Passing with the Stars:

Learning from coworkers in collaborative jobs *

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Abstract

How do workers learn from their coworkers in the workplace, especially when collaboration is essential? We investigate the mechanism of learning in a high-skill collaborative environment: elite male soccer.

We start by confirming positive effect of coworker quality found in administrative data. Our setting is conducive to find evidence of learning as it can compare players in very similar units of soccer squads. Instead of a wage, we can observe how much value a player could generate in another team over many years. This is our human capital estimate. Workers with coworkers of higher average human capital will see their human capital grow faster. We also confirm that beyond average, skewness matters, being together with stars is helpful in learning. However, proximity is not enough, learning happens via exposure to the best players and the depth of interaction with them. Our special dataset allows investigating details of what happens among coworkers. First, we show that players with high exposure to peers, playing more minutes in games, will experience higher growth of their human capital. Again, by collaborating with stars, learning will be more pronounced. Second, the strength of on the pitch interaction measured via passing intensity will point to even more learning opportunities. All results are especially important for younger players. Finally, integrating data measuring actual skills, such as short pass accuracy, we can tell apart actual learning from higher valuation due to better performance when surrounded by better coworkers.

Keywords: Learning, collaboration in teams, peer effects, stars, sports data

JEL-codes: E24, J31, O33, D83, Z20

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1 Introduction

How do workers learn from their coworkers in the workplace, especially when collaboration is essential? In this paper, we study human capital accumulation via learning in the workplace.

We focus on a specific industry of high-skilled workers that will allow improved detection and understanding of both the process of learning as well as its impact on perceived human capital. Our industry of relevance will have a workplace where collaboration is essential. Examples could include most high-skilled services jobs such as academia, consulting, marketing, but also mid-level management,

Workplace learning is about transferable human capital accumulation (HCA) – acquisition of new skills and knowledge that can be used elsewhere, and thus, it creates value for the worker and the employer[1]. The literature on learning from co-workers relied mostly on large administrative data to gauge the impact of better peers in the establishment on wages (Cornelissen et al., 2017) (no effect) or wage growth (Jarosch et al., 2021) (positive effect).

On peer effects, Hong (2022) ...

This paper contributes to the literature on human capital accumulation with an emphasis on learning from coworkers. We focus on an industry where collaboration is essential and show that exposure to peers is essential in human capital accumulation and that it also confounds results on peer effects.

Our paper will use a complex set of information from European footballers, we improve the estimation of learning from coworkers with a special focus on young talent. Football in the top European leagues created a very unified labor market, with players moving constantly between teams and countries. It is also a very high-skilled industry, with only the top players making it. This means that our empirical findings will be related to evidence in learning for the most skilled workers (in Jarosch et al. (2021) this would be the top wage decile, where the learning coefficient is three times the average).

We build a new dataset tracking the career trajectory of six thousand players from the top five European football leagues over 8 seasons. Our data include 6,090 players over a total of 33,148 player*half-season observations. We focus on career trajectory over 3 years or 6 half-seasons. This data is combined with very fine, event-by-event data on 15 thousand football matches to establish the relationship and the intensity between player development and interaction with peers.

[1]In addition, there may be learning of workplace-specific information that will increase productivity but is not transferable.

Interaction is characterized by shared minutes and passing. These data enable the direct observation of the collaboration's intensity, providing new and substantial evidence to the literature.

Human capital accumulation (learning, or skill development) will be captured via players predicted value on the transfer market. The market value aggregates the consensus view of experts with access to public information such as game footage (Poli et al., 2021). As an average view of people, the transfer value is an estimate of work-relevant human capital. In terms of this process, a player initially has some human capital (innate ability) to play football, which is affected by the team, by peers as he develops, resulting in a trajectory of the player's value[2].

We start by confirming positive effect of coworker quality found in administrative data. Our setting is conducive to find evidence of learning as it can compare players in very similar units of soccer squads. Instead of a wage, we can observe how much value a player could generate in another team over many years. This is our human capital estimate. Workers with coworkers of higher average human capital will see their human capital grow faster. We also confirm that beyond average, skewness matters, being together with stars is helpful in learning.

However, proximity is not enough, learning happens via exposure to the best players and the depth of interaction with them. Our special dataset allows investigating details of what happens among coworkers. First, we show that players with high exposure to peers, playing more minutes in games, will experience higher growth of their human capital. Again, by collaborating with stars, learning will be more pronounced. Second, the strength of on the pitch interaction measured via passing intensity will point to even more learning opportunities. All results are especially important for younger players.

Finally, integrating data measuring actual skills, such as short pass accuracy, we can tell apart actual learning from higher valuation due to better performance when surrounded by better coworkers.

Beyond the focus on collaboration, we also contribute to the literature by documenting peer effects overcoming measurement problems. While there have been great advances in identification methodology following Abowd et al. (1999), this literature – and possibly mixed results – suffers from several measurement problems.

[2]In semi-structured interviews, Werner and Dickson (2018) study peer learning in the Bundesliga and find that learning from others, knowledge sharing functions via four main channels: imitating, peer communication, labor mobility, and knowledge brokers.

2 Related literature

The past and current workplace environments are important contributors to worker performance and compensation. Important related literature uses matched employer-employee data to estimate what drives wages using worker and firm fixed effect with help of worker switching following Abowd et al. (1999), Card et al. (2013). They reveal that a great deal of wage variation may be explained by sorting and firm characteristics. Econometrically looking at sorting is rather difficult due to limited switching (Bonhomme et al., 2023). Closer to us, there is related stream of literature investigating the role of firms in explaining the variation in wage *growth* (Gregory, 2021). Finally, several papers looked at the heterogeneity of the work environment on learning. Arellano-Bover and Saltiel (2023) studied the learning of young employees with administrative datasets from Brazil and Italy.

Overall, this literature suggests that firm characteristics and heterogeneity across firms are key drivers of earnings at firms. There are several sources of why performance and earnings may be higher in some firms such as better management yielding better incentives, firm work culture, or in-house training programs[3].

The focus of this paper is another source of variation in wages: the impact of coworkers. Learning will come in many forms such as passive presence and observation of peers, interaction with them, and intensive collaboration.

In this literature, the starting point is measuring the wage premium of better coworkers. Cornelissen et al. (2017) argue workers may alter their productivity due to both peer pressure and learning from co-workers. Learning in particular will be stronger from better peers and may thus lead to more inequality. While the evidence for learning is mixed (both lab and observational), there is more evidence for peer pressure (Mas and Moretti, 2009). They use German linked-employer-employee data from Munich covering 26 years and focus on wages rather than productivity. A worker's peer group is defined at the firm and three-digit occupation level, and special attention is paid to sectors with high knowledge (e.g. doctors). In their model, peers have a positive effect on wages either as compensation for more effort or via generating more output (learning). In terms of estimating peer effects, Cornelissen et al. (2017) has a firm-level point estimate with firm fixed effects of 14.8% that falls to 6.6% once firm-occupation fixed effects are added and 1.1% with additional firm-year fixed effects. Occupation and firm-level shocks are indeed pretty important. However, for repetitive tasks, there is actually a 6% compared with basically zero for the most

[3] [add lit]

knowledge-intensive ones. This suggests learning is less important, while peer pressure matters.

The closest paper to ours is Jarosch et al. (2021) which also investigates learning at the workplace with German administrative data but focuses on wage *growth* rather than levels as in Cornelissen et al. (2017). They estimate a model where wage growth between time t and $t + h$ is a function of the quality of peers, and worker characteristics at time t. They find that in firms (firm-occupations) with 100% higher average wage of peers is associated with 7% higher wage *growth* within one year, rising over time, with cumulative growth reaching 21% over ten years. Furthermore, they show that having more highly paid coworkers is strongly associated with future wage growth. Also, unlike for wage levels, learning is there for top performers.

There is less evidence of what aspect of peers help HCA. Education is one: Nix (2020) considers the role of learning important as it manifests as an externality to workers. Using detailed Swedish data, she finds that increasing the average education of coworkers by 10 percentage points increases that worker's wages in the following year by 0.3%.

2.0.1 Peer effects

Beyond human capital accumulation, there could be peer effects: pressure, assistance of even self-confidence. First, better peers may help you by elevating your game. Arcidiacono et al. (2017) estimates the contribution of peers to perform better on the pitch. Unlike learning or peer pressure, this productivity spillover is related to actual assistance in work. In this paper, the identification of peer effects comes from observing a large variation in peers (of different positions) across games.

Second, peer effects can manifest themselves as social pressure, and may be even negative. Peer pressure was estimated to improve repetitive task performance in supermarkets (Mas and Moretti, 2009). Cohen-Zada et al. (ming) also uses sports data, Israeli soccer, to estimate effort peer effects in terms of making an effort. Even a single player's improvement can have substantial benefit for team activity and performance. Indeed a single relevant peer may have a negative effect: exposure to superstars might actually be detrimental for self-confidence. For instance, in competitive environments, the higher pressure may lead to more mistakes (Bilen and Matros, 2021).

The learning aspect of jobs is especially relevant in the first part of professional careers. Early career exposure to an established and experienced mentoring figure, be it a team member, a coworker, or a relative, might contribute substantially to the development of young professionals. Evidence to date on this relationship in detail in several domains, with mixed results. [4]. A closely related

[4]There is evidence that young-age exposure to experienced and impactful figures might lead to higher future

paper, also using sports data is Hoey (2023) which shows that the injury of stars helps young players play more, and thus helps talent discovery.

Another frequent finding in the literature is related to heterogeneity in peers. while Jarosch et al. (2021) documents large returns on interacting with high-earning colleagues. As the complexity of jobs increases, learning specialized know-how from coworkers becomes even more important in career advancement (Caicedo and Jr, 2019). Superstars, therefore, are expected to have substantial effects on coworker careers.

3 Data

We base our investigation on a recently assembled dataset (Békés and Ottaviano, 2022) that was web scraped from different sources including transfermarkt.com and whoscored.com. The dataset covers each event (each pass, tackle, etc.) from all matches, along with team composition and results of games in the top five men's football leagues (Premier League in England, Ligue 1 in France, Bundesliga in Germany, Serie A in Italy, La Liga in Spain, the Eredivisie in the Netherlands, and the Portuguese Primeira Liga) over eight sporting seasons (2012-13 to 2018-19, except for Portugal that starts in 2015-2016) [5]. Additionally, we have information on players' histories, their activity in teams, and their market values, together with information on key individual and team-level characteristics.[6] To track the development of their relevant skills, we use attribute ratings of the FIFA video games of EA Sports, collected at fifaindex.com.

3.1 Details of the dataset

The key datasets are:

- Player careers: players and team in every half-season
- Player valuations: market valuation for a player in every half-season. (Average when multiple values are available.)

success, or present spillovers in the context of industrial innovation (Bell et al., 2017), the fine arts (Fraiberger et al., 2018), research (Li et al., 2019). Superstars especially drive the differences across firms in many industries (Jarosch et al., 2021), including football teams (Hoegele et al., 2014)

[5] Data quality and coverage are both very high in our datasets. Nevertheless, small data cleaning steps were needed and we discuss these issues in Appendix (A.3)

[6] With 'European football', or simply 'football' henceforth, we refer to 'association football'. The Premier League, La Liga, Serie A, and Ligue 1 are all composed of 20 teams (playing 20×19=380 games), while there are 18 teams in the Bundesliga, in the Eredivisie, and the Primeira Liga (18×17=306 games). Due to relegation and promotion, we have a total of 167 teams in the sample, most of them followed for 7 seasons.

- Players and squads: information of squads for each team in every half-season (list of players who were ever listed in the lineup as starter or substitute.)
- Events: minutes spent together and number of passes between any two players
- Attribute ratings: scores of rating points of players describing offensive and defensive skill levels such as short passes, tackles, sprinting speed etc.

For every player, we follow the evolution of market value from potentially as early as playing in Under-19 youth teams of football clubs. We retrieve market values from transfermarkt.com, the site's methodology is explained in detail here. Their concept of market value differs from transfer fees as it targets the *expected value of a player in a free market*, ideal for our setup to study the evolution of human capital. Rather than building a statistical model only, they rely on augmenting player pricing models with the judgment of the website's community, taking into account a list of factors such as future prospects, peer groups, injuries, contractual and club-specific conditions (an exhaustive list can be found in Appendix A.4), more suited for the evaluation of complex and particular situations. Therefore their market value calculation combines several tangible and intangible aspects of a football player's market value, closely resembling how economists view human capital. It also has the additional advantage compared to transfer fees that we do not need to consider the issue of business practices in large vs. smaller leagues, legalities, tax and accounting considerations, and other distorting factors. Transfermarkt publishes market values twice in a season, usually after the end of a season, and once during a season after sufficiently many games were played. In our dataset, accordingly, we aggregate player market values to the season/half-season level, reflecting the updates in market value.

We also track the work interaction between players during all matches in terms of completed passes, pass combinations, and shared minutes on the pitch, enabling us to quantify and finely measure the nature of collaboration in their working environment. We then aggregate these measures to the season/half-season level to harmonize with the market value tracking, creating a dynamic directed network of pass interaction between teammates in a half-season. A half-season contains typically 16-20 games in either the Summer/Fall (August to December) or Winter/Spring (January to May). Collaboration is measured as the number of minutes and passes in games during regular season[7].

[7] There is evidence that players who collaborate more in training and drills will be played alongside and collaborate more on the pitch.

As a third pillar, we build on the combined team-level, temporal, and playing-position level distribution of player values to create individual indicators and team-level variables. First, we use the lineup information and combine it with the market values to produce the team's total market value, Herfindahl–Hirschman index, and related measures. Second, we identify star players as those that have been in the top 5% and 25% of the market value distribution in the relevant top 5 leagues conditional on the season/season-half and their respective playing position, in any period of the last two years. This segmentation of the players allows us to consider different types of interactions between the elite players, very good players, and regular players (keeping in mind that players in these football leagues are incredibly talented individuals in their respective fields).

Finally, while the market value encompasses several dimensions that can be developed while working with others, in our setup we can also pinpoint how certain job-related skills evolve over the lifetime of a player. Namely, we merge with our dataset EA Sports' popular video game's ratings, collected at fifaindex.com via Benz (2020). It contains yearly ratings of attributes, some that we expect to develop with collaboration such as short passing, along with ones that we expect to be quite exogenous such as sprinting speed.

Table 1 presents the mean, the standard devition, median as well as the p1 and p99 values for the key variables.

The distribution of player values, averaging €3.90 million, is right-skewed with a median of €2.00 million. The values range significantly from as low as €0.15 million (p1) to as high as €32.96 million (p99). There are a handful of players in the top 1 % with values close or even above 100 million. Teammates' combined value has a right-skewed distribution, with also a wide range from €8.59 million (p1) to €528.84 million (p99).

In terms of concentartion of quality, the HHI index has smaller variation, the top 1% has 0.12 which shows the presenece of stars in a squad of about 25 players. The Share of top 5% players in team (the 5% taken for the whole sample) indicates a skewed distribution where most teams rely very little on their top 5% of players, but some teams rely heavily, up to 79% (p99), with a broad dispersion (SD = 0.17). These are the star teams like Real Madrid or Manchester City. Share of top 25% players in team is more democratic, many teams have such players.

Players' total minutes on the field average 847.46 with a symmetric distribution but a very wide range in playtime.

We'll use several skill metrics that are normalized showing a balanced distribution.

Table 1: Key variables

	mean	sd	p1	p50	p99
Value (in mn EUR)	3.90	6.49	0.15	2.00	32.96
Teammates' value (in mn EUR)	97.20	106.21	8.59	61.77	528.84
HHI of team	0.07	0.01	0.05	0.06	0.12
Share of top 5% players in team	0.09	0.17	0.00	0.00	0.79
Share of top 25% players in team	0.35	0.21	0.00	0.36	0.82
Total minutes	847.46	543.87	9.00	835.00	2023.93
Short pass	0.08	0.62	−1.59	0.08	1.36

Note: All players, all teams. N=3,470. Selected variables.

Additional descriptive statistics of the final dataset are presented in Section A.2 of the Appendix. Each player appears in the dataset once with their first valid market value observation, and we track them over 6 half-seasons. The final dataset contains 3,340 players, the creation of the analysis sample is described in the appendix.

3.2 Comparing player career and admin data

Using sports data in general, and player career data in particular has some advantages over traditional admin data, but also has some shortcomings.

3.3 Advantages

A major advantage of our dataset over several usual administrative datasets with linked employer-employee information is that we can differentiate between simply having different types of coworkers in terms of productivity in close proximity or on our team vs. actively collaborating with them during work, which we can measure using the passes and the shared minutes on the pitch. Furthermore, the usual occupation categorizations are often overly general regarding the actual tasks employees have to perform and therefore require several steps to infer whether learning could actually take place meaningfully. In our setup, the work activity and the during-work interactions are directly related to the human capital accumulation of the employees. This establishes a solid connection between learning and interpersonal interactions at the workplace.

Beyond this aspect of collaboration, we (i) measure human capital accumulation rather than wage, (ii) measure peer effects in a meaningful team unit of fixed size, (iii) look at peers who might indeed provide source of learning. For more on this, see Section **??** in the Appendix.

3.4 Potential issues

4 Empirical setup

To estimate peer effects, we regress the future value of HC (HC_{t+h}) measured by $ln(value)$ as the function of its current level (HC_t) and the team quality ($HCteam_t$)[8]. The team value excludes the actual player. Control variables are in X_t. All right-hand side variables are measured at period (half-season) t, while future wage is measured $t+h$, h periods later.

As for the key variables, the **Market value** (Transfermarkt): mean market value of the player in the half-season, without evaluation the last valid evaluation is assigned to the player. The **Teammates' total market** value: the sum of the market value of the teammates' of the player based on their mean market value in the half-season. Section A.1 in the Appendix defines the key variables of the analysis in detail.

This is a pooled cross-section OLS regression, standard errors are clustered at the league*half-season*position level. Cross-section in the sense that variation comes from different players across different teams, and not within teams. The reason for this is that while there is churning, team value is correlated over our short time span of 8 seasons.

$$\mathbb{E}[HC_{t+h}|.] = \alpha HC_t + \beta HCteam_t + \gamma X_t$$

As a basic concept, our human capital measure shall capture all relevant information. However, we will use some corrections mostly to correct for less-than-perfect matching between human capital and measured valuation. While they can be matched to Mincerian controls in Jarosch et al. (2021), we also have industry-specific reasons.

First, valuations are drawn up bearing in mind that valuations reflect value for the team beyond sharing talent. Thus the best defender will have about half the value of the best forward because his skills can be translated less directly to goals. Thus, we added position dummies.

Second, player valuation will include some risks of injury. Older players are more likely to get injured, and very young players may have unknown injury potential. Thus, we add age as a control variable, measured in a non-parametric way (years of age dummies).

Third, contracting issues may also play a role. For now, they are captured by age, but we'll add some more.

[8] As values are in logs, it is equivalent to having the change in the value as the dependent variable (with the coefficient of current HC changing only)

Fourth, valuations of players may depend on leagues and seasons, because labor markets are closely but not perfectly integrated. Value inflation, possibly in a country-specific way could also matter. We add league × half-season dummies to all models.

5 Results 1: Evidence on Learning

5.1 Establishing evidence on learning

We start by presenting our findings on learning from peers. Table 2 shows the core evidence on learning for Equation 4. This is basically very close to what was estimated in Jarosch et al. (2021) but has a finer measure of human capital as the dependent variable and time is measured in half-seasons (half years), not years: 6 periods is in fact 3 years.

Table 2: Learning over time and peer quality: full sample

Dependent Variables:	h=1	h=2	h=3	h=4	h=5	h=6
			log(value$_{t+h}$)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.716***	0.704***	0.614***	0.605***	0.564***	0.560***
	(0.019)	(0.020)	(0.022)	(0.023)	(0.024)	(0.025)
log(teammates' total value)	0.134***	0.150***	0.206***	0.218***	0.223***	0.227***
	(0.018)	(0.019)	(0.022)	(0.022)	(0.025)	(0.027)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,470	3,470	3,470	3,470	3,470	3,470
R^2	0.736	0.710	0.586	0.575	0.531	0.520
Within R^2	0.674	0.645	0.489	0.468	0.382	0.363

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All players, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As the coefficients on peers suggest, the results are larger than what was shown in German administrative data. Conditioning on their current HC value, and partialing out key confounders, workers with better peers will develop HC more. The point estimate is growing steadily with time, meaning that being on a twice as valuable team is associated with 23% higher market value in 3 years. It is close to the 10-year estimate of the benchmark Jarosch et al. (2021) results, and two times the 3-year estimate. The difference disappears if instead of using each observation only once we would use repeated cross-sections as those authors do. These same regressions in a repeated cross-section setup yield an around 14% point estimate at the 3-year mark.

Given that for our main analysis we will look at the interaction between continuous variables, instead of million euros we also examine their standardized values (Z-scores), in Table 3. In this setup, the point estimates are actually pretty close, as one standard deviation is close to a log unit.

Table 3: Learning over time and peer quality: full sample, Z-score

Dependent Variables:	h=1	h=2	h=3	h=4	h=5	h=6
			log(value_{t+h})			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.725^{***}	0.716^{***}	0.632^{***}	0.624^{***}	0.582^{***}	0.578^{***}
	(0.018)	(0.018)	(0.020)	(0.021)	(0.022)	(0.023)
Teammates' total value (Z)	0.117^{***}	0.126^{***}	0.169^{***}	0.180^{***}	0.188^{***}	0.191^{***}
	(0.015)	(0.016)	(0.022)	(0.023)	(0.025)	(0.026)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,470	3,470	3,470	3,470	3,470	3,470
R^2	0.736	0.710	0.584	0.574	0.530	0.520
Within R^2	0.675	0.644	0.487	0.466	0.381	0.362

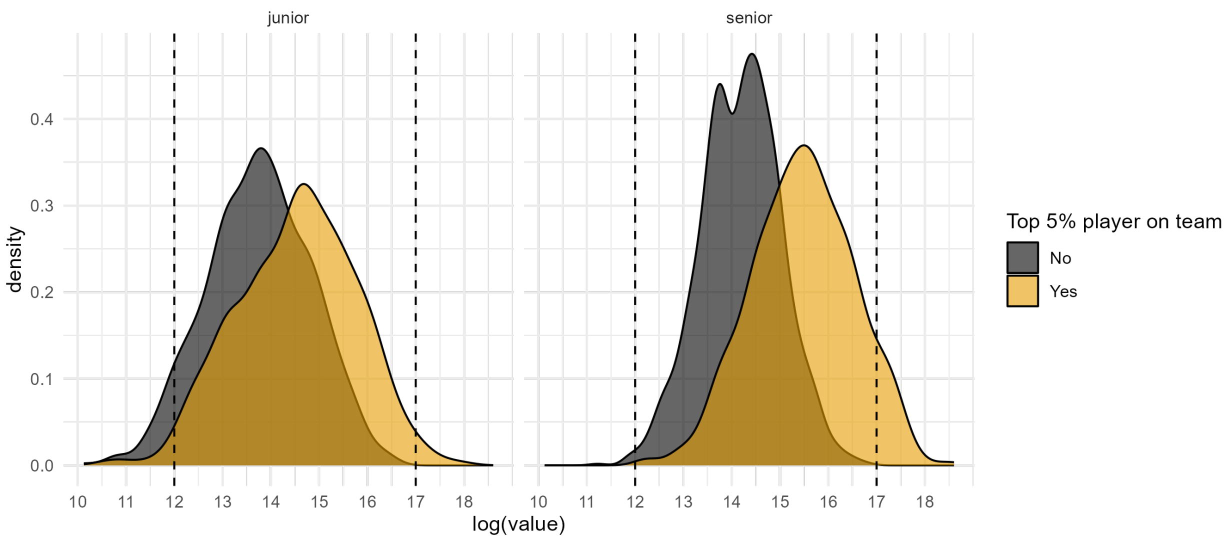
Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All players, all teams. Standard errors clustered at position × league × half-season level. $h = 1, \ldots, 6$ tracks half-seasons. $h = 1, \ldots, 6$ tracks half-seasons. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Going forward, all regression tables will present Z-scores, and interpretations will be based on comparing one SD difference in peer quality.

The core comparison in this project is players who have the same amount of human capital but vary in terms of peer quality. One key econometric problem here (and possibly in other datasets), is the lack of common support at either end of the player distribution. There are very few low-valued players at top teams, and very few very high-valued players at bottom teams. We help create a common support by focusing on the middle section of the distribution excluding players below the 1st and above the 99th percentile, around 160,000 EUR and 24 million EUR (log value falling between 12 and 17). Figure 1 displays the densities of log(market values) by seniority and whether the team has a top 5% player or not. We can see that for both age groups, there is a fair share of players between the two cut-off values (dashed vertical lines on the plot) in teams with and without an elite player.

Figure 1: Common support cutoffs



Note: Market value densities by types of teams in the sample.

Table 4 and Figure 2 repeat the previous exercise but now, for the subsample of medium-value players. Results are similar qualitatively but somewhat smaller in magnitude, a standard deviation higher team value is associated with around 15% higher market value in three years.

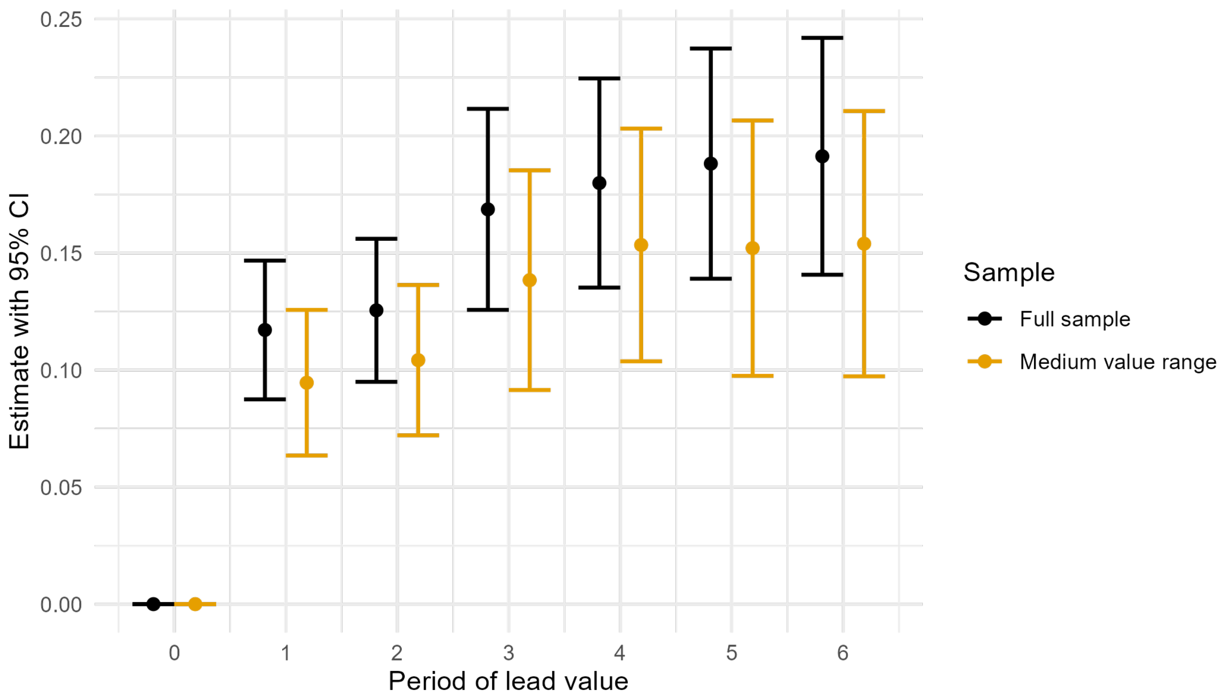
Table 4: Learning over time and peer quality: medium value range players

Dependent Variables:	h=1	h=2	h=3	h=4	h=5	h=6
			log(value$_{t+h}$)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.747***	0.733***	0.654***	0.640***	0.596***	0.593***
	(0.018)	(0.018)	(0.022)	(0.022)	(0.024)	(0.026)
Teammates' total value (Z)	0.095***	0.104***	0.138***	0.153***	0.152***	0.154***
	(0.016)	(0.016)	(0.024)	(0.025)	(0.028)	(0.029)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,330	3,330	3,330	3,330	3,330	3,330
R^2	0.711	0.678	0.552	0.541	0.506	0.497
Within R^2	0.647	0.607	0.443	0.418	0.332	0.313

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. $h = 1, \dots, 6$ tracks half-seasons. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2: Human capital gain over time: full sample vs. medium value players



Note: Association of market values with the team's total value evolving over the career, in the entire sample and the medium value range. $h = 1, \ldots, 6$ tracks half-seasons.

After the baseline results, let us turn to a better understanding of the mechanisms of learning. We will first look at the heterogeneity of learning by worker age. Then, we dissect the peer group into stars, high-flyers, and the rest. While we'll look at variation across these players, bear in mind that despite this dissection, we speak about the top 2% of global football players who broke into this elite[9]. This means, that finding in terms of this variation has limited external validity for this industry as a whole. Finally, we examine the evolution of relevant skills, and how switching teams might interact with the

5.2 Heterogeneity 1: Workers

In this section, we look at who benefits more and less from their peers. We repeat the exercise for the young players defined as age between 18 and 23. Learning should evidently matter more for the young, as on average, they are farther away from the frontier and should be more willing to learn and adapt.

[9] 98 teams in top 5, appr 26 men squads for 130,000 professionals globally. https://www.statista.com/statistics/1283927/number-pro-soccer-players-by-country/

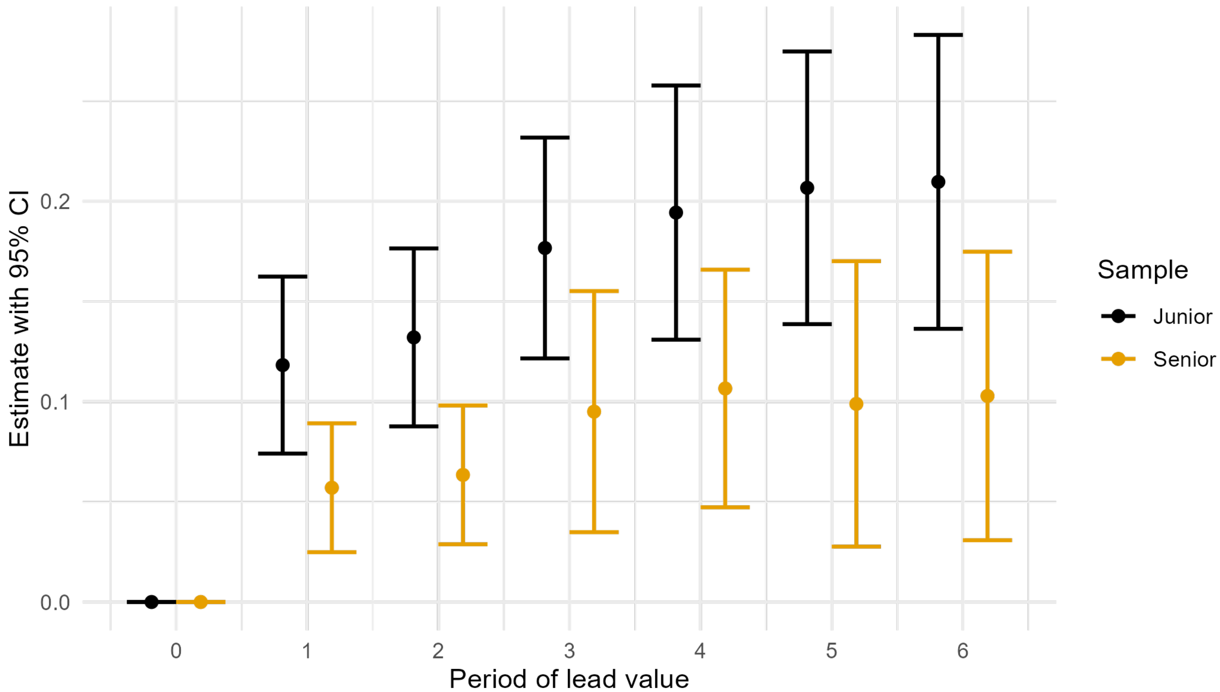
Table 5: Learning over time and peer quality: junior players

Dependent Variables:	h=1	h=2	h=3	h=4	h=5	h=6
			log(value$_{t+h}$)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.667***	0.651***	0.577***	0.566***	0.525***	0.516***
	(0.027)	(0.026)	(0.031)	(0.032)	(0.034)	(0.036)
Teammates' total value (Z)	0.118***	0.132***	0.177***	0.194***	0.207***	0.210***
	(0.022)	(0.023)	(0.028)	(0.032)	(0.035)	(0.037)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,287	1,287	1,287	1,287	1,287	1,287
R^2	0.599	0.563	0.432	0.430	0.366	0.351
Within R^2	0.530	0.486	0.340	0.321	0.247	0.230

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Junior players in the medium market value range, all teams. Standard errors clustered at position $\times$ league $\times$ half-season level. $h = 1, \ldots, 6$ tracks half-seasons. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 3: Human capital gain over time: juniors vs. seniors



Note: Association of market values with the team's total value evolving over the career, in the medium value range seniors vs. juniors. $h = 1, \ldots, 6$ tracks half-seasons.

Table 5 and Figure 3 confirm that young players learn substantially more from peers, one standard deviation of peer value translating into around 21% of market value after six half-seasons. In comparison, the same estimate is 10% for players above age 23.

5.3 Heterogeneity 2: Peers

In this section, we look at what kind of peers have the most influence on a player's value development. This question relates to the distribution of peers given average quality. One way to gauge it is to add the Hirschman–Herfindahl Index (HHI) of the market values on the team. A higher value implies more concentration, i.e. presence of star players – relative to the team average. Another approach is to look for absolute stars. Here we consider superstars, the top 5% of all players, and high-flyers, those in the top 25% but not in 5%, in terms of market value for a season.

In Table 6 we show the results, first for all players (in the middle-value section) followed by young players only. The point estimate of the HHI index is positive in the full and non-significant in the young player sample: higher HC growth is positively associated with a more skewed peer group for the entire sample (Column 2), but not for the younger players (Column 5, the latter possibly for lack of power).

However, the presence of top players contributes to everyone's and especially young players' development (Columns 3 and 6). Players with a 10pp higher share of highflyers in their team will on average experience a 3% higher market value growth, conditional on the teammates' total market value. For junior players, the size is larger (6%). However, the point estimate for being with superstars is negative and non-significant. This suggests that beyond the human capital accumulation benefits of having better peers in general, being in the proximity of very good players is additionally helpful, especially for junior players.

Table 6: Learning over time and peer quality: Playing with stars

Dependent Variable:	log(value$_{t+6}$)					
		Full sample			Junior	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.593***	0.591***	0.571***	0.516***	0.516***	0.494***
	(0.026)	(0.026)	(0.027)	(0.036)	(0.036)	(0.038)
Teammates' total value (Z)	0.154***	0.148***	0.225***	0.210***	0.205***	0.336***
	(0.029)	(0.029)	(0.082)	(0.037)	(0.038)	(0.124)
Team HHI		2.63**			1.71	
		(1.31)			(2.44)	
Share of top 5% teammates			-0.359			-0.653
			(0.398)			(0.643)
Share of top 25% teammates			0.310***			0.563***
			(0.096)			(0.183)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,330	3,330	3,330	1,287	1,287	1,287
R^2	0.497	0.498	0.500	0.351	0.351	0.360
Within R^2	0.313	0.314	0.317	0.230	0.230	0.241

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Columns (1) to (3), all medium market value range players, Columns (4) to (6) only young players. Teammates' values are measured as the Z-score. HHI is the team level Hirschman–Herfindahl Index. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To recap, we have confirmed Jarosch et al. (2021) for a super high-skilled segment, with well-identified peer groups and having human capital not wage. We also confirmed an asymmetry in peers, a skewed distribution with star workers is indeed helpful. Furthermore, young workers can learn better from peers, especially stars.

6 Results 2: Interaction with coworkers

With our data, we can make additional steps and shed more light on the mechanisms. This where our core contribution happens.

6.1 Working along with coworkers

In most work-place datasets, observing exposure to peers – time spent with coworkers is very rare (if any). Furthermore, we can also track the nature of exposure. In a workplace data, this would measure what projects people work on, and how much they can converse with people who are well connected in the business.

Indeed, workers will benefit from proximity to peers in general by being actively engaged with them. They benefit possibly even more with being exposed to brilliance of star workers in particular. Players who have more playing time in games are likely to have also trained more with the best peers.

An important addition is that exposure to peers here (and in any workplace) is also close to the concept of learning by doing. We capture this aspect with two variables: first, we measure exposure by the number of in-match minutes (standardized), and how important of a role the player plays in the team's pass system measured by the eigenvector centrality of the player (also standardized). A more central player (such as midfielder in our case, or mid-manager in a company) will interact more with colleagues and especially more with colleagues who themselves interact with others. Network centrality is calculated based on the network of directed passes aggregated to half-seasons and player-couples.

Our first measure is minutes spent on the pitch during the half-season. As Table 7's Column (2) shows, players who spend 0.1 sd unit more time with their peers are expected to experience 1.7% more human capital accumulation.

Note that as we added minutes, the point estimate of the teammates' total value increased from 0.15 to 0.27. So in peer effect regressions, exposure (activity) measured here with minutes played is a confounder. It is *negatively* correlated with team value (conditional on controls). In our case, this means players who play in higher-valued teams tend to play less. Indeed, it is harder to make it into the team when it is filled with stars and high-flyers.

Furthermore, we added a measure of how central players are to the team's functions in terms of passing (Column 2). The pass centrality captures if the player is not only on the pitch but is actively engaged with peers. Thus, this is another, more sophisticated metric of exposure. We find (Columns 2, 5) that higher centrality is also positively associated with higher human capital accumulation. Players who spend more time on the pitch or even highly engaged with peers will evolve more in terms of market value.

Table 7: Learning over time and minutes played: medium market value range players

Dependent Variable:	log(value$_{t+6}$)					
		Full sample			Junior	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.593***	0.463***	0.456***	0.516***	0.383***	0.371***
	(0.026)	(0.025)	(0.026)	(0.036)	(0.035)	(0.035)
Teammates' total value (Z)	0.154***	0.269***	0.292***	0.210***	0.325***	0.414***
	(0.029)	(0.029)	(0.035)	(0.037)	(0.039)	(0.052)
Total minutes (Z)		0.169***	0.164***		0.162***	0.146***
		(0.029)	(0.029)		(0.056)	(0.055)
Pass eigenvector centrality (Z)		0.202***	0.217***		0.298***	0.334***
		(0.029)	(0.030)		(0.050)	(0.051)
Teammates' total value (Z) × Total minutes (Z)			0.060**			0.123***
			(0.024)			(0.041)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,330	3,290	3,290	1,287	1,265	1,265
R^2	0.497	0.559	0.560	0.351	0.436	0.440
Within R^2	0.313	0.393	0.395	0.230	0.329	0.334

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Columns (4) to (6) we look at young players, where we see the same pattern, point estimates are similar or higher. But we see an additional result in Column (6). Higher peer value is magnified twice as much due to more exposure (as shown by the interaction term). Young players learn more from better players when they play more. Seniors less so.

6.2 Interaction with coworkers

One major advantage of this dataset is the fine grained measure of interaction with *all* other peers individually. Anything similar would be very hard to imagine from most work-place datasets.

It's possible that playing time is not equally shared with peers. Learning when playing with stars vs. the rest is not the same. So next, we add passing intensity and shared minutes on the pitch with stars (top 5%) and high-flyers (top 5-25%). In this section, we only consider players who have top 5% (and top 25%) peers, i.e. have the chance to learn from them on paper. Pass intensity is measured on a per capita basis, we look at the total number of passes with the types of players normalized by the number of them on the team (a team often has 1 top 5% player, but possibly several). The categories are created based on the distribution of passes in a half-season between all players: if it is low (lowest 25%), it means that compared to the number of passes exchanged between any two players, the player and the stars on the team interact relatively little.

In Table 8 we start with a categorical variable of pass intensity, with the reference category being low passing intensity (Column 1). We see that high-intensity passing – strong interaction with stars and high flyers – is what explains human capital growth a great deal. This is true even when we condition on team value: players with similar peer quality but higher pass count with stars see their human capital grow faster. Interestingly, this partially holds when we also compare players spending the same amount of minutes on the pitch (Column 2). No shared minutes on the pitch with stars is not significantly different from low amounts (but is also rare). The same results are reproduced with a continuous version of the pass count variable (in Columns 3 and 4) where we measure passes with standardized scores.

In all these cases, we see that learning is stronger from passes with high-flyers than from superstars.

In Columns 5 and 6 we examine a related statistic: the shared minutes on the pitch with the stars and the high-flyers. This variable measures that out of the total mass of shared minutes with everyone on the team, what proportion is attributed to the top 5% and top 25% players on the team. For the overall sample, we can see that even without controlling for total minutes on the pitch, we find no significant associations, suggesting that indeed it is the pass-interaction and not the shared minutes in general that drives the growth in human capital of the typical players.

Table 8: Learning over time and passing: medium market value range players

Dependent Variable:	log(value$_{t+6}$)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.504***	0.476***	0.497***	0.465***	0.624***	0.468***
	(0.032)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
Teammates' total value (Z)	0.217***	0.217***	0.199***	0.206***	0.052	0.171**
	(0.033)	(0.034)	(0.031)	(0.033)	(0.071)	(0.073)
Pass count with top 5% teammates (Z)	0.103***	0.059*				
	(0.034)	(0.033)				
Pass count with top 25% teammates (Z)	0.292***	0.217***				
	(0.045)	(0.049)				
Total minutes (Z)		0.151***		0.191***		0.350***
		(0.043)		(0.041)		(0.028)
Pass count with top 5%: no shared minutes			-0.481	-0.480		
			(0.729)	(0.699)		
Pass count with top 5%: in 25-75 percentile			0.043	-0.013		
			(0.092)	(0.090)		
Pass count with top 5%: in 75+ percentile			0.284**	0.115		
			(0.128)	(0.132)		
Pass count with top 25%: no shared minutes			0.078	0.068		
			(0.443)	(0.428)		
Pass count with top 25%: in 25-75 percentile			0.417***	0.313***		
			(0.081)	(0.081)		
Pass count with top 25%: in 75+ percentile			0.856***	0.590***		
			(0.102)	(0.113)		
Minutes shared with top 5% out of total (Z)					0.103	0.066
					(0.080)	(0.079)
Minutes shared with top 25% out of total (Z)					0.080	0.104*
					(0.064)	(0.060)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,350	1,350	1,350	1,350	1,341	1,341
R^2	0.575	0.580	0.569	0.577	0.512	0.565
Within R^2	0.422	0.428	0.414	0.425	0.334	0.407

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

For young players, we see similar patterns with higher point estimates regarding passes. Table 9 shows that for juniors passing with the stars is incredibly important. Being in the medium passing count group with high-fliers is as important as having one standard deviation higher team value. Being in the top group in terms of passing with high-flyers is associated with around 215% higher market value (log unit of 1.15), which still remains around 134% even after controlling for how much time the young player spends on the pitch in the half-season. The continuous measurements of the variables corroborate these findings: for young individuals work-related interactions are very important in terms of growth in their human capital, especially with high-fliers.

Moreover, in contrast to the full sample of medium-value range players, the time shared with top players has a different relation (Column 6). After controlling for the total minutes a young player spends in the games, sharing one standard deviation more minutes with high-flying peers is associated with around 20% higher market value in the 6 half-season span. Interestingly this association is not present for the shared minutes with star players. This is in accord with the results in Table 7, but we can see that the association found there is driven especially by the high-flyers: not star peers, but very good ones.

Table 9: Learning over time and passing: junior players

Dependent Variable:	log(value$_{t+6}$)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.399***	0.387***	0.387***	0.364***	0.543***	0.387***
	(0.044)	(0.043)	(0.050)	(0.048)	(0.050)	(0.046)
Teammates' total value (Z)	0.261***	0.264***	0.241***	0.255***	0.164	0.296***
	(0.044)	(0.045)	(0.044)	(0.045)	(0.123)	(0.107)
Pass count with top 5% teammates (Z)	0.095*	0.071				
	(0.053)	(0.056)				
Pass count with top 25% teammates (Z)	0.489***	0.438***				
	(0.054)	(0.068)				
Total minutes (Z)		0.085		0.212**		0.451***
		(0.076)		(0.082)		(0.055)
Pass count with top 5%: no shared minutes			-0.806	-0.750		
			(0.952)	(0.916)		
Pass count with top 5%: in 25-75 percentile			0.041	-0.018		
			(0.141)	(0.144)		
Pass count with top 5%: in 75+ percentile			0.331	0.147		
			(0.202)	(0.231)		
Pass count with top 25%: no shared minutes			0.642	0.610		
			(0.830)	(0.808)		
Pass count with top 25%: in 25-75 percentile			0.499***	0.391***		
			(0.115)	(0.115)		
Pass count with top 25%: in 75+ percentile			1.15***	0.852***		
			(0.176)	(0.189)		
Minutes shared with top 5% out of total (Z)					0.069	0.030
					(0.145)	(0.123)
Minutes shared with top 25% out of total (Z)					0.175	0.197**
					(0.109)	(0.098)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	585	585	585	585	579	579
R^2	0.472	0.473	0.451	0.460	0.363	0.442
Within R^2	0.382	0.383	0.358	0.367	0.253	0.347

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Junior players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Examining realized in-work interactions, we find a strong association between high-intensity interaction and growth in human capital. In addition, this channel is even more pronounced for junior players, whose in-match interactions via passes, or even joint presence during the game, are associated with large and statistically significant gains in market value.

7 Results 3: Development of skills via learning

7.1 Skill development

In this subsection, instead of market values, we shift our attention to skill attributes that connect relevant player abilities more directly to work-related interactions. These attribute scores are standardized, so they are to be understood in units of standard deviation. We focus on short passes, as they are the closest to the interactions we measure between players.

Table 10 demonstrates that having teammates that pass better on average is associated with higher future short passing ability, conditional on current ability and fixed effects. One standard deviation higher average in short passing is associated with an around 0.03 standard deviation higher ability in short passing, Recalling the earlier results of market value, we can see that along with an increased value, an increase in skill also manifests by having better teammates on average.

Table 10: Evolution of short pass skills vs. team's avg. skill level

Dependent Variables:	h=2		h=4		h=6	
			Short pass			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Short pass	0.864^{***}	0.859^{***}	0.770^{***}	0.763^{***}	0.683^{***}	0.675^{***}
	(0.014)	(0.014)	(0.018)	(0.018)	(0.017)	(0.018)
Teammates' avg. short pass	0.029^{***}	0.020^{**}	0.034^{***}	0.021^{**}	0.034^{***}	0.019^{*}
	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
Teammates' total value		0.021^{***}		0.028^{***}		0.034^{***}
		(0.007)		(0.009)		(0.010)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,321	3,321	3,321	3,321	3,321	3,321
R^2	0.827	0.827	0.737	0.738	0.662	0.663
Within R^2	0.760	0.760	0.635	0.636	0.530	0.532

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position $\times$ league $\times$ half-season level. $h = 1, \ldots, 6$ tracks half-seasons. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our data allow us to directly relate the amount of passing a player executes on the pitch, and short passing ability, conditional on how good the teammates are on average. This provides quite direct evidence that the improvement in ability does not just manifest in the vicinity of good teammates, but the interaction itself is also crucial in the improvement of skills (and as we saw earlier, market value), especially with star players. Table 11 reports the results of this exercise. We can see in Columns (1) and (2), that compared to the players in the lower 25% in passing with high-fliers, being in the top 25% is associated with an around 0.1 standard deviation higher short-pass ability 3 years later. The estimate on teammates's passing ability and the total minutes played is not significant, conditional on the amount of passes with stars. Using standardized variables corroborates these results. The average short-pass ability of the teammates is again not significant. Turning to minutes shared in Columns 5 and 6, we can see that even conditional on total minutes, higher minutes shared would translate to better short pass skills in 3 years' time.

Table 11: Short passing ability and passing with the stars

Dependent Variable:	Short pass$_{t+6}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Short pass	0.678***	0.679***	0.677***	0.677***	0.688***	0.666***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.023)	(0.026)
Teammates' avg. short pass	0.016	0.016	0.011	0.011	-0.026*	-0.023*
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Pass count with top 5% teammates	0.010	0.011				
	(0.014)	(0.016)				
Pass count with top 25% teammates	0.042***	0.043**				
	(0.012)	(0.017)				
Total minutes		-0.002		-0.0002		0.036***
		(0.017)		(0.014)		(0.011)
Pass count with top 5%: no shared minutes			-0.281	-0.281		
			(0.172)	(0.172)		
Pass count with top 5%: in 25-75 percentile			0.050*	0.050*		
			(0.029)	(0.029)		
Pass count with top 5%: in 75+ percentile			0.064*	0.064*		
			(0.033)	(0.034)		
Pass count with top 25%: no shared minutes			0.070	0.070		
			(0.093)	(0.093)		
Pass count with top 25%: in 25-75 percentile			0.020	0.020		
			(0.028)	(0.029)		
Pass count with top 25%: in 75+ percentile			0.095***	0.096**		
			(0.033)	(0.038)		
Minutes shared with top 5% out of total					0.072***	0.073***
					(0.019)	(0.019)
Minutes shared with top 25% out of total					0.046**	0.045**
					(0.019)	(0.019)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,349	1,349	1,349	1,349	1,340	1,340
R^2	0.700	0.700	0.701	0.701	0.699	0.702
Within R^2	0.570	0.570	0.572	0.572	0.566	0.571

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A possible counterargument could be that the detected association between passing and future short pass skill is somehow confounded by unobserved overall star potential which is revealed to the team after just getting a player and giving him the opportunity, impacting both the amount of passing and the rating updates. Table 12, using standardized pass values, reinforces that a significant association exists between short passes and the number of passes with top 25% teammates, and this association is only significant at the 5% level for short passes, and is not reflected in either finishing, interceptions, or speed. On a related measure of reactions, we can see a similar point estimate.

Table 12: Skill ratings and passing with the stars

Dependent Variables:	Short pass$_{t+6}$	Finishing$_{t+6}$	Interceptions$_{t+6}$	Reactions$_{t+6}$	Speed$_{t+6}$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Teammates' avg. short pass	0.016	-0.004	0.0006	0.124***	0.026
	(0.013)	(0.015)	(0.014)	(0.030)	(0.020)
Pass count with top 5% teammates	0.011	-0.006	-0.011	0.027	-0.022
	(0.016)	(0.009)	(0.010)	(0.028)	(0.016)
Pass count with top 25% teammates	0.043**	0.013	0.016*	0.054*	0.024
	(0.017)	(0.017)	(0.010)	(0.030)	(0.022)
Total minutes	-0.002	-0.0003	-0.004	0.105***	0.022
	(0.017)	(0.013)	(0.013)	(0.036)	(0.023)
Short pass	0.679***				
	(0.025)				
Finishing		0.774***			
		(0.025)			
Interceptions			0.803***		
			(0.023)		
Reactions				0.511***	
				(0.032)	
Sprint speed					0.838***
					(0.022)
Fixed-effects					
position	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	1,349	1,349	1,349	1,349	1,349
R^2	0.700	0.858	0.889	0.414	0.732
Within R^2	0.570	0.632	0.648	0.356	0.607

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

So we could document, that even with a different kind of measure that follows skill attributes more directly, it is not the overall average skill, but the higher amount of relevant work-related activity that transforms a player's ability, showing that the higher future market value is indeed evolving parallel with a higher relevant skill. This supports the argument that indeed we capture the learning channel, and the correlation does not only emanate from confounders.

7.2 Higher skills remain in new jobs

A worker's accumulated experience can elevate general or job-specific human capital. While the former would result in higher market value and skills appreciated everywhere, the latter would mean that leaving a certain organization would decrease the value of the individual. Changing teams is not a random event, however, in our setup, we can examine the different evolution of market value between players who switched teams vs. players who did not. To accomplish that, we compare the market value and the short passing skill attribute between those players who switch and those who do not.

Table 13 shows how the market value evolves as a function of teammates' value for those who switched during the previous year and those who did not. First, switchers have a lower market value overall, the sooner they switch, the higher the difference compared to those who remain: suggesting a possible negative selection by value into leaving the team, or also that some part of the market value is indeed job-specific.

Second, the higher initial value of teammates is associated with a significantly higher value for the remaining players. For those who stay, a standard deviation higher teammate value goes along with around 27% higher market value in three years, while for those who leave in one and two years, this association is 21% and 14% lower. So a substantial part of the increased market value is driven by those who could remain with the team, who are around a third of the sample.

Table 13: Market value evolution and switching teams

Dependent Variables:	h=1	h=2	h=3	h=4	h=5	h=6
			log(value$_{t+h}$)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log(value)	0.747***	0.733***	0.642***	0.626***	0.572***	0.568***
	(0.018)	(0.018)	(0.021)	(0.022)	(0.024)	(0.026)
Teammates' total value (Z)	0.095***	0.104***	0.175***	0.198***	0.265***	0.272***
	(0.016)	(0.016)	(0.027)	(0.030)	(0.041)	(0.042)
Switch in year 1			-0.312***	-0.330***	-0.460***	-0.479***
			(0.030)	(0.033)	(0.042)	(0.045)
Teammates' total value (Z) × Switch in year 1			-0.094**	-0.113***	-0.194***	-0.206***
			(0.036)	(0.039)	(0.050)	(0.052)
Switch in year 2					-0.279***	-0.288***
					(0.041)	(0.043)
Teammates' total value (Z) × Switch in year 2					-0.143***	-0.145***
					(0.045)	(0.047)
Fixed-effects						
position	Yes	Yes	Yes	Yes	Yes	Yes
player age	Yes	Yes	Yes	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,330	3,330	3,330	3,330	3,330	3,330
R^2	0.711	0.678	0.569	0.560	0.531	0.523
Within R^2	0.647	0.607	0.465	0.441	0.366	0.348

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. $h = 1, \ldots, 6$ tracks half-seasons. For comparison, we found earlier that a standard deviation higher value in teammates' total value is associated with 15% higher market value after three years, growing steadily from 10% after the first year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14 reports the results of the same exercise with the short pass ability. First, again we can see that on average those who leave the team are those who have lower short passing ability in the future. However, in contrast with the market value results, we cannot see a significant differential change along the teammates' average ability and future individual ability: a standard deviation higher average team short pass ability is not associated with higher short pass ability for those who remain vs. those who leave the team.

Jointly with the market value estimates, the results suggest that while some parts of the human capital evidence we present might reflect partially job-specific human capital increase or selection, learning seems to occur and stick with the players improving their general human capital.

Table 14: Short pass skill evolution and switching teams

Dependent Variables: Model:	Short pass$_{t+2}$ (1)	Short pass$_{t+4}$ (2)	Short pass$_{t+6}$ (3)
Variables			
Short pass	0.864***	0.765***	0.677***
	(0.014)	(0.018)	(0.018)
Teammates' avg. short pass	0.029***	0.036***	0.038***
	(0.007)	(0.008)	(0.014)
Switch in year 1		-0.070***	-0.095***
		(0.013)	(0.018)
Teammates' avg. short pass × Switch in year 1		-0.009	-0.009
		(0.012)	(0.014)
Switch in year 2			-0.069***
			(0.015)
Teammates' avg. short pass × Switch in year 2			-0.013
			(0.016)
Fixed-effects			
position	Yes	Yes	Yes
player age	Yes	Yes	Yes
league X half-season	Yes	Yes	Yes
Fit statistics			
Observations	3,321	3,321	3,321
R^2	0.827	0.740	0.667
Within R^2	0.760	0.639	0.538

Clustered (league X half-season X position) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Players in the medium market value range, all teams. Standard errors clustered at position × league × half-season level. $h = 1, \ldots, 6$ tracks half-seasons. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

8 Conclusions

This paper looked into the impact of peer interactions on skill development in a high-skilled and competitive environment. Using elite male soccer we highlighted the significance of exposure to high-skill peers and the role of collaboration in enhancing individual performance and human capital accumulation.

First, we showed that players benefit significantly from proximity to coworkers in general, and star workers in particular, leading to enhanced skill development and performance. This confirms results showing learning beyond peer pressure such as Jarosch et al. (2021). Despite a very specific setting, our data improves on measurement compared to Jarosch et al. (2021): in our case, people certainly work together, spend their time together, and units are thoroughly comparable.

Second, the analysis of minutes spent on the pitch reveals a positive correlation between peer exposure and human capital accumulation, emphasizing the importance of active engagement with high-skill colleagues. This observation is reinforced by leveraging a key advantage of the data: information about the *strength* of collaboration beyond spending time together. People who interact more with stars will gain the most from peer-effect.

Third, we turned attention to the development of skills through learning, shifting the focus from market values to skill attributes directly related to work-related interactions. By examining attributes like short passes, we showed how specific player abilities are honed through collaborative interactions, emphasizing the role of skill development in a team setting. Once again, the very specific and unique setting with observable skills (beyond wage, or human capital) has been essential.

This section underscores the importance of skill enhancement through collaborative learning processes and the direct impact of interactions on individual performance and skill acquisition.

An interesting finding was related to workers changing jobs. Here we found that moving to a new team on average hinders perceived human capital. However, skills acquired earlier remain. This last point supports policies of sending people to learn from the best even if eventually they will move to lower-ranked jobs.

Overall, the findings of this study underline the critical role of peer interactions and collaboration in fostering skill development and enhancing individual performance. By highlighting the mechanisms through which workers learn from their peers, we provided valuable insights for understanding the dynamics of skill acquisition and human capital accumulation.

True, our setting is special, it is a high-skilled, very competitive, and at the same time, very collaborative job environment. Our findings thus are relevant for similar jobs such as consulting, marketing, or even academia.

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A Appendix

A.1 Variable descriptions

Let us define the key variables of the analysis.

- **Market value** (Transfermarkt): mean market value of the player in the half-season, without evaluation the last valid evaluation is assigned to the player
- **Teammates' total market** value: the sum of the market value of the teammates' of the player based on their mean market value in the half-season
- **Total minutes**: total minutes spent on the pitch in the half-season by the player, measured in Z-scores (standardized with mean and standard deviation)
- **Pass eigenvector centrality**: based on the total pass network of the team in the half-season, calculates the eigenvector centrality of the player (proxies the importance of the player in the team's overall play), measured in Z-scores (standardized with mean and standard deviation)
- **Top 5% of players**: based on position, the player is or in the last 2 years was in one of the half-seasons in the top 5% of the market value distribution in the top 5 leagues
- **Top 25% of players**: based on position, the player is or in the last 2 years was in one of the half-seasons in the top 25% of the market value distribution in the top 5 leagues
- **Seniors vs. juniors**: players are split by age at 23 years of age
- **Pass count with top 5% or 25% of players categories**: per capita number of passes with top 5% and 25% of players, proxies the direct interaction with the top players on the team. Calculated only for those who have top 5% (and top 25%) peers.
  - No top player: no top player on the team
  - No shared minutes: no shared minute with a top player
  - lowest 25 percentile: the number of passes is in the 25-75th percentile of the pass distribution between couples of players in the full dataset in a half-season
  - middle 25-75 percentile: the number of passes is in the 25-75 percentile
  - top 75+ percentile: the number of passes is in the 75+ percentile

- **Pass count with top 5% or 25% of players** (numeric): number of passes with top 5% or 25% players in the half-season, measured in Z-scores (standardized with mean and standard deviation)
- **Minutes shared with top 5% or 25% of players out of total** (numeric): fraction of minutes shared with top 5% or 25% of players out of total shared minutes with all players, measured in Z-scores (standardized with mean and standard deviation)
- **Hirschman–Herfindahl Index**: HHI index of the market values of the squad members in the half-season
- **Share of top 5% or 25% players on team**: share of players in the top 5% or 25% of the players' market value distribution

Control sets of dummies (Fixed-effects) in the regressions:

- **League × half-seasons**: league indicators interacted with the half-seasons
- **Position**: broad position of the player, goalkeeper, defender, midfielder, forward
- **Player age**: player's age dummies

Skill attribute rating variables: we select from a set of highly correlated variables one that is representative of the overall skill group.

- **Short pass**: short pass ability, proxies passing ability
- **Finishing**: scoring ability, proxies shooting
- **Interceptions**: defensive mental attribute, ability to intercept a ball
- **Reactions**: how fast a player responds to a situation around him
- **Speed**: how fast a player can sprint

A.2 Descriptive statistics

Tables A1, A2 describe the key numeric and categorical variables of the analysis. Table A1 examines the distribution in the full sample, while Tables A4 and A5, along with A3 split the sample according to position in the market value distribution by excluding low and very high-valued players, and then also by seniority, splitting at the age of 25. Cutting off the tails of the distribution is a step towards creating common support in the regressions: the highest value individuals in the dataset skew the distribution as we can see in Table A4. The comparisons in Table A5 reveal that after the cut, junior and senior players are fairly comparable in their most relevant observables.

Table A1: Descriptives of the key numeric variables

	N	mean	sd	min	p1	p50	p99	max
Value (in mn EUR)	3470	3.90	6.49	0.03	0.15	2.00	32.96	120.00
log(value)	3470	14.46	1.18	10.13	11.92	14.51	17.31	18.60
Short pass	3470	0.08	0.62	−3.51	−1.59	0.08	1.36	1.88
Finishing	3470	0.07	0.88	−2.15	−1.75	0.27	1.58	2.24
Interceptions	3470	−0.01	0.92	−2.09	−1.82	0.35	1.36	1.69
Reactions	3470	−0.31	1.04	−5.00	−2.92	−0.19	2.07	3.48
Speed	3470	0.26	0.76	−2.75	−1.91	0.38	1.76	2.14
Teammates' value (in mn EUR)	3470	97.20	106.21	4.68	8.59	61.77	528.84	747.42
Teammates' value (Z-score)	3470	−0.13	0.88	−0.90	−0.85	−0.43	3.58	4.58
log(Teammates' value)	3470	17.97	0.90	15.36	15.97	17.94	20.09	20.43
HHI of team	3470	0.07	0.01	0.04	0.05	0.06	0.12	0.14
Share of top 5% players in team	3470	0.09	0.17	0.00	0.00	0.00	0.79	0.90
Share of top 25% players in team	3470	0.35	0.21	0.00	0.00	0.36	0.82	0.88
Total minutes	3470	847.46	543.87	0.00	9.00	835.00	2023.93	2533.00
Total minutes (Z-score)	3470	−0.07	0.98	−1.76	−1.69	−0.08	2.05	3.29
Pass eigenvector centrality (Z-score)	3427	0.00	0.98	−1.43	−1.43	−0.07	1.93	1.93
Pass count top 5% (Z-score)	1435	0.07	1.10	−0.93	−0.93	−0.33	3.92	8.11
Pass count top 25% (Z-score)	3254	0.22	1.16	−1.02	−1.02	−0.08	4.07	8.76
Minutes shared with top 5% (Z-score)	3440	−0.19	0.84	−0.64	−0.64	−0.64	2.74	2.98
Minutes shared with top 25% (Z-score)	3440	−0.07	0.93	−1.62	−1.62	0.01	1.74	1.96

Note: All players, all teams.

Table A2: Distribution of the key categorical variables

		N	%
Pass count with top 5%	1. no player	2035	58.6
	2. no minutes	6	0.2
	3. low	296	8.5
	4. mid	596	17.2
	5. high	537	15.5
Pass count with top 25%	1. no player	216	6.2
	2. no minutes	22	0.6
	3. low	531	15.3
	4. mid	1767	50.9
	5. high	934	26.9
Team switching	in year 1	1410	40.6
	in year 2	791	22.8
	none	1269	36.6

Note: All players, all teams.

Table A3: Distribution of the key categorical variables in groups

		tails of distr.				middle of distr.			
		junior		senior		junior		senior	
		N	Percent	N	Percent	N	Percent	N	Percent
Pass count with top 5%	1. no player	48	1.38	7	0.20	702	20.23	1278	36.83
	2. no minutes	0	0.00	0	0.00	5	0.14	1	0.03
	3. low	5	0.14	0	0.00	197	5.68	94	2.71
	4. mid	9	0.26	15	0.43	247	7.12	325	9.37
	5. high	4	0.12	52	1.50	136	3.92	345	9.94
Pass count with top 25%	1. no player	10	0.29	3	0.09	80	2.31	123	3.54
	2. no minutes	1	0.03	1	0.03	10	0.29	10	0.29
	3. low	19	0.55	8	0.23	276	7.95	228	6.57
	4. mid	28	0.81	44	1.27	662	19.08	1033	29.77
	5. high	8	0.23	18	0.52	259	7.46	649	18.70
Team switching	in year 1	27	0.78	14	0.40	560	16.14	809	23.31
	in year 2	12	0.35	15	0.43	320	9.22	444	12.80
	none	27	0.78	45	1.30	407	11.73	790	22.77

Note: All players, all teams.

Table A4: Descriptives of the key numeric variables by place in value distribution

	tails of distr.				middle of distr.			
	N	mean	sd	p50	N	mean	sd	p50
Value (in mn EUR)	140	19.39	21.10	25.00	3330	3.25	3.84	2.00
log(value)	140	14.69	2.89	17.03	3330	14.45	1.05	14.51
Short pass	140	0.38	0.81	0.23	3330	0.06	0.60	0.08
Finishing	140	0.44	1.00	0.55	3330	0.06	0.87	0.22
Interceptions	140	−0.07	0.96	−0.02	3330	0.00	0.92	0.35
Reactions	140	0.25	1.67	0.51	3330	−0.33	1.00	−0.19
Speed	140	0.42	0.81	0.58	3330	0.26	0.76	0.31
Teammates' value (in mn EUR)	140	226.32	200.53	163.80	3330	91.77	96.67	61.17
Teammates' value (Z-score)	140	0.99	1.71	0.40	3330	−0.17	0.80	−0.44
log(Teammates' value)	140	18.59	1.34	18.91	3330	17.94	0.87	17.93
HHI of team	140	0.07	0.02	0.07	3330	0.07	0.01	0.06
Share of top 5% players in team	140	0.30	0.32	0.14	3330	0.08	0.16	0.00
Share of top 25% players in team	140	0.28	0.19	0.25	3330	0.35	0.21	0.37
Total minutes	140	1007.01	666.12	1079.50	3330	840.75	537.21	832.00
Total minutes (Z-score)	140	0.26	1.24	0.44	3330	−0.08	0.96	−0.09
Pass eigenvector centrality (Z-score)	137	0.16	1.06	0.16	3290	−0.01	0.98	−0.09
Pass count top 5% (Z-score)	85	0.87	1.30	0.83	1350	0.02	1.06	−0.38
Pass count top 25% (Z-score)	127	0.01	0.97	−0.31	3127	0.22	1.17	−0.07
Minutes shared with top 5% (Z-score)	138	0.85	1.46	0.22	3302	−0.24	0.77	−0.64
Minutes shared with top 25% (Z-score)	138	−0.64	0.89	−0.89	3302	−0.04	0.92	0.06

Note: All players, all teams.

Table A5: Descriptives of the key numeric variables by seniority, middle of value distribution

	junior				senior			
	N	mean	sd	p50	N	mean	sd	p50
Value (in mn EUR)	1287	2.60	3.20	1.50	2043	3.66	4.14	2.00
log(value)	1287	14.19	1.08	14.22	2043	14.61	1.00	14.51
Short pass	1287	0.00	0.58	0.01	2043	0.10	0.61	0.16
Finishing	1287	0.01	0.83	0.22	2043	0.09	0.89	0.27
Interceptions	1287	−0.21	0.92	0.16	2043	0.13	0.89	0.49
Reactions	1287	−0.70	0.99	−0.62	2043	−0.09	0.94	−0.05
Speed	1287	0.38	0.66	0.46	2043	0.18	0.81	0.23
Teammates' value (in mn EUR)	1287	103.85	108.14	68.28	2043	84.16	87.86	56.62
Teammates' value (Z-score)	1287	−0.08	0.87	−0.38	2043	−0.23	0.74	−0.47
log(Teammates' value)	1287	18.04	0.92	18.04	2043	17.88	0.83	17.85
HHI of team	1287	0.07	0.01	0.06	2043	0.06	0.01	0.06
Share of top 5% players in team	1287	0.09	0.18	0.00	2043	0.07	0.15	0.00
Share of top 25% players in team	1287	0.37	0.21	0.40	2043	0.34	0.21	0.35
Total minutes	1287	692.20	521.72	627.00	2043	934.33	525.74	949.00
Total minutes (Z-score)	1287	−0.33	0.95	−0.45	2043	0.08	0.94	0.10
Pass eigenvector centrality (Z-score)	1265	−0.23	0.95	−0.43	2025	0.14	0.96	0.11
Pass count top 5% (Z-score)	585	−0.27	0.95	−0.64	765	0.24	1.09	−0.05
Pass count top 25% (Z-score)	1207	−0.03	1.07	−0.39	1920	0.38	1.20	0.11
Minutes shared with top 5% (Z-score)	1272	−0.17	0.82	−0.64	2030	−0.27	0.73	−0.64
Minutes shared with top 25% (Z-score)	1272	0.01	0.92	0.17	2030	−0.08	0.92	−0.02

Note: Middle value range players, all teams.

A.3 Data cleaning steps: sample selection

Sample selection steps were the following:

- We start from the histories of player values (N = 1,007,727). We discard all observations without a valid market value: meaning before the first valuation (mostly U17 or U19 player histories) as we complete the market value histories with past values if it is not available. (641,881 rows remain)
- Keep only those players who have at least 11 players with a valid valuation on their team. (433,770 rows remain)
- Keep those that are:
  - in the relevant seasons of 2012/2013-2019/2020
  - Top 7 European football leagues
  - at least 18 years of age

- data cleaning: has valid team id, has less than 50 players to interact with, and non-negative minutes
- additional steps:
  * keep those that have 6 half-seasons of lead market value observations (30,906 obs. remain)
  * exclude goalkeepers (28,613 obs. remain)
  * exclude those where lead FIFA data for 6 half-seasons is not available (15,586 obs. remain)
- additional steps: for each player keep the first valid half-season observations (3,470 remain)

So in the end, as each player is present once, 3,340 players remain in the sample.

A.4 Most important factors for TM market values

Via the website https://www.transfermarkt.com/market-value-definition/thread/forum/357/thread_id/3433 the following factors are considered when producing the market value of a player.

1. Most important factors:

   - Future prospects
   - Age
   - Performance at the club and national team
   - Level and status of the league, both in sporting and financial terms
   - Reputation/prestige
   - Development potential
   - League-specific features
   - Marketing value
   - Number & reputation of interested clubs
   - Performance potential
   - Experience level

- Injury susceptibility
- Different financial conditions of clubs and leagues
- General demand and ”trends” on the market
- General development of transfer fees
- External factors such as the coronavirus pandemic and its consequences

2. Individual modalities:
    - Transfers via an option to buy/obligation to buy
    - Loan fee
    - Only part of transfer rights acquired
    - Exit clause
    - Buyback option
    - Player swap deal
    - Contract length
    - Resale participation
    - Bonus payments
    - Improvement of financial balance

3. Situational conditions:
    - Pressure situations such as competitive, success or financial pressure, etc.
    - Will/desire/interests of the player
    - Club does not sell to highest bidder
    - Player goes on strike or similar
    - High salary
    - Club wants to sell player