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Beyond crowd judgments: Data-driven estimation of market value in association football

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ABSTRACT

Association football is a popular sport, but it is also a big business. From a managerial perspective, the most important decisions that team managers make concern player transfers, so issues related to player valuation, especially the determination of transfer fees and market values, are of major concern. Market values can be understood as estimates of transfer fees—that is, prices that could be paid for a player on the football market—so they play an important role in transfer negotiations. These values have traditionally been estimated by football experts, but crowdsourcing has emerged as an increasingly popular approach to estimating market value. While researchers have found high correlations between crowd-sourced market values and actual transfer fees, the process behind crowd judgments is not transparent, crowd estimates are not replicable, and they are updated infrequently because they require the participation of many users. Data analytics may thus provide a sound alternative or a complementary approach to crowd-based estimations of market value. Based on a unique data set that is comprised of 4217 players from the top five European leagues and a period of six playing seasons, we estimate players' market values using multilevel regression analysis. The regression results suggest that data-driven estimates of market value can overcome several of the crowd's practical limitations while producing comparably accurate numbers. Our results have important implications for football managers and scouts, as data analytics facilitates precise, objective, and reliable estimates of market value that can be updated at any time.

1. Introduction

With millions of players and billions of fans, association football ("football" hereafter) is the world's most popular sport. Because of its popularity, professional football teams generate enormous revenues; they are no longer just clubs but companies with shareholders and managers, sales and profits, and customers rather than fans. From a managerial perspective, the most important decisions that these "football companies" (Amir & Livne, 2005) have to make concern which players to employ. As player transfers have a tremendous impact on a club's chances for success (Pawlowski, Breuer, & Hovemann, 2010), researchers from various disciplines have long studied the factors that impact transfer fees (Frick, 2007).

More recently, though, researchers have begun to pay particular attention to players' market values. A player's market value is an estimate of the amount for which a team can sell the player's contract to another team (Herm, Callsen-Bracker, & Kreis, 2014). While transfer fees represent actual prices paid on the market, market values provide estimates of transfer fees, so they play an important role in transfer negotiations. Market values have long been estimated by football experts like team managers and sports journalists, while crowdsourcing websites like Transfermarkt (www.transfermarkt.com) have proved their usefulness in estimating market value during the past few years. However, data-driven approaches to estimating market value have not yet caught on in professional football.

Football has long lagged behind other major sports in the use of data analytics. In 2010, the New York Times still called football the "least statistical" of all major sports (Kaplan, 2010), in large part because the pool of data available at that time was comparatively weak. Today, however, sports-data companies like Opta (www.optasports.com) collect prodigious amounts of detailed performance data that could be used for player valuation in profes-

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sional football (see, e.g., Brandes & Franck, 2012). While some football clubs have started to analyze that data for training purposes and decisions about line-ups, only a few have realized the data's economic potential. They still ignore the "Moneyball" idea of using statistics to guide player scouting and recruitment (Zhu, Lakhani, Schmidt, & Herman, 2015).

In this paper, we evaluate the applicability of data analytics for estimating players' market values in professional football; in doing so, we make four primary contributions: 1) we identify the shortcomings of crowd-based estimations of market value, which justify the exploration of data-driven approaches to estimating market value; 2) we synthesize the academic literature on player valuation to identify the factors that determine players' market values; 3) we use a large sample of publicly available data on the five biggest professional football leagues in Europe over a period of six playing seasons to train a multilevel regression model for data-driven estimation of market value; and 4) we evaluate the accuracy of our model based on a comparison with actual transfer fees and crowd estimates and define the potential of data analytics in overcoming the crowd's limitations.

2. Background

2.1. Market values in professional football

Players are the most important investments in professional football from both a sporting perspective and a business perspective. While in the United States (U.S.), professional athletes are often traded for other athletes or for future draft picks (e.g., in American football or baseball), European football players are usually traded for cash settlements, which are referred to as "transfer fees" (Frick, 2007). Players' market values are estimates of the transfer fees that are most likely to be paid for them. Although there are conceptual differences, market values and transfer fees are comparable (He, Cachucho, & Knobbe, 2015). Accordingly, a player's market value can be defined as "an estimate of the amount of money a club would be willing to pay in order to make [an] athlete sign a contract, independent of an actual transaction" (Herm et al., 2014, p. 484). As such, market values inform selling clubs and buying clubs about football players' monetary value—even those whose contracts have not been sold recently—so they are important in transfer negotiations. Market values have traditionally been estimated by the clubs themselves or by sports journalists, but as football fans have developed an interest in market values, websites have emerged that provide estimates of players' market values. In particular, crowdsourcing has proved its usefulness in estimating market values.

2.2. Crowd-based estimation of market value

Transfermarkt is the leading website on the football transfer market. The site offers general football-related data, such as scores and results, football news, transfer rumors, and estimations of market value at the individual and team levels for most professional football leagues. Once a user has registered at Transfermarkt, he or she can follow discussion threads about players' market values, propose personal estimations based on players' current value and performance, and discuss their proposals with other community members. The final market values are then determined by aggregating the individual estimates. Launched in Germany in 2001, where it now ranks among the most frequently visited websites (Alexa, n.d.), Transfermarkt released an English-language version in 2009, and versions of the site have since been made available in Austria, Italy, Poland, Portugal, Spain, Switzerland, Turkey, and the Netherlands.

Transfermarkt's idea is that users can build an estimate of market value together as well as or better than a few football experts can, a style of judgment for which Surowiecki (2005) coined the term "wisdom of crowds." Some of the most influential newspapers and magazines in Europe regularly quote Transfermarkt's market values for football players (Bryson, Frick, & Simmons, 2012; Herm et al., 2014), which have been found to correlate closely with experts' estimates and player salaries (Franck & Nüesch, 2011; Torgler & Schmidt, 2007). Accordingly, Transfermarkt's market values have provided the foundation for several studies of the football transfer market (e.g., Franck & Nüesch, 2012; He et al., 2015). Transfermarkt's accuracy in estimating market value is remarkable, as crowdsourcing is generally associated with challenges like social influence, manipulation attempts, and lack of experience and knowledge (e.g., Lorenz, Rauhut, Schweitzer, & Helbing, 2011) that may bias estimations of players' market value. As Herm et al. (2014) explained, Transfermarkt has dealt with these challenges by implementing the "judge principle," a selective approach to information aggregation.

According to Herm et al. (2014), the judge principle of information aggregation works as follows. Transfermarkt does not estimate market values in a democratic way, such that all user estimates have equal value, but uses a hierarchical approach. Therefore, Transfermarkt does not calculate the final market values as the mean or median of all individual estimates but gives a few empowered community members, whom Herm et al. called the "judges," the final say. Accordingly, judges review other users' estimates and select and weigh them when making their decisions, so they can decrease or increase the influence of users they consider to be less or more qualified. Although the final market values are not calculated democratically, there is reason to believe that the selective-judge principle works better than purely democratic approaches to information aggregation would. For example, when little-known players receive only a few votes, user estimates that are clearly too high or too low would significantly bias the results–either because of manipulation attempts (e.g., by opportunistic sports agents) or because of a lack of knowledge (e.g., by inexperienced fans). Judges can exclude such estimates from the aggregation, which decreases the risk of bias. (For a more detailed description of how Transfermarkt works see Herm et al. (2014)).

However, despite its arguable benefits and its demonstrated accuracy, the crowdsourcing approach to estimating market value comes with several limitations. First, community members base their estimates on arbitrary indicators, which may happen even unconsciously, so they lack objectivity. (Transfermarkt suggests a list of evaluation criteria, but these are not mandatory.) Second, judges can independently determine the final market values based on personal evaluations of user estimates and other indicators, so they are not reproducible. (As Transfermarkt does not calculate the final values in a formal way, the question arises concerning who judges the judges.). Third, as crowd estimations require the participation of many users, market values are not updated on a match-by-match basis and may no longer be accurate after a few games, so crowd estimations are generally not efficient. (Transfermarkt usually estimates market values every six to twelve months.) Fourth, crowd estimates tend to be more accurate for players who are well known to a sufficiently large audience, so they often do not support player scouting in minor leagues. (The number of Transfermarkt's forum posts is rather low in some countries and leagues.) Fifth, crowd-estimated market values are public, so they do not offer a competitive advantage to clubs in transfer negotiations. (Transfermarkt's market values increasingly affect contract and wage negotiations on the football market.) As the next section explains, a data-driven approach to estimating market value would address these limitations.

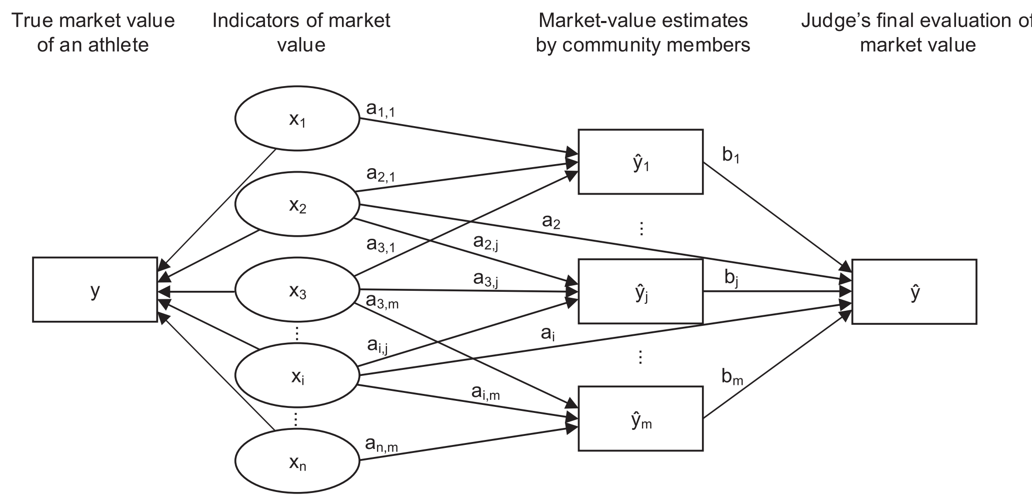

Fig. 1. Conceptualization of market-value estimation at Transfermarkt (adapted from Herm et al., 2014, p. 486)

2.3. Data-driven estimation of market value

Major League Baseball (MLB) was the first sport to make serious use of data analytics in player recruitment (Steinberg, 2015). At the end of the 1990s, Billy Beane, General Manager of the Oakland Athletics, began using statistical data for player scouting and decisions about the team roster, a story probably best known through the bestseller, "Moneyball," and its film adaptation by the same name (Lewis, 2004). Insights generated from player statistics helped the team's management to identify undervalued but talented players and overvalued players who had passed their zenith (Zhu et al., 2015). In the following two decades, the Athletics' innovative approach to player recruitment helped the team reach the playoffs roughly every second season, although they had one of the lowest budgets of all of the MLB teams, many of which later adopted Beane's ideas.

Professional football has long lagged behind sports like baseball and basketball in the use of quantitative data, so football clubs eschewed the Moneyball idea. For example, in 2010 the U.S.'s Major League Soccer (MLS) website displayed only six metrics per player, while the MLB website featured twenty-nine batting metrics alone (Kaplan, 2010). "Contrary to the situation in most American team sports, few individual performance measures are recorded in football" (Frick, 2011, p. 113). However, sports-data companies like Opta have begun collecting exhaustive and detailed data about football players, and some clubs have even begun to collect their own data during training and games. For example, during the 2014 FIFA world cup in Brazil, the German Football Association (DFB) used one of SAP's big-data solutions to analyze player performance (SAP, 2014). The software company estimated that only ten minutes of training with ten players and three balls produced more than seven million data points (also see Bojanova, 2014).

However, most clubs use the newly available data to adjust training plans and support decisions about line-ups, while the data's potential for supporting managerial decisions is ignored. Only a few clubs are known to use data analytics systematically for player valuation, but most of them are small or medium-sized clubs for which buying expensive superstars is not a viable strategy. For example, Danish Superliga club FC Midtjylland has begun to use statistical models to evaluate teams and players (Murtagh, 2015), and Dietmar Hopp, owner of German Bundesliga club TSG Hoffenheim and co-founder of SAP, has pushed the use of statistical analysis at Hoffenheim. After Hoffenheim received from FC Liverpool an all-time-high transfer fee of €41 million in 2015 for Roberto Firmino, who had cost Hoffenheim only €4 million four years earlier, Hopp identified two success factors for running the team in the future: being an early adopter of innovative technologies and identifying talented players early in their careers and developing them so they contributed on both the pitch and the balance sheet (Zhu et al., 2015). While data analytics is an innovative technology, its applicability to estimating market value and recruiting talented young players remains to be assessed.

Research on judgment and decision-making provides strong empirical and theoretical arguments that favor statistical estimates over human (heuristic) judgments (Dawes, Faust, & Meehl, 1989), particularly when it comes to complex decisions (Evans, 2006; Tversky & Kahneman, 1974) like estimating a football player's market value. A meta-analysis of 136 empirical studies that compared statistical predictions and human judgments in fields from clinical decision-making to economics showed that statistical techniques are, on average, 10 percent more accurate than human judgments are (Grove, Zald, Lebow, Snitz, & Nelson, 2000). The superiority of statistical methods over human judgments holds for trained, untrained, experienced, and inexperienced judges alike (Grove & Meehl, 1996). Therefore, our approach to data-driven estimation of market value uses a statistical model.

Brunswik's (1952) lens model, which Herm et al. (2014) used to conceptualize how the Transfermarkt crowd estimates market value, can also be used to explain our approach to data-driven estimation of market value (Fig. 1). On the Transfermarkt website, community members j make subjective estimations $\hat{y}_j$ of a football player's true, unobservable market value y based on arbitrary indicators x_i and subjective weightings $a_{i,j}$. A Transfermarkt judge then creates a final estimation of market value $\hat{y}$ based on selected user evaluations $\hat{y}_j$ and other indicators x_i, to both of which he or she assigns subjective weightings b_j and a_i. Accordingly, the crowd-based approach to estimating market values uses divergent indicators and weightings. In contrast, a data-driven approach to estimating market value uses a statistical model with consistent indicators x_i and empirically derived weightings a_i to estimate players' market values, so it overcomes the limitations of the crowd: Because the model uses the same indicators and weightings for all players, it is transparent and replicable; it is efficient, so market values can be updated on a match-by-match basis; it produces unbiased estimates for well-known and lesser known players alike, so it can be used for player scouting; and its use does not require public an-

Table 1
Indicators of market value.

Indicator	Description	Selected references
Player characteristics		
Age	Age reflects players' experience and potential.	(1)–(19)
Height	Height reflects heading ability, which can influence the probability of scoring or preventing goals.	(2), (4), (11), (18)
Position	Position reflects players' flexibility on the pitch and their crowd-pulling capacity.	(1)–(19)
Footedness	Two-footedness is an advantageous footballing ability that also reflects players' flexibility.	(2), (12), (18)
Nationality	Nationality refers to a player's country or continent of birth.	(2), (6), (8), (9), (14), (16), (17)
Player performance		
Playing time	Playing time refers to the number of games or minutes played at the national and international levels.	(1)–(13), (15)–(19)
Goals	Goals refers to the number of goals a player has scored.	(2)–(5), (7), (8), (10)–(19)
Assists	Assists refers to the number of a player's assists that helped other players score goals.	(7), (11)–(16)
Passing	Passing refers to the number of passes to other players or the accuracy of passing.	(7), (12), (16)
Dribbling	Dribbling refers to the number and success rate of a player's ball maneuvers.	(7), (11), (16)
Dueling	Dueling refers to the number and success rate of a player's tackles, clearances, blocks, and interceptions.	(7), (12), (14), (16)
Fouls	Fouls refers to the number of fouls committed or the number of times a player has been fouled.	(7), (11), (13)
Cards	Cards refers to the number of yellow, yellow/red, and red cards received by a player.	(7), (8), (13), (18)
Player popularity		
News	A player's news-worthiness is reflected in press citations.	(7), (13), (14)
Internet links	Popularity is reflected in the number of links reported by web search engines like Google.	(9), (12), (13)

References: (1) Brandes and Franck (2012); (2) Bryson et al. (2012); (3) Carmichael and Thomas (1993); (4) Carmichael et al. (1999); (5) Dobson et al. (2000); (6) Feess et al. (2004); (7) Franck and Nüesch (2012); (8) Frick (2011); (9) Garcia-del-Barrio and Pujol (2007); (10) Gerrard and Dobson (2000); (11) He et al. (2015); (12) Herm et al. (2014); (13) Kiefer (2014); (14) Lehmann and Schulze (2008); (15) Lucifora and Simmons (2003); (16) Medcalfe (2008); (17) Reilly and Witt (1995); (18) Ruijg and van Ophem (2014); (19) Speight and Thomas (1997)

nouncement, so it can offer the club that uses it an advantage in transfer negotiations.

The next section's literature review identifies indicators of market value in order to provide a conceptual background for developing such a model.

3. Indicators of market value

3.1. Overview

Research has identified several factors that can be used to estimate market values and these factors are similar to those the Transfermarkt crowd uses (see Herm et al., 2014). Table 1 organizes the most common indicators of market value into three categories—*player characteristics*, *player performance*, and *player popularity*—and shows selected studies that have used these indicators.

While researchers have studied indicators of transfer fees (e.g., Carmichael & Thomas, 1993; Carmichael, Forrest, & Simmons, 1999; Dobson, Gerrard, & Howe, 2000; Gerrard & Dobson, 2000; Medcalfe, 2008; Ruijg & van Ophem, 2014; Speight & Thomas, 1997) and market values (e.g., Franck & Nüesch, 2012; Garcia-del-Barrio & Pujol, 2007; He et al., 2015; Herm et al., 2014; Kiefer, 2014), studies on players' remuneration (e.g., Brandes & Franck, 2012; Bryson et al., 2012; Feess, Frick, & Muehlheusser, 2004; Frick, 2011; Lehmann & Schulze, 2008; Lucifora & Simmons, 2003) can also be used to identify indicators of market value. In fact, players' salaries are influenced by the same—or at least similar—factors as those that influence market values and transfer fees (see, e.g., Brandes & Franck, 2012; Bryson et al., 2012; Frick, 2007). Therefore, we explain the three indicator categories of market value by reviewing research on player valuation, payment, and transfer. (Text references to the indicators listed in Table 1 are italicized.)

3.2. Player characteristics

We conceptualize player characteristics as players' physical and demographic attributes. *Age* is an important indicator of market value, as it reflects both experience and potential (e.g., Carmichael & Thomas, 1993). Most studies on player valuation have used quadratic age terms to allow for non-linear relationships, considering that players' values usually increase into their mid-twenties and decline thereafter (e.g., Bryson et al., 2012). Age (age squared) has frequently been found to influence pay and value positively (negatively) (e.g., Lehmann & Schulze, 2008). In addition, a player's *height* has been found to significantly increase salary returns (Bryson et al., 2012) because it indicates good heading ability that may increase the probability of scoring or preventing a goal (Fry, Galanos, & Posso, 2014).

Another player characteristic that has been studied in player-valuation research is *footedness*. For example, Bryson et al. (2012) concluded that two-footed ability raises players' salaries, and Herm et al. (2014) found that it positively impacts their market values. Two-footedness is a generally advantageous football skill, but it also reflects flexibility because players who are adept with both feet can be used in various positions on the pitch (Bryson et al., 2012). Like the other player characteristics, footedness is a talent-related indicator of market value, but researchers have also studied whether players' *nationalities* influence their value and pay because of discrimination (Frick, 2007). For example, in their study of the Spanish professional football league, Garcia-del-Barrio and Pujol (2007) found that non-Spanish European players were systematically overrated, while non-European players were systematically underrated. However, Reilly and Witt (1995) found no evidence of discrimination of players in professional football, which was more recently confirmed by Medcalfe (2008).

Finally, a player's *position*—goalkeeper, defender, midfielder, or forward—is important in estimating market value. Several researchers have found that players' positions impact salaries and transfer fees, as they reflect players' degrees of specialization and crowd-pulling capacity. For example, Frick (2007) found that goalkeepers earn significantly less than midfielders because goalkeepers can be used less flexibly on the pitch. Garcia-del-Barrio and Pujol (2007) concluded that attackers receive much higher attention and rewards than goalkeepers, as attackers are more visible to the audience and so have higher crowd-pulling power (He et al., 2015).

3.3. Player performance

Player performance reflects how well players function on the pitch. *Playing time* has consistently been used in player-valuation research. For example, appearances in domestic leagues, in the European leagues, and on the national team have a positive impact on transfer fees and market values (e.g., Carmichael & Thomas, 1993; Garcia-del-Barrio & Pujol, 2007; Gerrard & Dobson, 2000). Researchers have distinguished between appearances during playing seasons and appearances during players' careers (e.g., Franck & Nüesch, 2012), and they have considered substitute appearances (e.g., Bryson et al., 2012) and minutes played (e.g., Ruijg & van Ophem, 2014) to account for the actual time spent on the field.

Several other performance measures can be used to estimate market values. *Goals*, including field goals, headers, and penalties, indicate players' scoring ability, so they are a largely unambiguous performance measure (Carmichael et al., 1999). Accordingly, the total and average number of goals, each across playing seasons and players' careers, have often been used in player-valuation research (e.g., Bryson et al., 2012; Carmichael & Thomas, 1993; Frick, 2011; Gerrard & Dobson, 2000). *Assists* refer to players' contributions that help others score goals, so they are also common indicators of player value. For example, Lucifora and Simmons (2003) provided evidence from Italian football that forwards' assist rates can increase their salaries, a finding that Lehmann and Schulze (2008) and Franck and Nüesch (2012) reinforced for German Bundesliga players.

Because of the protracted unavailability of detailed performance data in professional football, only a few researchers have used performance measures other than goals and assists to explain value and pay. Infrequently used are *passing* (e.g., Herm et al., 2014); *dueling* in the form of clearances, blocks, and interceptions (e.g., Franck & Nüesch, 2012); *dribbles* (e.g., Medcalfe, 2008); committed *fouls* (e.g., He et al., 2015); and yellow and red *cards* (e.g., Kiefer, 2014). Because the significance of performance indicators varies by position, researchers have also included interaction effects in their models of player value (e.g., Dobson et al., 2000; Gerrard & Dobson, 2000). For example, while forwards are supposed to score goals, defenders should win tackles, and midfielders are expected to defend and attack equally well. To account for the variety of performance indicators, some researchers have also replaced them with aggregated indices and expert estimations as proxies for player performance (e.g., Brandes & Franck, 2012; Feess et al., 2004; Garcia-del-Barrio & Pujol, 2007).

3.4. Player popularity

Theories on the emergence of "superstars" like actors and singers suggest that not only talent (Rosen, 1981) but also the externalities of popularity (Adler, 1985) can explain demand for football players (Franck & Nüesch, 2012). Therefore, players' market values also depend on their crowd-pulling power, independent of what they show on the pitch, as this power can sell their clubs' jerseys and seats. Accordingly, studies of the football transfer market have investigated popularity-related factors. While early studies left popularity to the error term (e.g., Carmichael & Thomas, 1993), the Internet has provided new ways to measure player popularity by, for example, analyzing online *news* and web *links*. For example, Lehmann and Schulze (2008) concluded that media presence, measured as the number of times a player's name is mentioned in the online version of the German sports magazine Kicker, relates to salary. Likewise, Franck and Nüesch (2012) found that non-performance-related press citations in the LexisNexis database are positively related to market value, and Brandes, Franck, and Nüesch (2008) counted how often German Bundesliga players' names were mentioned in newspapers and magazines to determine whether superstars boost attendance at home and away matches. Herm et al. (2014) and Garcia-del-Barrio and Pujol (2007) measured public attention as the total number of Google search hits and found it to be a significant factor in player valuation, while Kiefer (2014) measured popularity using Facebook "likes" and mentions on the UEFA website.

In summary, research has identified several indicators of market value, including player characteristics, performance, and popularity, with most of the extant studies relying on similar factors. The next section explains how we operationalized these factors and how we collected and analyzed data to train a statistical market-value estimation model.

4. Data collection and description

We gathered season-level data about players' characteristics, performance, and popularity from several Internet sources, including Google, Reddit, Transfermarkt, WhoScored, Wikipedia, and YouTube. We collected data for six playing seasons, from the 2009/10 season to the 2014/15 season, for players from the five top European leagues, that is, England's Premier League, Spain's La Liga, Germany's Bundesliga, Italy's Serie A, and France's Ligue 1. To increase the reliability of the performance data, and in line with previous research, we considered only those players who appeared on the pitch for at least ninety minutes in a given season (Brandes & Franck, 2012) and excluded goalkeepers from our sample (Bryson et al., 2012; Lucifora & Simmons, 2003), as their performance is measured in a considerably different way than that of outfield players. The resulting data set consisted of 10,350 observations from 4217 players on 146 teams. Table 2 provides an overview.

Our data-driven approach to estimating market value is conceptually similar to how the crowd estimates market values. To estimate a player's market value after a given season, we use his estimation of market value from the end of the previous season as a baseline and add data about his characteristics, performance, and popularity from that season. As the accuracy of Transfermarkt's estimations of market value has been repeatedly confirmed by researchers, and because of the unavailability of other credible sources that provide historical data, we used Transfermarkt's estimations of market value to train our model. We first collected the estimations that were made at the end of the six seasons (as per June 30) for all players in our sample. The average player across all leagues and seasons was worth around €5.6 million at Transfermarkt; players' market values ranged from €50,000 to €120 million with a standard deviation of around €8.2 million. (Appendix A provides a more detailed overview of the transfer market.)

To conduct our own estimation of players' market values, we collected data about their characteristics, performance, and popularity. We operationalized the player characteristics by means of a player's *Age* (years), *Height* (centimeters), *Footedness* (two-footed ability or not), *Nationality* (continent of origin), and *Position* on the pitch (defender, midfielder, forward). The average player in our data set was 26.5 years old and 181.5 centimeters (nearly six feet) tall. Eight percent of all players were adept with both feet, 41 percent of them were midfielders (21% forwards, 38% defenders), and 76 percent were from Europe (12% from South America, 10% from Africa, 2% from other continents). (Categorical variables are not displayed in Table 2.)

We measured player performance by means of the number of *Minutes played*, *Goals*, *Assists*, and *Yellow* or *Red cards* per season; the number and success ratio of *Passes*, *Dribbles*, *Aerial duels*, and *Tackles* per game; and the number of *Interceptions*, *Clearances*, and committed *Fouls* per game. The average player in our sample was on the pitch for 1612 minutes per season, during which he scored

Table 2
Descriptive statistics.

Variable	Measurement	Mean	Median	St. Dev.	Min.	Max.
Player valuation						
Transfermarkt's market value	EUR	5588,529	3000,000	8208,470	50,000	120,000,000
Player characteristics						
Age	Years	26.51	26.00	4.08	17.00	40.00
Height	Centimeters	181.49	182.00	6.15	161.00	203.00
Player performance						
Minutes played	total p.s.	1612.39	1612.00	884.85	90.00	3420.00
Goals	total p.s.	2.39	1.00	3.85	.00	50.00
Assists	total p.s.	1.64	1.00	2.25	.00	20.00
Passes	total p.g.	29.45	28.48	13.36	1.55	110.03
Successful passes	percent p.g.	.78	.78	.07	.43	1.00
Dribbles	total p.g.	1.21	.90	1.12	.00	9.58
Successful dribbles	percent p.g.	.51	.50	.24	.00	1.00
Aerial duels	total p.g.	2.22	1.79	1.71	.00	15.50
Successful aerial duels	percent p.g.	.47	.48	.18	.00	1.00
Tackles	total p.g.	2.21	2.09	1.21	.00	9.00
Successful tackles	percent p.g.	.71	.72	.14	.00	1.00
Interceptions	total p.g.	1.35	1.25	.92	.00	7.13
Clearances	total p.g.	2.09	1.07	2.35	.00	13.44
Fouls	total p.g.	1.10	1.03	.53	.00	4.27
Yellow cards	total p.s.	3.48	3.00	2.89	.00	18.00
Red cards	total p.s.	.20	.00	.46	.00	3.00
Player popularity						
Wikipedia page views	total p.s.	104,509.30	23,944.00	319,022.80	.00	8786,701.00
Google Trends search index	average index p.s.	13.36	13.21	12.38	.00	91.83
Reddit posts	total p.s.	15.42	2.00	38.79	.00	789.00
YouTube videos	total p.s.	36,075.46	918.50	141,882.30	.00	1000,000.00

Notes: p.s. = per season; p.g. = per game; N = 10,350

2.4 goals, gave 1.6 assists, and received 3.5 yellow and .2 red cards. In an average game, he made 29 passes (at a success rate of 78%), did 1.2 dribbles (51% successfully), and committed 1.1 fouls. He conducted 2.2 aerial duels (47% won) and made 2.2 tackles (71% successfully), 1.4 interceptions, and 2.1 clearances per game.

We used four Internet metrics to measure player popularity: the number of times a player's *Wikipedia* page was viewed, how often a player's name was searched on *Google*, the number of times a player's name appeared in the "soccer" forum on *Reddit*, and how many videos about a player were shared on *YouTube*. The average player had more than 100,000 Wikipedia page views and more than 35,000 YouTube videos. His name appeared in 15.4 forum posts on Reddit, and his average Google Trends search index was 13.4. (The data Google provides is scaled from 0 to 100 for a given time frame, so it refers to total searches for a term relative to the total number of searches over time.)

None of the independent variables were highly correlated, but an exploratory data analysis revealed that the distributions of the players' market values were highly right-skewed, which was also the case for the popularity variables. (Appendix B shows how the market values were distributed across seasons, leagues, and positions, and how the independent variables were correlated.) We log-transformed these variables to avoid violating the linearity assumption of linear regression. "Eyeballing" the associations between the players' market values that we collected from Transfermarkt and the numerical independent variables with scatterplots showed that all variables except age had reasonably linear relationships with market value. Therefore, we squared the age variable to get a more linear relationship with market value.

5. Results

5.1. Model specification

In order to build a statistical model with which to estimate players' market values, we fitted a series of regression models, which included as predictors the players' previous market values, and the players' characteristics, performance measures, and popularity metrics. As our data structure is hierarchical (players are nested within teams, and teams are nested within leagues) and longitudinal (players played multiple seasons), the model's residuals are likely not independent, which would violate a central assumption of linear regression. Therefore, we used multilevel models that we specified to include player, team, league, position, continent of origin, and season as random factors, and for which we allowed the intercepts to vary (notation adapted from Lee, 1975):

$$\begin{aligned} &\textit{Market value}_{i(t(l)^{*}p^{*}c)[s]} \\ &\quad = \alpha_{i(t(l)^{*}p^{*}c)[s]} + \beta \cdot \textit{Market value}_{i(t(l)^{*}p^{*}c)[s\text{-}1]} \\ &\quad + \chi' \cdot \textit{Player characteristics}_{i(t(l)^{*}p^{*}c)[s]} \\ &\quad + \delta' \cdot \textit{Player performance}_{i(t(l)^{*}p^{*}c)[s]} \\ &\quad + \gamma' \cdot \textit{Player popularity}_{i(t(l)^{*}p^{*}c)[s]} \\ &\quad + u_{i(t(l)^{*}p^{*}c)[s]} + u_{t(l)} + u_l + u_p + u_c + u_s + \varepsilon_{i(t(l)^{*}p^{*}c)[s]}, \end{aligned}$$

where $i(t(l)^{*}p^{*}c)[s]$ indexes a player i, who is nested within each of three factors that are crossed with each other—a team t (which is further nested in a league l), a position p, and the continent of origin c—corresponding to season observations s. *Market value*$_{i(t(l)^{*}p^{*}c)[s]}$ is the market value to be estimated; $\alpha_{i(t(l)^{*}p^{*}c)[s]}$ represents an individual intercept; *Market value*$_{i(t(l)^{*}p^{*}c)[s\text{-}1]}$ is the market value from the preceding season; *Player characteristics*$_{i(t(l)^{*}p^{*}c)[s]}$ consists of the predictors *Age*^{2}, *Height*, and *Footedness*; *Player performance*$_{i(t(l)^{*}p^{*}c)[s]}$ consists of the predictors *Minutes played*, *Goals*, *Assists*, *(Successful) Passes*, *(Successful) Dribbles*, *(Successful) Aerial duels*, *(Successful) Tackles*, *Interceptions*, *Clearances*, *Fouls*, *Yellow cards*, and *Red cards*; and, *Player popularity*$_{i(t(l)^{*}p^{*}c)[s]}$ consists of the predictors *Wikipedia page views*, *Google Trends search index*, *Reddit posts*, and *YouTube videos*. $u_{i(t(l)^{*}p^{*}c)[s]}$, $u_{t(l)}$, u_l, u_p, u_c, and u_s are random effects that are designed to capture the non-independence between 1) market values observed for the same player i over time s ($u_{i(t(l)^{*}p^{*}c)[s]}$), 2) market values observed for players on the same team ($u_{t(l)}$), 3) market values observed for teams in the same league (u_l), 4) market values observed for players who play the same position (u_p), 5) market values observed for players from the same continent of origin (u_c), and 6) market values observed for players in the same season (u_s), respectively. $\varepsilon_{i(t(l)^{*}p^{*}c)[s]}$ captures the remaining error. The random effects and the error term are assumed to be independently and identically distributed and follow a normal distribution with mean zero and standard deviation σ_μ.

5.2. Regression results

Table 3 shows the estimated coefficients, standard errors, and p-values of the fixed effects as well as the standard deviations of the random effects. Model 1 serves as a baseline model and contains only an intercept and the *Previous market value*. Model 2 adds player characteristics, Model 3 adds the player-performance variables, and Model 4 adds the player-popularity metrics. The goodness of fit, measured by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), improves with each block of variables added; likelihood ratio tests confirm that these improvements are significant (from Model 1 to 2: $\chi2$ (3) = 2439.00, p=.000; from Model 2 to 3: $\chi2$ (16) = 4843.20, p=.000; from Model 3 to 4: $\chi2$ (4) = 144.12, p=.000).

As our dependent variable is measured on the logarithmic scale, the models' coefficients can be interpreted roughly as percent changes. The coefficients of the log-transformed independent variables have to be interpreted as elasticities. For example, an additional *Goal (Assist)* per season increases a player's *Market value* by 2.4 (1.5) percent in Model 4, holding all other variables constant, and a 1 percent increase in the number of *Wikipedia page views* is associated with a .02 percent increase in *Market value*.

In Model 1, the baseline model, the *Previous market value* (.543; p < .001) is significant. The significant variables in Model 2 are *Previous market value* (.610; p < .001) and *Age*^{2} (−.002; p < .001). AIC drops from 17,416.2 to 14,983.2, indicating an improvement in goodness of fit. In Model 3, the significant variables from Model 2—that is, *Previous market value* (.495; p < .001) and *Age*^{2} (−.002; p < .001)—are still significant, and from the set of performance variables, *Minutes played*, *Goals*, *Assists*, *Passes*, *Successful passes*, *Dribbles*, *Aerial duels*, *Tackles*, and *Yellow cards* are also significant. With every minute a footballer plays, his market value increases by .03 percent (p < .001), each goal increases it by 2.60 percent (p < .001), and each assist increases it by 1.58 percent (p < .001). *Passes* (0.57%; p < .001), the ratio of *Successful passes* (30.05%; p < .001), *Dribbles* (3.02%; p < .001), and *Aerial duels* (1.33%; p < .001) further increase a player's market value, whereas *Tackles* (−2.08%; p < .001) and *Yellow cards* (−0.41%; p < .05) decrease it. The model's goodness of fit increases compared to Model 2, as AIC drops from 14,983.2 to 10,172.0.

Model 4 adds popularity data. The variables from Model 3 remain largely stable when *Wikipedia page views*, *Google Trends search index*, *Reddit posts*, and *YouTube videos* are added. Three of the four popularity variables are significantly related to a player's market value, with a .02 percent increase for each 1 percent increase in *Wikipedia page views* (p < .001), a .03 percent increase for each 1 percent increase in *Reddit posts* (p < .001), and a .01 percent increase for each 1 percent increase in *YouTube videos* (p < .01). The model's goodness of fit increases compared to the previous models, as AIC drops from 10,172.0 to 10,035.9.

The parameter estimates for the random effects (i.e., the standard deviations) remain largely stable across models (σ_2 to σ_6). However, unexplained player-specific variability (σ_1, the standard deviation for *Players* nested in *Teams* nested in *Leagues*) is comparatively large in Model 1 (.444) but decreases when additional fixed factors and covariates are added (Model 4: .185). In other words, these variables explain additional variability between players. In what follows, we evaluate the accuracy of Model 4 in estimating market value, as it is the model with the highest goodness of fit.

Table 3
Multilevel regression models.

Dependent variable: Log of market value	Model 1	Model 2	Model 3	Model 4
Fixed effects				
Intercept	6.789***	6.492***	7.432***	7.272***
	(.132)	(.219)	(.203)	(.200)
Log of previous market value	.543***	.610***	.495***	.486***
	(.006)	(.005)	(.005)	(.005)
Age^2		−.002***	−.002***	−.002***
		(.000)	(.000)	(.000)
Height		.002	.001	.001
		(.001)	(.001)	(.001)
Footedness		−.003	−.006	−.007
		(.022)	(.017)	(.017)
Minutes played			.000***	.000***
			(.000)	(.000)
Goals			.026***	.024***
			(.002)	(.002)
Assists			.016***	.015***
			(.002)	(.002)
Passes			.006***	.005***
			(.001)	(.001)
Successful passes			.301***	.286***
			(.083)	(.083)
Dribbles			.030***	.028***
			(.005)	(.005)
Successful dribbles			.035	.034
			(.019)	(.018)
Aerial duels			.013***	.014***
			(.004)	(.004)
Successful aerial duels			−.005	−.006
			(.028)	(.027)
Tackles			−.021***	−.018***
			(.005)	(.005)
Successful tackles			.049	.050
			(.030)	(.030)
Interceptions			−.013	−.010
			(.008)	(.008)
Clearances			.003	.003
			(.003)	(.003)
Fouls			.002	.004
			(.010)	(.010)
Yellow cards			−.004*	−.004*
			(.002)	(.002)
Red cards			.007	.007
			(.009)	(.008)
Log of Wikipedia page views				.016***
				(.002)
Log of Google Trends search index				.006
				(.004)
Log of Reddit posts				.026***
				(.005)
Log of YouTube videos				.007**
				(.002)
Random effects				
σ_1 (Player/Team/League)	.444	.298	.179	.185
σ_2 (Team/League)	.280	.217	.237	.219
σ_3 (League)	.138	.137	.150	.120
σ_4 (Position)	.083	.052	.056	.050
σ_5 (Continent of origin)	.057	.053	.034	.029
σ_6 (Season)	.107	.089	.089	.098
σ_7 (Residual)	.409	.411	.347	.343
Log Likelihood	−8699.1	−7479.6	−5058.0	−4986.0
AIC	17,416.2	14,983.2	10,172.0	10,035.9
BIC	17,481.4	15,070.1	10,374.9	10,267.8

Notes: * p < .05 ** p < .01 *** p < .001; standard errors are in parentheses. Number of observations: 10,350. Number of groups: Players, 4217; Teams, 146; Continents of origin, 6; Seasons, 6; Leagues, 5; Positions, 3.

5.3. Model evaluation

Market values are unobservable, which made it difficult to evaluate the accuracy of our statistical model. Still, market values are proxies for transfer fees (He et al., 2015), so we compared the model estimates with actual transfer fees. However, market values and transfer fees are not necessarily the same. For example, players can switch clubs after their contracts have expired without any transfer fee, but that does not mean that their market value is zero, and clubs sometimes pay unreasonably high fees for players, especially if they have to find replacements for injured players quickly or want to weaken competitors (Herm et al., 2014). Against this background, we also compared our model estimates with the crowd estimates, which provided another benchmark for evaluating our model's accuracy. We collected data on publically announced transfer fees for all six playing seasons, excluding players from the evaluation sample whose transfer fees were zero (because their contracts had expired or they were on loan) and players other than those who had been sold by one of the 146 clubs in our data set (because players they had bought may have come from leagues other than the European top five, so we would not have had their data). From this process we collected 845 transfer fees with which we could evaluate our model's accuracy.

Because our sample spanned several playing seasons, we could not use standard evaluation strategies for predictive models, such as k-fold cross-validation (see, e.g., Hastie, Tibshirani, & Friedman, 2017), as these strategies would have introduced the risk of leakage–that is, the use of data from the future to train a model in the past (Kaufman, Rosset, & Perlich, 2011). Therefore, we applied a time-series-based evaluation approach to ensure that a player's market value after a given season was estimated based only on data that was known at that point in time. For example, to estimate players' market values after the 2009/10 season, we trained the model on data from the 2009/10 season, and to estimate players' market values after the 2010/11 season, we trained the model on data from the 2009/10 and 2010/11 seasons. After we had obtained statistical estimates of market value for all 845 players in our evaluation sample, we calculated the differences between the model estimates and the transfer fees for each of them and, on that basis, the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) as aggregated measures. We calculated the same two measures for the crowd's estimates.

As Table 4 shows, the evaluation results indicate that the crowd's estimates are slightly more accurate in that they are closer to actual transfer fees than the model's estimates, with an RMSE that is 3.4% lower and an MAE that is 3.6% lower. However, a Diebold-Mariano test that compared the MAEs of the crowd's estimates and the model's estimates showed no statistically significant difference ($p < .340$) (Diebold & Mariano, 1995). On average, the crowd estimates deviate by €3241,733 from the players' transfer fees and the model estimates by €3359,743.

However, as the exploratory data analysis revealed, the distribution of players' market values was highly skewed and characterized by extreme outliers (Appendix B), as was the case with their transfer fees. Therefore, we evaluated the accuracy of both the model estimates and the crowd estimates for various price ranges. Fig. 2 shows the development of the difference in RMSE between the model's estimates and the crowd's estimates when the data set is filtered at various cut-off points. While the differences between the two estimation approaches are generally not large, the model tends to be more accurate for low- to medium-priced players, whereas the crowd tends to be more accurate for high-priced players.

Table 4
Model evaluation.

	RMSE	MAE
Crowd estimates	5793,474	3241,733
Model estimates	5996,341	3359,743
Relative difference	+3.4%	+3.6%

Notes: A positive value for relative difference indicates superiority of crowd. Actual transfer fees were used as ground truth. $N=845$

The crossover between the model's estimates and the crowd's estimates occurs at a transfer fee of approximately €18 million, which is at the 90th percentile of the distribution. (Fig. 3 provides a transfer-fee histogram.) In other words, the model produced more accurate estimates on average than the crowd did for the lower 90 percent of all transfers (i.e., for 769 out of 845 transferred players).

In contrast, the crowd produced more accurate estimates on average for players with high transfer fees, such as superstars like David Luiz and Edinson Cavani, who were both bought by Paris Saint-Germain F.C. for fees of €49.5 million and €64.5 million, respectively. (Appendix C provides more detailed evaluation results.)

6. Discussion

Overall, the results from the evaluation of our statistical model confirm the applicability of data analytics to estimating market value, as the estimated market values did not deviate considerably from actual transfer fees. The average deviation was around €3.4 million, which is not much considering the high transfer fees in today's football. (The players' transfer fees ranged from €1000 to €101,000,000 in our sample, with a standard deviation of €9414,575.) Still, it is difficult to draw conclusions from a comparison with transfer fees alone, because they are conceptually different from market values. To have another benchmark, we also compared our model estimates with Transfermarkt's estimates of market value, which we found to be more closely related to actual transfer fees. However, the difference was relatively small, with an RMSE that was only 3.4 percent lower and not statistically significant, so our evaluation results do not necessarily indicate that crowds are more accurate in estimating market value.

In fact, we found that the model tends to provide more accurate estimations for low- to medium-priced players, while the crowd tends to be more accurate for high-priced players. Specifically, the model produced more accurate market-value estimates on average for the lower 90 percent of the transfers we considered, even though the differences between crowd estimations and model estimations were often not large. However, especially for the smaller share of expensive players, the model estimations were disproportionally inaccurate, which skewed the average so the crowd was more accurate for the overall sample. There are at least two possible explanations for this finding. First, the model may not be able to value expensive players, especially superstars, accurately because it may lack important intangible indicators (e.g., players' potential to boost ticket or jersey sales). While the crowd can consider such factors, which can range widely from player to player, the statistical model uses the same set of predefined factors for all players. In other words, the crowd has more freedom in selecting relevant information for player valuation, which may be an advantage when it comes to setting a value on a superstar. Second, professional football clubs sometimes pay very high transfer fees for players, which may not reflect their "true" value, so the model has difficulty in estimating their prices. In that case, the crowd would be severely biased by these players' talent and popularity, while the statistical model would allow to de-

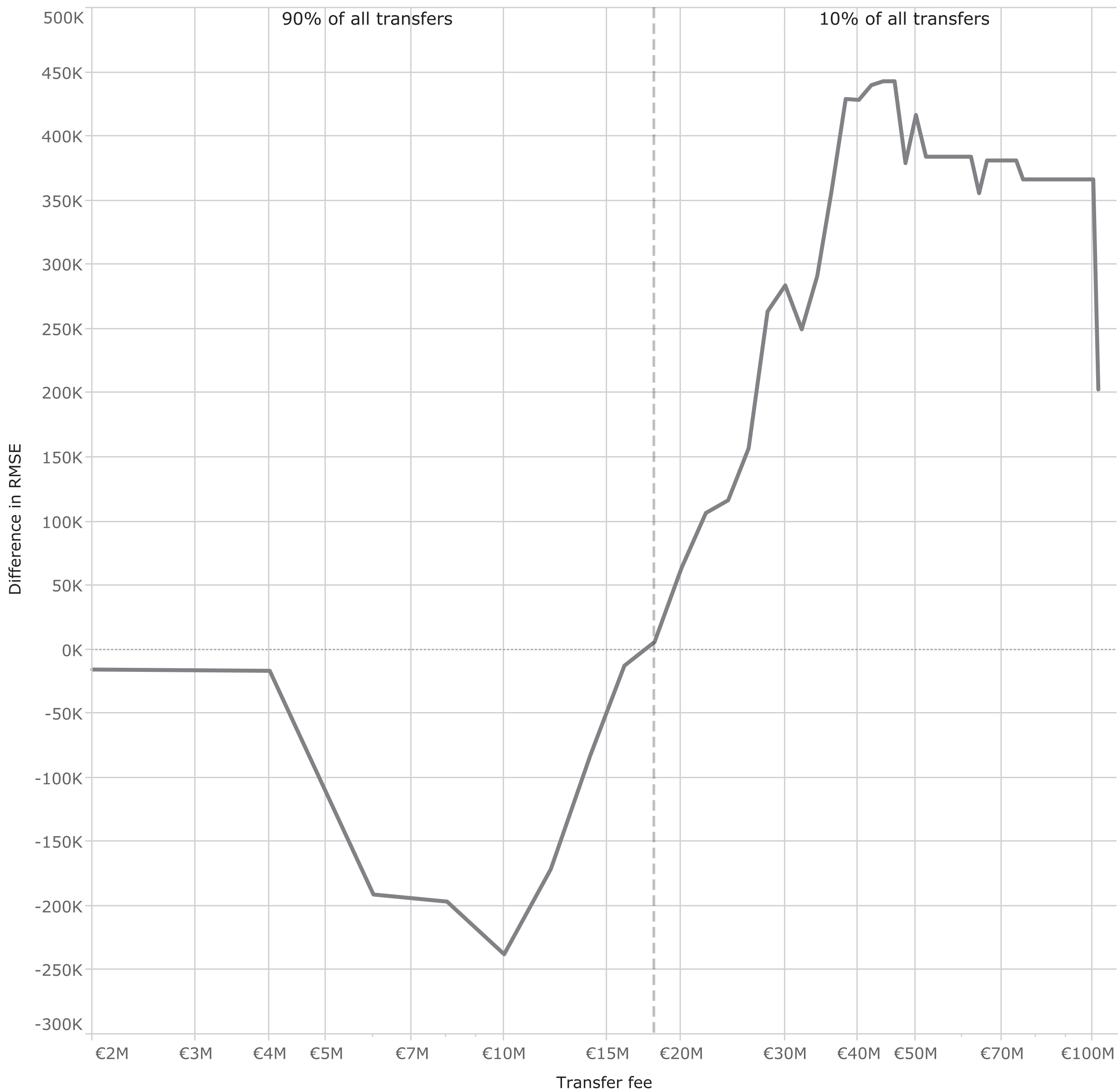

Fig. 2. Comparison of the model's and the crowd's estimates
Notes: The *x*-axis is log-transformed and it represents the upper limits of transfer fees. The *y*-axis shows the difference in RMSE between the model and the crowd, calculated based on a comparison with transfer fees. The dotted line separates the lower 90% of all transfers from the higher 10% of all transfers.

tect disproportionate and unreasonable payments on the transfer market.

Our findings have several implications for the practice of estimating market value in professional football. We argued that data-driven estimation of market value can overcome several limitations that are associated with crowd-based estimates of market value. The use of data analytics is arguably more transparent and reproducible than crowd judgments are, as the estimated regression coefficients directly quantify the impact of several variables on a player's market value. Transparency about the relationships of market values with player characteristics, performance, and popularity can help managers to make predictions about future market-value developments that can be repeated at minimal cost and with a high level of reliability. Because data analytics is efficient, it may even allow players' market values to be estimated on a match-by-match basis, while the crowd can update market values only infrequently. Based on a comparison with actual transfer fees, we showed that formal models can provide accurate estimates of market value that do not deviate much from crowd-based estimates, even though the crowd's estimates require considerably more time and effort. Therefore, our statistical results can form the basis for building real-time information systems that estimate and predict players' market values. In addition, our results may also be interesting for operators of fantasy-football websites, where participants slip into the role of club managers and choose their team rosters by buying and selling players, as such games likewise use performance data to determine players' value, yet in a much simpler way.

Furthermore, while crowdsourcing platforms like Transfermarkt produce public numbers, data analytics allows football clubs to evaluate players internally, so they can provide a competitive advantage to football clubs in transfer negotiations. In particular, data analytics can support clubs in player scouting, while the crowd often has difficulty evaluating lesser-known players (e.g., from less

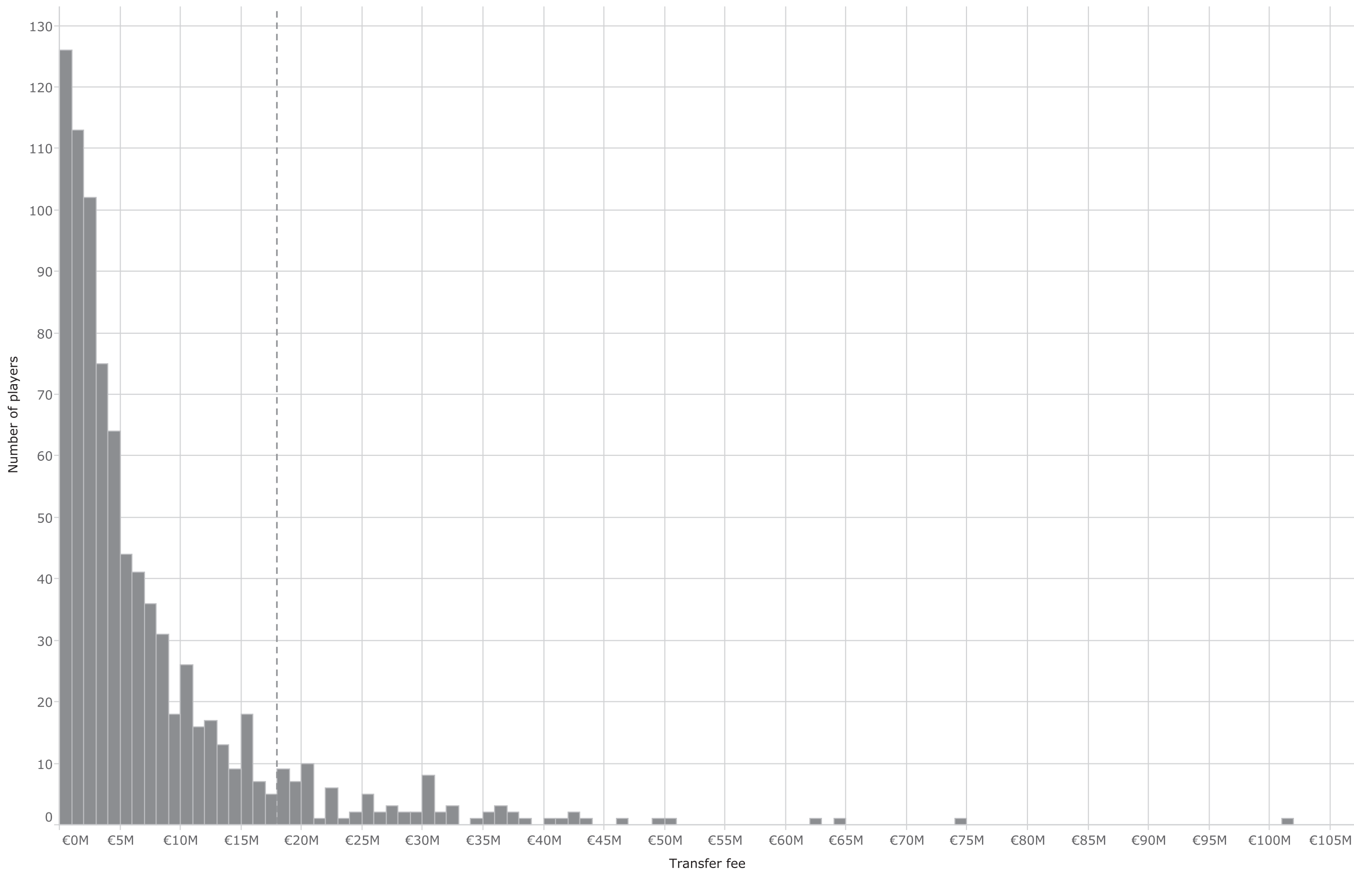

Fig. 3. Distribution of transfer fees
Note: The dotted line separates the lower 90% of all transfers from the higher 10% of all transfers.

popular leagues). Players who are largely unknown tend to receive only a few votes from the crowd, which increases the risk of biased estimations. Formal models have the potential to identify talented young players early in their careers, when their value is still unknown to the broader public. Against this background, our study demonstrates the applicability of the “Moneyball” idea in association football.

To the best of our knowledge, this study is grounded in the largest data set in terms of both coverage (five leagues, six years) and level of detail (more than twenty indicators) that has been used for research on estimating market value in professional football. Accordingly, our study can also inform future research in the field. In particular, we determined the significance of various indicators of market value that have guided related work, by which we proposed a multilevel model for estimating market value. However, although our model incorporated a large number of market-value indicators, commercial providers of sports data capture more than two hundreds metrics per player per game to which we did not have access. Therefore, future research is challenged to test the applicability of alternative model specifications and to determine the significance of additional indicators of market value. For example, it is likely that market values are a function of several other variables at the league level (e.g., UEFA coefficients), at the club level (e.g., team popularity), and at the individual level (e.g., appearances and performance on the national team or in the Champions League or Europa League), which we did not include in our model. Moreover, future research could investigate the added value of not only considering the volume of news shared on Reddit or keywords used on Google as indicators of market value, but also their sentiment (Pang & Lee, 2008). For example, research on the applicability of social-media data to predict politicians’ popularity has shown that combining information on volume and sentiment can enhance the accuracy of predictive models (see, e.g., Gayo-Avello, 2013).

Against this background, our study has several limitations. First, we could not confirm empirically the potential of data analytics in scouting young and/or unknown players. Because we used data from the five largest European leagues, most of the players in our sample were already well known to the public and crowd. Therefore, future research should conduct similar analyses using minor-league data, which may be a challenge because less data are available for the minor leagues. Second, we argued that data analytics can make estimating changes in players’ market value possible on a match-by-match basis, while crowd estimations require much more time and effort. However, this potential also remains to be empirically confirmed. Our model used seasonal data, so future research is challenged to conduct similar analyses with match-day data. Third, because of the unavailability of other credible sources that provide historical estimations of market value, we trained our model based on Transfermarkt’s estimates of market value–another reason why our evaluation results are difficult to interpret. Therefore, data analytics should not be viewed at this stage as an alternative but as a complementary approach to crowd-based estimation. As our model incorporated human judgment, it can be considered a “model of the judge” (Baron, 2008, pp. 366ff.)–that is, we used the subjective estimations by the Transfermarkt judges to train a statistical model based on objective market-value indicators. To evaluate the superiority of purely formal models over crowd estimates, or vice versa, future research should develop time-series based approaches to data-driven estimation of market value that predict market values in the future based on their own past estimations.

7. Conclusions

Based on an analysis of a unique data set of 4217 players on 146 teams from the top five European leagues and a period of six playing seasons, we demonstrated the value of using multilevel regression models to estimate players' market values. Comparing our results with crowd estimates shows that a data-driven approach to estimating market value can overcome several of crowdsourcing's practical limitations while producing comparatively accurate estimates. Given the increasing availability of data about football players in the form of data sets from commercial data providers and user-generated content from the web, we expect that the football industry will increasingly adopt data analytics to support player recruitment and transfer negotiations.

Acknowledgments

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Appendix A. Descriptive Overview of the European transfer market

We collected Transfermarkt's estimations of market value at the end of the six seasons (as per June 30) for all players in our sample. Fig. A.1 shows how the players' market values changed during the six-year period for the various playing positions, and Fig. A.2 shows how they changed during that time for the top five European leagues. For each of the five leagues, Fig. A.3 shows the

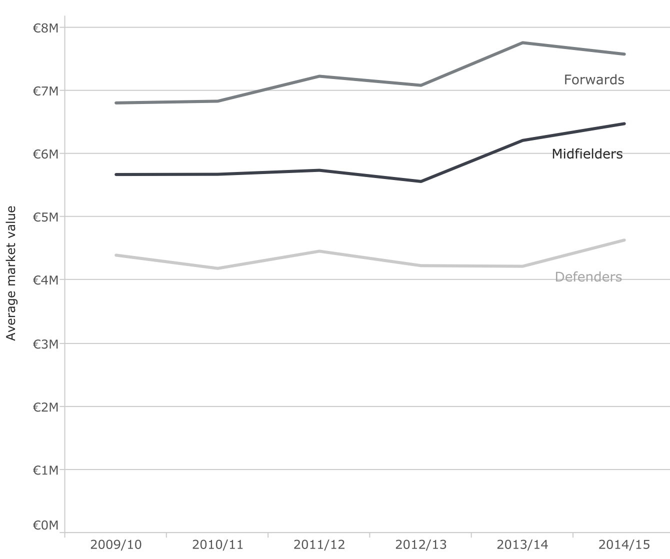

Fig. A.1. Development of market value across positions
Note: The figure displays estimations of market value at the end of the six playing seasons, as estimated on the Transfermarkt website.

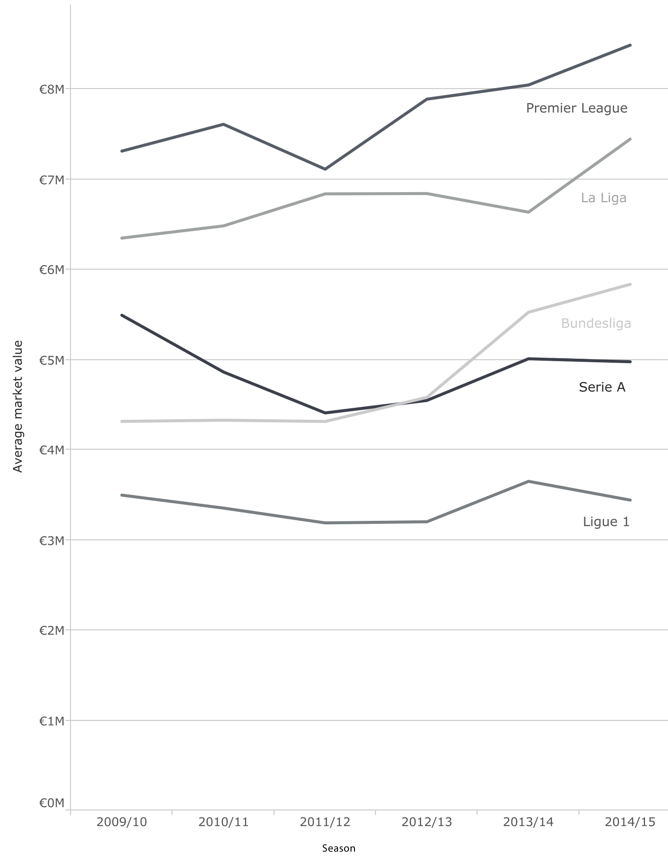

Fig. A.2. Development of market value across leagues
Note: The figure displays estimations of market value at the end of the six playing seasons, as estimated on the Transfermarkt website.

two teams with the highest average player values across all seasons. Across all leagues, the average player was worth €5.4 million in 2009/10 and €6.0 million by 2014/15, an 11 percent increase in only six years, which illustrates how important player valuation has become in recent years.

Market values have generally increased for all positions, but the amount of the increase has differed considerably among them. With an average market value of €4.4 million across all seasons, defenders had the lowest market values, while midfielders' and forwards' average market values were €5.9 million and €7.2 million, respectively. From 2009/10 to 2014/15, forwards' market values increased from €6.8 million to €7.6 million (11.8%), midfielders' market values increased from €5.7 million to €6.5 million (14.0%), and defenders' market values increased from €4.4 million to €4.6 million (4.5%).

England's Premier League had the highest average market value in every season. In 2009/10, its average market value was €7.3 million, and it increased to €8.5 million in 2014/15 (16.4%). The two most valuable teams were Chelsea F.C. (with an average player value of €19.3 million) and Manchester City (with an average player value of €18.8 million). Both of these teams were much less valuable than the two top teams from Spain, FC Barcelona (with an average player value of €29.4 million) and Real Madrid (with an average player value of €26.4 million), even though players in the Spanish league overall had considerably lower average market values (average of €6.8 million) across the six seasons.

German Bundesliga players' average market values increased from €4.3 million in 2009/10 to €5.8 million in 2014/15 (34.9%). The two most valuable clubs were FC Bayern Munich (with an

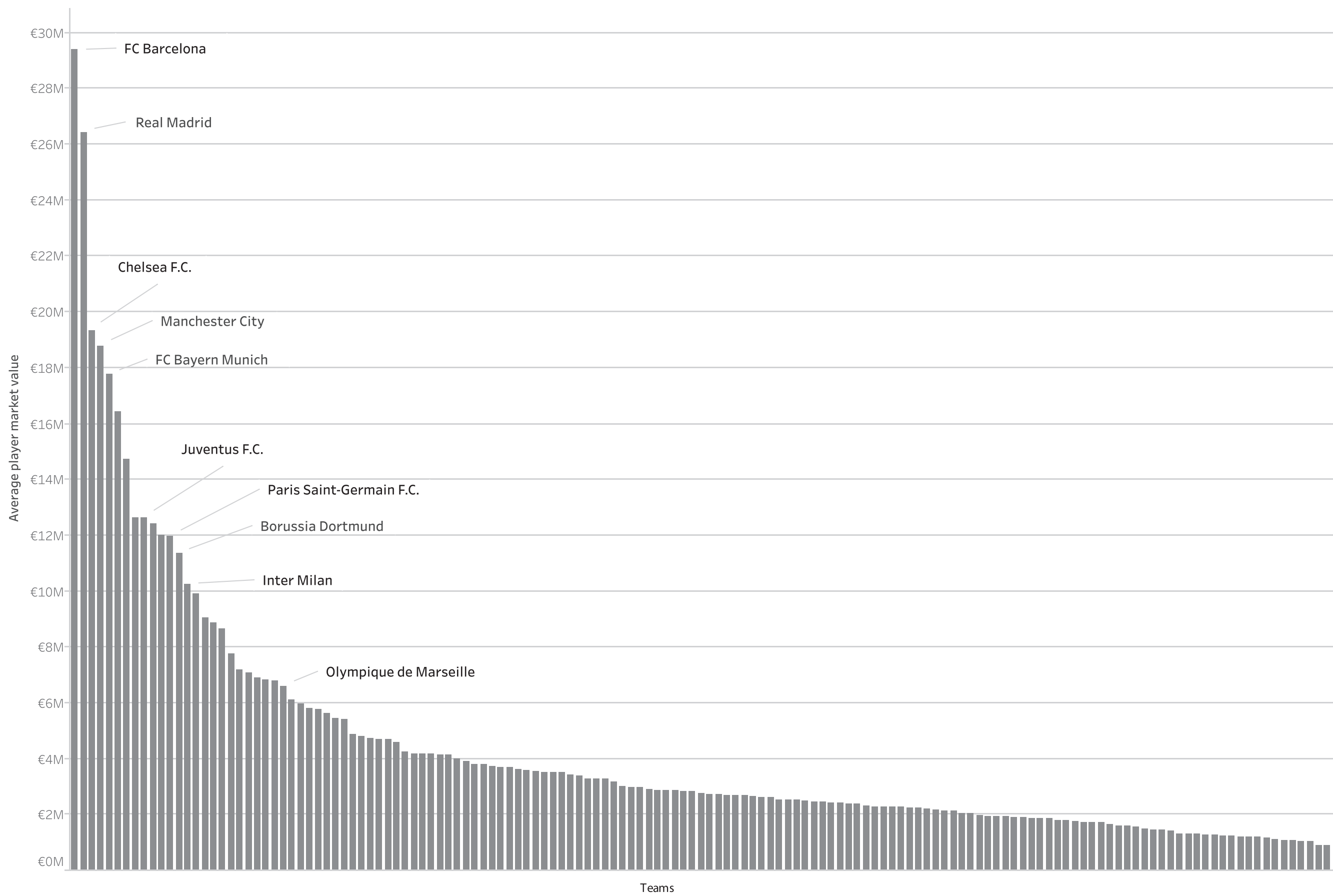

Fig. A.3. Teams with the highest average player market values
Notes: The figure displays the average player values, not the total team values, at the end of the six playing seasons, as estimated on the Transfermarkt website. The two teams with the highest average player values are shown for each of the five leagues.

average player value of €17.8 million) and Borussia Dortmund (with an average player value of €11.3 million). In contrast, Italy's Serie A players lost value, with average market values decreasing from €5.5 million in 2009/10 to €5.0 million in 2014/15, so the Serie A lost its place among the top three most valuable European leagues to Germany. The two most valuable teams were Juventus Turin (with an average player value of €12.6 million) and Inter Milan (with an average player value of €10.2 million).

Finally, players' market values in France's Ligue 1 remained largely stable over the six years under consideration, with an average market value of €3.5 million in 2009/10 and €3.4 million in 2014/15. The two most valuable teams were Paris Saint-Germain F.C. (with an average player value of €12.0 million) and Olympique de Marseille (with an average player value of €6.6 million).

Appendix B. Distribution and correlation of dependent and independent variables

As we used Transfermarkt's estimates of market value to train our model, we investigated the distributions of the players' market values. Fig. B.1 provides box plots that show how the market values were distributed across seasons, leagues, and positions. The distribution of the players' market values was highly right-skewed, with means that were above the medians for all seasons, leagues, and positions, which indicates that our sample contained a few players with exceptionally high market values, as well as a large number of players whose market values were below the average of around €5.6 million.

We also investigated how the indicators of market value that we used as independent variables in our regression model were correlated (Table B.1). All correlations were below the critical threshold of 0.7; in addition, all variance inflation factors (VIF) were below 4, well below the critical threshold of 10, so multicollinearity presented no problems.

Appendix C. Evaluation results

We used the sample of players who had transfer fees below €18 million to investigate our model's accuracy by evaluating how the estimates of market value differed from actual transfer fees across seasons, positions, and leagues. Table C.1 shows the evaluation results.

In the first four seasons, the crowd's estimates were closer to the actual transfer fees, especially in season 2012/13 (relative difference in RMSE of +20.0%), but in 2013/14 and 2014/15, the model's estimates were more accurate (−13.2% and −3.1%, respectively). While the model produced more accurate numbers for Germany's Bundesliga (−6.4%) and England's Premier League (−5.2%), the crowd provided more accurate estimates for Spain's La Liga (+0.9%), France's Ligue 1 (+2.1%), and Italy's Serie A (+9.4%). Finally, the crowd's estimates were closer to the actual transfer fees for defenders (+4.6%) and forwards (+7.3%), while the model was more accurate for midfielders (−8.4%).

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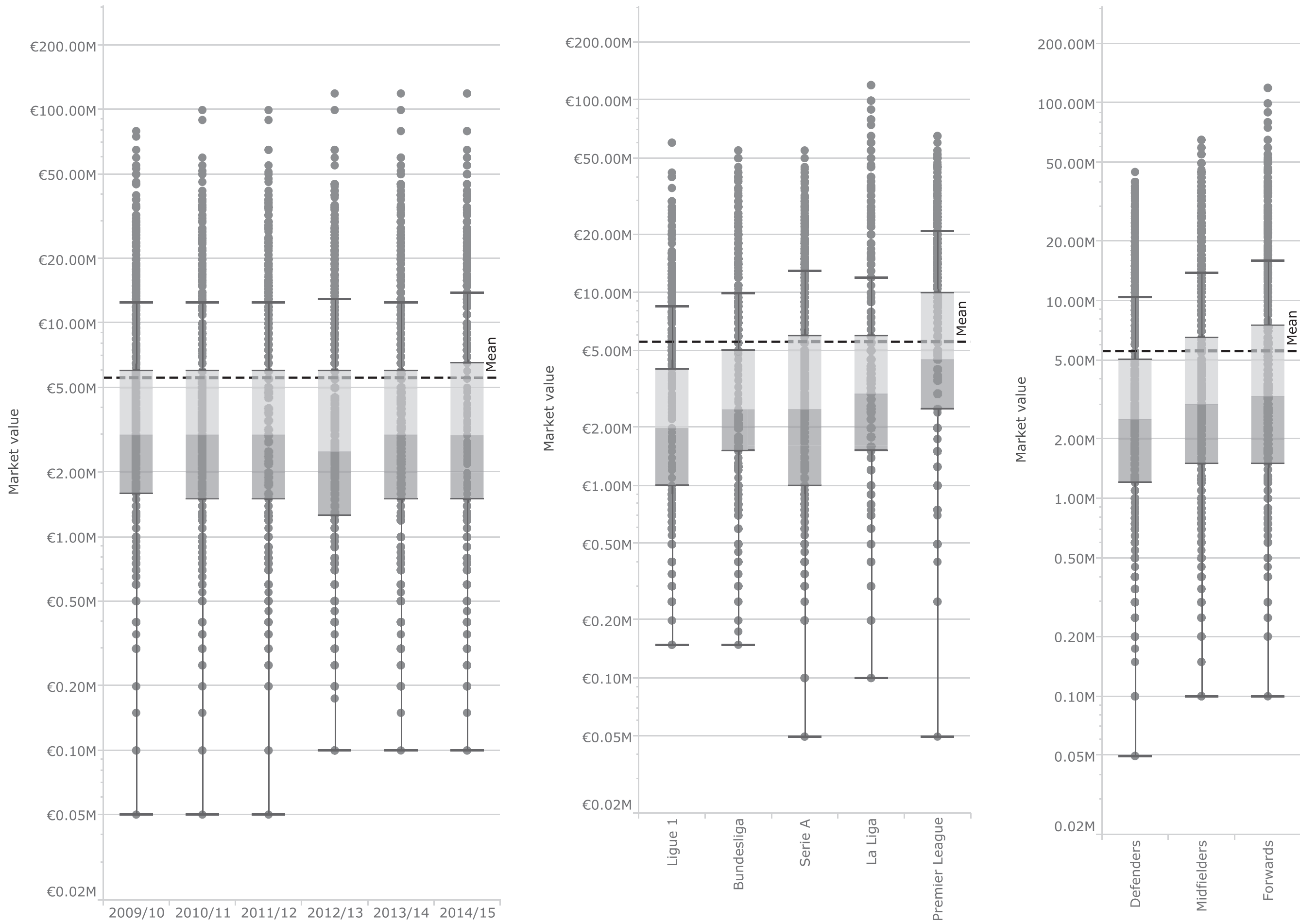

Fig. B.1. Distribution of market value across seasons, leagues, and positions
Notes: The figure displays box plots of market-value estimations at the end of the six playing seasons, as estimated on the Transfermarkt website. The y-axes are log-transformed. The whiskers (i.e., the lines at the bottom and top of each box) show the minimum and maximum values within 1.5 times the interquartile range; the bands in the boxes represent the 25th, 50th (median), and 75th percentiles. The dotted lines that cross the box plots show the mean market value.

Table B.1
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) Age	1																					
(2) Height	0.01	1																				
(3) Minutes played	0.10	0.02	1																			
(4) Goals	0.00	−0.01	0.37	1																		
(5) Assists	−0.02	−0.20	0.42	0.51	1																	
(6) Passes	0.13	0.02	0.52	−0.03	0.20	1																
(7) Successful passes	0.01	−0.13	0.07	−0.12	0.01	0.49	1															
(8) Dribbles	−0.22	−0.28	0.19	0.41	0.48	−0.02	−0.04	1														
(9) Successful dribbles	0.03	0.10	0.18	−0.09	−0.04	0.32	0.21	−0.06	1													
(10) Aerial duels	0.10	0.40	0.22	0.19	−0.04	0.06	−0.29	−0.09	0.07	1												
(11) Successful aerial duels	0.14	0.41	0.13	−0.21	−0.23	0.29	0.04	−0.34	0.19	0.25	1											
(12) Tackles	−0.02	−0.05	0.33	−0.24	0.00	0.56	0.18	−0.02	0.22	0.00	0.24	1										
(13) Successful tackles	0.00	0.09	0.10	−0.12	−0.11	0.13	0.09	−0.15	0.04	0.00	0.22	0.10	1									
(14) Interceptions	0.07	0.12	0.33	−0.31	−0.16	0.53	0.17	−0.26	0.25	0.06	0.44	0.62	0.25	1								
(15) Clearances	0.13	0.39	0.23	−0.27	−0.29	0.28	0.08	−0.42	0.25	0.29	0.53	0.22	0.28	0.55	1							
(16) Fouls	−0.02	0.10	0.26	0.10	0.05	0.21	−0.11	0.08	0.04	0.24	0.12	0.41	0.04	0.24	0.00	1						
(17) Yellow cards	0.11	0.03	0.58	0.09	0.15	0.38	0.05	0.01	0.12	0.13	0.17	0.40	0.09	0.37	0.19	0.49	1					
(18) Red cards	0.03	0.07	0.17	0.00	−0.01	0.11	0.00	−0.04	0.06	0.08	0.13	0.12	0.07	0.17	0.16	0.18	0.20	1				
(19) Wikipedia page views	0.02	−0.01	0.13	0.27	0.24	0.15	0.16	0.16	0.03	0.01	−0.06	−0.07	−0.01	−0.13	−0.09	−0.08	−0.02	−0.03	1			
(20) Google Trends search index	−0.03	−0.02	0.03	0.10	0.08	0.04	0.08	0.04	−0.03	−0.03	−0.03	−0.03	0.04	−0.03	0.00	−0.04	−0.03	0.00	0.15	1		
(21) Reddit posts	0.09	−0.03	0.13	0.17	0.17	0.18	0.18	0.11	0.09	0.18	−0.02	−0.02	−0.10	−0.11	−0.02	−0.14	0.04	−0.02	0.33	0.04	1	
(22) YouTube videos	0.07	−0.06	0.14	0.21	0.20	0.15	0.12	0.15	0.03	0.08	−0.05	−0.05	−0.05	−0.08	−0.06	−0.09	0.08	0.00	0.26	0.08	0.63	1

Table C.1
Model evaluation across seasons, positions, and leagues.

		RMSE Model's estimates	RMSE Crowd's estimates	Relative difference	N
Seasons	2009/10	3444,749	3382,450	+1.8%	101
	2010/11	3242,258	3217,317	+0.8%	147
	2011/12	4006,372	3808,920	+5.1%	120
	2012/13	3221,275	2635,404	+20.0%	130
	2013/14	3101,502	3541,482	−13.2%	129
	2014/15	4241,699	4374,319	−3.1%	141
Positions	Defender	3723,296	3556,600	+4.6%	240
	Midfielder	3175,083	3453,751	−8.4%	315
	Forward	3932,515	3653,805	+7.3%	213
Leagues	Bundesliga	2743,188	2923,510	−6.4%	164
	La Liga	3642,176	3610,105	+0.9%	102
	Ligue 1	3855,753	3775,886	+2.1%	128
	Premier League	4113,338	4332,412	−5.2%	144
	Serie A	3532,511	3215,505	+9.4%	230

Notes: The table shows RMSEs for transfer fees below €18 million. A positive value for relative difference indicates superiority of crowd. $N = 768$.

References

Adler, M. (1985). Stardom and talent. *The American Economic Review, 75*(1), 208–212.
Alexa. (n.d.). How popular is transfermarkt.de? Retrieved March 14, 2017, from http://www.alexa.com/siteinfo/www.transfermarkt.de.
Amir, E., & Livne, G. (2005). Accounting, valuation and duration of football player contracts. *Journal of Business Finance & Accounting, 32*(3–4), 549–586.
Baron, J. (2008). *Thinking and deciding* (4th edition). New York, NY, USA: Cambridge University Press.
Bojanova, I. (2014). IT enhances football at World Cup 2014. *IT Professional, 16*(4), 12–17.
Brandes, L., & Franck, E. (2012). Social preferences or personal career concerns? Field evidence on positive and negative reciprocity in the workplace. *Journal of Economic Psychology, 33*(5), 925–939.
Brandes, L., Franck, E., & Nüesch, S. (2008). Local heroes and superstars: an empirical analysis of star attraction in German soccer. *Journal of Sports Economics, 9*(3), 266–286.
Brunswik, E. (1952). *The conceptual framework of psychology*. Chicago, IL, USA: The University of Chicago Press.
Bryson, A., Frick, B., & Simmons, R. (2012). The returns to scarce talent: footedness and player remuneration in European soccer. *Journal of Sports Economics, 14*(6), 606–628.
Carmichael, F., & Thomas, D. (1993). Bargaining in the transfer market: theory and evidence. *Applied Economics, 25*(12), 1467–1476.
Carmichael, F., Forrest, D., & Simmons, R. (1999). The labour market in association football: who gets transferred and for how much? *Bulletin of Economic Research, 51*(2), 125–150.
Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science, 243*(4899), 1668–1674.
Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics, 13*(3), 253–263.
Dobson, S., Gerrard, B., & Howe, S. (2000). The determination of transfer fees in English nonleague football. *Applied Economics, 32*(9), 1145–1152.
Evans, J. S. B. T. (2006). The heuristic-analytic theory of reasoning: extension and evaluation. *Psychonomic Bulletin & Review, 13*(3), 378–395.
Feess, E., Frick, B., & Muehlheusser, G. (2004). Legal restrictions on buyout fees: theory and evidence from German soccer. IZA Discussion Paper No. 1180. Retrieved March 14, 2017, from http://ssrn.com/abstract=562445.
Franck, E., & Nüesch, S. (2011). The effect of wage dispersion on team outcome and the way team outcome is produced. *Applied Economics, 43*(23), 3037–3049.
Franck, E., & Nüesch, S. (2012). Talent and/or popularity: what does it take to be a superstar? *Economic Inquiry, 50*(1), 202–216.
Frick, B. (2007). The football players' labor market: empirical evidence from the major European leagues. *Scottish Journal of Political Economy, 54*(3), 422–446.
Frick, B. (2011). Performance, salaries, and contract length: empirical evidence from German soccer. *International Journal of Sport Finance, 6*(2), 87–118.
Fry, T. R. L., Galanos, G., & Posso, A. (2014). Let's get Messi? Top-scorer productivity in the European Champions League. *Scottish Journal of Political Economy, 61*(3), 261–279.
Garcia-del-Barrio, P., & Pujol, F. (2007). Hidden monopsony rents in winner-take-all markets–Sport and economic contribution of Spanish soccer players. *Managerial and Decision Economics, 28*(1), 57–70.
Gayo-Avello, D. (2013). A meta-analysis of state-of-the-art electoral prediction from Twitter data. *Social Science Computer Review, 31*(6), 649–679.
Gerrard, B., & Dobson, S. (2000). Testing for monopoly rents in the market for playing talent–Evidence from English professional football. *Journal of Economic Studies, 27*(3), 142–164.
Grove, W. M., & Meehl, P. E. (1996). Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: the clinical-statistical controversy. *Psychology, Public Policy, and Law, 2*(2), 293–323.
Grove, W. M., Zald, D. H., Lebow, B. S., Snitz, B. E., & Nelson, C. (2000). Clinical versus mechanical prediction: a meta-analysis. *Psychological Assessment, 12*(1), 19–30.
Hastie, T., Tibshirani, R., & Friedman, J. (2017). *The elements of statistical learning: data mining, inference, and prediction* (2nd edition). New York, NY, USA: Springer.
He, M., Cachucho, R., & Knobbe, A. (2015). Football player's performance and market value. In *Proceedings of the 2nd workshop of sports analytics, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECML PKDD)*. Retrieved March 14, 2017, from https://dtai.cs.kuleuven.be/events/MLSA15/papers/mlsa15_submission_8.pdf.
Herm, S., Callsen-Bracker, H.-M., & Kreis, H. (2014). When the crowd evaluates soccer players' market values: accuracy and evaluation attributes of an online community. *Sport Management Review, 17*(4), 484–492.
Kaplan, T. (2010, July 8). *When it comes to stats, soccer seldom counts*. The New York Times. Retrieved March 14, 2017, from *https://mobile.nytimes.com/2010/07/09/sports/soccer/09soccerstats.html.*
Kaufman, S., Rosset, S., & Perlich, C. (2011). Leakage in data mining: formulation, detection, and avoidance. In *Proceedings of the 17th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (pp. 556–563). San Diego, CA, USA.
Kiefer, S. (2014). The impact of the Euro 2012 on popularity and market value of football players. *International Journal of Sport Finance, 9*(2), 95–110.
Lee, W. (1975). *Experimental design and analysis*. San Francisco, CA, USA: Freeman & Co Ltd.
Lehmann, E. E., & Schulze, G. G. (2008). What does it take to be a star? The role of performance and the media for German soccer players. *Applied Economics Quarterly, 54*(1), 59–70.
Lewis, M. (2004). *Moneyball: the art of winning an unfair game*. New York, NY, USA: W. W. Norton & Company, Inc.
Lorenz, J., Rauhut, H., Schweitzer, F., & Helbing, D. (2011). How social influence can undermine the wisdom of crowd effect. *Proceedings of the National Academy of Sciences of the United States of America, 108*(22), 9020–9025.
Lucifora, C., & Simmons, R. (2003). Superstar effects in sport: evidence from Italian soccer. *Journal of Sports Economics, 4*(1), 35–55.
Medcalfe, S. (2008). English league transfer prices: is there a racial dimension? A re-examination with new data. *Applied Economics Letters, 15*(11), 865–867.
Murtagh, J. (2015, August 20). *Moneyball FC: how Midtjylland harnessed the power of stats to set up Euro showdown with Southampton*. Mirror. Retrieved March 14, 2017, from http://www.mirror.co.uk/sport/football/news/moneyball-fc-how-midtjylland-harnessed-6282271.
Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval, 2*(1–2), 1–90.
Pawlowski, T., Breuer, C., & Hovemann, A. (2010). Top clubs' performance and the competitive situation in European domestic football competitions. *Journal of Sports Economics, 11*(2), 186–202.
Reilly, B., & Witt, R. (1995). English league transfer prices: is there a racial dimension? *Applied Economics Letters, 2*(7), 220–222.
Rosen, S. (1981). The economics of superstars. *The American Economic Review, 71*(5), 845–858.
Ruijg, J., & van Ophem, H. (2014). Determinants of football transfers. Discussion Paper 2014/01, Department of Economics & Econometrics, Amsterdam School of Economics. Retrieved March 14, 2017, from http://ase.uva.nl/binaries/content/assets/subsites/amsterdam-school-of-economics/research/uva-econometrics/dp-2014/1401.pdf.
SAP. (2014, June 11). SAP and the German Football Association turn big data into smart decisions to improve player performance at the World Cup in Brazil. SAP News Center. Retrieved March 14, 2017, from http://www.news-sap.com/sap-dfb-turn-big-data-smart-data-world-cup-brazil.
Speight, A., & Thomas, D. (1997). Football league transfers: a comparison of negotiated fees with arbitration settlements. *Applied Economics Letters, 4*(1), 41–44.
Steinberg, L. (2015, August 18). *Changing the game: the rise of sports analytics*. Forbes. Retrieved March 14, 2017, from http://www.forbes.com/sites/leighsteinberg/2015/08/18/changing-the-game-the-rise-of-sports-analytics/#1f21bfdc31b2.
Surowiecki, J. (2005). *The wisdom of crowds*. New York, NY, USA: Random House.
Torgler, B., & Schmidt, S. L. (2007). What shapes player performance in soccer? Empirical findings from a panel analysis. *Applied Economics, 39*(18), 2355–2369.
Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: heuristics and biases. *Science, 185*(4157), 1124–1131.
Zhu, F., Lakhani, K. R., Schmidt, S. L., & Herman, K. (2015). *TSG Hoffenheim: football in the age of analytics*. Harvard Business School Case 616-010. Retrieved March 14, 2017, from *http://www.hbs.edu/faculty/Pages/item.aspx?num=49569.*