INFORMATION PRECISION IN ONLINE COMMUNITIES: PLAYER VALUATIONS ON WWW.TRANSFERMARKT.DE

Bernd Frick & Franziska Prockl

Paderborn University, Management Department, Chair of Organizational, Media and Sports Economics, Warburger Str. 100, D-33098 Paderborn.

May 2018

Working Paper

ABSTRACT

The benefits of crowd wisdom / swarm intelligence in the form of superior decision making and problem-solving skills have recently been analyzed and discussed by researchers from various fields. The goal of this paper is to identify the relevance of crowd wisdom for professional team sports leagues by analyzing, first, the emergence of crowd wisdom on a particular online platform (www.transfermarkt.de) and, second, by documenting the precision of the collectively gathered information. The authors evaluate the emergence and diffusion of information on that platform over ten consecutive years and find a pattern similar to the one proposed by Bass (1969) in a now seminal study. Moreover, using player values as well as player salaries from Major League Soccer for the seasons 2006 thru 2015, it appears that values are excellent proxies for salaries that are not disclosed, but remain private and confidential in most leagues. These findings encourage researchers to use information from sources like transfermarkt.de in their empirical studies.

Keywords: Crowd Wisdom, Swarm Intelligence, Player Salaries, Player Valuations, Major League Soccer.

JEL Classification: D70, D82, J31, L83, Z22

MOTIVATION

The origins of crowd sourcing can be traced back to 1907 when Sir Francis Galton elicited the *wisdom of a crowd* to estimate the weight of an ox. The currently used term *crowdsourcing* is much younger and was used for the first time by Howe (2006) in a now widely quoted article in Wired Magazine, and has in the meantime been complemented by the synonym *swarm intelligence* (the former is predominantly used by economists, the latter by computer scientists). The conviction underlying both, the turn of the century experiment and the contemporary use of the term, is that crowds can make better judgements or decisions than an individual can. A number of recent field and laboratory studies suggest that this may indeed be true (see e.g., Adams & Ferreira, 2010; Charness, Karni, & Levin, 2010; Charness & Sutter, 2012).

A recent online community that uses the wisdom of a crowd (or the intelligence of a swarm, respectively) is the platform www.transfermarkt.de. On this website, users first individually evaluate and judge the market values of soccer players. In a second step, this information is used by experts who then, based on the market values suggested by hundreds or even thousands of individuals, derive an "objective" value for each of these players. In most team sports leagues in Europe, player salaries are not disclosed, implying that "fair" estimates of market values enable researchers to better analyze various labor market phenomena, such as pay determination, contract and career length and transfer probabilities. This, however, requires that these market value estimates are reliable. In a first step, we therefore investigate the precision of the market value estimations provided by the user group on transfermarkt.de. We then try to answer the question how crowd wisdom, in this case an online platform, emerges, develops and matures. Once these two questions can be answered it should also be possible to evaluate the importance of crowd wisdom for the analysis of e.g. salary determination in professional team sports leagues.

In this paper, we use data from 10 consecutive seasons of Major League Soccer (MLS, 2006-2015) to answer our research questions. MLS is very young. It was founded in 1993 and the first season was played in 1996 with 10 teams. Moreover, MLS is a single-entity league, that is it is organized centrally. The commissioner (since 1999 Don Garber) has the full power, among others, to implement rules, determine which clubs are admitted to MLS and which investors can buy themselves into a particular team. Thus, all teams are owned by the league and investors can only buy shares of a particular team. Moreover, MLS is a closed league with no promotion and relegation system. Another consequence of the central organization is that the league formally contracts all players and pays the player salaries and bonuses. To extenuate the (bargaining) power of this central instance, a players union was founded in 2003 with the purpose to "ensure […] protection of the rights of all MLS Players, while also promoting their best interests" (MLSPA, 2016). The MLS Players Association negotiates a collective bargaining agreement (CBA) every five years that determines each team's salary budget, minimum and maximum salaries, health insurance benefits and other relevant factors. Finally, possibly to retain or even improve competitive balance among clubs, each team is limited in their player selection by two major regulations: (a) a maximum of currently 160 international roster spots that are divided equally among the currently 20 clubs (these spots can, however, be traded between clubs) and (b) a salary cap. In the 2015 season, the cap was set at $3.490 million for the senior roster (spots 1-20). In 2007, the league softened the strict cap implementing a new rule that is often referred to as the "*Beckham Rule*" because David Beckham was among the first players to benefit from it. Arguably, the rule was institutionalized just to bring him into the league. Officially it is called the *Designated Player Rule*, which allows the teams to bring in a certain number of "superstar" players, currently a maximum of three, and pay them outside of the CBA's maximum pay regulations and with limited effect on the salary cap.

Due to its unique characteristics, MLS has recently attracted the interests of an increasing number of sports economists (see e.g., Coates et al., 2016; Jewell, 2017; Kuethe & Motamed, 2010; Sonntag & Sommers, 2014; Twomey & Monks, 2011). We contribute to this literature by investigating the impact of crowd wisdom on the emergence and the accuracy of player valuations on transfermarkt.de as well as the overall relevance of crowd wisdom for the economic analysis of professional team sports leagues.

RELATED LITERATURE

Crowd Wisdom and Group Decision Making

In his famous crowd wisdom experiment mentioned above, Sir Francis Galton asked 787 visitors of a cattle show in Plymouth to estimate the weight of an ox. His result showed that “the vox populi is correct to within 1 percent of the real value, and that the individual estimates are abnormally distributed in such a way that it is an equal chance whether one of these, selected at random, falls within or without the limits of -3.7 percent and +2.4 percent of their middlemost value. This result is, I think, more creditable to the trustworthiness of a democratic judgement than might have been expected” (Galton, 1907, p. 451).

Recently, a number of field as well as laboratory studies have convincingly demonstrated that groups make better decisions than individuals. In a widely cited study, Adams and Ferreira (2010) compare guesses on ice break-ups in Alaska made by individual bettors with guesses from groups of bettors. They find that group decisions are more accurate, “either because groups have to reach a compromise when their members disagree or because individuals with more extreme opinions are less likely to be part of a group” (Adams & Ferreira, 2010, p. 882). While Charness and Sutter (2012) find that groups produce more rational output than individuals, Charness et al. (2010) document that groups in a lab experiment violate the conjunction fallacy less often than individuals. Finally, Sutter (2005, p. 41) shows – again in a lab experiment – that “teams with four members outperform teams with two members and single persons” in an experimental beauty-contest game.

Moreover, a rapidly growing strand of literature emphasizes the value of collective judgements or collective decision-making for assessing the probability of future events. Mollick and Nanda (2016) compare funding decisions for proposed theater projects made by distinguished experts and a crowdfunding website and find significant agreement between the two. Atanasov et al. (2017) compare the performance of prediction markets, where traders are motivated by profits to buy and sell shares of contracts about future events with the performance of prediction polls, where participants offer probabilistic forecasts (either independently or as members of a team) and update their beliefs as often as they wish. Their main finding is that “crowds of several hundred individuals can produce highly accurate predictions on a wide range of political and economic topics” (Atanasov et al., 2017, p. 15). Finally, using data from a large investment-related social media website, Chen, De, Hu, and Hwang (2014) find that the opinions revealed on this website very well predict future stock returns as well as earnings surprises.

A number of recent studies are closely related to the research questions addressed in this paper. Using data from transfermarkt.de, Herm, Callsen-Bracker, and Kreis (2014) find that in a sample of 67 player transfers occurring during the winter break 2011/12 in the German Bundesliga, the market values explain almost entirely (R^2=0.90) the variance in the actually paid transfer fees. Peeters (2018) finds in a sample of more than 1,000 qualifying matches and World Cup/Euro Cup matches over the period 2008 to 2014 that forecasts of match results based on the crowds’ evaluations are far more accurate than standard predictors such as the FIFA ranking or the ELO rating of the two opposing teams. Using wage bill estimations provided by a panel of experienced sport journalists and a team quality measure (expressed in school grades) provided by equally experienced “experts” (former national players and famous head coaches), Frick and Wicker (2016) find that in a model predicting the league table at the end of the season, both variables (relative grade and relative wage bill) are statistically significant, suggesting that the two types of predictions are complements rather than substitutes. Consequently, soccer experts and sports economists seem to rely on completely different sources of information when making their predictions. Finally, Herzog and Hertwig (2011) use respondents’ recognition knowledge of names as a proxy for their familiarity with football to predict the outcome of World Cup and Euro Cup matches and find that “ignorant crowds” perform as well as official rankings and only slightly worse that betting odds.

A second research stream deals with the optimal composition of different types of crowds. Lamberson and Page (2012), for example, show that group size plays a critical role in determining the optimal group. In small groups, accurate forecasters should dominate while in large groups consistent forecasters should form the majority. Budescu and Chen (2015) suggest as a strategy to improve the quality of crowd decision-making the successive elimination of poorly performing individuals from that crowd. However, a lab experiment conducted by Lorenz, Rauhut, Schweitzer, and Helbing (2011) demonstrates that already mild social influence can undermine the wisdom of the crowd effect. Providing information about the estimates of others narrows the initial diversity of opinions in three ways: Due to the "social influence effect", the diversity of opinions is diminished without improvements of the collective error. Due to the "range reduction effect", "the crowd becomes less reliable in providing expertise to external observers" and, finally, due to the "confidence effect", individuals' belief in their estimates increases despite lack of improved accuracy (Lorenz et al., 2011, p. 9020).

The Emergence of Online Communities

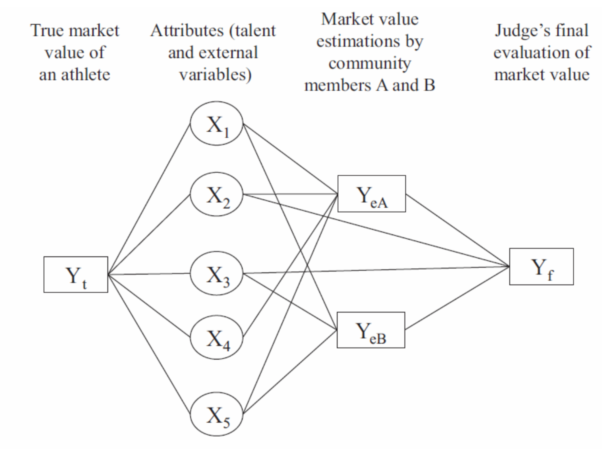
Online (or virtual) communities are "social aggregations that emerge from the Net when enough people carry on […] public discussions […], with sufficient human feeling, to form webs of personal relationships in cyberspace" (Rheingold, 1993, p. 6).

A well-known and fast-growing example of such a community is transfermarkt.de – a portal whose registered users discuss and express their opinions about, inter alia, the market values of players in designated forums. It was founded in Germany in 2000 and is by now available in eight languages; the English version for example was added in 2009. To become a user, one first has to register for participation in one or more of the various forums, abying to the "11 commandments"[1] and second to follow the structures of the respective sub-forum. The portal offers different levels of participation, the most exclusive ones being the discussion of market values, participation in the rumor mill and in surveys dedicated to particular topics. A user is admitted to the exclusive areas only after s/he has published a minimum of 100 qualitative posts, which leads to promotion to the status of an "expert". Individual users can also apply, after having reached a certain level of blog activity, for leadership positions such as e.g. data scout or godfather.

[1] E.g., upload of any type of terroristic, harassing or pornographic content is strictly forbidden. Violating one of the 11 commandments is sanctioned with point deductions. Compare http://www.transfermarkt.co.uk/intern/elfGebote

Transfermarkt.de is selective in the sense that player values are not simply calculated as the mean (or the median) of the individuals' suggestions. Instead, a particularly empowered community member – a "judge" – chooses to aggregate the information provided by the community on a case-by-case basis, implying that s/he is entitled to reduce the impact of values s/he considers "outliers" or even completely delete these. Thus, the judge performs the complex task of filtering, weighting, and aggregating information by taking into account the source of information (a person with a limited number of suggestions vs. an experienced community member with hundreds of suggestions) as well as the reason(s) provided as justification(s) for particular estimates (only one or two player characteristics vs. a lengthy description of that player's abilities). In this sense, transfermarkt.de is not an entirely "democratic" community. Figure 2.1 illustrates the process of decision-making on that platform (for further details see Herm et al., 2014).

Figure 1 Decision-Making on www.transfermarkt.de (Herm et al., 2014, p. 486)



The question, thus, is whether transfermarkt.de users can be considered a wise crowd? Simmons, Nelson, Galak, and Frederick (2011, p. 5) propose four conditions that need to be met before a crowd can be considered "wise": The individual members are knowledgeable, motivated to be accurate, independent and diverse. The conditions proposed by Surowiecki (2005) in his best-selling book *The Wisdom of Crowds* look quite similar (diversity, independence, decentralization and aggregation; see Figure 2.2).

Figure 2 How Wise Is the Crowd on www.transfermarkt.de?

Criteria (Surowiecki, 2005)	Transfermarkt.de
Diversity in opinion *("each person should have some private information, even if it's just an eccentric interpretation of the known facts")*	☑ Individual backgrounds of members, huge diversity in posts evident
Independence *("people's opinions are not determined by the opinions of those around them")*	☑ Own opinions incentivized with point system; but streams do develop
Decentralization *("people are able to specialize and draw on local knowledge")*	☑ Fans discuss across teams and across nationalities
Aggregation *("some mechanism exists for turning private judgements into a collective decision")*	☑ Achieved members function as judges

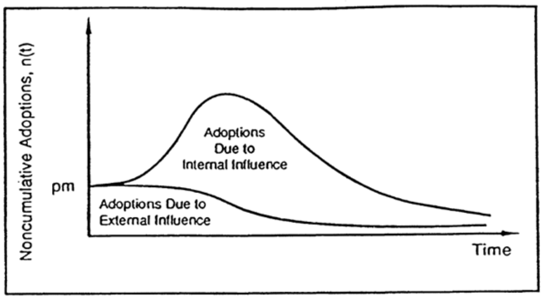
Football aficionados who have registered as users of the platform are indeed highly diverse and decentralized in the sense that they are located all over the world, discussing across teams and across national borders. The mechanism to aggregate the individuals' opinions and estimations is performed by particularly experienced members (the "judges"). With respect to *independence,* one might be tempted to argue that people are influenced in their opinions by the evaluations provided by others in the respective forums. To counter this convergence, transfermarkt.de incentivizes own opinions within its points system.

Based on the discussion so far, we can specify our first research question. How precise are the users' estimates of player market values at transfermarkt.de?

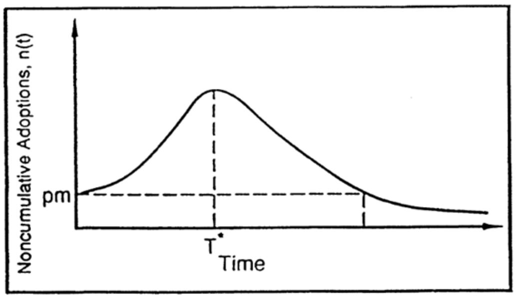
Explaining the Emergence of Online Communities: The Bass Model

In a now seminal paper, Bass (1969) developed a diffusion model to explain the adoption of new products and technologies using innovation, imitation and market size as potential determinants (Bass, 1969, 2004). Until today, the Bass model is one of the most widely used models in management science to describe, explain, and predict adoption as well as innovation patterns in many industries.

Figure 3 The Bass New Product Diffusion Model I (Mahajan, Muller, & Bass, 1990)



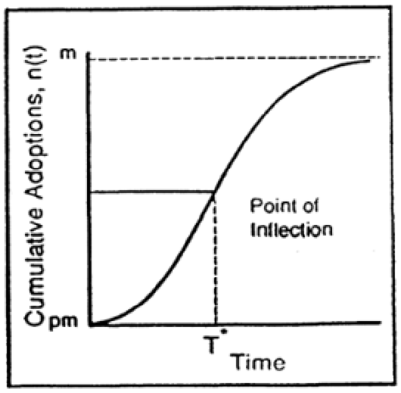
Adoption due to internal and external influences in the Bass model



Analytical structure of the Bass model

Applying this model to an analysis of www.wikipedia.org, Spinellis and Louridas (2008, p. 72) found that the "mean number of first references to entries […] rises exponentially until the referenced entry becomes an article". They call the "point in time when the referenced entry becomes an article" the *inflection point*, because "from then on the number of references to a defined article rises only linearly (on average)". This is comparable to the findings produced with an updated version of the Bass diffusion model presented by Mahajan et al. (1990).

Figure 4 The Bass New Product Diffusion Model II (Mahajan et al., 1990)



Analytical structure of the Bass model

The latter updated diffusion model has also been used to analyze e.g. the impact of open source software on firms' future profitability (Jiang & Sarkar, 2009), to better "understand how information diffusion influences tourists' consumption patterns" (Hsiao, Jaw, & Huan, 2009, p. 691) and, finally, to predict the size of an internet-based online community as well as the time it takes to maximize its membership (Firth, Lawrence, Clouse, & Koohang, 2006).

Building on these analyses, we expect the emergence of crowd wisdom on transfermarkt.de to follow a similar curve. This, in turn, will help us to answer our second research question: How does crowd wisdom emerge and develop over time?

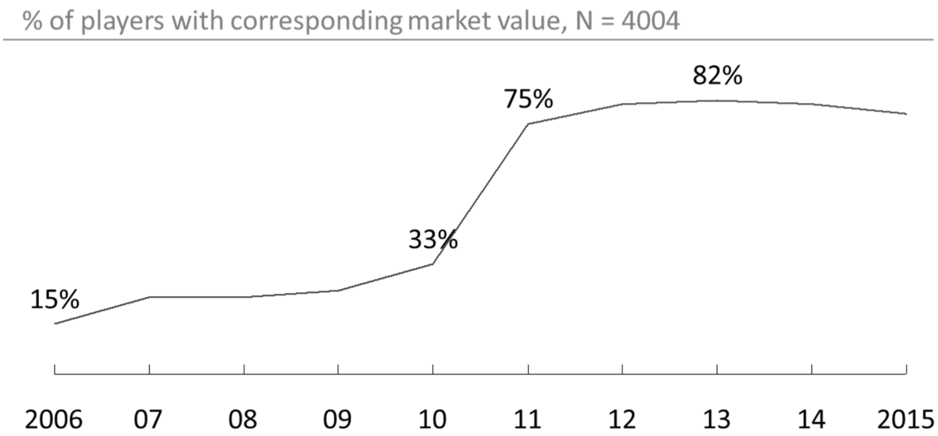
DATA

The data we use here covers 10 consecutive seasons of MLS from 2006 thru 2015. We use 2006 as our start date as it was the last season before the implementation of the rule that changed the entire salary system – the Designated Player Rule. Due to this event, more and more foreign and particularly more European players came to the US to play soccer, increasing the attention of European soccer fans in MLS. The first exclusive MLS discussion stream on transfermarkt.de started in July 2007, coinciding with the arrival of David Beckham at LA Galaxy. Two of our three dependent variables (annual base and guaranteed salaries, the latter including bonuses and benefits that are independent of performance) come from the MLS Players Association website while the third dependent variable (player market values) as well as a wide range of player characteristics (age, nationality, preferred foot and many more) were retrieved from transfermarkt.de. The complete data set includes 4,004 player-season-observations, of which around 1,500 cannot be used in the econometric analysis due to missing values on either the dependent or one of the independent variables.

RESULTS

It appears from Figure 5 that in the first season of our observation period (2006) market value information was available for only 15 percent of the players for whom salary information was provided by the MLS Players Association. This value increased only slightly (up to 33 percent) in 2010. However, in 2011 a steep increase occurred. In that year, the percentage of players for whom a market value was available on transfermarkt.de reached a record high of 75 percent.

Figure 5 Development of Market Value Availability

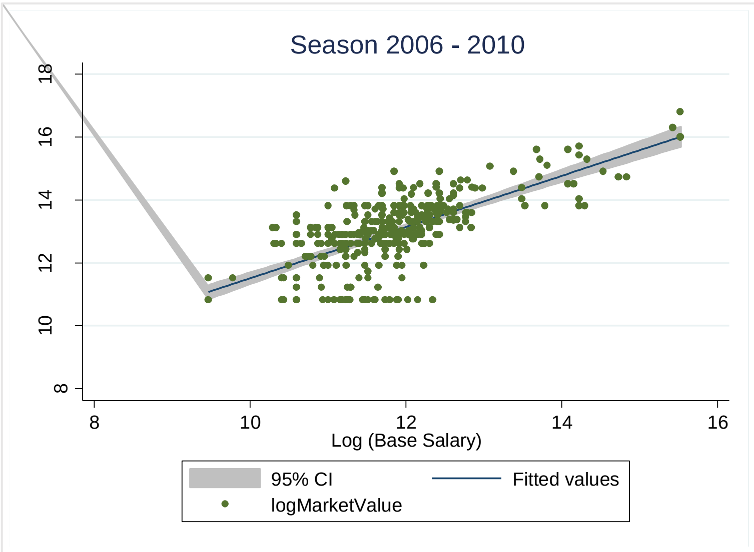


This rapid increase is to be explained by a number of simultaneous events. First, in the 2010 World Cup tournament, the US team won their group for the first time since 1930, leaving the team from England in the second place and qualifying for the knockout phase of the tournament. Although the US team was eliminated by Ghana in the round of 16 this was considered a huge and unexpected success for the US team. Second, in 2011 two new “big soccer city” teams were added to the league, Portland and Vancouver. Both cities are home to a passionate fan crowd and ever since belong to the teams that regularly sell out their home matches. Third, in 2011 a second huge increase in attendance was recorded (after a first jump that has been attributed to the arrival of David Beckham in 2007). Attendance increased by more than 7 percent compared to 2010, reaching an average value of 17.872 spectators per match. Finally, a new CBA was implemented in 2010 with the goal to grow attendance as well as TV ratings. At the same time the CBA was implemented, a new lucrative contract extension was signed with Fox Soccer Channel in 2011, next to the already existing broadcasting contract with ESPN. After the remarkable jump in 2011, the percentage of players for whom market values are available on transfermarkt.de increased only slightly up to 82 percent, a value that is comparable to the developments observed at Wikipedia by Spinellis and Louridas (2008) and fully in line with the predictions of the Bass model. After 2013, the value remains more or less constant.

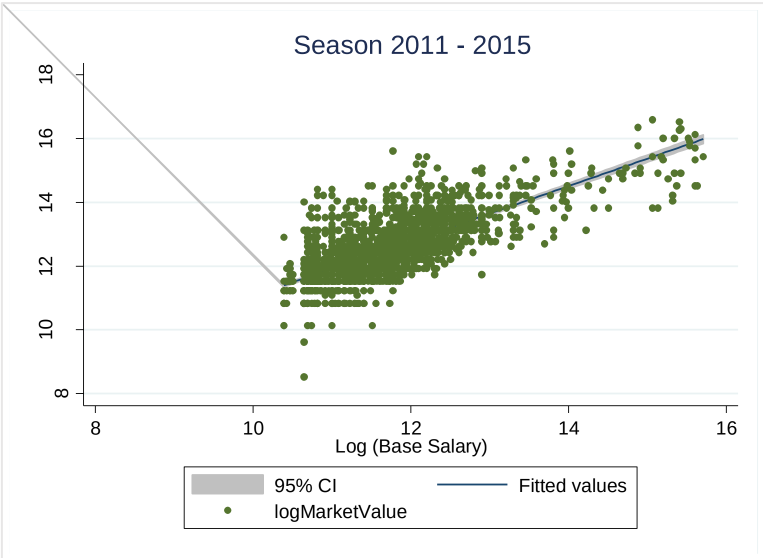
To answer the first research question (how precise are the transfermarkt.de estimates of players' market values?) we proceed in three different, yet closely related steps. First, we calculate Pearson correlation coefficients of market value and base and guaranteed salary separately for the two different time periods (2006 to 2010 and 2011 to 2015) and take a closer look at the corresponding scatterplots. Second, we estimate a simple OLS model with *Market Value, Base* and *Guaranteed Salary* as the dependent variables. Third, we compare the Kernel density estimates of the three dependent variables.

The scatterplots and the correlation coefficients for the two sub-periods are displayed in Figures 6 and 7 below. It appears that the picture for *Log(Market Value)* and *Log(Base Salary)* is very similar to the one obtained for *Log(Market Value)* and *Log(Guaranteed Salary).*

Figure 6 Scatterplot Market Value & Base Salary, 2006-2010 vs. 2011-2015

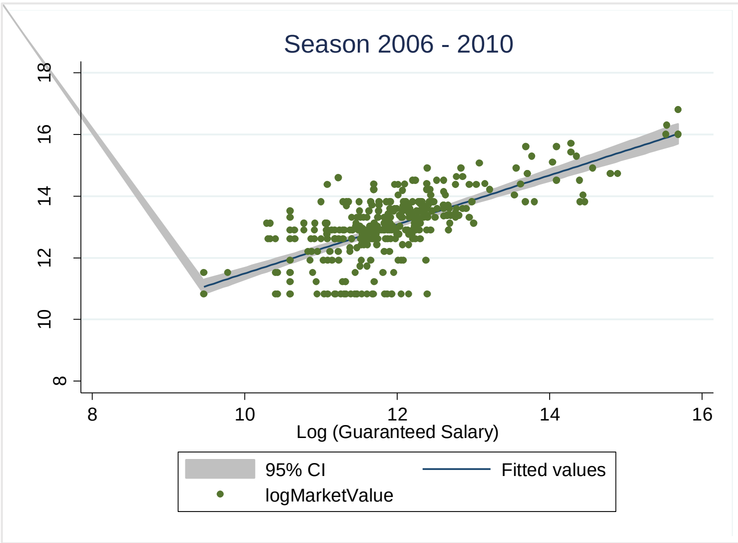


r = 0.7065

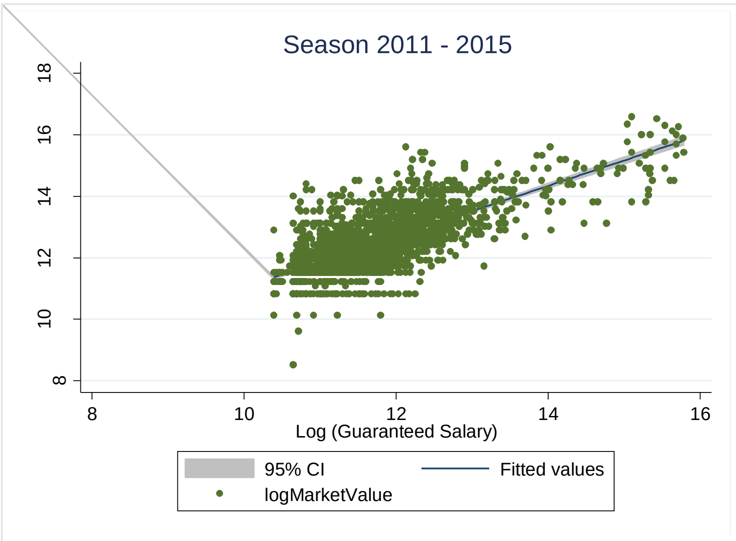


r = 0.7477

Figure 2.7 Scatterplot Market Value & Guaranteed Salary, 2006-2010 vs. 2011-2015



r = 0.7032



r = 0.7334

For the season 2006-2010 the data shows a statistically significant positive correlation of r=0.706 between market value and base salary. In the second half of the observation period (seasons 2011-2015) that value increased to r=0.747, suggesting that the market value estimations on transfermarkt.de have already initially been good proxies for player salaries and that this quality has even increased following the increasing attention for MLS. To control for reverse causality, we also regressed salaries lagged by one year (in t-1) on market values (in t=0) and obtained an R^2 of 0.22 only, suggesting that the market values available on transfermarkt.de are not driven by last year's salaries but reflect a player's skills instead.

Next, we present the results (see Table 1) of three OLS estimations with *Log (Market Value)*, L*og (Base Salary)* and *Log (Guaranteed Salary)* as dependent variables to demonstrate that their determinants are indeed very similar as long as we consider the players' individual characteristics.

Table 1 Regression Results: Determinants of Market Values, Guaranteed Salaries and Base Salaries in MLS, 2006-2015

Dep. Variable	Log (Market Value)	Log (Guaranteed Salary)	Log (Base Salary)
age	-1.071***	-1.005***	-0.859***
	(0.236)	(0.193)	(0.181)
age2	0.0469***	0.0403***	0.0363***
	(0.00878)	(0.00718)	(0.00675)
age3	-0.000611***	-0.000498***	-0.000463***
	(0.000108)	(0.0000879)	(0.0000826)
DP	1.426***	1.964***	1.920***
	(0.0616)	(0.0503)	(0.0473)
TP	0.952***	0.325***	0.277***
	(0.136)	(0.111)	(0.104)
YDP	1.055***	0.832***	0.876***
	(0.200)	(0.163)	(0.153)
position		*(ref.: goalkeeper)*	
defender	0.131**	0.0627	0.0387
	(0.0583)	(0.0476)	(0.0448)
midfielder	0.222***	0.107**	0.0780*
	(0.0581)	(0.0475)	(0.0446)
forward	0.397***	0.234***	0.191***
	(0.0600)	(0.0490)	(0.0460)
footedness		*(ref.: no info)*	
right foot	0.248***	0.130***	0.145***
	(0.0462)	(0.0378)	(0.0355)
left foot	0.270***	0.124***	0.146***
	(0.0554)	(0.0453)	(0.0426)
both feet	0.325***	0.364***	0.364***
	(0.0657)	(0.0537)	(0.0504)
2nd nationality	0.148***	0.0709***	0.0570**
	(0.0312)	(0.0255)	(0.0240)
team		*(ref.: CHI)*	
CHV	0.0162	-0.214***	-0.186***
	(0.0917)	(0.0750)	(0.0704)
CLB	0.0941	-0.0412	-0.0586
	(0.0857)	(0.0700)	(0.0658)
COL	0.0723	-0.0360	-0.0307
	(0.0855)	(0.0699)	(0.0657)
DAL	0.0708	-0.0874	-0.0960
	(0.0866)	(0.0708)	(0.0665)
DC	-0.0751	-0.0383	-0.0440
	(0.0869)	(0.0711)	(0.0668)
HOU	0.265***	0.157**	0.156**
	(0.0912)	(0.0746)	(0.0701)
KC	0.0227	0.0687	0.0769
	(0.0869)	(0.0711)	(0.0668)
LA	0.0677	0.0603	0.0759
	(0.0834)	(0.0682)	(0.0641)

Continued next page

Table 1 continued from previous page

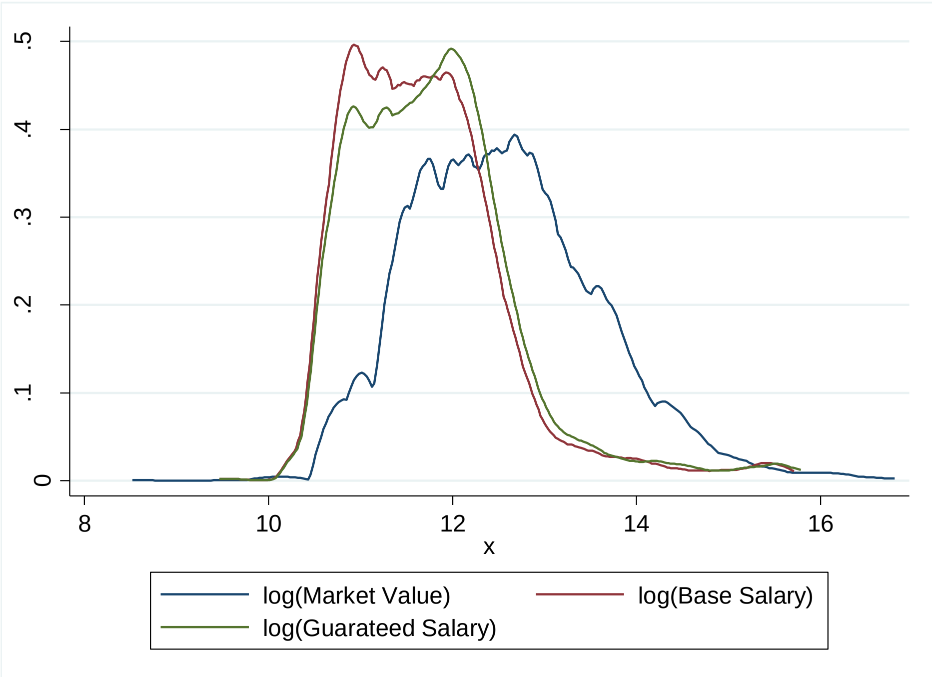
MTE	0.0976	-0.0133	-0.0332
	(0.0984)	(0.0804)	(0.0756)
NE	0.122	0.00877	0.00487
	(0.0907)	(0.0742)	(0.0697)
NYC	0.147*	0.0553	0.0705
	(0.0879)	(0.0718)	(0.0675)
NYCFC	-0.146	-0.174	-0.164
	(0.168)	(0.137)	(0.129)
ORL	0.147	-0.124	-0.113
	(0.158)	(0.129)	(0.121)
PHI	0.192**	0.123	0.123*
	(0.0932)	(0.0761)	(0.0715)
POR	0.0828	-0.102	-0.0729
	(0.0910)	(0.0744)	(0.0699)
RSL	-0.00508	0.00646	0.0131
	(0.0896)	(0.0732)	(0.0688)
SEA	0.0254	-0.188***	-0.158**
	(0.0868)	(0.0710)	(0.0667)
SJ	-0.0493	-0.148**	-0.124*
	(0.0868)	(0.0709)	(0.0666)
TOR	0.190**	0.0868	0.0758
	(0.0860)	(0.0703)	(0.0660)
VAN	0.182*	0.0371	0.0456
	(0.0935)	(0.0764)	(0.0718)
season		*(ref.: 2006)*	
2007	0.0149	-0.185	-0.166
	(0.175)	(0.143)	(0.134)
2008	-0.0713	-0.106	-0.0916
	(0.172)	(0.141)	(0.132)
2009	-0.0231	-0.150	-0.137
	(0.166)	(0.136)	(0.128)
2010	-0.0911	-0.164	-0.170
	(0.156)	(0.128)	(0.120)
2011	-0.562***	-0.242**	-0.268**
	(0.149)	(0.122)	(0.114)
2012	-0.377**	-0.200*	-0.232**
	(0.148)	(0.121)	(0.114)
2013	-0.191	-0.160	-0.179
	(0.148)	(0.121)	(0.114)
2014	-0.262*	-0.0633	-0.0781
	(0.149)	(0.122)	(0.114)
2015	-0.195	0.0404	0.0354
	(0.149)	(0.122)	(0.114)
constant	19.06***	19.13***	17.42***
	(2.086)	(1.705)	(1.602)
N of Observations	2,542	2,542	2,542

R2 * 100	50.2	56.7	60.1

*Standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01.*

The coefficients of player age, position, designated player status[2], footedness, and second nationality are surprisingly similar across the three models and are in line with previous research on either the determinants of player salaries (e.g. Bryson, Frick, & Simmons 2013 and Bryson, Rossi, & Simmons, 2014) or market values (e.g. Frick 2011). Moreover, in all three models the variance explained by the same set of independent variables is comparable and exceeds 0.50, which increases our confidence in the results presented above. Finally, we compare the Kernel density estimates (see Figure 8) for *Log(Base Salary)*, *Log(Guaranteed Salary)* and *Log(Market Value)* to document that their distributions are surprisingly similar, suggesting that in leagues, where player salaries are not disclosed but remain private and confidential, market values can indeed be used as proxies for player remuneration.

Figure 8 Kernel Density Estimates



[2] Regular designated player (=DP). A transfer designated player (=TDP) receives a special status due to the amount of transfer fee paid while a young designated player (=YDP) is a player under 23 earning more than the maximum but due to his age is not considered as a DP yet

DISCUSSION AND CONCLUSION

Our results show that the availability of market values for MLS players on transfermarkt.de can be well explained with the widely used Bass model. The increasing availability and especially the substantial increase in the percentage of players covered by transfermarkt.de between the 2010 and 2011 season is due to a number of different factors, starting with a new CBA, a new TV contract, new teams that have been admitted to the league and the unexpected success of the US soccer team in the 2010 World Cup tournament. These factors together spurred the public's interest in soccer and increased the popularity of soccer in general and MLS in particular.

As expected, the correlation of market values and player salaries (be it base or guaranteed pay) is close and increasing over time. Moreover, the determinants of market values on the one hand and base and guaranteed salaries on the other hand are very similar: Any form of *designated player* status is associated with significantly higher market values and salaries. Age also has a statistically positive, yet nonlinear impact on market values and salaries, as does the ability to handle the ball with both feet and being a *forward* or a *midfielder*. Finally, our Kernel density estimates show a similar distribution of player market values on the one hand and player salaries on the other.

Summarizing, 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 and will, therefore, play an increasing role in the sports economics literature.

NOTES

1. Note that Major League Soccer is properly referred to as ‘‘MLS’’ not ‘‘the MLS,’’ in much the same way as Major League Baseball is referred to as ‘‘MLB’’ rather than ‘‘the MLB.’’

2. E.g., upload of any type of terroristic, harassing or pornographic content is strictly forbidden. Violating one of the 11 commandments is sanctioned with point deductions. Compare http://www.transfermarkt.co.uk/intern/elfGebote

3. Regular designated player (=DP). A transfer designated player (=TDP) receives a special status due to the amount of transfer fee paid while a young designated player (=YDP) is a player under 23 earning more than the maximum but due to his age is not considered as a DP yet.

REFERENCES

Adams, R. and D. Ferreira (2010). Moderation in Groups: Evidence from Betting on Ice Break-ups in Alaska. *Review of Economic Studies*, 77, pp. 889-913.

Atanasov, P., P. Rescober, E. Stone, S.A. Swift, E. Servan-Schreiber, P. Tetlock, L. Ungar and B. Mellers (2017). Distilling the Wisdom of Crowds: Prediction Markets vs. Prediction Polls. *Management Science*, 63(3), pp. 691-706.

Bass, F.M. (1969). A New Product Growth for Model Consumer Durables. *Management Science*, 15(5), pp. 215-227.

Bass, F.M. (2004). Comments on “A New Product Growth for Model Consumer Durables: The Bass Model”. *Management Science*, 50(12) Supplement, pp. 1833-1840.

Bryson, A., G. Rossi and R. Simmons (2014). The Migrant Wage Premium in Professional Football: A Superstar Effect? *Kyklos*, 67(1), pp. 12-28.

Bryson, A., B. Frick and R. Simmons (2013). The Returns to Scarce Talent: Footedness and Player Remuneration in European Soccer. *Journal of Sports Economics*, 14(6), pp. 606-628.

Budescu, D.V. and E. Chen (2015). Identifying Expertise to Extract the Wisdom of Crowds. *Management Science*, 61(2), pp. 267–280.

Charness, G. and M. Sutter (2012). Groups Make Better Self-Interested Decisions. J*ournal of Economic Perspectives*, 26, pp. 157-176.

Charness, G., E. Karni and D. Levin (2010). On the Conjunction Fallacy in Probability Judgements: New Experimental Evidence Regarding Linda. *Games and Economic Behavior*, 68, pp. 551-556.

Chen, H., P. De, Y. Hu and B.-H. Hwang (2014). Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *Review of Financial Studies*, 27(5), pp. 1367-1403.

Coates, D., B. Frick and R.T. Jewell (2016). Superstar Salaries and Soccer Success: The Impact of Designated Players in Major League Soccer. *Journal of Sports Economics*, 17(7), pp. 716-735.

Firth, D.R., C. Lawrence, S.F. Clouse and A. Koohang (2006). Predicting Internet-based Online Community Size and Time to Peak Membership Using the Bass Model of New Product Growth. *Interdisciplinary Journal of Information, Knowledge, and Management*, 1(1), pp. 1-12.

Frick, B. (2011): Performance, Salaries, and Contract Length. Empirical Evidence from German Soccer. *International Journal of Sport Finance*, 6(2), pp. 87-122.

Frick, B. and P. Wicker (2016): Football Experts versus Sports Economists. Whose Forecasts are Better? *European Journal of Sport Science*, 16(5), pp. 603-608.

Galton, F. (1907). Vox populi. *Nature*, 1949(75), pp. 450-451.

Herm, S., H.-M. Callsen-Bracker and H. Kreis (2014). When the Crowd Evaluates Soccer Players' Market Values: Accuracy and Evaluation Attributes of an Online Community. *Sport Management Review*, 17, pp. 484-492.

Herzog, S.M. and R. Hertwig (2011). The Wisdom of Ignorant Crowds: predicting Sport Outcomes by Mere Recognition. *Judgement and Decision Making*, 6(1), pp. 58-72.

Howe, J. (2006, January 6). The Rise of Crowdsourcing. In *Wired Magazine*. Retrieved July 15, 2016, from: https://www.wired.com/2006/06/crowds/

Hsiao, J.P.H., C. Jaw and T.C. Huan (2009). Information Diffusion and New Product Consumption: A Bass Model Application to Tourism Facility Management. *Journal of Business Research*, 62(7), pp. 690-697.

Jewell, R.T. (2017). The Effect of Marquee Players on Sports Demand: The Case of U.S. Major League Soccer. *Journal of Sports Economics*, 18(3), pp. 239-252.

Jiang, Z. and S. Sarkar (2009). Speed Matters. The Role of Free Software Offer in Software Diffusion. *Journal of Management Information Systems*, 26(3), pp. 207-240.

Kuethe, T.H. and M. Motamed (2010). Returns to Stardom: Evidence from U.S. Major League Soccer. *Journal of Sports Economics*, 11(5), pp. 567-579.

Lamberson, P.J. and S.E. Page (2012). Optimal Forecasting Groups. *Management Science*, 58(4), pp. 805-810.

Lorenz, J., H. Rauhut, F. Schwitzer and D. Helbing (2011). How Social Influence Can Undermine the Wisdom of Crowd Effect. *Proceedings of the National Academy of Sciences*, 108(22), pp. 9020-9025.

Mahajan, V., E. Muller and F.M. Bass (1990). New Product Diffusion Models in Marketing. A Review and Directions for Research. *Journal of Marketing*, 54(1), pp. 1-26.

MLS Players Union (n.d.). *About the Union.* Retrieved June 20, 2016, from https://mlsplayers.org/about-us/.

Mollick, E. and R. Nanda (2016). Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. *Management Science*, 62(6), pp. 1533-1553.

Peeters, T. (2017). Testing the Wisdom of Crowds in the Field: Transfermarkt Valuations and International Soccer Results. *International Journal of Forecasting*, 34, pp. 17-29.

Reingold, H. (1993). *The Virtual Community: Homesteading on the Electronic Frontier*. Reading: Addison-Wesley.

Simmons, J. P., Nelson, L. D., Galak, J., & Frederick, S. (2011). Intuitive Biases in Choice versus Estimation: Implications for the Wisdom of Crowds. *Journal of Consumer Research*, 38(1), 1–15.

Sonntag, S.J. and P.M. Sommers (2014). Work Incentives and Salary Distribution in Major League Soccer. *Atlantic Economic Journal*, 42, pp. 471-472.

Spinellis, D. and P. Louridas (2008). The Collaborative Organization of Knowledge. *Communications of the ACM*, 51(8), pp. 68-73.

Surowiecki, J. (2004). *The Wisdom of Crowds*, 1st ed., New York, NY: Anchor Books.

Sutter, M. (2005). Are Four Heads Better than Two? An Experimental Beauty-Contest Game with Teams of Different Size. *Economics Letters*, 88, pp. 41-46.

Twomey, J. and J. Monks (2011). Monopsony and Salary Suppression: The Case of Major League Soccer in the United States. *American Economist*, 56(1), pp. 20-28.