TI 2025-020/V
Tinbergen Institute Discussion Paper

Labor Market Dynamics in a Highly Competitive Industry

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March 14, 2025

Abstract

We study labor market dynamics of workers in a highly competitive industry, focusing 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.

Keywords: Age-wage profile, productivity, job mobility
JEL-codes: J31, J62, Z22

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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 productivity measures are readily available. In individual sports, performance is straightforward to measure, and even in team sports, there are often clear indicators of individual performance.[1] For many sports, studying the relationship between age and productivity is relatively easy. However, analyzing the relationship between age and wage remains problematic due to the lack of accessible wage information.[2]

In this paper, we study the relationship between age, wage, and productivity, with a specific focus on the role of labor market dynamics, particularly job mobil-

[1]Some sports are carefully monitored because they are extensively covered in for example the popular media.

[2]The income of athletes is influenced not only by earnings from sports activities but also from sponsoring or commercial activities.

ity. 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 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.[3]

Using sports data to establish the relationship between age and productivity raises a question about external validity. Every type of sports has it's 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.[4] 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

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

[4]See Palacios-Huerta (2025) for a general discussion on the use of sports data to understand economic behavior.

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.

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 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 a.o. 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), Scarfe et al. (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.[5] 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.

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.

[5] 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)).

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.

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.[6] 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. 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.

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.[7] As an indicator of productivity, we obtained information a general rating variable for individual football players from *whoscored.com*. This is a measure of overall performance during a match (or season) based on a complex algorithm that takes into account about 200 different factors, which are then weighted differently based on the position of the player on the field. The performance measure ranges from 0 to 10, with 10 being the highest possible rating. Thus, we have an objective measure

[6] 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.

[7] Our dataset only records players who joined the league before the January transfer window. We have a total of 3,156 player-season observations. Appendix A provides more information about our sample, in particular about the sample dynamics.

of performance which we consider to be an indicator of productivity.

3.2 Descriptives

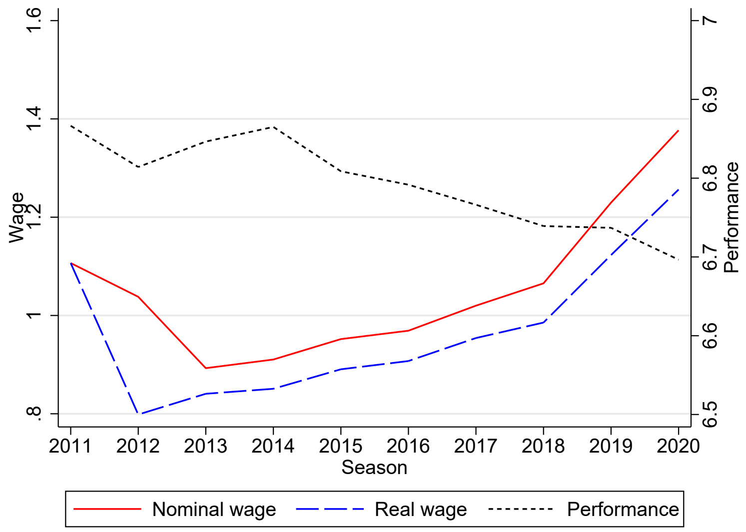
Figure 1 shows trends in nominal wages, real wages, and performance of football players in Italy's Serie A from 2011 to 2020. There is a slight downward trend in productivity from about 6.85 in 2011 to 6.7 in 2020. Average wages fell from 1.1 million euro in 2011 to 0.9 million euro in 2013. In this period, real wages in Serie A declined partly due to the introduction of UEFA's Financial Fair Play (FFP) regulations 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.[8] 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.[9] These dynamics suggest that in our analysis we have to account also for potential wage inflation.

Figure 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

[8]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.

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

Figure 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.

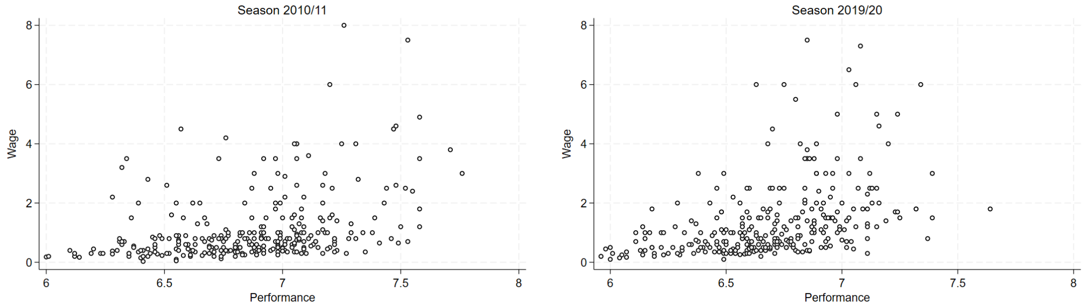
observations are below 1 million euro there were also players earning up to 8 million euro.

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, 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.[10] 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

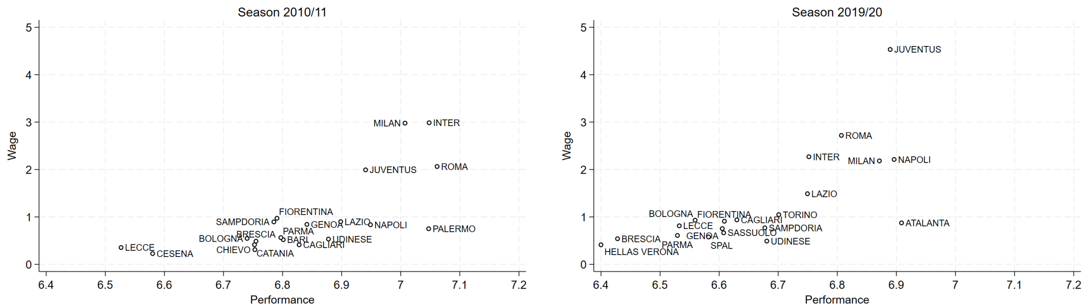
[10]Including Ronaldo the average wage for Juventus was close to 6 million euro.

Figure 2: **Average wages and performances by player and team; 2010/11 and 2019/20**

a. By player



b. By team



Note: Wages measured in million euro; performance measured on a scale from 0 to 10.

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. Figure 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 Figure 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

Figure 3: **Average wages, performance ad job mobility by age**

a. Wages and performance b. Job mobility

Note: Wages measured in million euro; performance measured on a scale from 0 to 10.

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 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

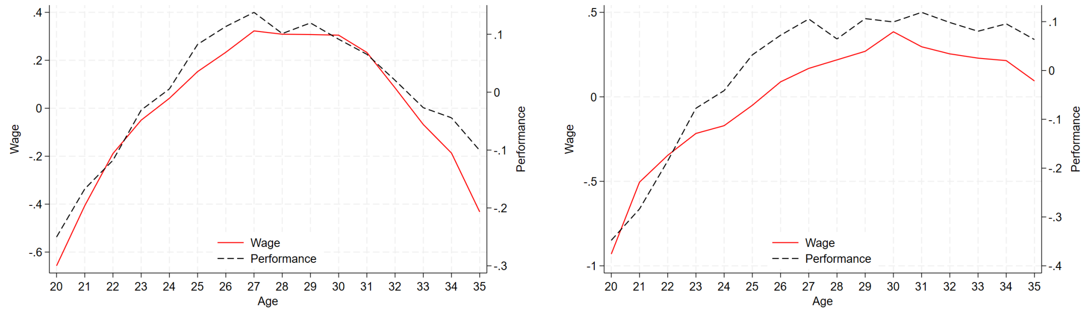
Figure 3 shows how average wage and performance vary with age. However, since we have an unbalanced sample the variation with age may be affected by players entering and/or leaving the sample at particular age. To correct for these sample variations we estimated log-wage and productivity equations which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

Figure 4: **Parameter estimates age effects in wage and performance of football players; with and without individual fixed effects**

a. With individual fixed effects b. No 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.

Panel a of Figure 4 shows the age gradient based on the estimates of equation 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 Figure 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 Figure 4 is very similar to Figure 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.

Table 1: **Parameter Estimates Job Mobility**

a. Pooled												
	Change jobs		Out of sample		Change jobs		Out of sample		Change jobs		Out of sample	
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; *** (**) significant at a 1% (5%) level.

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.

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:

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

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.[11] The parameter β is the indicator of the importance of learning from peers. The parameter 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

[11] 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.

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.[12] 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: **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; *** significant at a 1% level.

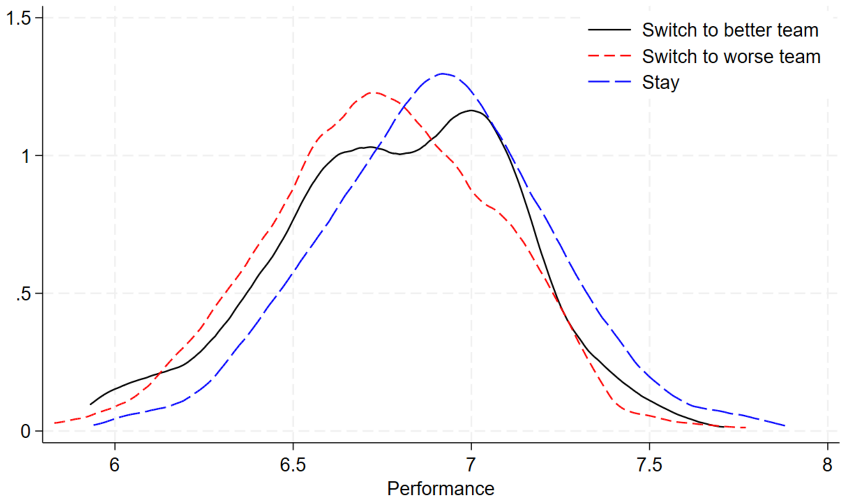
Table 2 presents the main parameter estimates of the future wages. The first three columns show the parameter estimates for one year ahead, the fourth column gives the parameter estimates for wage two years ahead. The first column shows that individual performance has a positive effect on the wage in 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

[12]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.

wages. [13] 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.

Figure 5: **Stay and switching jobs 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.

4.3 Wage growth between jobs

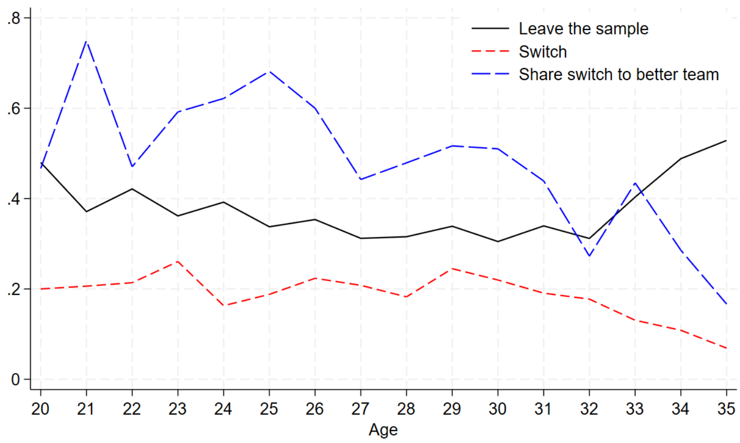
In a labor market characterized by frequent turnover of workers between teams, the learning process facilitated by collaborating with more skilled team members should culminate in higher wages, provided that the acquired skills are valued by other teams. In principle, worker mobility may be upward or downward, as depending on their performance workers have the ability to move towards either better or worse firms. Figure 5 depicts the rating distributions for players who

[13] We also estimate a version of the model in column 1 using the restricted sample of 1,238 observations present in column 4. The results are very similar and available upon request.

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.

Table 2 suggested that, on average, switching teams is unrelated to future wages. However, this effect may be age-specific. Figure 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. Figure 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).

Figure 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 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. 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.

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; *** (*) significant at a 1% (10%) level.

4.4 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.

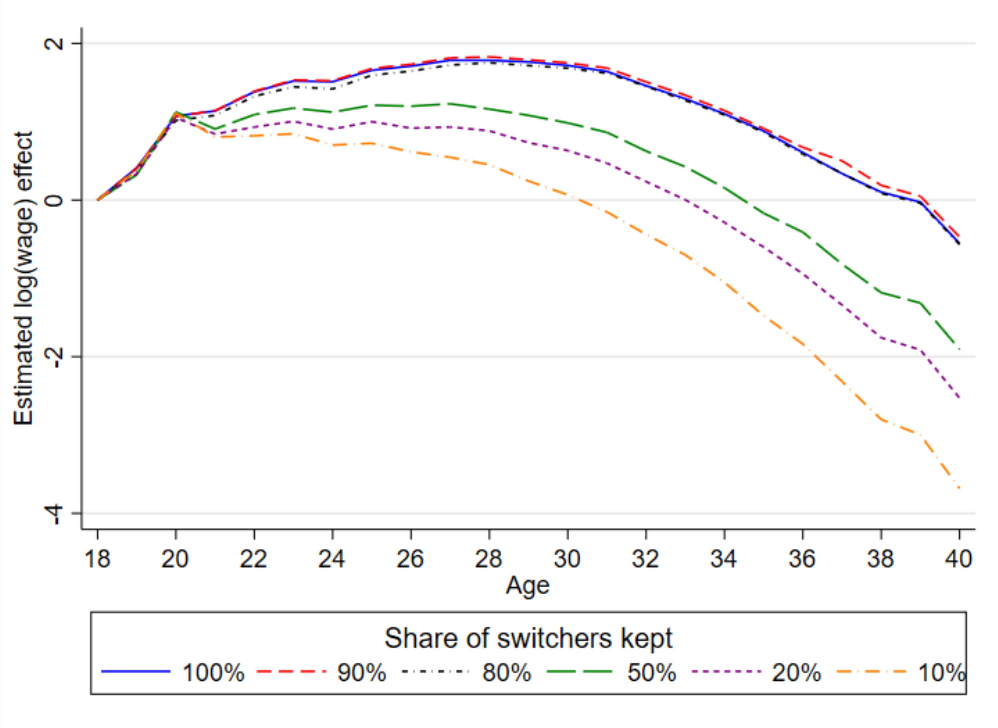
2. Record the identities of all firms employing the selected players, establishing a fixed sample of firms. This set remains constant throughout the exercise.

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 Figure 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.

Figure 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.

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.

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 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.

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. 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.

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Appendix A: Sample dynamics

Panel a of Table A.1 gives an overview of the dynamics in our sample of Italian football players.

Table A.1: **Sample Dynamics**

a. Season to season

Players	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Same team	148	155	169	154	143	160	143	154	156		1382
Different team	73	76	66	77	66	53	63	69	59		602
Out of sample	87	87	100	90	112	91	107	96	93	309	1172
Total	308	318	335	321	321	304	313	319	308	309	3156
New	308	97	104	86	90	95	100	113	85	94	1172
Mobility (%)											
Same team	48	49	50	48	45	53	46	48	51		49
Different team	24	24	20	24	21	17	20	22	19		21
Out of sample	28	27	30	28	35	30	34	30	30		30
Total	100	100	100	100	100	100	100	100	100		100

b. Flow dynamics

Participated in	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Started in											
2011	308	221	171	131	98	71	52	40	29	18	1139
2012		97	60	46	36	23	21	14	10	4	311
2013			104	58	43	28	18	12	11	8	282
2014				86	54	33	24	20	12	11	240
2015					90	54	37	31	22	18	252
2016						95	61	38	34	26	254
2017							100	51	41	31	223
2018								113	64	42	219
2019									85	57	142
2020										94	94
Total	308	318	335	321	321	304	313	319	308	309	3156

The football players in our sample tend to be very mobile. For example of the 308 players for whom we have information from 2011, in 2012 only 148 (48%) were still in the same team, 73 were in a different Italian team (24%) and 87 (28%) left the sample because they either moved abroad, to a team in a lower division or they retired. As shown this mobility remained high in later years with an annual average of 49% of the players staying in the same team, 21% moving from one team to a different team in the top league of Italian football and 30% leaving the sample. Panel b of Table A.1 presents information about how long players stay in our sample. For example, of the 308 players of whom we have information in 2011 after 10 ten years 18 (about 6%) were still in the sample. Of the 97 players entering our sample in 2012 in 2020 only 4 players were still in our sample. We can follow some players for several years but because of flow dynamics the sample reduces quickly as the number of years increase. It is also possible that a player leaves our sample in a particular year to re-enter a few years later.

Appendix B: Additional estimates job mobility

Table B.1 shows the parameter estimates of a multinomial logit model distinguishing between a transition to a team with a higher average team wage (a better team) and a team with a lower average team wage (a worse team).

Table B.1: **Additional parameter Estimates Job Mobility**

	To worse team		To better team		Out of sample	
Performance	-0.86	(0.43)**	0.31	(0.41)	-0.79	(0.35)**
Wage	-0.24	(0.37)	0.57	(0.35)	0.04	(0.32)
Team wage	2.96	(0.38)***	-3.89	(0.45)***	-0.15	(0.33)
Performance	-0.64	(0.39)*	0.39	(0.36)	-0.70	(0.34)**
Wage	1.51	(0.30)***	-1.53	(0.24)***	0.06	(0.27)
Performance	-0.89	(0.42)**	0.47	(0.40)	-0.77	(0.34)**
Team wage	2.85	(0.35)***	-3.53	(0.38)***	-0.11	(0.29)
N (n)			2179 (537)			

Note: The parameter estimates are obtained from a multinomial logit specification. Reference group: stayers. Wage and team wage are in logs. All specifications contain season fixed effects, age fixed effects and individual fixed effects. N = number of observations; n = number of individuals

The parameter estimates for "out of sample" are very much the same as those in Table 1. The parameter estimates for going to a worse team are opposite of those going to a better team. A higher individual performance makes it more likely to go to a better team and less likely to go to a worse team. Individual wages and/or team wages have a positive effect the transition to a worse team and a negative effect of going to a better team.