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Labor market dynamics in a highly competitive industry

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ABSTRACT

We study labor market dynamics of workers in a highly competitive industry with a highly competitive labor market. We focus on the relationship between workers' age, wages, and productivity. Our analysis uncovers an inverse U-shaped relationship. While some wage adjustments occur within the current firm, job mobility plays a crucial role in shaping wage trajectories. There is assortative matching with highly productive workers moving to highly productive firms, while less productive workers gravitate towards less productive firms. Our findings suggest that both in-firm wage progression and wage growth via job mobility contribute to a close alignment between wages and productivity throughout workers' careers.

1. Introduction

It is difficult to establish the age gradient of wage and productivity at the level of individual workers. The main challenge lies in finding an accurate measure of individual productivity. In the past, aggregate measures derived from matched employer–employee data sets have been used, but this approach is problematic for several reasons. Individual productivity is a complex phenomenon, influenced by factors such as physical strength, mental ability and work environment. Group productivity at the firm level is not only affected by the age distribution of the workforce but also by the nature and organization of the production process. When both productivity and age are aggregate measures at the firm-level, one must be cautious in drawing conclusions. One issue is reverse causality; growing firms tend to hire more workers, who are often younger. In this case, economic growth drives the average age of the workforce, rather than the other way around. Another issue is using earnings as an indicator of productivity, as union involvement in wage bargaining may not reflect individual productivity. Additionally, wages may follow a lifetime perspective with delayed payment contracts, where workers are underpaid early in their careers and overpaid later on. Alternatively, direct measures of productivity, such as the quantity and quality of items produced, can also be used. However, this approach is limited to piece-rate work (see for example Lazear (2000) and Ku (2022)).

Because of the difficulty in measuring individual productivity, researchers began using sports data where various individual productivity measures are readily available. Some sports are carefully monitored because they are extensively covered in for example the popular media. In individual sports, performance is straightforward to measure, but also in team sports, there are often clear indicators of individual performance. Therefore, due to the abundant availability of data, for many sports, studying the relationship between age and productivity is relatively easy.[1] Using sports data to analyze economic relationships is increasingly popular. In his survey of contributions of sports to economic analysis, Palacios-Huerta (2025) presented a variety of studies based on sports data including discrimination, industrial organization, decision making and labor economics issues including assortative matching, performance under pressure and job mobility. Our study is in this relatively new empirical tradition of analyzing sports data to understand economic relationships with implications that extend beyond the sport itself.

In this paper, to study the relationship between age, wage and productivity and the role of job mobility, we use information on professional football players in the top tier of Italian football, Serie A. We have information from ten seasons (2010/11 to 2019/20) on wages and performance of individual players. We study labor market dynamics for professional football because this is a highly competitive

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[1] Analyzing the relationship between age and wage can be problematic due to the lack of accessible wage information. The income of athletes, for example, is influenced not only by earnings from sports activities but also from sponsoring or commercial activities.

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industry. Unions have no role in wage determination and workers are quite mobile. In theory, this should imply that wages and productivity are in line with each other. This is indeed what we find. There is an inverse U-shaped age profile in wages and productivity. We also find that this relationship is influenced by job mobility. Competition within the industry of professional football prevents firms from exploiting monopsony power and pay wages below productivity.[2]

Following the Becker (1962) distinction between firm-specific and general skills also in football in theory team-specific can be distinguished from general skills. Team-specific skills are needed to understand how team members play and what the team strategy is. General skills depend on individual talent. Team-specific skills are not valuable in the labor market as they cannot be used in other teams. Weidmann and Deming (2021) studied how individual workers contribute to teamwork finding that some workers are team players who consistently cause their teams to improve performance. When discussing the contribution of human capital to the production process Deming (2022) argued that higher-order skills such as teamwork are increasingly economically valuable but it is not clear how and why that is. In the football industry on-the-job training is part of the production process that does not require investments. Since football players are very mobile between clubs team-specific human capital is presumably not very important (Ribeiro and Lima, 2019). Furthermore, firm-specific human capital of football clubs may vary over time as managerial changes for example often coincide with changes in the style of play. No doubt teamwork is important in the football production process.

Using sports data to establish the relationship between age and productivity raises a question about external validity. Every type of sports has its own peculiarities. In team sports, contracts have a different meaning than contracts of regular workers. Whereas for many regular workers contracts are permanent in sports they usually only last for a couple of years. In sports workers cannot simply terminate their contract and quit their job. Clubs interested in hiring a player from a different club often have to pay a transfer fee. Sometimes clubs persuade workers to sign a longer contract by paying them a higher wage. For clubs this can be beneficial because this may increase the transfer fee if that worker wants to leave before the contract expires. In sports, the overall career of a player usually does not last more than ten to fifteen years and often the career is even shorter than that although after retiring some players may take a different position in a club, for example as a coach. Nevertheless, we think that studying the labor market of professional football players has external validity because it helps to understand economic behavior and relationships, including the relationship between age and productivity. Professional football players have relatively short careers, typically starting around age 20 and retiring in their early 30s. Their labor market experience resembles a fast-paced version of the broader labor market, characterized by frequent job mobility and short tenures. This also means that, within a short period, we can track entire careers. Aside from these unique aspects, the labor market we study is representative of other highly competitive industries with frequent job transitions. We consider the football players as high-skilled professionals who in terms of labor market are comparable to other high-skilled professionals such as workers from engineering disciplines, researchers, scientists, academic staff at universities, IT specialists and so on. The common element is that these workers are high-skilled with human capital that can be easily used by competing firms.

The strength of our analysis lies in the availability of individual performance data. Uniqueness of performance information in the football industry is a key strength of research based on football data. Individual performance is measured regularly and with great accuracy. Whereas it is hard or even impossible for regular workers to measure their individual productivity this is no issue whatsoever in football. With individual football performance data it is possible to track developments over time as players age and in different circumstances as they change teams. There is a clear tradeoff between uniqueness of an empirical setting and generalizability. The more an empirical setting is unique the more difficult it is to generalize. The more general an empirical setting is the less likely it is to reveal new economic insights. We think that our analysis is interesting for highly competitive industries. In industries and labor market with less competition wage and productivity do not need to go hand-in-hand as workers age. If unions are involved in wage negotiations they may go for long – sometimes implicit – contracts preventing a decline in wages as workers grow older and their productivity declines. Because of the highly competitive labor market wage and productivity are likely to be highly correlated as workers grow older and this is indeed what we find.

List (2020) argues that empirical work can be valid regardless of its external validity if it allows testing particular mechanisms that are difficult to investigate with general data. Balafoutas et al. (2019) argue that sports data are well-suited for studying economic behavior because actions are observable and well-documented. Such behavior occurs in environments governed by clear rules and involves experienced participants who often face strong incentives. Moreover, sports data are highly versatile, enabling research on a wide range of topics in economics, management, and psychology that are otherwise difficult to examine—such as strategic effort provision by individuals and teams, unethical behavior, risk attitudes, performance under pressure, and biases among game officials. Examples of recent papers illustrating the diversity in studies where sports data have been used to study economic phenomena are Gauriot and Page (2019) using football data to study the effect of luck on performance evaluations, Caselli et al. (2023) analyzing discriminatory behavior using data on Italian football, Amodio et al. (2024) on integration and learning in cultural diverse organizations using data on the influx of Russian hockey players in the North American National Hockey League after 1989, and Anderson et al. (2025) studying winning strategies using data about elite tennis players. When discussing how important teamwork skills can be Deming (2022) refers to sports because productivity measures are usually accurate mentioning a paper by Arcidiacono et al. (2017) who analyze basketball data to understand the interaction between players and teamwork.

Our contribution to the literature on age, wage and productivity is threefold. First, whereas previous studies often rely on group productivity or subjective measures of individual productivity, we use an objective measure of individual productivity. Second, we study a highly dynamic labor market in which we are able to track workers over a substantial part of their working career. Third, we are able to disentangle the effect of within-firm wage growth and wage growth through job mobility.

Our paper is set-up as follows. In Section 2 we present an overview of previous studies distinguishing between studies on the relationship between age, wage and productivity and studies on wage growth within a firm or wage growth related to job mobility. Section 3 presents our data and gives a descriptive analysis of wages and worker performance over time and in relationship to their age. Section 4 discusses the results from our empirical analysis where we make a distinction between mobility and wages in relation to learning on the job and job mobility. In Section 4 we also revisit the relationship between age, wage and productivity. Section 5 concludes.

2. Previous studies

2.1. Age, wage and productivity

There are quite a few studies on the relationship between age and productivity based on industry data or activities that allow for an

[2] See Manning (2021) for an overview and Ye et al. (2022) for a recent empirical study on monopsony in the US labor market.

easy measurement of individual productivity. Oster and Hamermesh (1998) is an early study on the age-productivity relationship among US economists. Productivity of academic researchers is measured in terms of publications in top economics journals. The main finding is that publishing diminishes with age. Börsch-Supan and Weiss (2016) study the relationship between age and productivity in work teams of a large German car manufacturer. Accounting for selective participation in teams they find that productivity does not decline at least up to age 60.

There are also studies on the relationship between age and productivity based on sports data. Van Ours (2009) analyzes various data from the Netherlands to investigate the relationship between age and productivity, i.e., data on running and publishing in economics journals. For running and publishing there is no wage information by age. Running is done by amateurs who run for fun, publishing is done by academics whose productivity does not only concern publishing but also teaching. Running performance indicating physical productivity is found to decline after age 40. Publishing in economics journals indicating among others that mental productivity does not decline with age – not even after age 50. Castellucci et al. (2011) investigate age-productivity profiles for F1 drivers. Productivity is measured as the number of points awarded to each driver at the end of each race. Using driver fixed effects, team fixed effects, match driver-team fixed effects and age as well as age-squared they find that productivity peaks around age 30.

Bertoni et al. (2015) study the age productivity profile for chess players using their ELO-ratings as an indicator for productivity. Their main worry is about selective attrition, i.e. less able chess players discontinue playing as professional. To address selective attrition they use an imputation procedure based on the assumption that self-selection depends on age and ability but is invariant across equally aged adjacent cohorts of birth. Their main conclusion is that productivity increases from age 15 to a peak at age 21 to substantially decline after that. The authors also conclude that without accounting for selective attrition the productivity decline would be under-estimated. Scarfe et al. (2024) study the age–wage–productivity profile using data from American professional football. Their wage measure includes the base annual salary, payments for signing with a team or related to marketing but does not include performance related payments. Productivity is measured by minutes played and ratings of players. The main finding is that productivity peaks at age 20 while wages peak at age 30. The authors do not solve the puzzle of younger and older workers being underpaid relative to their productivity. The Scarfe et al. (2024) study resembles our study in terms of the type of sport being studied. However, the regulations of the football industry in the U.S. and Italy are very different. In the U.S., all football players sign a contract with the MLS (Major League Soccer). The wages are determined by collective bargaining agreements. So, whereas Italian football is a highly competitive industry U.S. football is highly regulated.

Other studies which use football data to analyze determinants of wages are Carrieri et al. (2018), Scarfe et al. (2020, 2021) and Carrieri et al. (2020). These studies all have age and age-squared as determinants to account for age effects but age itself is not a topic of particular interest. Carrieri et al. (2018) use data from Serie A to study wages distinguishing between three possible determinants of so called superstar effects: talent (Rosen, 1981), popularity (Adler, 1985) and bargaining power (Bebchuk and Fried, 2003). The main finding is that talent, popularity and bargaining power are all significantly associated with higher earnings. Scarfe et al. (2020) study assortative matching in U.S. football, i.e., whether high wage footballers play for high wage teams. Using a simple two-way fixed effects wage regression approach they find a negative correlation between player and team fixed effects.[3] Carrieri et al. (2020) study the effect of a negative productivity shock – an injury – to professional football players in Italy. A 30-day injury is found to reduce the probability of contract negotiation and have a large negative effect on wages. This is related to precautionary motives rather than a shock-induced reduction in current player's performance.

By and large, earlier studies on the relationship between age and productivity do not include wages in their analysis or they investigate the determinants of wages without a particular reference to age. As we indicate, a US-based study has a similar set-up as ours focusing on age-related wage and productivity though in a setting with a highly regulated market with collective bargaining. Our contribution to the literature on age, wages and productivity is that we study them in a integrated way.

2.2. *Wage growth on the job or between jobs*

Wages may change with age due to learning on the job. Wages may also change because of job mobility if it is profitable for workers to move to a more productive firm. Jarosch et al. (2021) analyze administrative data from a sample of German firms from 1999 to 2009. They relate the development of individual wages to the mean firm wage excluding that individual. The relationship between firm wages and (later) individual wages is interpreted as indicator for the importance of learning from peers. They find that this effect increases over time to the extent that over a period of 10 years a doubling of the peers' wages leads to a twenty percent increase in the individual wage.

Woodcock (2015) analyzing US data distinguishes between wage returns to person, firm and match effects. He concludes that match effects are an important determinant of earnings dispersion explaining a large part of the change in earnings when workers change employer. Abowd et al. (2019) conclude from an analysis of US earnings that it is important to take endogeneity of job mobility into account. Allowing for endogenous job mobility reduces the contribution of employer and match effects to the variation in earnings. Jinkins and Morin (2018) analyze Danish wage data focusing on wage changes related to job-to-job transitions. Their main conclusion is that changes in the quality of the worker–firm match explain about two-thirds of the variance in the log wage growth experienced by job changers.

Spillovers between individual workers through peer effects have also been studied using sports data. Filippin and van Ours (2015) analyze assortative matching of athletes and teams of 24 athletes participating in a sequence of 24-hours runs in Italy. They investigate mobility between teams from one year to the next both in terms of accessions as well as separations. The main conclusion is that there is positive assortative matching with better runners moving to better teams. Arcidiacono et al. (2017) find that in professional basketball there are productivity spillovers in team production. Cohen-Zada et al. (2024) analyze effort peer effects in the workplace focusing on Israeli football. They measure individual effort as running speed. The total distance run by all players of a team has a positive effect on game outcomes while the distance run by the opponent team has a negative effect. They show that the effort of individual players depends on the efforts of his team members. Molodchik et al. (2021) analyze individual performances of about 5000 professional football players in 234 teams over the period 2010–2015 using performance information from EA Sports (a sports video game). They investigate peer effects by relating individual player rating to lagged team rating (excluding the individual player). The main conclusion is that football players improve their rating in a stronger team.

By and large, earlier studies investigate wage growth without taking individual productivity into account. If productivity is studied there is no wage information in the analysis or the effects of job mobility are not taken into account. We contribute to the literature by investigating wage growth in relation to productivity both within and between jobs.

[3] In itself this is not very surprising as it is a common finding related to negative correlation in measurement errors if two types of fixed effects are based on one equation (Peeters and van Ours, 2022).

3. Data & descriptives

3.1. Data

We have compiled a unique dataset containing information about professional football players in the Italian Serie A league in one or more of the 10 seasons, from 2009–2010 to 2019–2020.[4] The panel is unbalanced because of players entering and leaving the Serie A due to promotion or relegation of their team from or to Serie B and individual international mobility to and from foreign clubs. There is a high level of turnover among players in the league, although the types of players involved in these transfers are often diverse. In fact, less talented players are traded with teams playing in minor leagues and more talented players are traded with top European clubs. This helps to mitigate concerns about selective attrition (Carrieri et al., 2020). In Appendix A we provide details about the turnover in our sample. Turnover is high both because of within league transfers from one club to another. Also, quite a few players left the sample because they went playing in a different European league, because their team relegated to Serie B or because they retired as a professional football player. On average, from one season to the next on average 49% of the players stayed in their team, 21% moved to a different team in the top league of Italian football and 30% left the sample. For many players we only have a limited number of sequential observations but there are also players who leave the sample to re-enter after many years. We observe about 15% of the players in our sample for at least 6 seasons while we observe about 19% of the players over an age range of at least 6 years.

We gathered data from various sources to obtain comprehensive information about Serie A players. We extracted individual player's characteristics such as their birth year, position on the field, and international appearances. Furthermore, we obtained data on players' annual wages, excluding any performance-related bonuses and recorded net of taxes, from an annual report published by La Gazzetta dello Sport, published at the start of each football season.[5] Outside of Italy's Serie A, reliable salary data are essentially unavailable. We discuss this in more detail in Appendix B where we also provide a validation exercise for our wage data. As an indicator of productivity, we obtained information a general rating variable for individual football players from *whoscored.com*. The player rating used in our analysis is constructed using a weighted additive model that aggregates over 200 match-level performance variables into a standardized 0–10 scale. Each action — such as passes, tackles, shots, or interceptions — is assigned a weight that reflects both its impact on team performance and its relevance to the player's position. For example, defensive metrics such as clearances or tackles receive greater weight for defenders, while attacking contributions such as key passes or goals carry more weight for forwards. Actions are further contextualized by factors such as field location and match state (e.g., a successful intervention in a high-threat area receives more credit than the same action in a low-stakes situation). These weights are derived from a combination of empirical performance data, expert football knowledge, and role-specific expectations, ensuring that the final rating reflects a comprehensive and position-aware assessment of individual contribution.

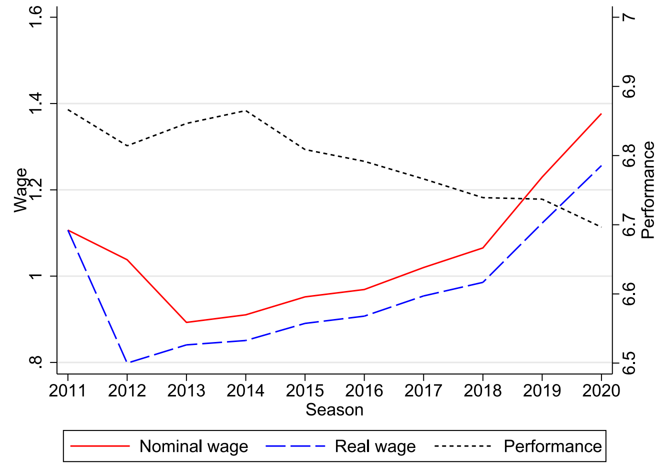

Fig. 1. Average wages and performance by player; 2010/11-2019/20.
Note: Wages measured in million euro; real wages in million euro of 2011; performance measured on a scale from 0 to 10.

3.2. Descriptives

Fig. 1 shows trends in nominal wages, real wages, and performance of football players in Italy's Serie A from 2011 to 2020. There is a slight downward trend in productivity from about 6.85 in 2011 to 6.7 in 2020. Average wages fell from 1.1 million euro in 2011 to 0.9 million euro in 2013. In this period, real wages in Serie A declined partly due to the introduction of UEFA's Financial Fair Play (FFP) regulations in 2010, which forced clubs to control spending and align wages with their revenues. As many Italian clubs faced financial difficulties, they had to cut player salaries or slow wage growth to comply with these new rules. At the same time, Serie A was losing its competitive edge to leagues such as the Premier League and La Liga, where clubs had stronger financial backing. This led to an exodus of top players, reducing wage pressure in Italy and contributing to the overall decline in real wages. Thereafter, there was a steady increase in both real and nominal wages, reaching approximately 1.4 million euro in 2020. This growth was driven by increased foreign investments and club takeovers, which injected fresh capital into the league.[6] At the same time, Serie A clubs sought to regain competitiveness against the Premier League and La Liga, leading to higher wages to attract and retain top players. This trend culminated in high-profile signings, such as Cristiano Ronaldo's move to Juventus in 2018, signaling the league's renewed financial capacity.[7] These dynamics suggest that in our analysis we have to account also for potential wage inflation.

Fig. 2 shows four scatter plots of wages and performances in the first season and the last season of our sample. Panel a shows the variation of wages and performance at the level of the players in 2011 and 2020. Panel b shows the averages of wages and performance across the clubs in 2011 and 2020. In all four scatter plots there is a positive correlation between performance and wages but there is also a lot of variation. Whereas for the wages of the players most observations are below 1 million euro there were also players earning up to 8 million euro.

Individual performance is just one of the determinants of the wage of the players. Team performance may be important too. The left-hand-side graph of panel b shows that in 2010/11 for all clubs except four, the average wages were below one million euro. At Juventus and Roma,

[4] We focus on outfield players and have excluded goalkeepers, which is a common practice in this literature (Lucifora and Simmons (2003); Carrieri et al. (2020)) This is because performance of goalkeepers is evaluated differently from outfield players.

[5] Our dataset only records players who joined the league before the January transfer window. We have a total of 3156 player-season observations. Appendix A provides more information about our sample, in particular about the sample dynamics.

[6] Several clubs benefited from foreign ownership, including Inter Milan (Suning in 2016) and AC Milan (Chinese investors in 2017), which contributed to increased wage spending.

[7] Ronaldo had a wage of 31 million euro in 2019/20 and is excluded in Figs. 1 to 3.

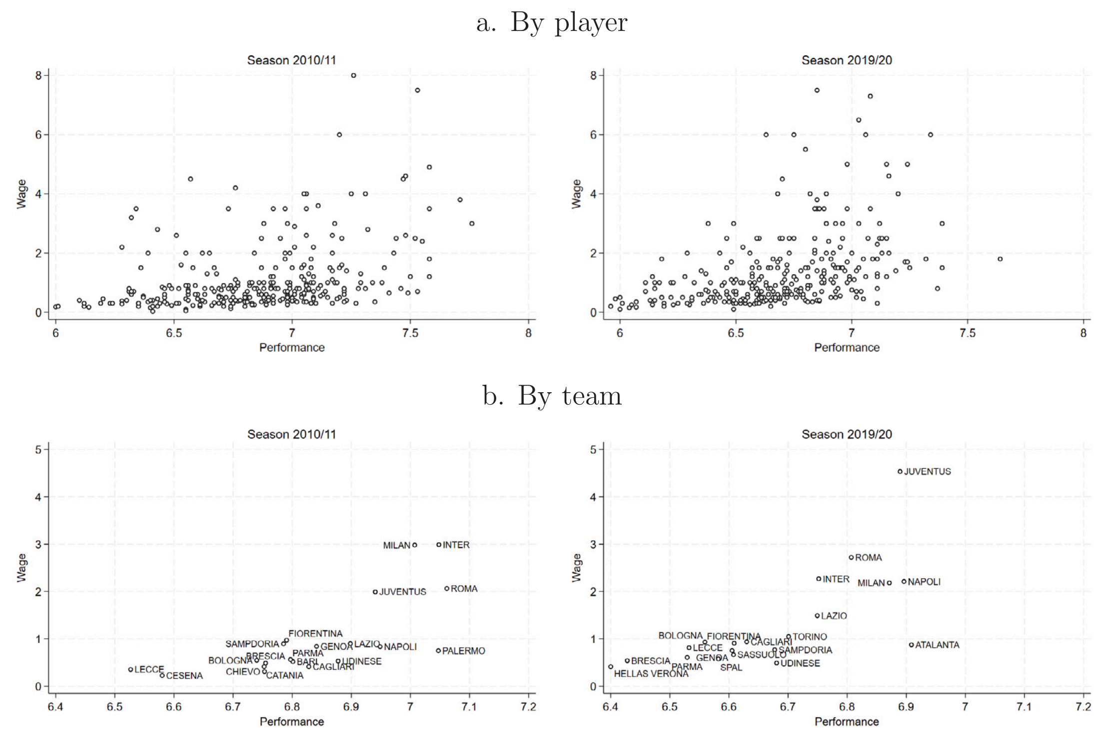

Fig. 2. Average wages and performances by player and team; 2010/11 and 2019/20.
Note: Wages measured in million euro; performance measured on a scale from 0 to 10.

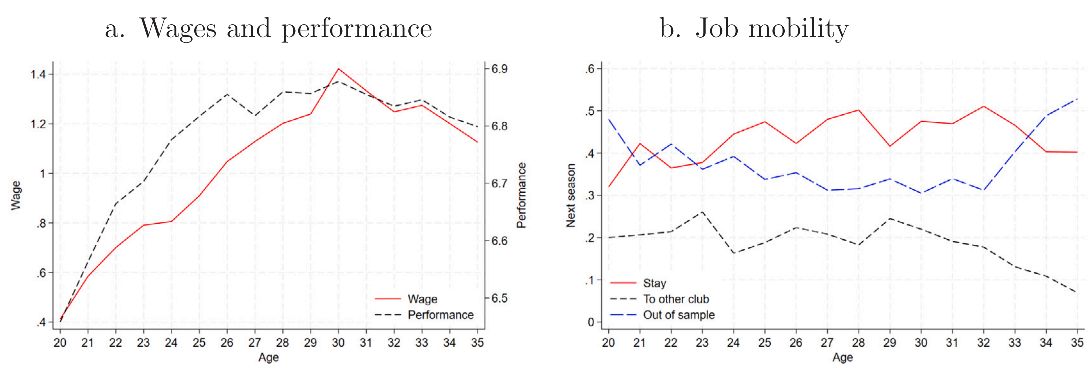

Fig. 3. Average wages, performance ad job mobility by age. Note: Wages measured in million euro; performance measured on a scale from 0 to 10.

the average wage was about 2 million euro, while at Inter and Milan, it was around 3 million euro. In the 2019/20 season, the situation was quite different. Lazio had an average wage of approximately 1.5 million euro, while Inter, Milan, Napoli, and Roma had average wages between 2 and 3 million euro. Juventus had the highest average wage at around 4.5 million euro.[8] Clearly, average team performance is correlated with average team wage but this relationship is far from perfect. The average wage of the Napoli squad is more than twice the average wage of the Atalanta players while the average performance of the two teams is about the same. With the same average performance, the average wage at Juventus is more than four times as high as the average wage at Atalanta. Some clubs are more productive than other clubs, i.e., with the same average performance they are able to generate more revenues (see Peeters and van Ours (2022)).

We are interested in the relationship between age, wage and productivity and how this is influenced by within-firm wage growth and wage growth related to job mobility from one season to the next. Fig. 3 shows how average wage, performance and mobility vary with age. Panel a shows that initially both average wage and average performance go up with age. Average wage and performance are highest at age 30 and decline thereafter. Panel b of Fig. 3 shows how average job mobility varies with age. The average seasonal probability to stay with the same club increases somewhat at younger ages but is approximately constant and fluctuates between 40% and 50% later on. The job mobility is very high compared to a regular market but is in line with the fast-paced version that the labor market for professional football players represents. The full career of a players is much shorter but usually with a lot of turnover during that career. The average seasonal probability to make a transition to a different club is about 20% up to age 30 and declines to about 10% for players in their mid-30s. The remaining category of being out of the sample in the following season goes down from about 45% in the early 20s to about 30% when players are in their early thirties. After age 32 there is a steep increase to leave the sample to more than 50% at age 35. Although we have no information about the destination of the players who leave our sample we assume

[8] Including Ronaldo the average wage for Juventus was close to 6 million euro.

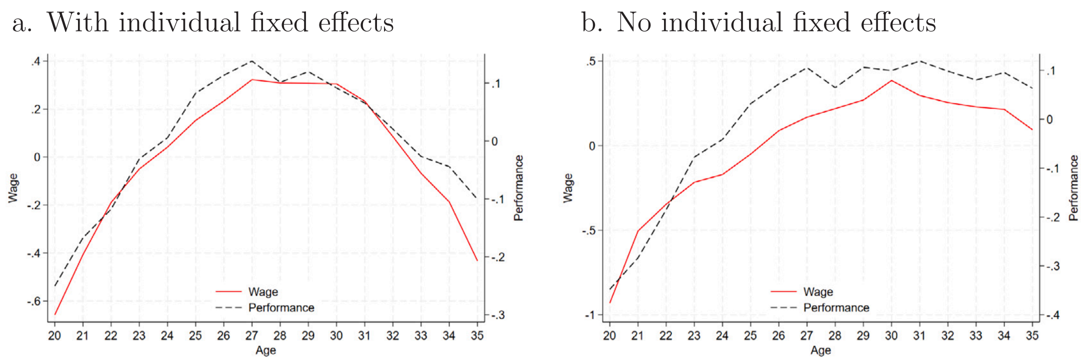

Fig. 4. Parameter estimates age effects in wage and performance of football players; with and without individual fixed effects.
Note: Age fixed effects for estimates of log(wages) and one-season lagged performance; the fixed effects are normalized to average of 0. All estimates included seasonal fixed effects.

that at a higher age they leave to a club in a lower Italian league or stop playing professional football altogether.

3.3. Age, wage and productivity

Fig. 3 shows how average wage and performance vary with age. However, since we have an unbalanced sample the variation with age may be affected by players entering and/or leaving the sample at particular age. To correct for these sample variations we estimated log-wage and productivity equations which include individual fixed effects, seasonal fixed effects and age fixed effects:

$$y_{it} = \alpha_i + \beta_t + a_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} represents either log(wages) or performance of player i in season t. Furthermore, α_i represent the individual fixed effects and β_t are season fixed effects to account for season-specific changes in overall wages and productivity. The seasonal fixed effects also account for developments in wage and price inflation. The a_{it} parameters represent the age fixed effects.

Panel a of Fig. 4 shows the age gradient based on the estimates of Eq. (1) in which the average age effect is normalized to zero. Clearly, both wages and productivity have an inverse U-shape relationship with age. The peak of the wage profile is at age 27, the peak of the (lagged) productivity profile is very similar between ages of 27 and 30.

Panel b of Fig. 4 shows the age effect estimates when individual fixed effects are ignored. Now, the increase of both wage and performance is similar to panel a but from age 27 onward neither average wage nor average performance change much. Panel b of Fig. 4 is very similar to Fig. 3. The comparison of the two graphs in panels a and b seems to suggest that at the high end of the age distribution selective attrition is important. Players whose wage and performance go down with age seem to be more likely to leave the sample.

4. Empirical analysis

4.1. Job mobility

Our analysis is focused on establishing the relationship between age, wage and productivity including the role of job mobility in this relationship. We start our empirical analysis investigating player mobility. From one season to the next there are three possibilities: the players stays at his club, the player moves to a different club in the Italian Serie A or the player leaves the sample. If the player leaves the sample we do not know whether this is because he makes a transition to a club outside Italy, to a lower Italian league like Serie B or to a life outside football, i.e., retiring as a professional football player.

To investigate potential determinants of job mobility we estimate a multinomial logit model with two transitions: changing jobs within Serie A or leaving the sample. Table 1 shows the relevant parameter estimates. The estimates in the first two columns of panel a show that without including individuals fixed effects performance has a significant negative effect on player mobility. A higher performance in one season makes it more likely that a player stays at his club. Also wages have significant negative effects on both types of transition. In the third and the fourth columns average team wage is included as additional explanatory variable. This does not affect the relationship between performance and job mobility but it does effect the relationship between individual wage and mobility because individual wages and team wage are highly correlated. This is confirmed in the fifth and sixth column in which individual wages are excluded. Now, team wages have significant negative effects on job mobility.

Panel b of Table 1 shows the parameter estimates if in addition to seasonal fixed effects and age fixed effects we also include individual fixed effects. Now individual performance still has a negative effect on the transition to out of sample but the negative effect on a change of jobs disappears. This suggest that the within individual variation in performance affects the change to out of sample but not job change. Apparently this is influenced by the average performance. The within individual variation in wage has a negative effect on job change but no significant effect on the change to out of sample.[9]

4.2. Wage growth on the job

An individual player can increase his wage by staying at his current team or by moving to a different team. At the same team, the wage can go up because of learning on the job. To investigate this phenomenon we use Jarosch et al. (2021) as a point of reference. We relate the development of individual i log wages to the mean firm log wage excluding individual i:

$$w_{i,t+h} = \alpha_i + \beta \overline{w}_{-i,t} + \gamma w_{i,t} + \omega_x + \delta S_{i,t+1} + \varepsilon_{i,t} \tag{2}$$

where $w_{i,t+h}$ is log wage of individual i in year t+h, $\overline{w}_{-i,t}$ is log mean wage of the other workers in the firm, α_i are individual effects, ω_x accounts for fixed effects related to age and season and S is an indicator for switching firms which has a value of 1 if the individual is at a different firm in year t+1 and a value of 0 otherwise.[10] The parameter β is the indicator of the importance of learning from peers. The parameter

[9] We also investigated whether relative performance – within a team or within a team-by-position group – affects job mobility finding parameters with the correct sign but imprecisely estimated. From this, we conclude that own absolute performance is a more significant predictor of job mobility compared to relative performance measures.

[10] Note that Jarosch et al. (2021) do not include individual fixed effects in their analysis but a series of fixed effects for age, tenure, gender, education, occupation and time.

Table 1
Parameter estimates job mobility.

	Change jobs		Out of sample		Change jobs		Out of sample		Change jobs		Out of sample	
a. Pooled												
Performance	−0.76	(0.18)***	−1.71	(0.17)***	−0.75	(0.18)***	−1.72	(0.17)***	−0.80	(0.17)***	−1.92	(0.16)***
Wage	−0.39	(0.07)***	−0.39	(0.07)***	−0.10	(0.11)	−0.50	(0.10)***				
Team wage					−0.42	(0.13)***	−0.18	(0.11)	−0.51	(0.08)***	−0.24	(0.07)***
N	2750				2750				2750			
b. Individual fixed effects												
Performance	−0.08	(0.27)	−0.69	(0.33)***	−0.09	(0.28)	−0.70	(0.33)**	−0.15	(0.27)	−0.72	(0.33)**
Wage	−0.38	(0.17)**	−0.13	(0.25)	−0.22	(0.22)	−0.06	(0.31)				
Team wage					−0.20	(0.18)	−0.11	(0.27)	−0.32	(0.14)**	−0.15	(0.22)
N (n)	2165 (531)				2165 (531)				2165 (531)			

Note: The parameter estimates are obtained from a multinomial logit specification. Reference group: stayers. Wage and team wage are in logs. All specifications in panel a and b contain season fixed effects and age fixed effects. In the estimates of panel b also individual fixed effects are included. N = number of observations; n = number of individuals; standard errors clustered by individual. See Appendix C sample descriptives.

*** Significant at a 1% level.

** Significant at a 5% level.

Table 2
Parameter estimates future wages.

	One year ahead		One year ahead		One year ahead		Two years ahead	
Performance	0.226	(0.040)***	0.219	(0.040)***	0.267	(0.039)***	0.267	(0.049)***
Own wage	0.154	(0.032)***	0.216	(0.026)***			−0.021	(0.040)
Team wage	0.088	(0.028)***			0.170	(0.023)***	0.045	(0.035)
Switch teams	0.001	(0.021)	−0.002	(0.021)	0.003	(0.021)	0.012	(0.025)
N (n)	1783 (452)		1783 (452)		1783 (452)		1238 (332)	

Note: All wages in logs. All specifications contain age fixed effects, season and individual fixed effects. N = number of observations; n = number of individuals; standard errors clustered by individual. See Appendix C sample descriptives.

*** Significant at a 1% level.

δ indicates whether making a transition to a new club coincides with a change in the future wage. This is not a causal effect but explores whether or not there is a correlation between going to a new club and the individual wage at that club. If a player changes to a better paying club δ will be positive; if he goes to a worse paying club δ is expected to be negative.

The method used by Jarosch et al. (2021) is applicable to football players who may benefit from their team members. However, the dynamics in the labor market for football players is very different from the regular labor market. In the data of Jarosch et al. (2021) every year 4.9% of the workers leave their firm, i.e. expected tenure is about 20 years. In contrast our sample of Italian football players has an annual transition rate of 50% implying an average tenure of 2 years.[11] Taking this into account it is clear that the dynamics are different in the football labor market so it is less likely that a player will benefit for many years.

Table 2 presents the main parameter estimates of the future wages. The first three columns show the parameter estimates for one year ahead, the fourth column gives the parameter estimates for wage two years ahead. The first column shows that individual performance has a positive effect on the wage in the following year. The same holds for own wage. The significant positive effect of the team wage can be interpreted as evidence of on-the-job learning. As indicated before, we included an indicator for future change of jobs to explore whether such a change coincides with a wage change. The parameter estimate for 'switch teams' is not significantly different from zero indicating that on average changing teams and wage change are uncorrelated. This also suggests that selectivity of the switch into a different team does not bias our parameter estimates (Wooldridge, 2010) and it suggests that non-random attrition is no issue either.

In the second column, team wage is removed from the estimates and because of this part of the effect of team wage being transferred to the own wage. Similarly in the third column which excludes own wage as a right-hand-side variable part of the effect of own wage is transferred to team wage. The fourth column shows that two years ahead only the individual performance has a significant effect on individual wages.[12] Comparing the parameter estimates in the first and fourth columns, indicates that different from Jarosch et al. (2021) the learning effect diminishes quickly over time. After one year the β-parameter has a value of 0.088, after two years this is 0.045 (and insignificantly different from zero). However, one should take into account that the labor market of professional football players is a fast-paced version of a regular labor market, with a pace that may be up to five times as fast in relative terms the learning effect does not diminish that fast.

4.3. Wage growth between jobs

In a labor market characterized by frequent turnover of workers between teams, the learning process facilitated by collaborating with more skilled team members should culminate in higher wages, provided that the acquired skills are valued by other teams. In principle, worker mobility may be upward or downward, as depending on their performance workers have the ability to move towards either better or worse firms. Fig. 5 depicts the rating distributions for players who transfer to a better or a worse team. As expected, players moving to higher-tier clubs generally exhibit higher ratings compared to those relocating to lower-tier clubs. Nevertheless, staying at a club is not very different from switching to a better club. And, the ability distribution of leavers is not very different from the ability distributions of players who switch to a better or to a worse team.

[11] In our sample, every season about 25% of the players transfer to a different Italian club and about 25% leaves the sample, i.e. retires or transfers to a foreign league or lower Italian league.

[12] We also estimate a version of the model in column 1 using the restricted sample of 1238 observations present in column 4. The results are very similar and available upon request.

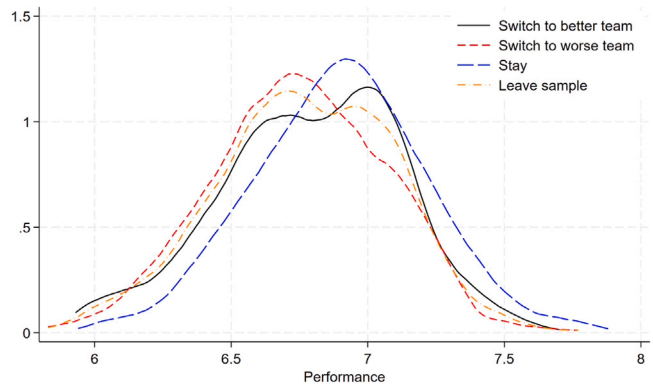

Fig. 5. Stay, switching jobs and leaving sample by performance.
Note: A better team is a team with a higher average wage than the original team; similarly a worse team is a team with a lower average wage than the original team.

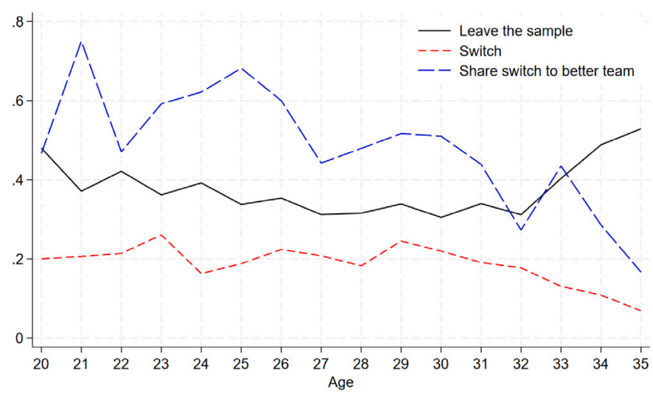

Fig. 6. Average shares leaving the sample, switching teams and shares of switching to a better team; by age.
Note: Share of switching to better team is conditional on switching. A better team is a team with a higher average wage than the original team.

Table 2 suggested that, on average, switching teams is unrelated to future wages. However, this effect may be age-specific. Fig. 6 shows the relationship between age and the average share of players leaving the sample or switching to a different club (in Serie A). The share of players leaving the sample decreases from about 45% at a young age to about 30% at age 27 to stay constant at that level until age 32. Thereafter, the share of leaving the sample increases to more than 50% at age 35. The share of players changing teams is roughly constant at 20% up to age 30 to decrease to less than 10% at age 35. Fig. 6 also shows the share of switchers going to a better team. This share fluctuates a lot but overall there is a steep decline. Whereas at age 21 about 70% of the switchers goes to a better team and at age 26 this is about 50% at age 35 less than 20% of the switchers goes to a better team (and thus 80% goes to a worse team).

Table 3 shows the parameter estimates for future wages distinguished by age: younger than 28 years or older than 27 years. For the one year ahead estimates the effect of performance on the wage in the next season is about the same. For the younger part of the sample a higher team wage is correlated with a higher wage in the next season. If they switched teams from the current to the next season this coincides with a significant higher wage while for the older group their own wage influences their wage in the next season while switching teams coincides with a significant lower wage in the next season. For the younger players, team wages seem to be more important than individual wages. For the older players, own wages seem to be more important but here own wage is strongly correlated with team wage.

Table 3
Parameter estimates future wages by age.

a. One year ahead	Age≤27		Age>27	
Performance	0.258	(0.067)***	0.202	(0.051)***
Own wage	−0.054	(0.049)	0.374	(0.045)***
Team wage	0.162	(0.043)***	−0.035	(0.041)
Switch teams	0.131	(0.035)***	−0.150	(0.026)***
b. One year ahead	Age≤27		Age>27	
Performance	0.256	(0.068)***	0.202	(0.051)***
Own wage	0.046	(0.041)	0.349	(0.035)***
Switch teams	0.110	(0.035)***	−0.150	(0.026)***
c. One year ahead	Age≤27		Age>27	
Performance	0.240	(0.065)***	0.254	(0.053)***
Team wage	0.135	(0.036)***	0.174	(0.033)***
Switch teams	0.134	(0.035)***	−0.146	(0.027)***
N (n)	796 (252)		894 (239)	
d. Two years ahead				
Performance	0.326	(0.076)***	0.127	(0.067)*
Own wage	−0.098	(0.058)	0.063	(0.061)
Team wage	0.062	(0.048)	−0.066	(0.057)
Switch teams	−0.021	(0.040)	0.023	(0.035)
N (n)	572 (184)		605 (176)	

Note: All wages in logs. All specifications contain fixed effects for age, season and individual. N = number of observations; n = number of individuals; standard errors clustered by individual. See Appendix C sample descriptives.
*** Significant at a 1% level.
* Significant at a 10% level.

Comparing panels b and c, it is clear that if one of them is dropped from the analysis the other is highly significant. All in all, from panels a to c it is clear that for wages one year ahead the team wages are important for younger players while this is less the case for older players. This supports the idea of learning by younger players. For the wage two years ahead the estimates are presented in panel d. The effect of performance is stronger for the younger group while none of the other parameter estimates is significantly different from zero.

4.4. Sensitivity analyses

To investigate the robustness of our main findings we performed of number of sensitivity analysis of which the results are presented in more detail in Appendix D.

First, we address the issue whether our result are dependent on our performance indicator based on an algorithm. In Appendix D1, we show parameter estimates of future wages in which passes per game are used as a more basic performance metric. The main results are basically unchanged.

In Appendix D2, we present additional estimates of job mobility distinguishing between moving to a worse team, moving to a better team and leaving the sample. The parameter estimates for leaving the sample are very similar to those presented in Table 1b. As was to be expected a higher individual performance make it less likely that the job mobility is to a worse team. Both individual wages and team wages are positively related to job mobility to a worse team.

As discussed in the data section our data have information about some players whom we observe over a limited number of seasons. Therefore, we have two sensitivity analyses based on a restricted sample in which only individual players are included if they are observed over an age range of at least six years. In Appendix D3, we show that the parameter estimates for the future wage are not much affected if based on this restricted sample. In Appendix D4, we show that the relationship between wages, performance and age is not much affected either if based on the same restricted sample.

Finally, additional robustness checks are reported in Appendices D5–D7. Appendix D5 investigates heterogeneity using injury information in the one-year-ahead wage regression by splitting the sample at

30 days of injury-related absence. Among high-injury players, the team-wage coefficient flips sign and becomes statistically insignificant, which may reflect reduced learning or weaker information flows resulting from prolonged absence, while the performance and switching-team coefficients remain broadly unchanged. Appendix D6 focuses on individuals who are observed continuously between ages 27 and 33 and re-estimates the fixed-effects age profiles for this subsample, providing a focused test on the wage and performance trajectories around the peak ages. Appendix D7 implements a monotone-selection bounding exercise in the spirit of Lee (2009) to assess the potential impact of non-random attrition. Across these analyses, the wage profile consistently exhibits a clear inverse-U shape with a peak around age 30, reinforcing the robustness of our main findings.

4.5. Age, wage and productivity revisited

While our previous results are primarily descriptive, a potential issue in examining the role of job mobility in shaping the age-wage profile is that the subsample of movers is not randomly selected. Workers and clubs that choose to separate for various reasons may differ significantly from those worker-club pairs that tend to remain together. This has been identified as a possible source of bias in a fixed effects framework aimed at studying labor market dynamics (Andrews et al., 2008).

Ideally, to examine how mobility affects the wage-age profile, one would randomize the probability of players switching teams across the sample. To mimic this in our setting, we begin by restricting our sample to players observed in our data for a minimum of four seasons. We then conduct a controlled experiment to increase the number of switchers while maintaining a constant sample of firms. This involves randomly removing movers within each firm using a prespecified sampling probability and re-estimating the profiles. This approach allows us to investigate how the estimates change as we reduce the number of movers while keeping the set of firms approximately the same. More formally, we implement the following steps:

1. Select players who have been observed in the dataset for a minimum of four seasons.
2. Record the identities of all firms employing the selected players, establishing a fixed sample of firms. This set remains constant throughout the exercise.
3. A prespecified sampling probability p is applied to randomly selected players within each firm to remove from the dataset, effectively simulating varying levels of player mobility.
4. Gradually vary the sampling probability p (e.g., 0.1, 0.2, 0.5, 0.8, 0.9 and 1.0) to observe how changes in the number of switchers affect the wage-age profile.

In Fig. 7, we report the age-wage profile estimates for different samples built by randomly selecting samples with a varying proportion p of switchers kept (e.g. p = 90%; 80%;..;10%). The figure illustrates that as the proportion of switchers in the samples decreases, there is a more pronounced reduction in the wage profile, indicating that these profiles are predominantly influenced by movements between firms. Switching between firms can provide workers with increased opportunities to negotiate higher wages. Firms compete for skilled workers, and those that move between firms may benefit from this competition. Higher wages may be offered to attract talent, contributing to a more favorable wage-age profile for those who switch across firms. In other words, workers who do not switch firms are confronted with a large wage drop that starts earlier in their life than workers who switch a lot. Presumably a declining productivity that start for workers in their later 20s to early 30s causes their wages to drop. Some of them move to different firms where their skills are more valuable and valued and wages do not drop as fast as they would have done when staying in their firm.

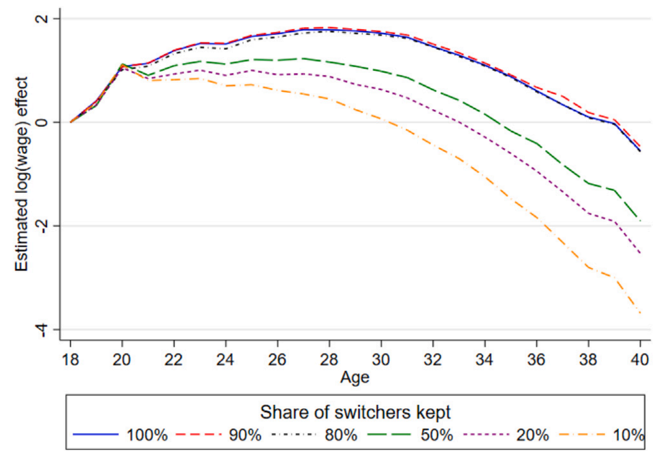

Fig. 7. Wage-age profiles with random samples.
Note: The figure illustrates estimated log(wage effects) by age, based on fixed-effects regressions with varying shares of job switchers included in the sample.

5. Conclusions

Studying the relationship between age, wages, and productivity at the individual level is challenging due to the difficulty in obtaining reliable indicators of individual productivity. In our analysis, we overcome this issue by focusing on data from professional athletes, whose productivity is frequently and accurately measured. Specifically, we concentrate on professional football players in the top league of Italian football, a highly competitive industry with a highly competitive labor market where there is no union involvement in wage formation and significant worker mobility between clubs.

Professional football players are high-skilled workers with relatively short careers compared to the general workforce. While regular workers often retire in their 60s, football players typically end their careers before their mid-30s. This "high-speed" career trajectory makes professional football players an ideal subject for studying labor market dynamics, enabling us to investigate both wage growth within a firm and the role of job mobility in wage increases.

Our findings indicate an inverse U-shaped relationship between age, wages, and productivity, where wages and productivity closely follow similar patterns over a player's career. Players who join stronger teams benefit from on-the-job learning, but many do not stay with the same club for long. On average, each year about half of the players either move to another Italian club, retire, or transfer to a foreign club.

Our analysis reveals that the wage-age relationship is heavily influenced by assortative matching: top players tend to transfer to stronger teams, while less skilled players move to weaker teams. We show that the wage-age profile is largely shaped by job mobility, which is itself age-dependent. Younger players often experience wage increases when moving to a new club, whereas older players tend to face wage declines with such moves. These dynamics are also age-specific: while clubs compete intensely for young talent, older players frequently have limited options and may be forced to accept lower-paying roles or retire.

As we stress throughout the paper, the strength of our analysis lies in the availability of individual performance data. Individual performance is measured regularly and with great accuracy. Whereas it is hard or even impossible for regular workers to measure their individual productivity this is no issue whatsoever in football. With individual football performance data it is possible to track developments over time as players age and in different circumstances as they change teams. We think that our analysis is interesting for highly competitive industries. In industries and labor markets with less competition wage and productivity do not need to go hand-in-hand as workers age. If unions are involved in wage negotiations they may go for long – sometimes implicit – contracts preventing a decline in wages as workers grow older and their productivity declines. Because of the highly competitive labor market wage and productivity are likely to be highly correlated as workers grow older and this is indeed what we find.

Our main findings extend beyond professional football and team sports, offering external validity in the context of highly competitive labor markets. The labor market for professional football players serves as a representative model for industries where frequent job mobility is common. Other industries where this is common are for example universities competing internationally for high-skilled academics, engineering companies, research institutes and so on. In such markets, some workers are able to increase their wages over time through firm-specific skill development and by benefiting from positive spillover effects from colleagues. Others achieve higher wages by changing jobs, finding that outside opportunities offer better compensation than remaining with their current employer.

CRediT authorship contribution statement

Francesco Principe: Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Jan C. van Ours:** Writing – original draft, Software, Formal analysis, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.labeco.2025.102845.

Data availability

Data will be made available on request.

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