Long-term Economic Effects of Relative Age - The Case of Serie A

by

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Abstract. In sport and school contexts, children are divided into age-groups which are arbitrary constructions based on the admission dates. This age-group system is thought to determine differences in maturity between pupils within the same group, that is, relative age (RA). In turn, these within-age-group maturity differences produce performance gaps, that is, relative age effects (RAE), which might perpetuate throughout the human capital accumulation process and affect the labor market outcome. We analyze the long-term effects of RA using a unique dataset providing information on a particular group of workers: footballers in the Italian major football league, that is, Serie A. In line with previous studies, we find evidence of the existence of RAE, reflected by a skewed month of birth distribution where players born relatively early in the age-group are overrepresented. Moreover, we find that footballers born relatively late in the age-group receive lower gross wages than footballers born relatively early; this finding is sensitive to different model specifications though. Finally, we did not find evidence that the wage gap varies with age. Combining these results, we conclude that, since we control for footballers' experience, relative maturity and "tangible" productivity, this gap might be due to lower levels of "intangible" characteristics (e.g., leadership skills) of relatively young players.

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1 Introduction

In sport and school contexts, age-groups are formed using arbitrary admission dates which affect achievements in early life. Admission dates determine some children to be older than others within the same age-group; this chronological difference, called relative age (henceforth RA), is responsible for early differences in maturity—in terms of both cognitive and physical development (see for instance, Bedard & Dhuey, 2006, and Musch & Hay, 1999), which cause a performance gap, usually referred to as relative age effect (henceforth RAE).[1] Since the RAE is generated by a maturity gap between children in the same age-group, it is expected to decrease throughout puberty and eventually to disappear; however, it might persist, or even widen, because of the streaming process. This process can be more or less formal (Bedard & Dhuey, 2006). On one hand, when it is formal, children in each age-group are further divided, depending on their perceived talent, into ability groups; therefore, there is a visible selection of the children. On the other hand, when the streaming is less formal, children in the same age-group receive different education or training (Bedard & Dhuey, 2006), without being separated into different ability groups. In this process, relatively old children enjoy an advantage over relatively young children, since their higher maturity is mistaken with higher talent. Two additional mechanisms may further contribute to the RAE. First, in case of formal streaming, a crucial mechanism influencing RAE is the level of competition during the selection into ability groups; the larger the total amount of children compared to the available places in a certain ability tier the more likely old children are streamed into higher tiers compared to relatively young children (Musch & Grondin, 2001). Second, psychological factors may play an important role amplifying the RAE. For instance, the Pygmalion effect predicts that expectations on people's ability trigger self-fulfilling

[1] For instance, consider the case where all children who turn 6 in a given calendar year—thus the cut-off date is the 1st of January—are required to start the first grade of primary school. In the same class, we might have some children who turn 6 in January and some children who turn 6 in December; relatively old pupils born in January are 17% older than relatively young pupils born in December. This biological difference is the RA, which causes differences in terms of maturity, leading to a performance gap; this difference in the performance is the RAE.

prophecies (Musch & Grondin, 2001, and Hancock et al., 2013). Psychological factors and competition affect the RAE throughout the streaming process; eventually, the performance gap might be so large and persistent that it ultimately affects even the labor market outcome (see for instance, Allen & Barnsley, 1993, and Bedard & Dhuey, 2006).

The analysis of RAE might be complicated by the presence of seasonal effects, which are unrelated to within-age-group maturity differences, such as climatic, environmental, sociocultural and biological factors (Musch & Grondin, 2001). In fact, these alternatives explain the differences in children's performances with *the position of their birth-dates within the calendar year*; while, the RA concept explains the performance gaps with *differences in birth-dates within the same age-group*. Another factor which complicates the analysis of RAE is the possibility that age-groups might contain children whit an age which differs from the age of typical children in that group. For instance, children might repeat a grade or, as in the US, the school entry might be deferred (Bedard & Duhey, 2006).

However, in the long-run these seasonal effects have a mitigate effect in a particular labor market: that for professional footballers. There is cross-cultural evidence that the admission date is the major, if not the only, responsible for the RAE in professional football (see for instance, Munch and Hay, 1999, Helsen et al., 2000, and Williams, 2010).[2] Additionally, seasonal confounders may hardly offer the explanation to RAE between footballers born in two adjacent months, where one month is before and one after the

[2] Munch and Hay (1999) compare samples of players from the best football leagues in Germany, Brazil, Australia and Japan. In all four countries the authors find a peak in the month of birth distribution corresponding to the admission date despite a number of differences. Germany, Brazil, and Australia had the same admission date, 1st of August, but they are located in different hemispheres, and have different climates, which rules out environmental, climatic and biological factors as possible explanations for skewed distributions. Japans' admission date was the 1st of April, in which they find a peak in the distribution of month of birth, ruling out also sociocultural factors. Munch and Hay (1999) also study the effect of the shift in the cut-off date in Autralia. In 1988 the admission date shifted from the 1st of January to the 1st of August; the authors observe that, years after the change in the admission date, a corresponding shift of the peak in the month of birth distribution occurred in the Australian first football league. Also in Belgium, Helsen et al. (2000) find an equivalent shift of the peak in the month of birth distribution, after that in 1997 the admission date passed from the 1st of August to the 1st of January. Furthermore, analyses of international competitions, such as the Under-17 world cup (Williams, 2010), seem to suggest that the RAE is also independent from the schooling year; the teams in international competitions come from countries with different school admission dates, but besides some African countries, they all present an overrepresentation of relatively old footballers.

admission date; this consideration is common to other sports, as hockey (see for instance, Barnsley & Thompson, 1988). Finally, in some countries, the age-grouping system is strict and this facilitates the analysis; neither redshirting, that is, the deferment of children's entry in the next age-group, nor their retainment in the current age-group is possible.[3]

The favorable setting provided by the football game offers a suitable field for our research, which analyzes different effects of RA in the long-run. We use unique panel dataset from the Italian football major league. We analyze the month of birth distribution of Italian footballers, and find that relatively old players are overrepresented; this is the typical method to investigate the presence of RAE. This result is in line with the general literature, and with the finding in Salinero et al. (2013), who also analyze the month of birth distribution for Italian footballers in Serie A. Furthermore, we analyze the long-run RAE in terms of gross wage gaps. The streaming process previously illustrated suggests that on average relatively old players should perform better (Allen & Barnsley, 1993) and thus should receive larger wages. We find evidence to support this hypothesis, but this finding is sensitive to different model specifications. Differently, the sole previous study on RAE in terms of footballers' wages, by Ashworth and Heyndels (2007), provides evidence for reverse RAE in terms of gross wages, that is, larger gross wages for relatively young footballers. However, our two studies differ because of a number of features, the most important of which are the period being investigated[4] and the econometric strategy. Moreover, our dataset covers seven seasons; hence, we can investigate whether the gross wage gap varies through players' career; this is our main contribution to the literature. At the beginning of the footballers' careers, part of the wage gap might still be due to a difference in sheer maturity, still evident up to the early

[3] For instance, according to rules set by the Italian Football Federation (FIGC), out of seven juvenile categories, only in the last category a team may deploy one overage player on the pitch, and only in one intermediate category a team may deploy three underage players.

[4] Ashworth and Heyndels (2007) analyze data from the period immediately after the "Bosman ruling", European Court of Justice, December 1995. The "Bosman ruling" bans restrictions on the number of foreign EU players, within EU leagues. We analyze data from a later period; hence, both teams and players have had time to fully adjust to the new rules. This ruling might have affected the streaming process for footballers in their late teens, since footballers' migration within EU is facilitated.

twenties.[5] In later stages of the career, when the maturity gap is filled, the wage gap might be disappeared, widened or reduced, depending on the streaming process. We find that, the wage gap does not vary during the footballers' career. Since in our investigation we control for footballers' experience, relative maturity and "tangible" performance, we think this gap might be due to the lack in "intangible" characteristics, such as charisma, which are measured by our data.

The reminder of the paper proceeds as follows. Section II presents a summary of the literature review on RAE in education and sport; Section III discusses the data and presents descriptive statistics; Section IV present the empirical methodology; Section V illustrate the results; finally, Section V concludes.

2 The Relative Age Effect

In this section we present some of the most important evidence on RAE for both school and sport context. In both fields, scholars typically find evidence of negative RAE; however, a few studies which focus on the long-run find reverse or null RAE. Beside the similarities in the results, the two fields present differences to be discussed; these differences are important for our analysis.

In school, RAE is caused by initial differences in children's cognitive development. These differences, first, trigger misjudgments on pupils' talent and, then, more or less flexible streaming, which widens the initial maturity gap. Ultimately, the consequences on children's school achievements may differ; for instance, late born children are more likely to be retained for an additional year in the same grade or to be assigned to remedial classes (Dixon, Horton, & Weir, 2011), they are more likely to be diagnosed with learning disability (Dhuey & Lipscomb, 2009), or to be left falling farther behind (Bedard & Dhuey, 2006). Additionally,

[5] The physical development reaches its top at 20 years of age (see for instance, cdc.gov/growthcharts/data; and canadiansportforlife.ca/sites/default/files/resources/MonitoringGrowth.pdf), while the cognitive development reaches its top between 20 and 25 years of age (Salthouse at al., 2004).

the streaming process cause psychological reactions in all the agents involved in the children growth (Hancock et al., 2013), further widening the RAE. Thus, the RAE might be evident even in later educational stages and can be represented by lower school attendance rate (Cobley et al., 2009), lower performance as well as lower probability to enroll at the university (Bedard & Dhuey, 2006). Moreover, the RAE emerged in the educational system might have repercussions on personality traits and social skills (Pellizzari & Billari, 2012);[6] Finally, a few studies investigate RAE in the labor market, reporting contrasting results. On one hand, RAE in terms of wages in the labor market might initially still disadvantage relatively young workers but ultimately reverses and benefits them, with an overall null RAE. A possible explanation is that different performances on the labor market reflect only chronological age differences (Larsen & Solli, 2012). In alternative, RAE might disappear because employers get to know better the employees, rewarding their productivity irrespectively of the educational achievements, which are biased in favor of relatively old students (Crawford et al., 2013). On the other hand, Du at al. (2012) find that RAE is still evident in terms of representativeness among CEOs, that is, relatively old CEOs are overrepresented among the 500 S&P firms; this result is similar to what is usually found in sport competitions and suggests that the RA might have long lasting effects.

Although the sport context is similar, there are a few differences which determine stronger evidence of RAE in this area. First of all, RAE in sport is caused by initial differences in children's cognitive *and physical* development. Moreover, in sport, competition in the selection process is tougher since early ages (Allen & Barnsley, 1993), and its effect in terms of representativeness are amplified by the possibility for children to drop out (Barnsley

[6] For instance, lower probability to develop leadership skills (Dhuey & Lipscomb, 2008), lower self-esteem (Thompson et al., 2004), lower socialization skills (Pellizzari & Billari, 2012), and even higher probability to suicide (Thompson et al., 1999). However, Pellizzari and Billari (2012) also explain that, since relatively young students spend less time in social activities, they may devote more time to study and manage to perform better at the university.

& Thompson, 1988, and Helsen et al., 1998).[7] While sport is based on voluntary participation (Musch & Hay, 1999, and Musch & Grondin, 2001), school is compulsory in early ages. Finally, also in sport, performances as well as drop outs are affected by psychological reactions (Hancock et al., 2013). This repeated streaming process causes skewedness in the month of birth distribution since early stages of sport competitions, where, in general, early born children are overrepresented in each age-group;[8] this process also causes performance gaps, which might be long-lasting up into adult competitions (Allen & Barnsley, 1993, Musch & Grondin, 2001, and Hancock et al., 2013).[9] However, in the long-run, a few studies find evidence of either null or reverse RAE. Those studies which find evidence of null RAE explains that this evidence is artifactual, and it is found when the possibility of deferred entry into professional competition is not taken into account[10] (Harvey et al., 2013, and Böheim & Lackner, 2012), this possibility is typical of sports with draft systems. Other studies find RAE in terms of skewed month of birth distribution, and, at the same time, reverse RAE in terms of wages, with relatively young athletes receiving higher wages (Ashworth & Heyndels, 2007); or, reversed skewed distribution among the very best athletes,[11] with relatively young athletes being overrepresented (Gibbs et al., 2011). They explain these results with the existence of both a positive selection of relatively young athletes—the few relatively young athletes left are the very best of their group (Ashworth & Heyndels, 2007), and peer effects—training with (older and thus) stronger athletes in youth categories strongly benefits relatively young

[7] Children can also change sport, opting for one in which the cut-off date either provides them with a positive RAE (Thompson et al., 1999) or has lower or no importance (Williams, 2010).
[8] There is evidence of RAE when the month of birth distribution of the athletes' sample is statistically significantly different from the month of birth distribution of the underlying general population, and its peak corresponds to the admission date.
[9] Evidence of RAE is found among professional athletes; for example, in football (see for instance, Musch & Hay, 1999) and in tennis (Edgar & O'Donoghue, 2005), in both summer and winter Olympic games (Joyner, et al., 2013), and in NFL (Böheim & Lackner, 2012).
[10] Moreover, Allen and Barnsley (1993) suggest that RAE could disappear with the end of the initial maturity gap if the streaming process is not enough strong; in this case, there would be evidence of RAE in professional competitions, in terms of skewedness, but not in terms of wages and thus in terms of performances.
[11] That is athletes selected for the all-star and Olympic team rosters.

athletes (Gibbs et al., 2011, and Ashworth & Heyndels, 2007).[12] However, the effect of these two mechanisms is not straightforward.

Therefore, both in education and sport, the RAE emerges from a maturity difference and evolves throughout a complex streaming process. On one hand, the school literature provides evidence that this streaming process affects not only children's school "tangible" performance, but also children's "intangible" characteristics. On the other hands, sport literature focuses on the effects of children's "tangible" characteristics. The findings from both fields of studies help us to interpret the results from our analysis. In particular, they are useful to interpret a possible wage gap between relatively old and young footballers. In fact, we think that this possible wage gap might be divided into three parts: a part owed to a maturity difference, which determines, for instance, differences in strength, another part owed to differences in "tangible" productivity, for instance, number of goals, assists and international experience, and a last part owed to differences in "intangible" productivity, such as competitiveness and leadership. While the maturity difference and the "intangible" productivity cannot be directly measured by individual performance indexes, like for the "tangible" productivity, they still affects the players' performance and that of their teams.

3 Institutional Context and Data

The context of our analysis is the Italian football major league, that is, Serie A. It is currently composed by 20 teams, but these teams do not permanently play in the major league; in fact, since Italian football has a tiered structure, there are promotions and relegations at the end of each season. The last three teams in the ranking are relegated to Serie B, that is, the second national division, which is composed by 22 teams, while the top three teams from Serie B are promoted to Serie A. We have observations on 508 Italian footballers, who played at least in

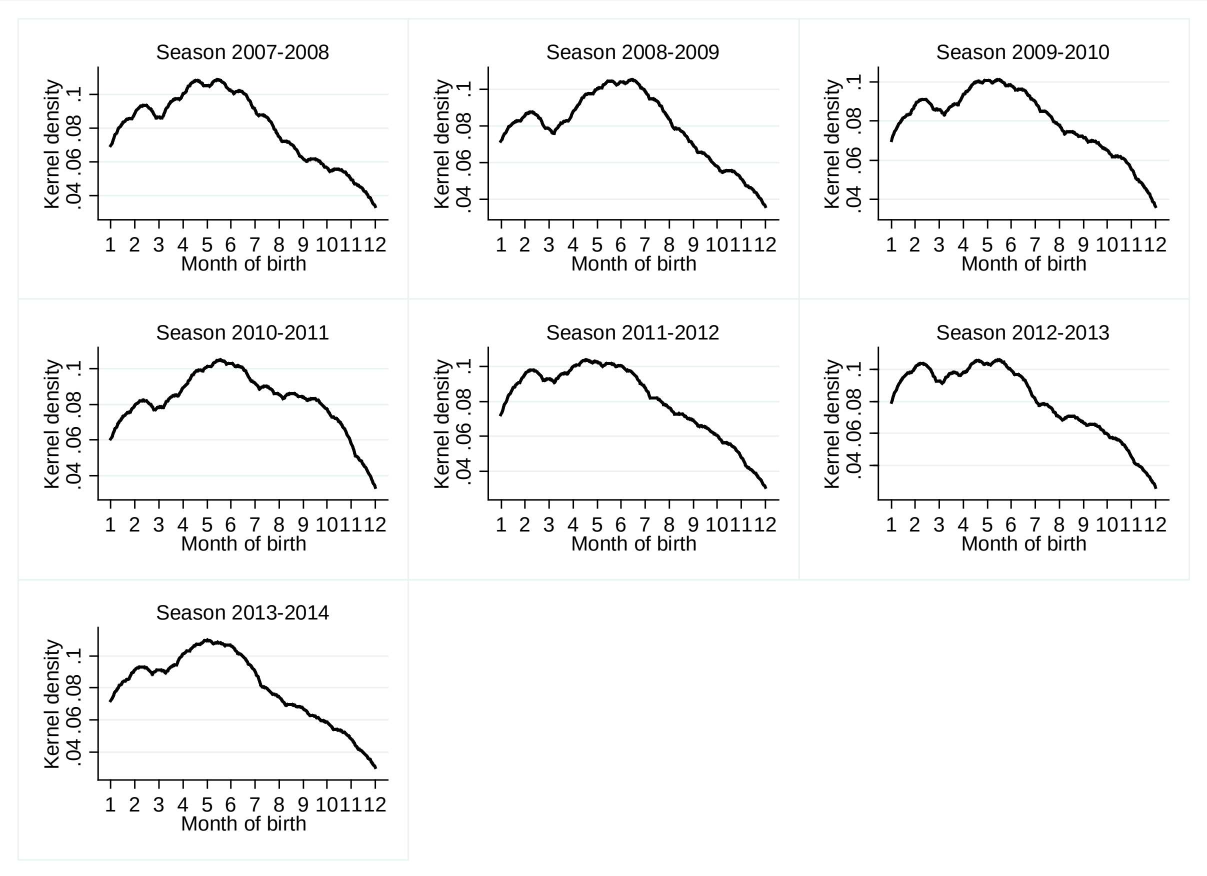
[12] Moreover, Williams (2010) suggests that in the long-run RAE might reverse because, while relatively young athletes have a complete training, relatively old athletes put less emphasis on skills development, since they are selected primarily upon their physical attributes.

one match for one Serie A team, during the seven seasons in analysis.[13] In total, the unbalanced panel data contains 1,703 Italian footballer-season observations.[14] In Italy, the 1st of January is the current relevant admission date on which the age-grouping system is based; depending on the category, children born in different years might play and train together. The lowest age category is for children from 5 to 7 years; they are put in the same age-group, i.e., "Piccoli Amici" (Small Friends), for both training and competitions. In the next two categories, children of different ages are still grouped together for training, but they are divided based on year of birth for competing. These categories are "Pulcini" (i.e.,Chicks), for children under 11 years of age, and "Esordienti" (i.e., Newcomers), for children under 13 years of age. Up to three underage players may participate in the games for "Esordienti." In the next categories teenagers with different ages are put together for both training and competition. These categories are "Giovanissimi" (i.e., Very Young), for players under 15 years of age; "Allievi" (i.e., Cadets), for players under 17 years of age; and finally "Primavera" (i.e., Spring), for players under 20 years of age. In all these categories excluded the last one, no overage is allowed; in "Primavera" only one overage player per team may participate to the competitions.[15]

Figure 1 illustrates the footballers' month of birth distributions, in Serie A, for each of the seven seasons. This figure suggests the presence of RAE, that is, in each season the relatively old footballers are overrepresented.

Figure 1

[13] We focus on Italian footballers to be certain to analyze a set of players trained with the same admission date. Moreover, finding complete information on admission dates from other countries is a complex task: admission dates might differ between countries, and within countries in different youth categories.
[14] Most of the footballers appear in our dataset for one or two seasons, 139 and 100 footballers respectively; 56 and 48 footballers are present for 3 and 4 seasons respectively; 53 and 45 footballers are present for 5 and 6 seasons respectively; 45 footballers are present in all the 7 seasons.
[15] More information on the Italian cut-off age and youth categories can be found on the official web-site of the Italian Football Game Federation (FIGC).



First insights on the possible wage gap can be obtained comparing the distribution of the gross wages for relatively old and young players. For descriptive purposes, we define the relatively old Italian footballers as those players born in the first semester of the calendar year, while the relatively young Italian footballers are those players born in the second semester. Our analyses in Section 4 are instead implemented using a continuous discrete variable for RA, which is based on the months order within the competition year. Hence, in Figure 2, we compare the kernel density distributions of the natural log of the deflated gross wages[16] before taxation—without either bonuses or image rights or other deals. Since players

[16] The information on gross wages is obtained from annual reports completed by the Italian sport dedicated newspaper *Gazzetta dello Sport*. For each season, we deflate the gross wages at the 2013 price level; we use the annual coefficients provided by ISTAT (Italian National Institute for Statistics).

can change team during the season, we consider only the gross wages that players receive from the team with which they start the season.[17]

Figure 2

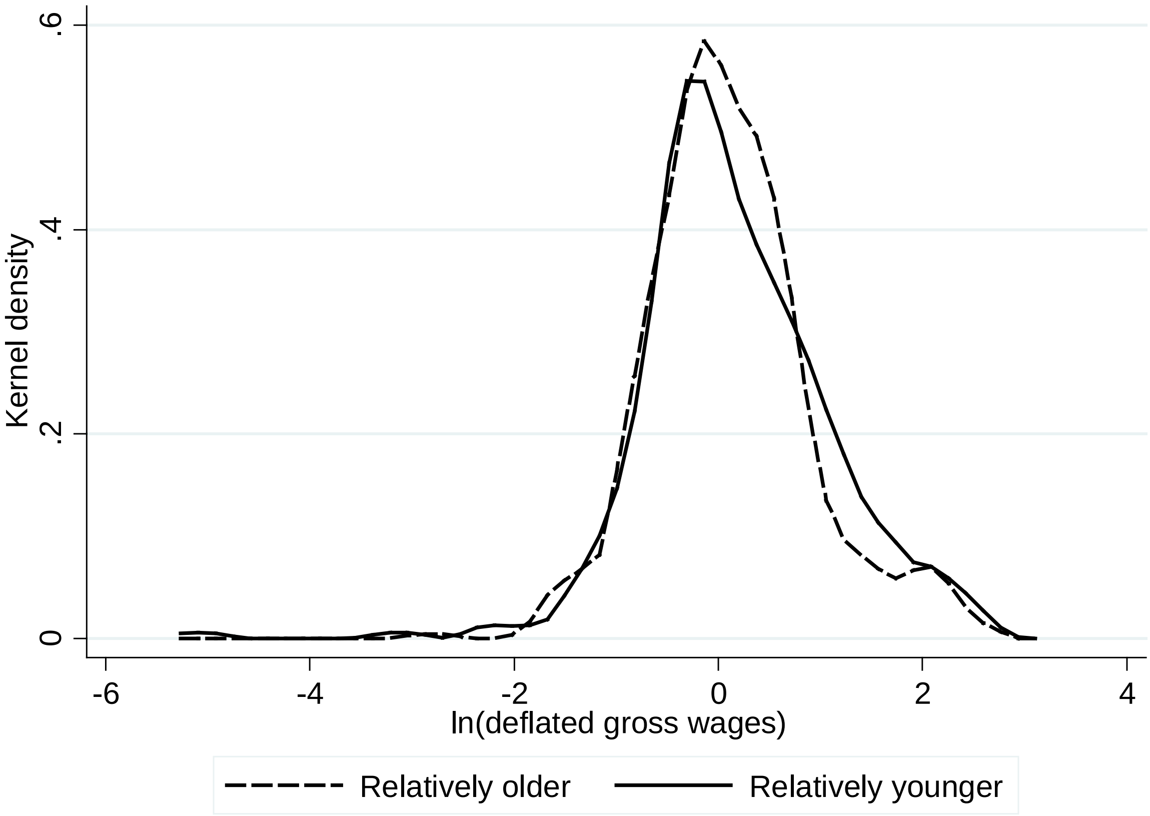


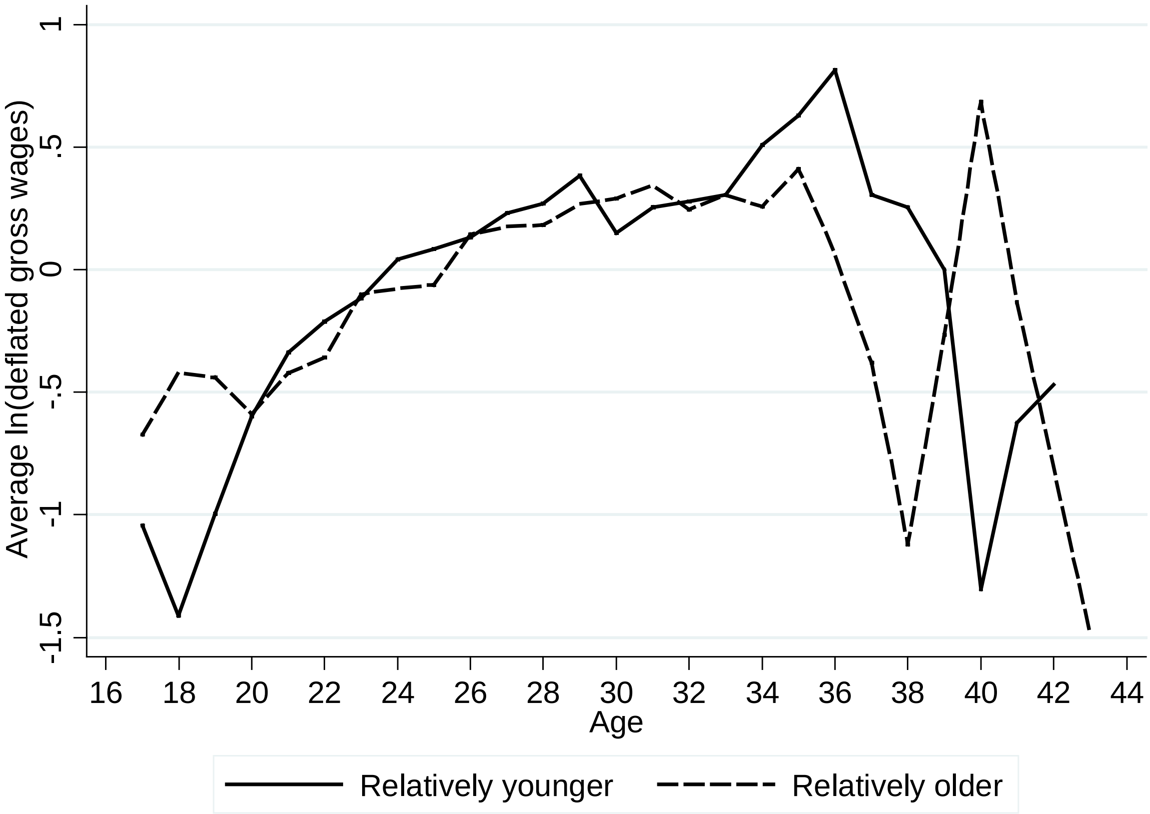
Figure 2 shows that both sub-samples have a leftwards skewed distribution and that the distribution of the relatively young players' wages has a thicker right tail. Therefore, splitting the sample based on the semester of birth, it seems that relatively more players born in the second semester receive gross wages in the top quartile of the gross wage distribution.[18]

[17] Teams trade players in two main market sessions: in summer, which separates different football seasons, and during the Christmas break, which is toward the end of the first half of the season. To players who change team during the latter session and come from another Serie A team, we assign the gross wage they received from the previous team at the beginning of the season. To players who join a Serie A team during the Christmas break and come either from abroad or from a lower domestic league we assign the new wage.

[18] The two-sample Kolmogorov-Smirnov test for the equality of distribution functions rejects the null hypothesis, that is, the distributions of the deflated gross wages for relatively old and young footballers differ in a statistically significant manner at the 95% level.

Additional insights on the nature of the wage gap might be gained with the investigation of its dynamics through footballers' career. With this purpose, in Figure 3, we plot the average natural logarithm of the gross wages against age for both groups.

Figure 3



We observe an entry wage gap which tends to disappear in the early twenties; then, around the early thirties a new wage gap becomes evident, now in favor of relatively young footballers. Around 40 years of age a gap in favor of relatively old players appears anew. This graph suggests that at the beginning of the career there might still be a maturity differential. For extreme ages, the indications provided by the graph have to be considered carefully because of the low amount of observations.[19] In fact, the presence of a few outliers in terms of

[19] There are 27 footballer-season observations at 18 years of age, or less, and 33 footballer-season observations at 37 years of age, or more.

wages,[20] in those small age-groups, might drive up the average wages.[21] Moreover, the analyses in Section 4 are instead implemented using a continuous discrete variable for RA, which mitigates the average wage gaps.

In the next section, we present the methods to formally test our research hypotheses:

- *Hypothesis 1*: there is a skewed month of footballers' birth distribution in the Serie A football league.
- *Hypothesis 2*: there are wage gaps between relatively old and young players.
- *Hypothesis 3*: there are different wage dynamics between relatively young and old footballers.

In the appendix, we further analyze the wage gaps, differentiating the footballers depending on their role. The literature suggests that in different roles the extent of the RAE might differ, since footballers' roles differ in terms of physical requirements (see for instance, Salinero, Pérez, Burillo & Lesma, 2013, and Ashworth & Heyndels, 2007).

4 Methods

4.1 Month of birth distribution

To formally test for *Hypothesis 1*, that is, the presence of a skewed footballers' month of birth distribution, we implement a method used in the sport literature (see for instance, Musch & Hay, 1999, and Ashworth & Heyndels, 2007). We pool the observations from the seven seasons and compute the Pearson correlation between two month rankings. The first month ranking is given by the *months representativeness* in Serie A and it is based on the differences between the expected amount of footballers, where their birth-dates are supposed to be randomly distributed along the year, and the observed amount of footballers in each

[20] The outliers in terms of wages might be referred to as *superstarts* (see for instance, Bryson, Rossi & Simmons, 2014, Lucifora & Simmons, 2003, Adler, 1985, and Rosen, 1981).

[21] For this reason the analyses are implemented on the sample where the 1st and 99th percentile of the age distribution, that is, players with 18 years of age or less and those with 37 years of age or more, are excluded.

month. When the difference between the expected and the observed amount of observations is negative, the footballers born in that month are overrepresented; vice-versa, with a positive difference there is underrepresentation. The first place in the ranking is assigned to the most underrepresented month, while the last place is assigned to the most overrepresented month. The second month ranking is based on the *months order* within the competition year (i.e., January has the first position, while December has the last position), which represents the RA. Therefore, on one hand, if the estimate of the correlation is negative and statistically significant, there is evidence for RAE, that is, footballers born in early months are overrepresented. On the other hand, if the correlation is positive and statistically significant, there is evidence of reverse RAE (see for instance, Ashworth & Heyndels, 2007, and Gibbs et al., 2011), that is, footballers born in late months are overrepresented.

4.2 Wage gap

To formally test for *Hypothesis 2*, that is, the presence of wage gaps between relatively old and young footballers, we can choose between alternative econometric strategies. Three econometric models usually employed in the analysis of panel data are discarded because not suitable to our analysis: the pooled OLS regression with standard errors clustered on footballers, the least-square dummy variable regression, and the random-error effect. The pooled OLS regression with clustered standard errors would provide biased estimates; in fact, we expect unobservable time-invariant characteristics effects, e.g., footballers' innate ability, to be correlated with the variables for footballers' "tangible" productivity, i.e., the IVG performance index,[22] and experience, e.g., caps in Serie A and caps with the national team. The least-square dummy variable regression controls for time-invariant characteristics, but without distinguishing between observable time-invariant

[22] The IVG (General Valuation Index) is measured on a scale from 0 to 30, and represents the individual player's quantitative contribution to his team. It does not capture more intangible measures of productivity, such as charisma, tactical leadership, and competitiveness. For more information on IVG see http://www2.raisport.rai.it/eventi/euro2000/ivgdescr.html

characteristics, e.g., RA which is our variable of interest, and unobservable time-invariant characteristics, e.g., footballers' innate ability. The random-effect estimator might be excluded for reasons similar to those which lead to the exclusion of the pooled OLS regression with clustered standard errors. In fact, the random-effect estimator is based on strict assumptions that we expect not to hold in our analyses: both the time-variant and the time-invariant regressors have to be uncorrelated with the stochastic part of the error term; moreover, they have to be uncorrelated with the time-invariant part of the error term. In our analysis, these unobservable individual effects might be related with the set of covariates representing players' productivity and experience.[23]

We opt for a fourth alternative model: a two-steps approach suggested in Jusko and Shively (2005), Donald and Lang (2007), and Bryan and Jenkins (2013). This approach consists of a first regression at the individual level with time-variant characteristics, that is, age, experience and productivity variables, and a second regression at the individual level with time-invariant characteristics, that is, month and year of birth as well as players' role.[24] In the first step the within-group estimator is used, while in the second step the between-group estimator is used.[25] We opt for this model for two reasons. First, the within-group estimator provides unbiased estimates even in presence of the correlation between the regressors and the time-invariant individual effects; in fact, the within-group transformation eliminates all the individual effects. We expect this correlation to exist since the players' productivity

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[23] In Section 5, for each analysis, we present also the results from the tests on this correlation. We implement the Sargan-Hansen test of overidentifying restrictions, which is based on the artificial regression approach described by Arellano (1993). The Sargan-Hansen statistics is the Chi-square from the Wald test of the significance of the additional regressors in an augmented random-effects model; where the additional variables are the deviations from the mean of the original time-variant regressors.

[24] The usage of age and experience is motivated by the fact that in European sports, there is no drafting system, so that athletes may enter professional competitions at different ages. Differently, in studies on US sports, the introduction of both variables would create multicollinearity, as the drafting system is such that athletes enter professional leagues at a somewhat uniform age. (Lucifora & Simmons, 2003).

[25] This second step amounts to regressing the predicted individual effects residuals, obtained from the first step, on the observable individual time-invariant characteristics, that is, players' year and month of birth, as well as on individual characteristics that seldom vary through time, that is, players' role. The within-group estimator in the first step would provide inefficient estimates for the effect of players' role on the gross wage, given the small variation across seasons.

regressors should be related to the time-invariant individual effects. Second, the second step of this approach allows us to retrieve unbiased estimates of the RA long-run effects on wages, conditionally on the *non-astrology assumption* (Allen & Barnsley, 1993), that is, the month of birth is unrelated to innate ability.

Therefore, to test *Hypothesis 2*, that is, there are wage gaps between relatively old and young players, we proceed as follows. First, we estimate the effects of individual time-variant characteristics with Step 1 of Model 1, which is a within-group estimator.

$$Ln(w_{it}) = \beta_0 + \beta_1 age_{it-1} + \beta_2 age^2{}_{it-1} + \boldsymbol{\beta Prod_{it-1}} + e_i + v_{it-1} \qquad (1.1)$$

The dependent variable, i.e., $Ln(w_{it})$, is the natural logarithm of the gross wage in seasons *t* for player i, deflated at 2013 prices; this outcome variable is regressed on a set of control variables measured in *t-1*, since the wage at the beginning of the new seasons is determined by the past players' performances. The set of control variable is composed by age, which is a continuous variable, and age^2, which captures the decreasing returns to age, both of them refer to player *i*'s age in season *t-1*; $\boldsymbol{Prod_{it-1}}$ is a vector of both "tangible" productivity and indicators of different types of experience;[26] v_{it-1} represents the purely stochastic error term, while e_i represents the individual time-invariant error component for footballer i, which combines both unobserved and observed individual time-invariant characteristics, in our case month, year of birth and role on the pitch. The individual time-invariant error component can be re-written as $e_i = \boldsymbol{\alpha z_i} + u_i$; where $\boldsymbol{z_i}$ represents a vector of observable individual time-invariant characteristics, while u_i is the unobservable time-invariant counterpart, which for

[26] We introduce a dummy variable for player *i* being an Italian national team player in *t-1* and an equivalent dummy for being an Italian national U21 team player (the last youth national team), a continuous variable for the total amount of Serie A caps in career for player *i* until season *t-1* and an equivalent variable for total amount of Serie B caps, a continuous variable for total minutes played by footballer *i* in season *t-1*, a continuous variable for the amount of Serie A caps for player *i* in season *t-1*, a continuous variable for the amount of seasons player *i* spent in Serie A until season *t-1* and the equivalent for seasons in Serie B, and the IVG index, which measures the footballer *i*'s performance in season *t-1*.

instance includes innate ability. The estimate of the effect of RA on the natural logarithm of gross wages could not be obtained from this Step 1, since the within-group transformation eliminates the time invariant variables. Therefore, we retrieve it from the between-group estimator in Step 2 of Model 1:

$$\hat{e}_i = \gamma_0 + \gamma_1 RA_i + \boldsymbol{\gamma Role_i} + \boldsymbol{\gamma Year_i} + \eta_i \qquad (1.2)$$

$\hat{e}_i$ is the predicted value of the individual fixed-effect residual for footballer *i*; it is derived from the estimates in the first step as $\hat{e}_i = \overline{Ln(w_i)} - \hat{\beta}_1 \overline{age}_i - \hat{\beta}_2 \overline{age^2}_i - \boldsymbol{\hat{\beta}} \overline{\boldsymbol{Prod}}_{\boldsymbol{it-1}}$, where the bars indicate mean values taken over all seasons for player *i* (Bryan & Jenkins, 2013). *RA* is the variable of interest, it is a continuous variable for the RA—thus ranging from 0 to 11 with January being the reference month—of footballer *i* and is represented by the months order within the competition year; its coefficient, γ_1, is thus the effect of RA on the natural logarithm of gross wages. ***Year*** is a vector of players' years of birth; $\boldsymbol{Role_i}$ is a vector of players' roles, that is, goalkeeper, defender, and midfielder, with forward being the reference role; η_i represents the residual individual unobserved effect for footballer *i*, and it is given by $\eta_i = u_i + \hat{e}_i - e_i$ (Bryan & Jenkins, 2013). As a robustness check, the analyses are re-run adding vectors of fixed-effects for season and team in the Step 1. The estimate for the effect of *RA* is the average effect of being born one month further away from the admission date on the natural logarithm of gross wages. Assuming that the football labor market is efficient and there is no discriminatory behavior against relatively young footballers, and since in the first step we control for footballers' "tangible" productivity and experience, we can interpret the estimate for effect of RA as reflecting both differences in sheer maturity, for players of the same age, and in "intangible" productivity, e.g., leadership skills, charisma, and competitiveness. We cannot disentangle the two factors in this analysis.

4.3 Wage dynamics

Hypothesis 3, that is, there are different wage dynamics between relatively young and old footballers, is tested using the same two-steps approach; yet, now we add to Model 1 interactions between *RA*, age and age^2, see Step 1 of Model 2.

$$Ln(w_{it}) = \beta_0 + \beta_1 age_{it-1} + \beta_2 age^2{}_{it-1} + \beta_3 RA_i * age_{it-1} + \beta_4 RA_i * age^2{}_{it-1} + \boldsymbol{\beta Prod_{it-1}} + e_i + v_{it-1} \quad (2.1)$$

Where β_3 and β_4 represent the evolution of the effect of RA on the natural logarithm of the gross wage across different ages. Thus, they communicate how the effect on wages of the differences in terms of sheer maturity change with age, assuming that "intangible" productivity does not vary through time. However, also in this model, the estimate for the average effect of RA could not be obtained from this Step 1; therefore, we retrieve it from the between-group estimator in Step 2 of Model 2.

$$\hat{e}_i = \gamma_0 + \gamma_1 RA_i + \boldsymbol{\gamma Role_i} + \boldsymbol{\gamma Year_i} + \eta_i \quad (2.2)$$

Based on the assumption that "intangible" productivity does not vary, the coefficient, γ_1, can now be interpreted as the effect of RA, in terms of "intangible" productivity, on the natural logarithm of gross wages. As a robustness check, the analyses are re-run adding vectors of fixed-effects for season and team in Step 1.

5 Results

5.1 Month of birth distribution

The descriptive statistics suggest the presence of RAE in Serie A. To formally test for *Hypothesis 1*, that is, the presence of RAE in terms of skewed month of birth distribution, we estimate the Pearson correlation between the two month rankings described in Section 4: *months representativeness* and *months order*. Table 1 shows the results of our analysis.

Table 1. Correlation between months representativeness and months order.

	Months representativeness				Months order
Month	Expected counts	Actual counts	Difference	Ranking	Ranking
January	144.6	234	-89.4	12	1
February	130.6	119	11.6	5	2
March	144.6	154	-9.4	9	3
April	139.9	139	0.9	8	4
May	144.6	206	-61.4	11	5
June	139.9	189	-49.1	10	6
July	144.6	138	6.6	7	7
August	144.6	136	8.6	6	8
September	139.9	115	24.9	4	9
October	144.6	111	33.6	3	10
November	139.9	89	50.9	2	11
December	144.6	73	71.6	1	12
Pearson	-0.779 (0.000)				
N	1,703				

Note: The shaded areas include the figures of interest. "Expected counts" is computed as 1,703/365= 4.666, which is then multiplied by the amount of days per month, e.g., 31 for January and 28 for February. It represents the expected amount of players born in each month. On the contrary, "Actual counts" is the observed amount of players born per month. The first place in the ranking "Months representativeness" is assigned to the most underrepresented month, December, i.e., the month with the largest positive difference; while the last place is assigned to the most overrepresented month, January, i.e., the month with the largest negative difference. In "Months order", the ranking follows the order of the months within the competition year, e.g., January is 1st and March is 3rd. "Pearson" is the estimate of the Pearson correlation between the two month rankings; the corresponding P-value is in parenthesis.

Table 1 reports a highly statistically significant and negative correlation between months representativeness and months order. This result is in line with the only other study analyzing the RAE in Serie A (Salinero, Pérez, Burillo & Lesma, 2013), and represents evidence for the presence of RAE in Serie A, in terms of skewed footballers' month of birth distribution: relatively old players are overrepresented.

5.2 Wage gap

The descriptive statistics suggest that there are relatively more players born in the second semester to receive gross wages in the top quartile of the distribution. However, the footballers are divided by semester, in lieu of by month, and we leave in the analysis 1st and 99th percentile of the age distribution, that is, players with 18 years of age or less and those with 37 years of age or more. Thus, we do not gain clear insights on the presence of wage gaps. To formally test for *Hypothesis 2*, that is, the presence of a wage gaps between relatively young and old footballers, we use Model 1 illustrated in Section 4. The main analyses are conducted with a continuous discrete variable for RA, which is based on month of birth instead of semester of birth, and we exclude the 1st and 99th percentile of the age distribution.[27] The estimates obtained from Model 1, with robustness checks, are reported in Table 2.

Table 2. Long-run economic effect of RA, in terms of wages.

	Model 1		Model 1 (rob. check)	
Estimates	Step 1	Step 2	Step 1	Step 2
Age	0.671***		0.577***	
	(0.078)		(0.075)	
Age^2	-0.012***		-0.010***	
	(0.001)		(0.001)	
RA		-0.007		-0.052
		(0.088)		(0.079)
Constant	-9.703***	0.342	-8.781***	0.492
	(1.343)	(0.388)	(1.301)	(0.344)
Prod. and Exp. vector	Y	N	Y	N
Roles F.E.	N	Y	N	Y
Team and Season F.E.	N	N	Y	N
R-square	0.404	0.186	0.529	0.209
Sargan-Hansen	-		176.043	
	(-)		(0.000)	
N Footballer-Seasons	1,405	1,405	1,405	1,405
N Footballers	433	433	433	433

Note: The shaded areas include the estimates of interest. In the robustness check, Team, and Season F.E. are introduced in Step 1. The Sargan-Hansen statistics is the Chi-square from the Wald test of the significance of the additional regressors in an augmented random-effects model; where the additional variables are the deviations from the mean of the original regressors. If the H0 is rejected, the within-group estimator is to be preferred over the random-effects estimator. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[27] Therefore, we now exclude a total of 60 footballer-season observations.

This table does not provide evidence for long-run effects of RA on wage gaps; however, the results must be considered carefully. In fact, Figure 3, which is drawn dividing footballers by semester of birth, suggests that the lack of any effect might be owed to the absence of the interaction of RA with age. For instance, the presence of a maturity gap in favor of relatively old footballers at the beginning of the career and the presence of higher “intangible” characteristics for relatively young footballers might balance each other out, explaining the results. Analyses conducted using semester of birth are implemented as further robustness checks; the results are confirmed.

5.3 Wage dynamics

To formally test for *Hypothesis 3*, that is, the wage gap between relatively young and old players varies with age, we use Model 2. In this model, we add the interactions between RA, age and age^2 in Step 1; these additional terms should control for sheer maturity changes across ages. Also for this analysis we exclude the 1st and 99th percentile of the age distribution, and we use a continuous discrete variable for RA. The estimates obtained from Model 2, with robustness checks, are reported in Table 3.

Table 3. Long-run economic effect of RA, in terms of wage dynamics.

	Model 2		Model 2 (rob. check)	
Estimates	Step 1	Step 2	Step 1	Step 2
Age	0.619***		0.614***	
	(0.132)		(0.126)	
Age^2	-0.011***		-0.011***	
	(0.002)		(0.002)	
RA		1.390***		-0.810***
		(0.089)		(0.079)
RA*Age	-0.088		0.066	
	(0.185)		(0.175)	
$RA*Age^2$	-0.001		-0.001	
	(0.003)		(0.003)	
Constant	-9.677***	1.152	-8.769***	0.112***
	(1.345)	(0.389)	(1.303)	(0.345)
Prod. and Exp. vector	Y	N	Y	N
Role F.E.	N	Y	N	Y
Team and Season F.E.	N	N	Y	N

R-square	0.231	0.488	0.443	0.345
Sargan-Hansen	63.823 (0.000)		175.607 (0.000)	
N Footballer-Seasons	1,405	1,405	1,405	1,405
N Footballers	433	433	433	433

Note: The shaded areas include the estimates of interest. In the robustness check, Team, and Season F.E. are introduced in Step 1. The Sargan-Hansen statistics is the Chi-square from the Wald test of the significance of the additional regressors in an augmented random-effects model; where the additional variables are the deviations from the mean of the original regressors. If the H0 is rejected, the within-group estimator is to be preferred over the random-effects estimator. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

These estimates provide evidence for the existence of a wage gap between relatively old and young footballers. On average, being born one month further away from the admission date halves footballers' gross wage.[28] Moreover, although the estimates are not statistically significant and small in size, this table suggests that the part of wage gap due to sheer maturity differential reduces throughout the footballers' career. These results are sensitive to the model specification though, since they are obtained after the introduction of team, role, and season fixed-effects. Furthermore, given that we control for "tangible" productivity as well as footballers' experience, we interpret the negative and statistically significant effect of RA on the natural logarithm of gross wages as being due to a lack of "intangible" characteristics in relatively young footballers, such as leadership, charisma and competitiveness. Also with this model, the analyses are re-conducted using semester of birth, in lieu of month of birth: the sign and the statistical significance of the results are confirmed; moreover, the effects of interest greatly increase in size.

6 Conclusions

Chronological differences between individuals within the same age-group, i.e., relative age (RA), determine maturity gaps during childhood, both in school and in sport contexts. These differences reflect into a performance gap (see for instance, Musch & Hay, 1999,

[28] Since [exp(-0.810)-1]*100=55%.

Musch & Grondin, 2001, Bedard & Dhuey, 2006, and Dhuey & Lipscomb, 2009), that is, relative age effect (RAE), which should disappear over time. However, because of streaming, competition and psychological factors which influence the human capital accumulation process, the performance gap might extend to the long-run (see for instance, Allen & Barnsley, 1993, and Bedard & Dhuey, 2006), even affecting labor market outcomes.

In this paper, we study different aspects of RAE in the long-run, in the labor market. We focus on a particular group of workers: footballers in the Italian major football league. We find a statistical significant evidence for RAE, in terms of skewed month of birth distribution where relatively old players are overrepresented (see for instance, Barnsley & Thompson, 1988, Musch & Hay, 1999, Musch & Grondin, 2001, and Böheim & Lackner, 2012). This result is in line with existing empirical work, and in particular with the only other study analyzing the RAE in Serie A (Salinero, Pérez, Burillo & Lesma, 2013). We also find a statistically significant evidence of a long-run effect of RA on wages, with relatively old footballers, that is, players born early in the competition year, earning higher gross wages. Moreover, we find that this wage gap does not statistically significantly change throughout the career. Although these results should be considered carefully, since they are sensitive to different model specifications, we interpret the wage gap as being produced by differences in "intangible" characteristics, such as leadership skills (Dhuey & Lipscomb, 2008) and self-esteem (Thompson, Barnsley, & Battle, 2004), while sheer maturity does not seem play an important role in determining the wage gap.

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Appendix

Analysis by role

We also investigate whether the gross wage gap differs by players' position on the pitch. The literature suggests that in different roles the extent of the RAE might differ, as each role differs in terms of physical requirements (see for instance, Salinero, Pérez, Burillo & Lesma, 2013, and Ashworth & Heyndels, 2007). Although also this analysis is conducted with the two-steps model, now we add interactions between *RA* and players' role in Step 2. Therefore, Step 1 of Model A is the same as Step 1 of Model 2.

$$Ln(w_{it}) = \beta_0 + \beta_1 age_{it-1} + \beta_2 age^2{}_{it-1} + \beta_3 RA_i * age_{it-1} + \beta_4 RA_i * age^2{}_{it-1} + \boldsymbol{\beta Prod_{it-1}} + e_i + v_{it-1} \qquad (A.1)$$

Since the estimates for the long-term effect of RA on wages and its interactions with players' role could not be obtained from Step 1; we retrieve them from the between-group estimator in Step 2 of Model A.

$$\hat{e}_i = \gamma_0 + \gamma_1 RA_i + \boldsymbol{\gamma} RA_i * \boldsymbol{Role_i} + \boldsymbol{\gamma Role_i} + \boldsymbol{\gamma Year_i} + \eta_i \qquad (A.2)$$

Where RA_i still represents the continuous variable for the RA of footballer *i*; its interaction with the vector of players' roles, that is, $\boldsymbol{Role_i}$, communicates whether the wage gaps differ by players' role. As a robustness check, the analyses are re-run adding vectors of fixed-effects for season and team in the Step 1. The estimates obtained from Model A, with robustness checks, are reported in Table A.1.

Table A.1. Long-run effect of RA, in terms of wage dynamics and differentiated by players' role.

	Model 3		Model 3 (rob. check)	
VARIABLES	Step 1	Step 2	Step 1	Step 2
Age	0.619***		0.614***	
	(0.132)		(0.126)	
Age^2	-0.011***		-0.011***	
	(0.002)		(0.002)	
RA		1.459***		-0.864***
		(0.220)		(0.195)
RA*Age	-0.088		0.067	
	(0.184)		(0.175)	
RA*Age^2	0.001		-0.001	
	(0.003)		(0.003)	
RA*Defender		0.085		0.224
		(0.230)		(0.236)
RA*Goalkeeper		-0.309		-0.131
		(0.356)		(0.315)
RA*Midfielder		-0.189		-0.043
		(0.267)		(0.237)
Constant	-9.678***	1.261**	-8.769***	0.138**
	(1.345)	(0.416)	(1.303)	(0.369)
Prod. and Exp. vector	Y	N	Y	N
Role F.E.	N	Y	N	Y
Team and Season F.E.	N	N	Y	Y
R-square	0.231	0.492	0.443	0.348
Sargan-Hansen	65.735		174.031	
	(0.000)		(0.000)	
N Footballer-Seasons	1,405	1,405	1,405	1,405
N Footballers	433	433	433	433

Note: The shaded areas include the estimates of interest. In the robustness check, Team, and Season F.E. are introduced in Step 1, while Role F.E. are introduced in Step 2. The players' role of reference is the Forward. The Sargan-Hansen statistics is the Chi-square from the Wald test of the significance of the additional regressors in an augmented random-effects model; where the additional variables are the deviations from the mean of the original regressors. If the H0 is rejected, the within-group estimator is to be preferred over the random-effects estimator. Standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

While the estimates confirm the findings from Section 5.3 on wage dynamics and the long-run effect of RA on gross wages, they also suggest that the wage gap between relatively old and young players do not statistically significantly differ by players' role. As before, the analyses are re-conducted using semester of birth; the results are confirmed and the effects of interest greatly increase in size.