins

(F) Forwards: goals per 90 mins

Notes.- Estimates relate to Column 1 of Table 1. For each player, their performance and team-level statistics are first computed within season, and then an average is taken over the years each player appears in the MLS. In panel (C), there are 1,410 players represented. There are 573 players in panel (D) whose primary position was midfield, and 343 players in panels (E) and (F) whose primary position was forward.
compare the estimated player fixed effects with these team level productivity measures. Given the negative correlation we observe between $\text{Corr}_i(\hat{\alpha}_i, \hat{\phi}_j(t))$, we would not necessarily expect our estimates of $\alpha_i$ to correlate positively with overall measures of productivity. Figure 4(A) plots each player’s estimated fixed wage effect against the average over seasons of the points per game achieved by the team they play for each season. The correlation between the two statistics is slightly positive but weak at just 0.084. Similarly, in Figure 4(B), the correlation between each player’s estimated fixed wage effect and their teams’ average home attendance is practically zero.

Our prior assumption, based both on economic theory and sports knowledge, would be that the most productive soccer teams pay the highest wages, and this ought to be reflected in the estimates of the team fixed effect $\phi_j$. Figure 5(A) shows that there is a negative correlation between the average over seasons of the league points achieved per game and the team fixed effects. The Pearson correlation is -0.52, suggesting that teams which pay a high wage premium to all players have tended to have less success in the league. Similarly, panel (B) shows that the negative correlation between average home attendance and the estimates of $\phi_j$ is even stronger than for points per game, which rather counter-intuitively suggests that the better supported teams, with larger stadiums and revenues, pay lower wage premiums than the less well supported teams. The allocation monies distributed by MLS to less successful teams may partially account for this result, though they do not generally compensate entirely for differences between teams in their ability to generate revenue.

**FIGURE 5:** Correlation of estimated player fixed wage effects with their teams’ performance and average attendance, and selected player performance statistics

(A) Points per game

(B) Average home attendance

Notes.- Estimates relate to Column 1 of Table 1. Averages were taken of each year’s value over seasons when the team appeared in MLS between 2007-2017
Taken together, the evidence above suggests that our estimates of \( \alpha_i \) do reflect individual player productivity, but that our estimates of \( \phi_j \) are not reflective of team level productivity. Although the most productive players do play for the most productive teams, the most productive teams do not pay high wage premiums. One plausible explanation for the estimated small negative correlation between player and team wage premiums in MLS is the existence of some non-pecuniary attraction or compensating wage differential that players receive for playing for high productivity and well-supported teams. In other words, due to their preferences, the ‘best’ players might be willing to accept a lower team wage premium in order to play for the ‘best’ teams. For example, players may perhaps receive extra utility from doing well in the league. Alternatively, playing for a more productive club may lead to greater outside or future earnings potential, either through endorsements or corporate sponsorship deals, or through transferring to another league. This would give some teams greater ability to attract players in the market for talent. Further, this is not a labour market where wages are posted, but where wages are negotiated after player and teams have decided they are likely to be a good match. If more productive teams have higher bargaining power in these negotiations, then this explanation would also be consistent with the sports intuition that high productivity players in fact do play for high productivity teams, only that we are unable to identify this from wage data alone in this case. To offer some support for this conclusion, we consider the correlation between the players’ own estimated values of \( \alpha_i \) and the mean of their teammates, or co-workers, over all player-year observations in the sample, i.e. \( \text{Corr}_{it}(\hat{\alpha}_i, \hat{\alpha}_{J(it)}) \), where \( \hat{\alpha}_{J(it)} \) is the mean level of \( \alpha_i \) among the teammates of player \( i \). As Lopes de Melo (2018) explains, this provides a measure of co-worker segregation from the AKM wage model estimates. In the MLS, we estimate this correlation to be 0.22. There is suggestive evidence of positive co-worker sorting in this labour market. This implies that the distribution of player types or ability levels is not the same across firms, despite the finding that high wage players do not play for high wage teams, as evidenced by our small and negative estimate of \( \text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_{J(it)}) \).

As mentioned before, Drut and Duhautois (2017) find very different results in Italian football, with evidence from wage data of substantial positive assortative matching between players and teams. Ribeiro and Lima (2019) also find that players in Portugal receive wage increases when they move to teams further up in the domestic leagues, indicating that the high productivity teams in Portugal pay high wages. However, professional Italian and Portuguese football and US soccer differ in one key respect, that being competitive balance. Italian football, like most European leagues, has a much clearer hierarchy, as evidenced by Drut and Duhautois (2017) finding that the team fixed effects can account for a over a quarter of wage variation there. The equivalent estimate from MLS is just 1%, despite there being significant differences in these premiums between teams. The Portuguese first division is even less competitive: only four different teams have won the league since its inception in 1934. Therefore, one plausible
explanation for the differences between MLS and Italian or Portuguese football is that the presence of regulation and the salary cap has largely prevented the most productive teams from paying high wage premiums to attract the most productive players in the market for football talent. Instead, they must rely on other non-pecuniary attractions, such as the opportunity to win more often, or the potential for higher future earnings, as discussed above. If this is true, we should not expect to be able to observe positive assortative matching through wage data alone.

4.1 Robustness checks

We perform two sets of robustness checks. Firstly, despite using approximately the universe of players in this period, we nonetheless check that limited mobility in the sample is not biasing the estimated value of \( \text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_{J(it)}) \) downwards, as shown to occur when estimating this type of wage equation by Andrews et al. (2008). This might indicate that in fact there is a correlation between player and team fixed effects, and that high wage footballers do indeed play for high wage teams. To do this we drop at random 10%, 20% . . . 90% of the observations and re-estimate Equation (1) for the remaining largest connected sets of players and teams. In Figure 6 we plot the estimated correlation between the player and team fixed wage effects from each of these smaller samples against the number of observed player moves per team, \( M/J \). As per Andrews et al. (2012), we find that in smaller samples of MLS players the negative bias is substantial, and decreasing with the amount of mobility, \( M/J \), asymptoting to the figure of approximately -0.1 when we increase the sample size.

Secondly, we check that our results are not driven by a small group of particular players. To do so, we estimate three alternative versions of Equation (1). In Column (2) of Table 1, we show results using all player-year observations rather than only those who played for their teams during a season. This increases the number of player-year observations by almost 20% and adds 410 players, or 30%, reflecting that these players do not tend to stay in the MLS as long as those who are playing in games. There is very little change in our estimate of \( \text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_{J(it)}) \), suggesting that our results hold regardless of how much time players spend on the pitch.

Column (3) drops designated player-year observations from the sample used in the preferred results, including the 90 players who held designated status for their whole MLS careers. Although we address an average designated player wage premium in our preferred results of column (1), we nonetheless check whether our results are affected by any high wage outliers from the mega superstars of MLS (e.g. David Beckham, Kaká, Steven Gerrard, David Villa or Thierry Henry). There are three reasons why our results might be sensitive to the inclusion
FIGURE 6: Limited mobility bias and the estimated correlation between player and team fixed wage effects, $\text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_{J(it)})$

Notes.- Estimates are calculated by drawing random 10%, 20% etc. samples of player-year observations from those who started at least one game during the year. $M/J$ gives the average number of player moves per team in the resulting dataset’s largest connected set of players and teams.

of designated players in our sample. First, designated players are not subject to the same salary regulations as other players in the league. Second, they are less mobile within MLS than other players. Third, it is likely that a greater proportion of their salary comes from product endorsements and corporate sponsorship. $^9$ If this is true, then these players may be less concerned about bargaining a high wage when playing for a high productivity team. As we would expect, the standard deviation of both log wages and player fixed effects is lower in this specification. However, our estimate of $\text{Corr}_{it}(\hat{\alpha}_i, \hat{\phi}_{J(it)})$ is similar to that from our original specification. This suggests that the negative correlation we find is not due to a small number of designated players.

Column (4) drops from the analysis any players who featured in MLS for less than 3 years of the sample period, to focus on a subset of players which will generally have higher mobility. This drops 804 player observations, or 57%, but just 26% of the player-year observations. Finally, column (5) uses the preferred sample of column (1), but instead has as the dependent variable the log of wages per minute played during the season. Because the wages in our data are annual salaries, this specification estimates player and team fixed wage effects which are

$^9$For example, in 2016 Forbes estimated that Kaká earned $2$million, more than 25% of his salary, through endorsements. https://www.forbes.com/pictures/mlb45hdf/1-kaka-orlando-city-sc
more likely to be strongly correlated with innate values of realised productivity on the football pitch. Across all these different specifications, the main result on $\text{Corr}_{\alpha_i, \hat{\phi}_{f(i)}}$ remains robust, with the estimate varying between -0.08 and -0.12. Therefore, the estimates are not sensitive to the superstars in MLS, nor are they driven by the mobility of players who actually play very little, nor by players who leave MLS after only a short period.

5 Conclusion

In this article we show that high wage professional footballers do not play for teams that pay a high wage premium, at least as far as MLS is concerned. This is despite intuition and some existing empirical evidence suggesting that the most talented, or productive, footballers do play for the most successful teams.

We are able to use data on individual player productivity to show that the player fixed effects in an AKM wage equation do seem to reflect individual player productivity. However, the team fixed effects do not appear to reflect overall team productivity: those teams which pay a high wage premium have tended to have less success in the league. There are plausible reasons why this may be the case. Firstly, there may be some compensating wage differential that players receive from playing for a successful team, which means that successful teams do not need to pay high wage premiums to attract talented players. Alternatively, in this particular labour market the presence of regulations, including a salary cap, may have prevented the most productive teams from paying high wage premiums to their players. If this is the case, then this result may not generalise to other markets with fewer salary regulations, such as the sports talent markets outside of North America. Further research would be required to determine which explanation is the most likely.

Our findings also provide a cautionary example, by adding to a growing literature which suggests wage data alone can be insufficient to identify assortative matching on productivity between firms and workers.
References


