**The Wisdom of Crowds and Transfer Market Values**

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Abstract

Crowd-sourcing of information has become popular in the years since James Surowiecki published *The* *Wisdom of Crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations.* In sports, crowd-sourced estimates of players’ values and abilities are common, particularly in football where salary information is generally unavailable. The analysis here first considers the characteristics of a good crowd-sourced value then turns to an empirical analysis which applies those characteristics and their implications to assess the quality of the commonly used crowd-sourced values from Transfermarkt. Our empirical results show systematic influences from some obvious factors indicating that the crowd-sourced transfer fees are biased as predictors of the true market determined fees. The findings are useful because they address the question of whether these values can reasonably be used as proxies for unknown salary in academic research. Additionally, because Transfermarkt values are often used in negotiations between clubs and players, it is useful to both parties to know the accuracy and the bias of the crowd-sourced values.

Keywords: Forecasting; Decision Support, [Wisdom of Crowds](https://econpapers.repec.org/scripts/search.pf?kw=Wisdom%20of%20Crowds);  [Football](https://econpapers.repec.org/scripts/search.pf?kw=Football); [Transfermarkt](https://econpapers.repec.org/scripts/search.pf?kw=Transfermarkt), FIFA video game

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An important advantage in the study of sports is the availability of an enormous amount of data. In every game or match, numerous events are recorded which identify the player and his or her actions. Unlike most other workers, the contribution of every player in a match can be linked to the production of his or her team. When the player’s compensation is known, this combination of performance and pay enables testing theories about the workplace that cannot be tested in any other industry. Unfortunately, for the most popular sport in the world, football (soccer), in its richest market, Europe, player contracts are rarely observed, so player compensation is unknown. Not knowing player pay makes it difficult to study the market for players’ labor.

An approach to addressing the lack of player pay data in European football is to use crowd-sourced estimates of the value of players to clubs; the best known of these is from transfermarkt.de and is known as the transfer market value. The impetus to crowd-sourcing is the ability to get input from many people quite quickly at relatively low cost, especially afforded by the internet. Of course, the use of crowd-sourcing is only justified if the information it provides is a good predictor of the unmeasured, unreported or uncertain outcome of interest.

The literature on crowd-sourcing has grown substantially since its beginnings in 1907, when Sir Francis Galton assessed peoples’ judgement of the weight of an ox. Summarizing and synthesizing academic research from a variety of fields, James Surowiecki’s *The* *Wisdom of Crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations* (Surowiecki, 2004) describes the circumstances when a group’s information and knowledge are better or more accurate than that of an individual. Key circumstances for groups to improve upon the knowledge and information of any individual are that the individuals within the group have diverse perspectives and that the individuals provide their assessments independently. These individual assessments must then be aggregated in some fashion, while “(e)xtensive research in the forecasting, decision making, and groups literatures has confirmed that averaging is a powerful and robust way of reducing error in quantitative judgment (Larrick & Soll, 2006).”[[1]](#footnote-1).

The objective of this research is to examine crowd-sourced estimates of players’ values and abilities. The results will be of interest to both sports economists who wish to understand the market for playing talent and to anyone using crowd-sourcing to make predictions or forecasts, including football clubs, and players and their agents. The first purpose of this research is to determine whether readily available information can be used to improve the ability to predict actual transfer fees relative to the existing crowd-sourced values. In other words, we address whether crowd-sourced values, such as that from Transfermarkt, are like stock price predictions under the efficient markets hypothesis in that no easily available information exists with which one could construct a better (point) prediction of the true transfer fee. Indeed, if crowd-sourced values can be improved upon by using readily available information, the second purpose is to determine of whether systematic bias exists between the true value of the transfer fee and the Transfermarkt prediction of that value. The forecasting literature (Davis-Stober, Budescu, Broomell, & Dana, 2015; Lamberson & Page, 2012) focuses on minimizing the variance of a crowd sourced forecast, but has paid little attention to the potential bias in those forecasts. A tightly focused forecast that does not include the actual value of the variable being forecast may be less valuable than a less accurate, that is, larger variance, forecast that does engulf the true value of the variable.

The argument is laid out in three steps. In the first step, we describe the transfer market for football players and the sports economics literature studying that market. The second step discusses the optimal crowd-sourcing literature. The third step lays out the hypotheses, the data and the empirical analysis. The paper ends with a discussion of the results and concluding thoughts.

1. Transfer markets and crowd-sourcing

In football, clubs can sell the rights to a player to other clubs in exchange for a fee. It is often argued that player values can be approximated by the value of this transfer fee. While such transfers are commonplace, some players are never transferred from one club to another this way and, of course, not all players are transferred each year. Consequently, there is no observable market-determined value for each player in every season. There is, however, a crowd sourced value of every player produced and reported regularly at transfermarkt.co.uk (for the English language version) or transfermarkt.de (for the German language version). The German magazine *Kicker* also reports estimates of player market values, though the figures are limited to players active in the German league. In addition, video game manufacturers use crowd-sourcing to evaluate the skills of actual professional soccer players for modeling that player’s production for the game.

To be clear about the process, in the case of the Transfermarkt values, note that members of the transfermarkt group make predictions about the transfer value of many players each year, far more in fact than are transferred in a season. The values submitted by members of transfermarkt, which is free to join, go through layers of assessments before the ultimate production of the value that gets reported. The process of assessment is only generally described, but boils down to scrutiny of the reports by established members for plausibility and reliability. Only in a relatively small number of cases are the true values revealed, that is, are players whose values have been predicted by the transfermarkt group actually transferred for a fee. Nonetheless, these guestimates and those of the staff of Kicker magazine are commonly used by clubs and researchers. Interestingly, Christian Schwarz, Transfermarkt’s international head of market values, “admitted he had been surprised by the growing influence its estimates are having on the industry. ‘Clubs shouldn’t make transfer decisions based on the figures on our website.’” “Our method is not scientific.”(Top Football Clubs Relying on Transfer Valuations Made by Volunteers, 2020).

Numerous examples exist of crowd-sourced market values of football players being used as a proxy for the true value of the players. Franck and Nuesch (2012), Haas, Kocher, and Sutter (2004) and Torgler and Schmidt (2007) use the market values published by *Kicker* magazine. Bryson, Frick, & Simmons (2013); Frick (2007); Herm, Callsen-Bracker, & Kreis (2014); Müller, Simons, & Weinmann (2017); Peeters (2018); Prockl & Frick (2018) all use transfermarkt.de values. Researchers utilize the crowd-sourced values when the purpose is to understand the labor market for football players, often with the *Kicker* or Transfermarkt values serving as a proxy for the largely unknown salary of the players in European football.

A number of papers examine the factors which determine the actual transfer fee when one club purchases the contract of a player from another club. Carmichael, Forrest, and Simmons (1999), Carmichael and Thomas (1993), Dobson, Gerrard, and Howe (2000), Reilly and Witt (1995) and Speight and Thomas (1997) all estimate models of the determinants of transfer prices. The results are not surprising and those factors that make a transfer fee large also tend to explain both a larger player salary and a greater likelihood of being transferred (Frick, 2007). Better players and star players have higher transfer prices than weaker and less well-known or less highly regarded players. Of course, how better players are identified varies between studies. Dobson et al. (2000) find that transfer fees at the lower levels of English football are largely driven by the same factors as found by Carmichael and Thomas (1993). Reilly and Witt (1995) find that transfer fees of black players are 9% lower than the fees for otherwise identical white players. Frick (2007) is a good review of the literature before 2007.

More closely related to the purpose of this study are those by Herm, Callsen-Bracker, & Kreis (2014), Müller, Simons, & Weinmann (2017), Kirschstein & Liebscher (2019) Peeters (2018), and Prockl & Frick (2018) Singh & Lamba (2019) which evaluate the quality of the crowd-sourced values, though from different perspectives. For example, Peeters (2018) uses Transfermarkt values aggregated to the team level to predict the outcome of football matches and compares those results to the predictions based on FIFA rankings and ELO ratings. The crowd-sourced values perform better than do the FIFA and ELO scores.[[2]](#footnote-2) Prockl & Frick (2018) evaluate the Transfermarkt values as proxies for player salary. Major League Soccer, in the United States, is the only football league for which player salaries are known for all players for a large number of seasons. Prockl & Frick (2018) use data covering the 10 seasons from 2006 through 2015 to investigate the precision of the Transfermarkt values and to understand how crowd wisdom emerges, develops and matures. For our purposes, the precision of the Transfermarkt values is all that is relevant. They find a positive and statistically significant correlation of .7 or higher between the natural log of the Transfermarkt values and the natural log of either base or guaranteed salary of players in MLS. Prockl & Frick (2018) then estimate “salary” regressions with the same explanatory variables but with each of the log Transfermarkt market values, log of base salary and log of guaranteed salary as the dependent variable. They find that the estimated results are quite similar across all three equations; if a variable is statistically significant in one equation it is nearly always significant in the others. Prockl & Frick (2018) conclude by saying “our results suggest that player market values generated by the wise crowd on transfermarkt.de are very good proxies of current as well as future player salaries.”

The remaining studies focus on accurately predicting the Transfermerkt crowd-sourced values of players. Herm et al. (2014), for example, discuss alternative approaches of data aggregation in crowd-sourcing, highlighting the difference between an integrative approach and a selective approach. The integrative approach is likened to democracy in which each individual’s assessment is treated identically. Alternatively, this method can be described as completely anonymous, as the identity, qualifications, and prior participation are all unutilized in the aggregation process. The selective approach, or “judge principle”, involves a second layer of evaluation in which some people take account of precisely those bits of information that are unused in the integrative approach. For example, a “judge” may determine that one individual’s valuation is more plausible, believable, or accurate than another person’s valuation based on the first individual having participated longer or having a record of good evaluations. They suggest that the selective model will produce better estimates than the integrative model. In the end, Herm et al. (2014) regress Transfermarkt values for a sample of 338 individuals who played in at least one match during the first half of the 2011/12 season of the German Bundesliga against a list of player and team characteristics taken from the existing literature on player values. In other words, they evaluate whether the crowd-sourced value is influenced by commonly used variables in studies of the labor market for football players. They also compare those Transfermarkt values with observed transfer fees for 67 players transferred during the winter 2011/2012 transfer window. Clearly, the Herm et al. (2014) analysis is hindered by the small sample size. More importantly, having raised interesting questions about integrative and selective crowd-sourcing, they are unable to really address them.

Müller et al. (2017) conduct an analysis similar to Herm et al. (2014) but on a much larger sample; they have over 4000 players in the top five football leagues in Europe over the six season period 2009/10 to 2014/15. The total number of player-year observations is 10,350. However, only 845 players are actually transferred for a fee in their data. Müller et al. (2017) estimate a model which explains the current Transfermarkt value using the lagged Transfermarkt value, player characteristics, performance and skill metrics, and measures of popularity. The model is then used to predict the value of each player and this value compared to the observed transfer fee for those players who were transferred. The authors also compare the Transfermarkt value to the observed transfer fee. Comparison is done by computing the difference between the observed transfer fee and each of the Transfermarkt value and the forecasted value of the Transfermarkt value based on the estimated model. The root mean squared error and the mean absolute error are computed for each of these differences, with the crowd-sourced, Transfermarkt value difference having a lower RMSE and MAE than the model by about 3.5%. However, delving deeper, this comparison indicates that the model does better than the crowd for the lowest 90 percent of transfers but that the Transfermarkt value is better for the very large transfer fees.

The finding that the authors’ model and the crowd-sourced values do not perform equally well throughout the transfer value distribution suggests an alternative empirical method may provide some insights. For example, a quantile regression model allows the influence of a given variable to be different at the tenth-, twentieth-, or fiftieth-percentile than at the ninetieth-percentile. We utilize quantile regressions below to explore this possibility below.[[3]](#footnote-3)

Kirschstein & Liebscher (2019) also address the quality of the Transfermarkt values of players from the first and second Bundesliga in the single season, 2016, utilizing data from EA Sports FIFA video game in their analysis. Because of the large number of variables, they conduct principal components analysis to reduce the number of variables. Given their explanatory variables, they are unable to provide useful economic interpretations of their coefficient estimates and rely instead on measures of goodness of fit. Evaluating their predicted values against the actual values, Kirschstein & Liebscher (2019) note there are some substantial outliers. They use a quantile estimator in evaluating these under- and overvalued players in their data. Interestingly, they find that “all undervalued players have a comparatively small market value whereas all overvalued players have a market value greater than 1 million euros.”

Finally, Singh & Lamba (2019) estimate models of the Transfermarkt value which then are used to predict those values. They include EA Sports data, daily average Wikipedia hits as a measure of player popularity, and a list of typical variables like goals, assists, minutes played and player age in their models. A unique feature of their data is the inclusion of Fantasy League values from fantasy-liga.com, a website that bills itself as “Spanish Fantasy Football At Its Best”. They do not provide individual regression coefficients but rather simply the R2 and RMSE for their models. Their results suggest, via comparison of the R2, that popularity and “Crowdsourcing”, which is not clearly defined, add little explanatory power beyond the inclusion of the performance statistics. None of the papers cited suggests that Transfermarkt values are anything other than a proxy for either player salaries or the actual transfer fee that would be paid by one club to another in exchange for a player’s contract. All indicate that the Transfermarkt values and salaries or actual transfer fees paid are highly correlated. Of course, that the variables in question are correlated is not at issue. However, an evaluation of these crowd-sourced variables as good estimates of the truth requires more than that the true values and the crowd-sourced values are correlated. Indeed, finding that the two variables are correlated is not the same thing as finding that the crowd-sourced variable is an unbiased predictor of the other or that it produces a guess of the true value that is better than other means of producing a guess. Moreover, the intuition of the wisdom of crowds suggests that large, diverse crowds who provide independent assessments will produce better guesses of the true value than small, homogenous crowds whose assessments are interdependent. One might suspect, therefore, that combining information from two distinct crowds could produce a better judgement than using the information of just one crowd. However, ultimately, the question is whether the crowd-sourced values have properties that make them useful estimators of the unknown variables which are of interest.

1. Optimal crowds

The forecasting and operations research literature addresses the issue of the best composition of a crowd (Davis-Stober, Budescu, Broomell, & Dana, 2015; Lamberson & Page, 2012). Best in this literature is defined as that which minimizes the mean square (forecast) error. Davis-Stober et al., (2015) builds upon Lamberson & Page (2012) generalizing that work to allow both for bias in the responses of the crowd members and to allow that which is forecasted to be a random variable. Here the application is to understanding the crowd-sourced valuation of professional football players as done by Transfermarkt or *Kicker* magazine, or the player ratings as done for EA Sports for that company’s FIFA video game. The true value of the player, whether monetary or playing ability, is represented by Vp and is assumed to be a fixed but unknown value. This assumption differs from Davis-Stober, Budescu, Broomell, & Dana (2015) but is identical to P. J. Lamberson & Scott E. Page (2012). Because the evaluations are done for many players, the subscript p makes clear that this is the value of a specific player.

Each of M individuals sends a signal, forecast or guess, of the player’s value, sip= Vp+δip+εip. The guess is the true value plus a measure of the bias of the guesser toward this player, δip, plus a completely random component, εip. Sp=(s1p, s2p, …, sMp) simplifies the notation. Diversity in the crowd can be thought of as little or no correlation between the δip and δjp and between the εip and εjp. The greater the correlations between these idiosyncratic pieces of the guesses, the less diverse the crowd opinions. Likewise, the smaller the correlations, the greater the diversity in the crowd’s guesses. Crowd-sourcing also requires that the individual signals are aggregated in some fashion; let G(Sp) be the function that represents this aggregation. A common means of aggregation in the crowd-sourcing literature is averaging. Let ; that is, the aggregation is the weighted average of the individual signals.

The weighted average of the individual signals produces the true value, in expectation, under certain circumstances. If the weights are constants, wip that sum to one, and 0≤wip≤1, and both the random component, εip, and the bias, δip, have a mean of zero in expectation, then the aggregation by weighted average produces the true value of the player, in expectation. Alternatively, if the weights sum to 1 and are independent of the bias and random components, E(∑wipδip)=E(∑wipεip)=0, the expected value of the weighted average is the true player value.

Of course, if the weights are not independent of Sp, then the weighted average produces a biased estimate of the true value Vp. Specifically, the bias in the estimator of the true value, Vp, is the expected value of the weighted sum of the random error and the individual crowd members’ idiosyncratic dislike or like of the player:

Transfermarkt’s description of its evaluation process makes it clear that there are arbiters whose role it is to evaluate the importance, plausibility or accuracy of the guesses by the people in M; in other words, there are people who determine the weights to apply to individual guesses based on judgements about those guesses. Therefore, the weights used by Transfermarkt are conditional on the signals, that is, in general, , so that the final Transfermarkt valuations of the players are biased predictions of the true value; on average the Transfermarkt values do not represent the true value of the player, and this is because of the method of construction.

Biased crowd-sourced estimates may be less concerning if the bias is small and the accuracy is high.[[4]](#footnote-4) Accuracy in crowd-sourced forecasts is often measured by either the root mean squared error, the mean squared error, as in Davis-Stober, Budescu, Broomell, & Dana (2015) and P. J. Lamberson & Scott E. Page, (2012), or as the absolute error or absolute percentage error (Mannes et al., 2014), and weights can be selected for the individual signals to minimize these measures of error variance. Nonetheless, as a football manager or a player agent who may use the Transfermarkt values in negotiations, it is important to know if these values tend to be higher than or lower than the true worth of the player; that is, to know the sign of . Moreover, there is no way to know if Transfermarkt’s weights improve on the accuracy of a simple average of the signals sent by the individual members, to say nothing of whether Transfermarkt has selected the optimal weights. Müller et al. (2017) tested their model against the Transfermarkt values, finding it to be an improvement.

Methods and Hypotheses

The purpose here is to understand the nature of the bias in Transfermakt values as predictors of actual fees paid by one club to another club for the acquisition of a player. To be concrete, take the Transfermarkt value *trans* as an estimator of the true transfer fee *fee* which is a function of a vector of variables z; *.* The function f(.) represents the process by which Transfermarkt converts the information, z, provided by its members, into the organization’s published guess, or prediction, of the true fee. Only Transfermarkt knows the f(.) it uses. If the Transfermarkt is an unbiased estimator of the true market value, then , but if not, In a random sample of players, the mean difference between the transfer fee and the market value should not be different from zero, if the function is an unbiased predictor of *fee*. In the data we have on over 5000 actual transfers, excluding goal keepers, the mean difference between the fee and the reported transfer value is 244,503 British Pounds; a t-test rejects the null of equal means. Shmueli (2010) emphasizes that one facet of the distinction between an explanatory model and a predictive model relates to the expected prediction error.[[5]](#footnote-5) An explanatory model focuses on minimizing bias while the goal of a predictive model is to minimize the variance arising from sum of the variance of the bias and the variance of the estimation ( Variance in results from use of a sample to estimate the function f(.); bias arises from misspecification of f(.), possibly from an incorrect functional form, which would include over or under-weighting of variables in z, or omitted variables. One possible omitted variable is time remaining on the player’s contract. We address this possibility in our estimations.

We estimate the relationship between the observed transfer fee *fee* and the Transfermarkt value *trans* including a variety of covariates X, many of which we understand are likely to be included in z. Any such variable whose influence on *fee* is entirely captured in *trans* should be insignificantly different from zero in our model. The set of variables in X differs across models, by adding additional covariates, including an alternative crowd-sourced measure of ability, and additional variables addressing player ability or stardom. Selection of the variables in X is described below.

If the Transfermarkt value is an unbiased estimator of the true transfer fee, then the parameters a0 and bk will be zero and a1 will equal 1; this is equivalent to . Consequently, the main hypothesis to be tested is *Hypothesis 1*: H0: a0 = bk =0, for all k, and a1 = 1, H1: some a0 ≠ 0, bk ≠0 for some k, or a1 ≠ 1. Of course, the null hypothesis may be rejected if any of these, a0 ≠ 0, bk ≠0 or a1 ≠ 1, is not true. However, if bk ≠0 we can conclude that information exists which reduces the bias in the Transfermarkt prediction of the true transfer fee compared to simply using the crowd-sourced value from Transfermarkt. Moreover, looking at the individual coefficients bk rather than the entire vector of coefficients, suggests which readily available variables may be most relevant to the bias.

It is unclear what variables belong in or are among those in X. For our basic model, we include the player’s age and its square, whether the player had been a member of his country’s national team prior to the transfer, whether he was a defender or midfielder, how many matches he had played and the number of goals and assists he recorded per 1000 minutes of playing time.[[6]](#footnote-6) All of these variables are quite easy to acquire from the internet. Moreover, Transfermarkt’s website says, “The market values are not only based on a player’s performance. It’s the product of many factors like performance, age, talent, reputation, market development etc.” (*Market Values: Rules and FAQ - Market-Value (MLS) - Forum | Page 1 | Transfermarkt*, n.d.) If the Transfermarkt player valuation process uses all available information efficiently, none of these variables should be statistically significant in regression equation 2. We add to this list of variables time remaining on the contract, but this is more difficult to find and, in fact, was available for only about one third of our sample. Moreover, Transfermarkt is explicit that differences between their value and actual fees may arise because “Some factors may have appeared after the last transfer update, are not decisive for our evaluations (contract length, bidding wars, forced sale etc.), etc.  
To be more precise at the next market value update those factors have to be taken into account.” (*Market Values: Rules and FAQ - Market-Value (MLS) - Forum | Page 1 | Transfermarkt*, n.d.)

To the extent that clubs and players use Transfermarkt values in their analysis, they will find the analysis here valuable as they negotiate transfers or player compensation. The time remaining on an existing contract ought to influence the fee paid, with more time left indicating a larger transfer fee paid by the purchasing club to the selling club. Performance indicators are also natural possibilities. Carmichael and Thomas (1993) argue fees depend upon player ability and the “crowd-pulling power” of the transferred player as well as characteristics of the club including its degree of risk aversion. Of course, the evaluators at Transfermarkt could reasonably be thought to account for player ability and popularity (crowd-pulling power) and, perhaps, the time remaining on a contract, but it is difficult to imagine how they could include the club’s risk aversion. The fee is determined by the interests of both the selling and the buying club, but Transfermarkt evaluators cannot know which is the buying club. Player evaluations are done periodically throughout the year, and the website includes rumors about transfers, but there is no clear statement that players whose values are being reconsidered are among those rumored to be the subject of transfer discussions between clubs. A potential means of addressing such issues is club fixed effects. Such effects are, unfortunately, impractical as our data includes 955 clubs that sold a player to another club and 598 clubs that purchased a player from some other club while many clubs participate in only a single transfer[[7]](#footnote-7). Because of issues such as these and motivated by the results in Müller et al. (2017) that suggest that the relationship between transfer market values, their model predictions and actual fees differ between low and high value players, we also estimate the relationship splitting our sample into transfers involving clubs from the top five leagues, which are the focus of Müller et al. (2017), and all other leagues. To further address differences in the relationship across the distribution of fees paid, we finish our analysis using quantile regression.

**Data**

We have two crowd-based estimates, one of player value and one of player quality. The first is Transfermarkt estimates of a market value which is supposed to include individual performance, age, future perspective of a player, the current demand for this player and marketing potential of the player (Müller et al., 2017a). The second estimate is from the FIFA video game simulator developed by EA Sports. Sherif (2016) and Coates et al. (2018) explain the process of evaluating the skills for the FIFA video game. In the first step of this process, a "network of over 9000 members reviews the player’s abilities, watch him play, and help assign him various ratings." As in the Transfermarkt process, in the next stage, this data is reviewed. At EA Sports this is done “by 300 editors, which arrange it into 300 fields and 35 attribute categories.” After that EA “uses this feedback in conjunction with its own stats (scoured from other agencies) to determine ratings.” Summarizing, from the EA Sports crowd-sourced player evaluations, our data includes the overall rating and ratings in 25 attribute categories.

We concentrate only on those players, which (1) were sold from one club to another at least once and (2) for which we observe the actual transfer price paid. We collect the data from transfermarkt.de for the period from 1996 through 2016. Since Bosman’s case had dramatically changed the market, we do not include the earlier transfers. We exclude the transfers which do not fit the criteria above. Finally, the merged data from three datasets consists of 5,860 observations. Among these observations are transfers involving 598 purchasing clubs and 955 selling clubs. Purchasing clubs come from 56 countries, selling clubs from 77 countries. Transfers are made from clubs in 171 different leagues to clubs in 96 distinct leagues. There are 304 goal keepers which are dropped from the analysis. The sample is further reduced because observations are missing values for goals and/or assists, reducing the sample by 2535 (1,610 have no goals scored information, and 2,062 are missing information on assists). Some observations are missing data on their transfer fee or their Transfermarkt crowd-sourced value; 278 have no value for the number of matches played;. 6 observations lack minutes of playing time and 1 observation is dropped because the FIFA rating is missing. When these missing data are accounted for, there remains 3324 observations. Table 1 provides descriptive statistics for this sample, omitting the individual attribute ratings from EA Sports which are provided in Table 2.Of these 3324 observations, we were able to collect time remaining on their existing contract at the time of their transfer for 883. The average time remaining on a player’s contract is 921 days, or about 2.5 years; and the minimum time left on the contract in our sample is just under 1.5 years. We are concerned about using the time remaining variable in our estimates for two reasons. First, including the variable reduces the sample size to about a quarter of its size without time remaining. Second, non-randomness of the value of time remaining is possible given that none of the players have less than 1.5 years remaining on their contracts. For these reasons, we estimate models both including and omitting the time remaining variable.

**Table 1: Descriptive statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | N | Mean | Median | Std. Dev. | min | max |
| Real fee paid in thousands of pounds | 3324 | 4950.369 | 1801.802 | 7966.53 | .23 | 96136.359 |
| Real Transfermarkt value in thousands of pounds | 3324 | 4680.772 | 1880.878 | 6433.711 | 24.287 | 62252.965 |
| FIFA overall rating | 3324 | 71.749 | 71 | 6.221 | 43 | 90 |
| National team player | 3324 | .487 | 0 | .5 | 0 | 1 |
| Matches | 3324 | 33.318 | 31 | 9.058 | 2 | 75 |
| Goals per 1000 minutes | 3324 | 2.969 | 2.196 | 2.388 | .201 | 43.478 |
| Assists per 1000 minutes | 3324 | 1.893 | 1.546 | 1.457 | .216 | 43.478 |
| Age | 3324 | 24.404 | 24 | 3.051 | 17 | 36 |
| Midfield | 3324 | .323 | 0 | .468 | 0 | 1 |
| Defend | 3324 | .181 | 0 | .385 | 0 | 1 |
| Time remaining on contract | 883 | 921.657 | 725 | 292.393 | 485 | 2363 |
| Top league (EPL, Bundesliga, La Liga, Ligue 1, Serie A) | 3324 | .674 | 1 | .469 | 0 | 1 |

Descriptive statistics of the EA Sports FIFA video game crowd-sourced ratings of each player are in Table 2. Scores on these characteristics range, theoretically, from 1 to 100, but in practice the range is from 5 to 97. On some attributes the range is substantially smaller. Interestingly, the highest average rating is for player potential while the lowest is for “marking”, that is, defending against a single player.

Apart from the time remaining on the contract, missing values for goals and assists cause the largest loss of observations. For this reason, we have created alternative goals and assists variables replacing the missing values with zeros; we also created dummy variables indicating those observations for which a zero has replaced the missing value. We estimate the models both on the sample of data that simply takes the missing values as given, dropping those observations, and by replacing the missing values with zeros and including the dummy indicator for observations whose missing value was replaced. We include the tables with the results in the Appendix (Tables A1 – A4).

**Table 2: Video game player evaluations**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | N | Mean | Std. Dev. | min | max |
| potential | 3324 | 77.167 | 5.957 | 50 | 94 |
| crossing | 3324 | 61.7 | 13.356 | 8 | 92 |
| finishing | 3324 | 62.43 | 15.368 | 7 | 94 |
| heading accuracy | 3324 | 61.998 | 12.917 | 7 | 94 |
| short passing | 3324 | 68.19 | 9.808 | 17 | 94 |
| volleys | 3312 | 60.515 | 14.47 | 5 | 92 |
| dribbling | 3324 | 69.147 | 11.553 | 6 | 97 |
| curve | 3312 | 60.796 | 14.528 | 11 | 92 |
| free kick accuracy | 3324 | 56.881 | 15.413 | 10 | 93 |
| long passing | 3324 | 60.041 | 13.122 | 13 | 93 |
| ball control | 3324 | 71.344 | 9.094 | 6 | 96 |
| acceleration | 3324 | 74.251 | 9.662 | 25 | 96 |
| sprint speed | 3324 | 74.341 | 9.11 | 29 | 96 |
| agility | 3312 | 71.86 | 10.538 | 31 | 95 |
| reactions | 3324 | 69.724 | 8.413 | 35 | 96 |
| jumping | 3312 | 67.81 | 11.073 | 24 | 95 |
| stamina | 3324 | 71.578 | 9.294 | 21 | 95 |
| long shots | 3324 | 63.282 | 13.55 | 8 | 94 |
| aggression | 3324 | 61.358 | 14.811 | 11 | 93 |
| interceptions | 3324 | 51.105 | 19.349 | 10 | 88 |
| positioning | 3324 | 66.544 | 12.621 | 10 | 93 |
| penalties | 3324 | 62.377 | 12.573 | 11 | 95 |
| marking | 3324 | 41.948 | 20.662 | 7 | 89 |
| standing tackle | 3324 | 46.339 | 20.714 | 6 | 93 |
| sliding tackle | 3312 | 43.572 | 21.238 | 7 | 91 |

The standard deviation of actual price paid is nearly twice the mean, and the standard deviation in the expert estimates is about 50% larger than its mean. A bit under 50% of the observations are players who appeared on their country’s national team before they were transferred. The average player is just less than 24.5 years old, participated in 33 games during their career and, for those with non-missing values of goals and/or assists, records about 2.97 goals and 1.89 assists per 1000 minutes of playing time.[[8]](#footnote-8) We have also included a dummy variable indicating the players which were transferred from or to Serie A (Italy), English Premier League, 1st Bundesliga (Germany), Ligue 1 (France) or La Liga (Spain), which we designate as the top leagues. The share of such player transfers is 67%.

**Empirical results**

Table 3 contains the regression results on the sample when observations with goals or assists missing are dropped from the analysis; Table 4 reports results when time remaining on the contract is included as an explanatory variable. Model (1) presents the results of a regression model with only the Transfermarkt value and an intercept, in Table 3, and including time remaining in Table 4. The second column reports a model with inclusion of easily available player performance statistics, age, and a dummy variable for National team players, and the third column introduces the EA Sports video game overall player rating. The fourth column adds indicator variables for the year and for the country to which and from which a player was transferred. For each regression, the tables report the adjusted R-squared, the Akaike Information Criteria value and the root mean squared error of the regression.

In Tables 3 and 4 we report the results of two hypothesis tests concerning the coefficient on Transfermarkt. First, directly below the coefficient estimate, we report the t-statistic for the standard null hypothesis that the coefficient is zero against the alternative that it is not zero. The Transfermarkt variable is statistically significant in every model. The second hypothesis is that the coefficient equals 1. In every model, with or without time remaining on the contract as a regressor, the null hypothesis is rejected. Also in every case, the estimated coefficient is larger than 1 implying that the Transfermarkt crowd-source value of player transfer values under-estimates the true value of the fee paid for the player. Interestingly, inclusion of the time remaining on the contract does not make the coefficient on Transfermarkt closer to 1 but rather makes it larger still.

Examining the other results, matches played, goals per thousand minutes, assists per thousand minutes and player age are each individually significant in Table 3, while none of them is in Table 4. The implication is that these variables capture influence of time remaining on the contract when that variable is omitted from the model. However, both for the models in Table 3 and those in Table 4, one rejects the null hypothesis that the coefficients on all the personal characteristic and performance variables have zero coefficients. This is documented in Table 5 which shows the p-value for the joint hypothesis test that all coefficients are zero except those on *trans*, time remaining, FIFA video game rating and the constant.

The null *Hypothesis 1* stated above is that all coefficients in the model are zero, including the intercept, except the trans coefficient which equals one. This hypothesis is rejected in every case. In other words, in no model does the analysis indicate that E(*trans*-fee) = 0; the Transfermarkt prediction, , of the true fee paid for transfer of a player, represented by the Transfermarkt crowd-sourced value, *trans,* is biased with or without inclusion of the time remaining on the contract.

Time left on the contract is worth considering more carefully. The variable is days remaining on the contract, so the coefficient indicates the increase in the transfer fee paid by one club to another, all other things held constant, for one additional day remaining on the contract. The estimates in Table 4 indicate that an additional year remaining on a contract will increase the transfer fee of that player by over £800,000 for the first column and over £550,000 for the remaining three columns. Consider the transfer of Neymar from Barcelona to Paris St. Germaine in 2017. Neymar had signed a five year contract with Barcelona in 2016, leaving four years remaining on his contract. This implies between £2.2 and £3.2 million of the record £198 million transfer fee paid to Barcelona, or between 1.1 and 1.6% of the fee, was due to the four years remaining on Neymar’s contract.

One might object that our analysis has not included the wide array of player skills that have been used in previously published papers (Herm et al., 2014; Kirschstein & Liebscher, 2019; Müller et al., 2017b; Singh & Lamba, 2019). First, we note that these papers have focused on the determinants of the Transfermarkt value, not on whether that value is a good predictor of the actual fee paid. Second, our analysis generally covers more players from more leagues and over a longer time period than those papers. Third, we have incorporated time remaining on the contract which none of these other papers have done. Nonetheless, we have added measures of player ability from EA Sports FIFA video game into our analysis. Regressions of the fee on these attributes included with the *trans*, time remaining, and personal characteristics and attributes of the previous models are presented in Appendix Table A5. The key implications of these models are 1) the coefficient on *trans* remains statistically significantly larger than one, 2) time remaining on the contract is positive and significantly different from zero, and 3) these specific skill variables are not, as a group, statistically significant while the original personal attributes are. This last point indicates our result is consistent with those earlier papers because it means that any influence these performance statistics have on the actual fee has been incorporated efficiently into the Transfermarkt crowd-sourced value. Summarizing, introducing this wide array of individual player skills and characteristics into the model does not alter the basic conclusion of the analysis.

An additional objection to the analysis is that the Transfermarkt values are a better approximation of the actual fee for players from the top leagues, like Serie A, La Liga, Ligue 1, the Bundesliga and the English Premier League. To assess this possibility, we split our sample into players from the top leagues and players from the lesser leagues. This designation as lesser leagues is not meant to denigrate the leagues but rather to recognize that they are either the first division from smaller countries with financially weaker football markets or from the second or third division in their countries.

Table 6 focuses on clubs from the top leagues, as in Müller et al. (2017). The first two columns use the data dropping observations with missing values for goals and assists, the third and fourth columns replace the missing values with zeros and include indicator variables identifying those observations. As before, the Transfermarkt value is statistically significant and the addition of the player age, performance, National Team participation and position dummy variables are jointly statistically significant. As above, the coefficient on Transfermarkt value is statistically different from one though only at the 10% level in column 2. Table 7 reports results from the lesser leagues. For players from these leagues, the coefficient on the crowd-sourced transfer value is not different from one. Nonetheless, as Table 5 shows, one must reject the null hypothesis that the player characteristic and performance variables all have zero coefficients and, more importantly, for the lesser leagues one still must reject null *Hypothesis 1*.

**Table 3: Regression analysis results. All models do not include contract time remaing.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Real fee paid | Real fee paid | Real fee paid | Real fee paid |
| Real Transfermarkt estimate | 1.095\*\*\* | 1.106\*\*\* | 1.117\*\*\* | 1.102\*\*\* |
|  | (33.14) | (31.48) | (25.61) | (24.01) |
| H0: Coefficient = 1, p-value | 0.004 | 0.003 | 0.008 | 0.026 |
|  |  |  |  |  |
| National team player |  | -134.0 | -102.3 | 45.56 |
|  |  | (-0.97) | (-0.82) | (0.32) |
|  |  |  |  |  |
| Matches played |  | 23.66\*\* | 24.17\*\* | 15.73 |
|  |  | (2.73) | (2.82) | (1.75) |
|  |  |  |  |  |
| Goals per thousand minutes played |  | 113.2\*\* | 110.8\*\* | 96.71\* |
|  |  | (2.97) | (2.91) | (2.49) |
|  |  |  |  |  |
| Assists per thousand minutes played |  | -143.7\*\* | -140.8\*\* | -111.4\* |
|  |  | (-3.14) | (-3.06) | (-2.42) |
|  |  |  |  |  |
| Player's age |  | -749.9\*\* | -730.6\*\* | -700.3\* |
|  |  | (-2.75) | (-2.67) | (-2.56) |
|  |  |  |  |  |
| Player's age squared |  | 9.026 | 8.846 | 8.076 |
|  |  | (1.68) | (1.65) | (1.50) |
|  |  |  |  |  |
| Midfielder |  | -190.9 | -198.4 | -236.7 |
|  |  | (-1.29) | (-1.34) | (-1.55) |
|  |  |  |  |  |
| Defender |  | 137.8 | 124.7 | 75.65 |
|  |  | (0.83) | (0.75) | (0.44) |
|  |  |  |  |  |
| FIFA video game rating |  |  | -20.02 | -29.44 |
|  |  |  | (-0.96) | (-1.34) |
|  |  |  |  |  |
| Constant | -174.7 | 11863.5\*\*\* | 12861.3\*\*\* | 15321.1\*\*\* |
|  | (-1.40) | (3.51) | (3.62) | (4.40) |
| Observations | 3324 | 3324 | 3324 | 3324 |
| Adjusted *R*2 | 0.782 | 0.796 | 0.796 | 0.806 |
| *AIC* | 64093.5 | 63875.4 | 63875.5 | 63787.5 |
| RMSE | 3721.1 | 3596.7 | 3596.2 | 3504.6 |

*t* statistics in parentheses \* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001. Model 4 also includes indicator variables for the year and the country to and country from which a player was transferred.

**Table 4: Regression analysis results. All models include contract time remaing.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Real fee paid | Real fee paid | Real fee paid | Real fee paid |
| Real Transfermarkt estimate | 1.190\*\*\* | 1.207\*\*\* | 1.221\*\*\* | 1.204\*\*\* |
|  | (24.24) | (23.40) | (20.30) | (18.24) |
| H0: Coefficient = 1, p-value | 0.000 | 0.000 | 0.000 | 0.002 |
|  |  |  |  |  |
| Time left on current contract | 2.297\*\*\* | 1.507\* | 1.564\* | 1.563\* |
|  | (3.40) | (2.38) | (2.47) | (2.36) |
|  |  |  |  |  |
| National team player |  | -163.6 | -96.12 | 39.27 |
|  |  | (-0.49) | (-0.30) | (0.11) |
|  |  |  |  |  |
| Matches played |  | 23.01 | 23.84 | 17.23 |
|  |  | (1.01) | (1.05) | (0.71) |
|  |  |  |  |  |
| Goals per thousand minutes played |  | 141.2 | 135.1 | 56.78 |
|  |  | (1.57) | (1.51) | (0.57) |
|  |  |  |  |  |
| Assists per thousand minutes played |  | -102.6 | -94.50 | -89.98 |
|  |  | (-0.78) | (-0.71) | (-0.63) |
|  |  |  |  |  |
| Player's age |  | -343.0 | -274.3 | -208.9 |
|  |  | (-0.45) | (-0.35) | (-0.28) |
|  |  |  |  |  |
| Player's age squared |  | -1.750 | -2.673 | -4.485 |
|  |  | (-0.11) | (-0.17) | (-0.31) |
|  |  |  |  |  |
| Midfielder |  | -653.4 | -676.2 | -833.8\* |
|  |  | (-1.71) | (-1.77) | (-2.07) |
|  |  |  |  |  |
| Defender |  | 413.2 | 394.7 | 304.6 |
|  |  | (0.83) | (0.80) | (0.56) |
|  |  |  |  |  |
| FIFA video game rating |  |  | -35.72 | -33.76 |
|  |  |  | (-0.78) | (-0.66) |
|  |  |  |  |  |
| Constant | -2244.9 | 6952.7 | 8252.3 | 9114.4 |
|  | (-4.11) | (0.76) | (0.90) | (1.05) |
| Observations | 833 | 883 | 883 | 883 |
| Adjusted *R*2 | 0.814 | 0.826 | 0.826 | 0.840 |
| *AIC* | 17513.6 | 17458.7 | 17459.9 | 17432.9 |
| RMSE | 4897.5 | 4726.1 | 4726.8 | 4531.9 |

*t* statistics in parentheses. \* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001. Model 4 also includes indicator variables for the year and the country to and country from which a player was transferred.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table 5: Test of player characteristics and performance have zero coefficients – p-values | | | | | | |
|  | Table.Model | | | | | |
|  | 3.2 | 3.3 | 3.4 | 4.2 | 4.3 | 4.4 |
|  | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
|  |  |  |  |  |  |  |
|  | Table.Model | | | | | |
|  |  | | | | | |
|  | Top leagues | | | Lesser leagues | | |
|  | 6.2 |  | 6.4 | 7.2 |  | 7.4 |
| Omits remaining | 0.000 |  | 0.000 | 0.000 |  | 0.000 |
| Incudes remaining | 0.000 |  | 0.000 | 0.002 |  | 0.001 |

Table 6: **Regression analysis results for the subsample of** top leagues

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Real fee paid | Real fee paid | Real fee paid | Real fee paid |
| Real Transfermarkt estimate | 1.092\*\*\* | 1.095\*\*\* | 1.088\*\*\* | 1.088\*\*\* |
|  | (29.73) | (21.17) | (33.67) | (24.57) |
| Coefficient = 1, p-value | 0.012 | 0.066 | 0.006 | 0.047 |
|  |  |  |  |  |
| FIFA video game rating |  | -43.31 |  | -22.21 |
|  |  | (-1.41) |  | (-1.09) |
|  |  |  |  |  |
| National team player |  | 79.52 |  | -10.57 |
|  |  | (0.39) |  | (-0.07) |
|  |  |  |  |  |
| Matches played |  | 19.19 |  | 17.96\* |
|  |  | (1.52) |  | (2.38) |
|  |  |  |  |  |
| Goals per thousand minutes played |  | 122.2\* |  | 58.50\* |
|  |  | (2.07) |  | (2.01) |
|  |  |  |  |  |
| Assists per thousand minutes played |  | -142.7\* |  | -74.49 |
|  |  | (-2.23) |  | (-1.49) |
|  |  |  |  |  |
| goalsmissing |  |  |  | -45.40 |
|  |  |  |  | (-0.31) |
|  |  |  |  |  |
| astmissing |  |  |  | 126.4 |
|  |  |  |  | (0.83) |
|  |  |  |  |  |
| Player's age |  | -835.7\* |  | -483.6 |
|  |  | (-2.15) |  | (-1.88) |
|  |  |  |  |  |
| Player's age squared |  | 9.775 |  | 3.419 |
|  |  | (1.29) |  | (0.68) |
|  |  |  |  |  |
| Midfielder |  | -300.9 |  | -285.0 |
|  |  | (-1.38) |  | (-1.82) |
|  |  |  |  |  |
| Defender |  | -13.74 |  | -6.187 |
|  |  | (-0.06) |  | (-0.04) |
|  |  |  |  |  |
| Constant | -119.1 | 19132.9\*\*\* | -23.55 | 12456.4\*\*\* |
|  | (-0.66) | (3.92) | (-0.18) | (4.01) |
| Observations | 2242 | 2242 | 3584 | 3584 |
| Adjusted *R*2 | 0.767 | 0.798 | 0.763 | 0.795 |
| *AIC* | 43953.6 | 43706.7 | 69282.2 | 68839.9 |
| RMSE | 4371.9 | 4067.8 | 3813.4 | 3545.0 |

*t* statistics in parentheses \* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001. Columns 2 and 4 include year dummies and indicators of the country a player left and the country to which a player was traded.

Table 7: **Regression analysis results for the subsample of lesser leagues**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Real fee paid | Real fee paid | Real fee paid | Real fee paid |
| Real Transfermarkt estimate | 1.087\*\*\* | 1.097\*\*\* | 1.015\*\*\* | 1.013\*\*\* |
|  | (12.05) | (8.68) | (11.92) | (8.49) |
| Coefficient = 1, p-value | 0.334 | 0.443 | 0.350 | 0.916 |
|  |  |  |  |  |
| FIFA video game rating |  | -27.10 |  | -5.543 |
|  |  | (-1.45) |  | (-0.38) |
|  |  |  |  |  |
| National team player |  | -10.77 |  | -51.31 |
|  |  | (-0.08) |  | (-0.50) |
|  |  |  |  |  |
| Matches played |  | 8.295 |  | 10.59\* |
|  |  | (1.12) |  | (2.28) |
|  |  |  |  |  |
| Goals per thousand minutes played |  | 77.21\*\* |  | 33.38 |
|  |  | (2.85) |  | (1.49) |
|  |  |  |  |  |
| Assists per thousand minutes played |  | -9.113 |  | 5.911 |
|  |  | (-0.19) |  | (0.14) |
|  |  |  |  |  |
| Goals missing |  |  |  | 169.9 |
|  |  |  |  | (1.68) |
|  |  |  |  |  |
| Assists missing |  |  |  | -32.98 |
|  |  |  |  | (-0.34) |
|  |  |  |  |  |
| Player's age |  | -513.3\* |  | -348.5\* |
|  |  | (-1.98) |  | (-2.08) |
|  |  |  |  |  |
| Player's age squared |  | 7.379 |  | 4.635 |
|  |  | (1.42) |  | (1.36) |
|  |  |  |  |  |
| Midfielder |  | -39.44 |  | -148.1 |
|  |  | (-0.32) |  | (-1.51) |
|  |  |  |  |  |
| Defender |  | 192.4 |  | -73.83 |
|  |  | (1.33) |  | (-0.71) |
|  |  |  |  |  |
| Constant | -242.2 | 9693.4\*\* | -93.96 | 6338.7\*\* |
|  | (-1.65) | (2.80) | (-0.80) | (2.79) |
| Observations | 1082 | 1082 | 1709 | 1709 |
| Adjusted *R*2 | 0.720 | 0.752 | 0.681 | 0.718 |
| *AIC* | 19187.2 | 19127.5 | 29968.9 | 29842.0 |
| RMSE | 1714.2 | 1611.7 | 1764.1 | 1462.1 |

*t* statistics in parentheses \* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001. Columns 2 and 4 include year dummies and indicators of the country a player left and the country to which a player was traded.

**Quantile Regression Analysis**

The analysis to this point has indicated that Transfermarkt values are highly correlated with but ultimately biased forecasts of the actual fees paid in a transfer of a player. The results for top leagues and “lesser” leagues suggest that the Transfermarkt evaluation is different between them. Next we use quantile regression to explore the entire distribution of the fees paid rather than just the mean of the distribution.[[9]](#footnote-9) Rather than produce large tables of coefficients, we present the results in graphical form (Figure 1) for the full sample and for the large and small leagues separately.

The figures make clear that the relationship between the Transfermarkt crowd-sourced values and the actual transfer fees paid differs between the top and the lesser leagues and between the lower and the higher deciles of the fee distribution. At the lower deciles, Transfermarkt’s values are too big indicating that the crowd-sourced values over-estimate the fee at which low fee players will be sold. At the upper end of the distribution the reverse is the case, with the crowd-sourced values underestimating the fee for the higher transfer fee players. Additionally, the distinction between the top and lesser leagues is informative. Players from lesser leagues for which the actual fee is small have larger overestimated values than do the players from top leagues whose actual fees are low. Moreover, at the upper end, transfer fees of players from top leagues are underestimated but for players from lesser leagues they are not.

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**Top Leagues Lesser Leagues**

Figure 1. Quantile regression results: Transfermarkt crowd-sourced values

![Chart, line chart

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Top Leagues Lesser Leagues

Figure 2. Quantile regression results: Time remaining

Time remaining (Figure 2) has a positive and statistically significant impact on fee paid in the middle deciles of the fee distribution. At the extreme deciles of the distribution the coefficient estimates are positive, but they are not statistically different from zero. However, the point estimate of the coefficient for the top league players is always larger than the relevant coefficient for the lesser league players; the former is at its largest (statistically different from zero) value, 1.034, at the 70th percentile, while the latter is 0.565. The largest value for the lesser leagues occurs at the 60th percentile, 0.679, while the coefficient for the top league players is 0.767.

**Conclusion**

This paper sought to examine crowd-sourced estimates of players’ values and abilities. According to our results, crowd-sourced Transfermarkt values are correlated with but biased estimates of the actual fees paid in a transfer of a player. Crowd-sourced metric tends to underestimate the value of the player as indicated by the coefficient on the Transfermarkt value generally being larger than one. The size of the bias differs between the top and the lesser leagues and between the lower and the higher deciles of the fee distribution of the actual price paid. Actual fees for players with time remaining on their contract rise by between £550,000 and £800,000 per year of time left.

These results have two set of implications. The first is that since crowd-sourced “market values” reported by Transfermarkt are a biased predictor of the true fee value, one should consider this while doing sports economics research. For those who uses transfer fees as a proxy for actual fees or player salaries, our findings are a warning. Our results do not say that Transfermarkt should not be used in regression analysis of football labor markets, but they do indicate that caution should be exercised when doing so. In addition, this finding is important for the contract negotiations between players and clubs or between clubs as Transfermarkt estimates present a misleading picture of the true value of a player.

The second set of implications is broader. We have shown that this popular crowd-sourced forecast can be improved by using readily available public information. The forecasting literature has paid little attention to the potential bias in crowd-sourced forecasts. For example, Peeters (2018) uses Transfermarkt values to predict the outcome of football matches and compares those results to the predictions based on FIFA rankings and ELO ratings. The crowd-sourced values perform better than do the FIFA and ELO scores. According to our findings, the forecast may be improved by using publicly available team statistics.

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1. Citations from the quote have been dropped to enhance readability. [↑](#footnote-ref-1)
2. Frick & Wicker (2016) conduct a similar exercise comparing the accuracy of predictions made by football experts, former players and coaches, with those of sports economists about season outcomes. Economists’ predictions use team wage bills, the football experts use their knowledge and intuition. Actual outcomes are better predicted if both the experts’ ratings and the team wage bills are used than if only one is used. [↑](#footnote-ref-2)
3. [↑](#footnote-ref-3)
4. The bias may also be less concerning if the estimates are consistent, meaning the bias disappears and the variance approaches zero as the sample grows larger. [↑](#footnote-ref-4)
5. We thank an anonymous referee for recommending Shmueli (2010) to us. [↑](#footnote-ref-5)
6. Our explanatory variables overlap somewhat with both Herm, et al (2014) and Muller, et al (2017), though their focus is on what determines the crowd-sourced Transfermarkt value while ours is to determine whether the crowd-sourced value accurately reflects the actual fee paid. Neither of them use time remaining on the player’s contract in their analysis. [↑](#footnote-ref-6)
7. We have tested fixed versus random effects with Hausman tests, according to which fixed effects are preferable. [↑](#footnote-ref-7)
8. Goals per 90minutes = (90/1000)\*2.969=0.267; assists per 90 minutes = (90/1000)\*1.893=0.170. [↑](#footnote-ref-8)
9. Quantile regressions do not include the to and from country dummy variables as the model does not converge when they are included. [↑](#footnote-ref-9)