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# The Wisdom of Crowds and Football Players

*An Investigation of the Underdog Bias and the Valuation of Football Players in the English Premier League*

Master Thesis Economics and Business

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# Abstract

In this thesis, I apply the effect of uninformative cues on collective judgements to the field of football. More specifically, I investigate whether the underdog bias is present in the crowds' valuation of football players in the Premier League. I define underdogs based on the Human Development Index category in the player's country of birth, which turns out to be unrelated to performance. Although more research is needed to support the findings, this thesis provides initial evidence for the presence of the underdog bias in the estimated market value of football players by the crowds. This shows that uninformative performance cues affect the way we value other people.

*Keywords*: cognitive biases, underdog bias, wisdom of crowds, uninformative cues, valuation of football players

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I would also like to acknowledge Thomas L.P.R. Peeters of the Erasmus School of Economics as he is the first reader of my thesis. Besides, it was his idea to test whether cognitive biases impact the crowds' valuation of football players.

Finally, I am very grateful for the way my parents have motivated and supported me at times when I was struggling with my research. They provided the right conditions for me to work on my thesis.

# Table of Contents

# Chapter 1: Introduction

In the current research, I test some of the theory about cognitive biases in the field of football, which is generally considered as the most popular sport in the world (Müller, Simons & Weinmann, 2017; Sawe, 2017). Many other academics delved into the world of professional team sports to test all kind of psychological and economic theories before. To some extent, it turned out that some of the phenomena that are demonstrated in the lab or in the business world can be applied in professional team sports as well (e.g. Frey, Schaffner, Schmidt, & Torgler, 2013; Kahane, Longley, & Simmons, 2013; Meier & Leinwather, 2013; Coates, Humphreys, & Zhou, 2014).

Sports, and football in particular, offers great opportunities to investigate theoretical concepts. Because of its popularity, football is a very convenient context to make science more attractive for the general public. More important, a wide range of sports related data is available on the internet (Frick, 2007). As this detailed data can be easily obtained, sports is very suitable for scientific research.

In more detail, this thesis is about the possible existence of an underdog bias in the crowds' valuation of football players. I define underdogs in a way that is unrelated to performance, so I can regard the fact that a player belongs to the underdog category as an uninformative performance cue. By doing so, I determine whether crowds judge the performance of others (in this case: football players) on the quality of the performance solely, or whether other aspects are involved as well.

I focus on football players in the Premier League, the top-tier football league in England. Compared to other domestic football competitions, the broadcasting rights of the Premier League are the most expensive worldwide. For that reason, the Premier League is considered as the most popular domestic football league globally (Ahmed, 2017). This makes the research interesting for a large audience.

The research question in this thesis is stated formally as follows:

*"Is the underdog bias reflected in the crowds' collective valuation of football players in the English Premier League?"*

In this thesis, the collective player value is determined based on the principles of the wisdom of crowds. It simply means that under the right circumstances, collective group decisions are often smarter than the decisions made by each individual member of the group.

Even if most of the group members are ignorant and cannot be considered as experts. In practice, collective intelligence can solve a wide range of decision problems that differ greatly in difficulty levels and contexts (Surowiecki, 2005).

For groups of people to be collectively intelligent, four conditions must be met (Surowiecki, 2005, p.10). Each member of the group must have some private information, or at least an own interpretation of the facts (diversity of opinion). Besides, the individual opinions must not be affected by other members of the group (independence). Also, people should be able to specialize and gain local knowledge (decentralization). Finally, it must be possible to collect all individual opinions and to convert them into a collective decision (aggregation). Additionally, Simmons, Nelson, Galak and Frederick (2011) argued that people should be motivated to express relevant knowledge and to be accurate (Peeters, 2018).

I obtain collective player values that are based on the principles of the wisdom of crowds from an online platform, which is called *Transfermarkt*. The platform aggregates the estimated player valuations of individual users to determine a collective player value. Those collective values are consulted by many other researchers before. For instance, Peeters (2018) researched whether the results of international football matches can be forecasted based on the collective values on *Transfermarkt*. He found that predicted results based on the crowds' valuations are more specific than forecasts based on standard predictors. Also, Herm, Callsen-Bracker and Kreis (2014) showed that the collective estimates of the market values of football players accurately predict the actual transfer fees paid.

In this thesis, I test whether the valuations on *Transfermarkt* are biased. It is widely believed that the opinions, decisions and judgements of individuals are subject to a number of heuristics and biases. Even experienced researchers and specialists in the field of human behavior are sensitive to cognitive biases (Tversky & Kahneman, 1974). Other researchers have argued that those biases may apply to groups of people, called crowds, as well (Simmons, Nelson, Galak & Frederick, 2011).

Although cognitive biases and the effects of uninformative cues are investigated in a countless amount of contexts and settings for individual subjects (e.g. Bertrand & Morse, 2011; Simon, Houghton & Aquino, 2000), much less work has been done about the effects of such biases and uninformative cues in aggregated group behavior. So, the main contribution of my thesis is the fact that I test for cognitive biases in the behavior of crowds instead of individuals. Despite some other studies in this area, the current thesis is unique in its kind. To the best of my knowledge, the underdog effect, as defined in this study, has never been researched in this particular setting before. This makes my thesis exciting for people who like football in general and especially for those who are interested in the market values of football players' and its composition.

The relevance of this research is the fact that I apply an existing theory to a new field. Even though the fact that it is relatively underexposed, I am not the first researcher who investigates whether uninformative cues affect crowds' behavior and their decision-making process (e.g. Resnik & Stern, 1977). In fact, my thesis is just an application of an existing concept with the aim to increase the external validity of the findings in previous studies and to make it more practically oriented.

Since the practical use of science becomes more and more important, increasing the external validity of theoretical concepts is very relevant these days. In the past, scientists focussed more on testing theoretical constructs in the lab. However, the conditions in the lab are often not very comparable to those in real life. For instance, researchers frequently use students as their main subjects. As a sample that consists of students only do not reflect the real-life population, it is unlikely that the exact same findings (in size and magnitude) can be applied to the field as well. So, to make science more usable in practice, theoretical concepts should be tested in the field (Winer, 1999). This is exactly what I do in my thesis.

The remainder of this research is structured as follows. In the next chapter, I discuss some relevant theory about cognitive biases (the underdog bias is particular) and the valuation of football players. In Chapter 3, I describe the methods and models that are used to test for the underdog effect. Besides, I present the descriptive statistics of the football players in the sample. Chapter 4 contains the main results and the robustness checks, whereas Chapter 5 concludes the research with some implications, limitations and directions for further research.

# Chapter 2: Theoretical Framework

In this chapter, I start with a short introduction about cognitive biases in general and how they affect people's behavior. I discuss the underdog bias and present the definition of underdogs that is used in the rest of this research. The second part of this chapter is about the valuation of football players. I summarize the key components of the market value of football players. Besides, I discuss the collective player valuations by the crowds on a recognized online platform. Finally, I present a tool that is developed by the CIES Football Observatory to predict market values of footballers.

## 2.1 Cognitive Biases

During life, each individual makes an innumerable amount of decisions. In fact, everything we do either consciously, or unconsciously is a result of some decision we have made. People collect information that helps them to understand the situation and to evaluate the possible choices and its consequences. Based on the information available, they pick the best alternative available (Saaty, 2008).

However, as the capacity of the human mind is limited (Cooper, Folta & Woo, 1995), people often fail to consider and correctly interpret all the relevant information in the decision-making process. To deal with the limited cognitive capacity, they rely on heuristic principles (Barnes, 1984; Schwenk, 1986). These 'mental shortcuts' or 'simplifying strategies' are helpful in the decision-making process as they reduce the complexity of decisions by lowering the amount of information that needs to be considered to come to an acceptable decision. On the other hand, they may lead to systematic errors and cognitive biases as well (Tversky & Kahneman, 1974; Simon et al. 2000).

Cognitive biases are often defined as "*subjective or predisposed opinions that may emanate from specific heuristics*" (Busenitz & Lau, 1996; Bazerman, 1990). They mainly occur in situations in which people make complex decisions with an uncertain outcome. Other researchers have distinguished several cognitive biases (Simon et al. 2000). For example, there is the availability heuristic. This heuristic simply means that people's judgements and choices are biased by what is most available in their minds. So, if there have been an excessive number of deadly car accidents in the news broadcasts recently, it is likely that people overestimate the probability of get themselves involved a fatal car accident. This overestimation will probably be higher if a person witnessed such an accident (Tversky & Kahneman, 1974).

### 2.1.1 The Underdog Bias

In this thesis, the focus is on the underdog bias, of which its existence is proven in multiple settings. The underdog is commonly defined as "*the one who is disadvantaged and who is therefore expected to lose*" (Paharia, Keinan, Avery & Schor, 2010; Houghton Mifflin Company, 2006). Depending on the context of the research, other researchers adjusted this broad definition to a more specific concept.

In some of the studies it turned out that people may have a favourable attitude towards underdogs, which is generally called the underdog effect. This cognitive bias may have various causes and it occurs in a variety of contexts. For instance, Fleitas (1971) and West (1991) found an underdog bias in people's voting behavior. The share of voters who vote for the candidates that are expected to lose is larger in case the voters are aware of the election polls. Besides, Paharia, Keinan, Avery and Schor (2010) showed that brands can take advantage of the people's identification with underdogs. When companies use underdog brand biographies in the right way, it positively affects consumers' purchase intentions, real choice and brand loyalty. More important, McGinnis and Gentry (2009) focus on the existence of the underdog bias in the context of sports among other things. They argue that a significant amount of sports fans support teams or individual athletes that are expected to lose. This is commonly explained by the fact that people empathize with the state of the underdogs.

In my research, I define underdogs based on the standard of living in a football player's county of birth. Football players who are born in underdeveloped countries start life at a disadvantaged position and would therefore be considered as underdogs. An important part of the standard of living is the economic wealth. Other scientists have shown that people generally feel sympathy for the poor and disadvantaged in the society (Weiner, Osborne & Rudolph, 2011). As I do not want to limit myself to the economic wealth exclusively, I focus on level of human development in countries.

#### 2.1.1.1 The Human Development Index

The effects of race or origin in the context of football have been investigated by some other researchers before. For instance, Reilly and Witt (1995) studied the impact of skin colour on the wages of football players, whereas Szymanski (2000) focussed on the effect on the transfer fees paid. In both studies, it was assumed that football clubs discriminate against dark skinned players in terms of wages and transfer fees. Rather than race or skin colour, I focus on the degree of human development in a football player's country of origin.

The Human Development Index (HDI) is a composite measure that is introduced by the United Nations in the Human Development Report of 1990. It is created to underscore that the development level of countries should be based on the richness of life, rather than the richness of the economy solely. The inhabitants and their capabilities and opportunities should be included as well. So, the Human Development Index captures some measures of health, education and income. The higher the life expectancy at birth, the mean years of schooling and the gross national income per capita, the higher the HDI score (United Nations Development Programme, 2017a, 2017b; Wolff, Chong & Auffhammer, 2011).

Originally, the United Nations grouped countries into three categories; low, medium and high human development. An extra category was added in the Human Development Report of 2009; very high human development. This classification of countries into four different groups is still relevant in the current reports (United Nations Development Programme, 2007, 2009, 2015). It is used in politics, science and the business world. For instance, some companies use the grouping of countries based on the Human Development Index in their international pricing strategy (Wolff et al. 2011).

In this thesis, I define the underdogs based on this Human Development Index classification. Football players who are born in countries in the low or medium HDI category represent the underdogs in the sample. Footballers from the remaining countries are considered as non-underdogs. Although the Human Development Index is not inequality adjusted, I assume that football players who are born in countries that score low or medium on HDI grew up in disadvantaged conditions. The degree of human development in a football player's country of birth is unrelated to performance (see *Results)*. For that reason, the underdog classification should be considered as an uninformative performance cue.

## 2.2 The Valuation of Football Players

Buying and selling football players on the transfer market is an important business of football clubs (Frick, 2007). For a player transfer to occur, the buying and selling club must come to an agreement about the transfer fee that the buying club has to pay to terminate the player's contract with the selling club. In most cases, the transfer fees rise up to many millions of Euros.

However, there is no generally accepted way to determine the monetary amount of the transfer fee (Müller et al. 2017).

In this thesis, I focus on the market or transfer value of a football player. It is commonly defined as '*an estimate of the amount of money a club would be willing to pay in order to make this athlete sign a contract, independent of an actual transaction*' (Herm, Callsen-Bracker & Kreis, 2014). So, a transfer *fee* is about actual money that is paid for a footballer on the transfer market, whereas the market or transfer *value* is just an estimate of the transfer fee that would have been paid in case a player were sold to a new club (Müller et al. 2017).

### 2.2.1 The Key Indicators

Other researchers investigated the valuation of football players before. Frick (2007) argued that most of the factors which influence a player's market value can also be used to explain the differences in player salaries (Bryson, Frick & Simmons, 2013; Müller et al. 2017). This means that market values and wages are highly correlated (Torgler & Schmidt, 2007). In general, two types of factors can be distinguished; some player characteristics or performance/talent attributes and some team characteristics or popularity attributes (Carmichael, Forrest & Simmons, 1999; Franck & Nüesch, 2012; Herm et al. 2014; Müller et al. 2017; Poli, Ravenel & Besson, 2015, 2016, 2017). As I do not want to go into too much detail, I only discuss the indicators that are most regularly investigated by others and those that are relevant for this thesis.

#### 2.2.1.1 Player Characteristics and Talent/Performance Attributes

The age of a football player is an important player characteristic in the market valuation, as it reflects potential and experience (Carmichael & Thomas, 1993). Young players will develop their abilities, whereas older players rely more on their experience. Many researchers found a positive, but diminishing effect of age (Bryson et al. 2013, Franck & Nüesch, 2012; Herm et al. 2014; Lucifora & Simmons, 2003; Müller et al. 2017). For young players, the increase in experience prevails. At a certain age, the ideal combination of potential and experience is reached. After that point, the player's development falters and his physical abilities, like acceleration and stamina start to decline. The disadvantages of physical discomforts overrule the benefits of increased experience and the end of the player's career is getting closer (Carmichael & Thomas, 1993; Carmichael et al. 1999; Torgler & Schmidt, 2007).

Next to age, the position on the pitch is an important indicator as well. In general, four positions are distinguished; forward, midfielder, defender and goalkeeper (Carmichael & Thomas, 1993; Carmichael et al. 1999; Lucifora & Simmons, 2003; Müller et al. 2017; Torgler & Schmidt, 2007). Some researchers have found that forwards are more valuable than midfielders in terms of market value or wage. In their turn, midfielders earn a premium in value compared to defenders and goalkeepers (Bryson et al. 2013; Frick, 2007).

Another relevant factor is the contract duration. In case a player's contract with his club expires, the player is allowed to sign for another club on a free transfer. Otherwise, the buying club must pay a financial compensation to the selling club to terminate the player's contract (Frick, 2007; Poli, Ravenel & Besson, 2015, 2016). In other words, a lengthy player contract warrants a transfer fee for the selling club in the future. So, intuitively it makes sense that the more years remaining on a player's contract with his current club, the higher his estimated market value (Bryson et al. 2013; Carmichael et al. 1999).

In addition, the amount of matches played is also an important indicator of the market value. The number of appearances, either during the player's career so far or during some recent season(s), positively affects the market value (Carmichael & Thomas, 1993; Carmichael et al. 1999; Franck & Nüesch, 2012; Müller et al. 2017). The impact of recent matches is larger than that of appearances in the past (Bryson et al. 2013; Poli et al. 2016). Most researchers argued that the more matches the footballer has played, the higher his market value, whereas some others found a non-linear effect as well (Bryson et al. 2013; Lucifora & Simmons, 2003).

Besides, the effect of the number of goals scored positively affects the market value of football players. It turned out that the more goals a player has scored, the higher his transfer value (Bryson et al. 2013; Carmichael & Thomas, 1993; Franck & Nüesch, 2012; Frick, 2007; Herm et al. 2014; Müller et al. 2017). As scoring goals is more important for forwards than for other players, Carmichael, Forrest and Simmons (1999) linked the number of goals scored to the position on the pitch.

Finally, an important indicator is the representation of a country in the national A-team. Football players who perform remarkably well at club-level are likely to play international matches for their countries. In turn, these international caps have a positive influence on a player's market value. In some studies, it turns out that the size of the effect differs per country, whereas some researchers focused on international status rather than the amount of international caps played (Carmichael et al. 1999; Frick, 2007; Lucifora & Simmons, 2003; Poli et al. 2015, 2016).

#### 2.2.1.2 Team Characteristics and Popularity Attributes

In several studies, the effect of team performance or club characteristics on the market value of individual football players is investigated. Some examples of club performance whose effects have been studied are goal difference, ranking in the competition, club attendance and financial success (Carmichael & Thomas, 1993; Herm et al. 2014). Other researchers investigated the effects of the division level at which the club performs (Carmichael et al. 1999; Poli et al. 2015, 2016). Next to the characteristics of the player's current club, the characteristics of the clubs that are likely to buy the player are relevant as well (Carmichael & Thomas, 1993; Poli, Ravenel & Besson, 2017).

Next to the club characteristics, the popularity of a football player is an important predictor of the market value as well. Prominent players are more profitable in economic terms. For instance, the popular players in the team contribute more to the merchandising, receipts and broadcasting revenues (Herm et al. 2014; Müller et al. 2017). Researchers who investigated the effects of popularity used several indicators. Some examples are, the number of links reported by Google, the Google Trend search index, Wikipedia page views, the amount of shared videos on YouTube and the number of articles in which a player is mentioned in highly respected newspapers (Franck & Nüesch, 2012; Herm et al. 2014; Müller et al. 2017).

### 2.2.2 Player Valuations by the Crowds

To determine the crowds' collective valuation of football players, I consult a football statistics website called *Transfermarkt*. This website is considered as one of the primary football sites and it provides a wide variety of football-related data, football news and transfer rumours. It also allows registered users to discuss the market values of thousands of football players all over the world. For each player, members may propose adjustments in the current valuations that are often reinforced by an explanation. To keep the discussion going, the valuations of each registered user are visible for other members in the player's discussion thread. At pre-announced times in the football season, moderators of the *Transfermarkt* community update the market value of a player based on the suggestions made by the users (Herm et al. 2014; Müller et al. 2017; Peeters, 2018). An example of a *Transfermarkt* discussion thread about the valuation of a football player (Angeliño – NAC Breda) can be found in Appendix 1.

To overcome potential problems that are associated with crowd sourcing, like social influence (Lorenz, Rauhut, Schweitzer, & Helbing, 2011), manipulation attempts and lack of knowledge (Müller et al. 2017), *Transfermarkt* uses the judge principle. Empowered community members, called judges, determine the competence of registered users and the validity of their arguments. Based on this, the judges decide on the influence of each individual user on the player's final market value. So, all registered members may discuss the market value of a player and suggest modifications. However, only a few authorized members are allowed to filter, weigh and aggregate the information and valuations by other users to determine the final estimate of the market value (Herm et al. 2014; Müller et al. 2017). Those collective valuations on *Transfermarkt* are an accurate predictor of the actual transfer fees paid (Herm et al. 2014) and it is often referred to in scientific literature and in the popular press (Peeters, 2018).

Müller, Simons and Weinmann (2017) conceptualized the determination of the market value on *Transfermarkt*, which can be found in Figure 1 of the current thesis. Registered users $j$ make individual estimates $\hat{y}_j$ of the actual, unobservable market value $y$ depending on their interpretation of arbitrary indicators $x_i$ (e.g. age, matches played or goals scored) and collective weightings $a_{ij}$. The judges determine the final, collective estimate of the market value $\hat{y}$ based on the individual estimates $\hat{y}_j$ and other indicators that they consider relevant $x_i$, weighted against their collective importance $b_j$ and $a_i$ (Herm et al. 2014; Müller et al. 2017).

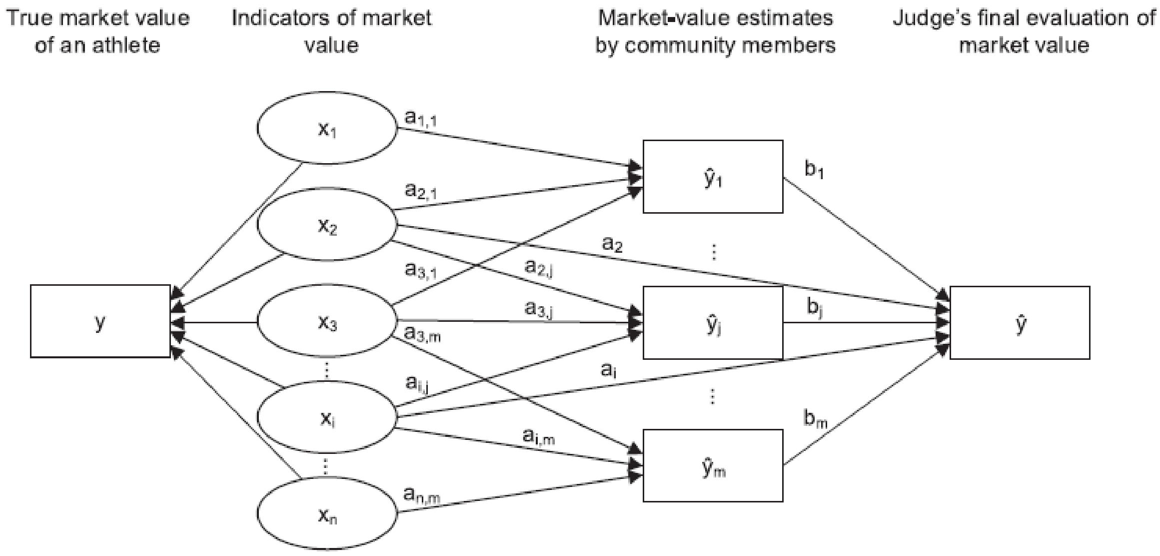


*Figure 1: The conceptualization of the market value at Transfermarkt (Müller et al. 2017)*

To investigate the underdog effect, I compare the collective valuations by the crowds with the objectively determined market values of football players. Those objective values are based on (performance) statistics and they are calculated by means of the Transfer Value Calculator.

### 2.2.3 The Transfer Value Calculator

The International Centre for Sports Studies (CIES) Football Observatory is commonly known for statistical analysis of football. This research group deals with the estimation of transfer values among other things. In this context, it developed a statistical model that contains objective data solely. The underlying algorithm is based on player transfers during the previous five seasons and it is updated after every transfer window. The model can be used to predict the transfer values of players in the big-five leagues in Europe; the Premier League (England), the 1. Bundesliga (Germany), the Primera División (Spain), the Serie A (Italy) and the Ligue 1 (France). Since the summer of 2013, the correlation between the market values estimated by CIES Football Observatory and the actual transfer fees paid on the transfer market is around 80% (Poli et al. 2015, 2016, 2017).

The exact model and algorithm are not publicly available. However, a simplified tool can be found on the CIES Football Observatory website. The tool is called the Transfer Value Calculator and it includes three types of factors; objective player characteristics, domestic league performance statistics and international status and caps statistics (CIES Football Observatory, 2014A, 2014B).

The Transfer Value Calculator includes three important player characteristics; age, position on the pitch and the end date of the contract duration at his current club. To compute a valid transfer value, a player must be in the age of eighteen to thirty-three years. In addition, the calculator distinguishes six different positions on the field; goalkeeper, centre back, full back, central midfielder, attacking midfielder and forward. Additionally, the amount of contract years remaining should be at least one, whereas the maximum duration that could be included in five years (CIES Football Observatory, 2014B).

The domestic league performance statistics capture the number of domestic matches played, the amount of goals scored in those matches, the country of the league, the level of the league in the national hierarchy and the average number of points achieved during the matches a footballer has played. The performance statistics of the last two years are included for each semester separately. To determine an accurate transfer value, the footballer must have played at least four matches in one of the big-five leagues during the previous semester (CIES Football Observatory, 2014B).

Finally, the Transfer Value Calculator includes whether the player has represented the national A-team of a country. To calculate the market value, the name of the country and the number of caps during the previous year are required (CIES Football Observatory, 2014B).

After providing the relevant data, the Transfer Value Calculator computes the minimum and the maximum level of the player's market value. As the exact formula and algorithm are not publicly accessible, CIES Football Observatory sends the requested market values by email. The Transfer Value Calculator as it is shown on the CIES Football Observatory website and the resulting output can be found in Appendix 2.

## 2.3 Concluding Remarks

To sum up, it is widely believed that individuals rely on heuristic principles in the decision-making process. In this research, I focus on the underdog bias, which means that people have a favourable attitude towards the ones who are disadvantaged and who are therefore expected to lose. I distinguish the underdogs from the non-underdog by looking at the human development in the country of birth. I call players who are born countries in the low or medium Human Development Index category the underdogs. As the development level in a player's native country is unrelated to performance on the pitch, it can be considered as an uninformative performance cue.

In this thesis, I consider the market value of football players instead of the actual transfer fees paid. The market value of a footballer is defined as the transfer fee that would have been paid in case a player were sold. I obtain the valuations from *Transfermarkt*, one of the highly qualified football statistics websites. On this website, the player valuations of individual users are aggregated to a collective market value by the crowds. Those collective values are used in this thesis.

The valuation of football players has been investigated by many other researchers before. Broadly speaking there are two types of factors; some player characteristics or performance statistics and some team characteristics or popularity attributes. Examples of determinants that are covered in the first category are the age of a player, the number of matches played, and the amount of goals scored. The second category contains factors like the ranking of the team, financial success of the club and Wikipedia page views.

Additionally, the CIES Football Observatory developed the Transfer Value Calculator. This calculator captures some of the most important player characteristics and performance statistics. The valuation by this calculator is based on objective player statistics solely. Since the correlation between the calculated value and the actual transfer fees paid is very high, the Transfer Value Calculator is an accurate predictor of transfer fees paid.

# Chapter 3: Methods

In this chapter, I explain the methods and models that are used in this thesis. I describe the data sources and I conclude the section with the descriptive statistics of the sample.

## 3.1 Methods and Models

To test for the underdog effect, I perform several multiple regression analyses. This method is commonly used to demonstrate the relationship between one dependent variable and one or more independent variable(s). The standard form of a multiple regression model looks as follows (Janssens, Wijnen, De Pelsmacker & Van Kenhove, 2008):

$$Y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n + \varepsilon$$

In this regression model, $Y$ is the dependent variable and the $x_n$'s are the independent variables that are included in the model to explain the differences in the dependent variable. The $b_n$'s are the estimated coefficients and reflect the size of the effect of each independent variable. Finally, $\varepsilon$ represents the residuals, which are the differences in the dependent variable that cannot be explained by the independent variables of the model.

In a multiple regression analysis, the coefficients are estimated in such a way that the sum of square of the residuals (the difference between the actual and the predicted value) is as small as possible. This is called the ordinary least squares (OLS) method and it requires several assumptions, like the absence of multicollinearity and normally distributed residuals (Janssens et al. 2008; Moore, McCabe, Duckworth & Alwan, 2008).

### 3.1.1 Models

I use two models to test for the underdog effect. In Model 1, I include the objective player value that is calculated by the Transfer Value Calculator of the CIES Football Observatory. To capture the popularity of a football player, I also add the amount of followers or fans on social media. Finally, I use the Human Development Index category in a player's native country to determine whether he should be considered as an underdog or not. The model is expressed as follows:

$$ln(COLV) = b_0 + b_1OBV + b_2FANS + b_3HDI + \varepsilon$$

- *COLV*: the collective value of a football player (in millions of euros) that is determined by the *Transfermarkt* community based on the principles of the wisdom of crowds. For more information about *Transfermarkt*, I refer to Chapter 2.2.2. To improve the normal distribution of the residuals, I take the natural logarithm (ln) of the collective value. Other researchers argued that transforming the dependent variable is an appropriate technic to obtain normally distributed residuals (Stafford & Sabin, 1990). I will elaborate on this in the *Results* section of this thesis.
- *OBV*: the minimum, the maximum and the average objective value of a football player (in millions of euros) that is calculated by the Transfer Value Calculator. The effects of the three values are calculated in the model separately, which means that I run three regressions. To determine the objective values, I use data of the 2014/2015 and 2015/2016 football season. I expect a positive effect, meaning that the higher the calculated objective value, the higher the collective market value on *Transfermarkt*. For more information about the Transfer Value Calculator and its components, I refer to Chapter 2.2.3.
- *FANS*: the amount of fans or followers on a football player's social media accounts expressed in millions of people. I consider three prominent social media platforms (Facebook, Instagram and Twitter) and I select the platform with the highest amount of fans for each player individually. In line with other researchers, I predict a positive effect of popularity; the more followers on a player's social media accounts, the more popular he is and therefore the higher his market valuation by the crowds (Franck & Nüesch, 2012; Herm et al. 2014; Müller et al. 2017).
- *HDI*: the Human Development Index of a football player's native country. The effect is included as a dummy variable that takes the value one in case a country is in the low or medium HDI category and zero otherwise. This variable distinguishes the underdogs from the non-underdogs (Chapter 2.1.1.1) and I suppose a positive effect. In case a player is born in an underprivileged country, the collective valuation by the crowds is biased upwards, suggesting an underdog effect.

To support Model 1, I use an extra model which includes all the variables that are captured in the Transfer Value Calculator separately. As discussed in Chapter 2.2.1, other researchers have demonstrated the significant effect of most of these parameters before. In contrast to the Transfer Value Calculator, I focus on the player statistics of only one season to limit the number of variables in the model. As the effect of recent performance on a player's market value is larger than that of performance in the past (Bryson et al. 2013; Lucifora & Simmons, 2003), I select the data of the previous season (2015/2016). Model 2 is expressed as follows:

$$ln(COLV) = b_0 + b_1AGE + b_2AGE^2 + b_3GK + b_4MID + b_5FW + b_6CY + b_7M + b_8M^2 + b_9G + b_{10}PM + b_{11}CAPS + b_{12}FANS + b_{13}HDI + \varepsilon$$

- *COLV:* equal to the *Collective Value* variable in Model 1.
- *AGE*: the age of a player (in years) at the end of the 2015/2016 season. To capture the positive but diminishing effect of age on a player's market value, I add a linear and a quadratic term. I predict a positive impact of *AGE* and a negative effect of $AGE^2$ (Bryson et al. 2013; Carmichael & Thomas, 1993; Carmichael et al. 1999; Franck & Nüesch, 2012; Lucifora & Simmons, 2003; Müller et al. 2017).
- *GK*, *MID* and *FW*: dummy variables that catch the effect of a football player's position on the pitch. I distinguish between goalkeepers (*GK*), defenders (default option), midfielders (*MID*) and forwards (*FW*). To limit the amount of variables in the model, I use a less extensive classification than the Transfer Value Calculator. In line with other researchers, I expect that the impact of *MID* and *FW* on the crowds' market valuation of a football player is positive, whereas the size of the effect is larger for forwards than for midfielders (Bryson et al. 2013; Frick, 2007).
- *CY*: the amount of years remaining on the player's contract with his current club at the end of the 2015/2016 season. I suppose a positive effect of contract years, suggesting that the more years remaining on a player's contract, the higher his collective market value by the crowds (Bryson et al. 2013; Frick, 2007).
- *M*: the number of Premier League matches played during the 2015/2016 season. Other researchers showed that the impact of matches played on a player's market value is positive (Bryson et al. 2013; Carmichael & Thomas, 1993; Carmichael et al. 1999; Franck & Nüesch, 2012, Müller et al. 2017) but diminishing (Frick, 2007; Lucifora & Simmons, 2003). For that reason, I add a linear and a quadratic term. I expect a positive effect of *M* and negative effect of $M^2$.
- *G*: the amount of goals a player has scored in Premier League matches during the 2015/2016 season. I predict a positive effect (Bryson et al. 2013; Carmichael & Thomas, 1993; Franck & Nüesch, 2012; Frick, 2007; Herm et al. 2014; Müller et al. 2017), meaning that the more goals a player has scored, the higher his collective market value by the crowds.

- *PM*: the average number of points achieved per Premier League match played by a football player during the 2015/2016 season. I expect a positive effect, suggesting that the higher the average amount of points per match, the higher a player's market value by the crowds.
- *CAPS*: the amount of matches played in the national team during the 2015/2016 season. As the size of the sample is not very comprehensive in this thesis, I cannot capture the effect of *CAPS* for each country separately. So, to limit the number of variables in the model, I assume that the size of the effect of international caps is equal for all countries. In line with other researchers, I expect a positive effect of the number of matches played in the national team on a player's collective market value by the crowds (Carmichael et al. 1999; Lucifora & Simmons, 2003).
- *FANS*: equal to the *FANS* variable in Model 1.
- *HDI*: equal to the *HDI* variable in Model 1.

For a schematic overview of the variables in Model 1 and Model 2 and the expected signs of the effect, I refer to Table 1. As all players in the sample are under contract with clubs in the Premier League during the 2015/2016 season, I ignore the competition level. It would have been the same for all players in the sample anyway.

In both models, I calculate the variables by means of a cross section approach, meaning that I use data from a single point of time for several subjects (Janssens et al. 2008). Regarding the collective player value on *Transfermarkt*, I take the first available value after the 2015/2016 season (the value of most Premier League players was updated on 01-08-2016). The *FANS* variable is based on the amount of followers on social media in September 2016. The objective player values in Model 1 are determined after the summer transfer window of 2016. This means that the values are calculated by the updated Transfer Value Calculator algorithm right after the season(s) of interest. In Model 2, I capture the age of a player and the amount of years left on his contract at the end of the 2015/2016 season. The position variables, amount of matches played, number of goals scored, points per match played and international caps are retrieved from *Transfermarkt* in September 2016. Any adjustments in the statistics after that month are not incorporated in the dataset.

| *Parameters Model 1* | *Name* | *Predicted Sign* | *Parameters Model 2* | *Name* | *Predicted Sign* |
|---|---|---|---|---|---|
| Objective Value | *OBV* | + | Age | *AGE* | + |
| Fans | *FANS* | + | Age Squared | $AGE^2$ | - |
| Human Development Index | *HDI* | + | Goalkeeper | *GK* | +/- |
| | | | Midfielder | *MID* | + |
| | | | Forward | *FW* | + |
| | | | Contract Years | *CY* | + |
| | | | Matches | *M* | + |
| | | | Matches Squared | $M^2$ | - |
| | | | Goals | *G* | + |
| | | | Points per Match | *PM* | + |
| | | | International Caps | *CAPS* | + |
| | | | Fans | *FANS* | + |
| | | | Human Development Index | *HDI* | + |

*Table 1: Variables in the Models and their Predicted Sign*

## 3.2 Data

In this thesis, I use the *Transfermarkt* community as the main data source. First of all, it provides the collective player values based on the principles of the wisdom of crowds (see Chapter 2.2.2). The website of this community is also used to obtain the relevant player and performance statistics. The player's age, his position on the pitch, the remaining years on his contract, the amount of Premier League matches played, the number of goals scored, the average points per Premier League match played and the number of international caps can all be found (or calculated based) on the *Transfermarkt* website.

Additionally, I consult the Facebook, Instagram and Twitter accounts of football players to obtain the amount of fans or followers on social media. Finally, the Human Development Index of a country is found in the Human Development Reports by the United Nations Development Programme (United Nations Development Programme, 2009, 2015).

### 3.2.1 Descriptive Statistics

To qualify for the sample, a football player must meet the criteria of the Transfer Value Calculator (see Chapter 2.2.3). In addition, the majority of the domestic matches he played in the 2015/2016 season must have been in the Premier League. Finally, he must be in possession of an account on Facebook, Instagram or Twitter.

In the Premier League, there are 308 football players who meet those requirements. The average age of the Premier League players in the sample is approximately twenty-six years (26.40). The sample includes 18 goalkeepers, 104 defenders, 82 midfielders and 104 forwards. The mean collective value of a football player is approximately twelve million euros, with a minimum of 0.5 million euros and a maximum of 65 million euros. Table 2 presents the sample mean, median, minimum and maximum value for all the relevant variables in this research.

| | *Mean* | *Median* | *St. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|---|
| ***Collective Value (x 1,000,000 €)*** | 11.869 | 8.000 | 11.108 | 0.500 | 65.000 |
| ***Objective Value (x 1,000,000 €)*** | 14.819 | 7.675 | 21.464 | 0.750 | 250.000 |
| ***Fans (x 1,000,000)*** | 1.011 | 0.230 | 2.760 | 0.005 | 31.621 |
| ***Age*** | 26.396 | 26.000 | 3.345 | 18.000 | 33.000 |
| ***Contract Years*** | 3.380 | 3.000 | 1.137 | 1.000 | 6.000 |
| ***Matches*** | 24.390 | 26.000 | 9.173 | 4.000 | 38.000 |
| ***Goals*** | 2.766 | 1.000 | 4.006 | 0.000 | 25.000 |
| ***Average Points per Match*** | 1.428 | 1.431 | 0.449 | 0.000 | 2.600 |
| ***Caps*** | 4.299 | 3.000 | 4.781 | 0.000 | 16.000 |

*Table 2: Descriptive Statistics*

The allocation of football players over the Human Development Index categories is of great importance in this thesis, because it distinguishes the underdogs from the non-underdogs. As a reminder, underdogs are the players who are born in a country that is in the low or medium HDI category. I consider the HDI categorisation of two years; 2015 and 1990.

To start with, I look at the most recent Human Development Index classification (2015). In this case, I assume that the members of the *Transfermarkt* community base their feelings of sympathy towards the underdogs on the current living conditions in a country. I suppose that they project the current standard of living in a country on the circumstances in which a player grew up. This feels like an appropriate assumption, as the community members are not necessarily specialists on the historical developments of countries and may thus be unaware of the living conditions in the past. In case I consider the HDI of 2015, it turns out that 31 (28 + 3) footballers are classified as underdogs.

However, as this assumption is arbitrary and may not necessarily hold, I also capture the Human Development Index of the year in which a football player is born. This involves some difficulties as the classification and scoring standards of the HDI have been adjusted over time. So, comparing players who are born in different years based on the Human Development Index in their native country would be hard. Additionally, as the HDI is only available since 1990, players who are born earlier could not have been incorporated in the research. To overcome these complications, I decide to look at the Human Development Index classification of the year in which the *average* player in the sample is born; 1990. In case I do so, 46 (30 + 16) underdogs are distinguished. A graphical representation can be found in Figure 2.

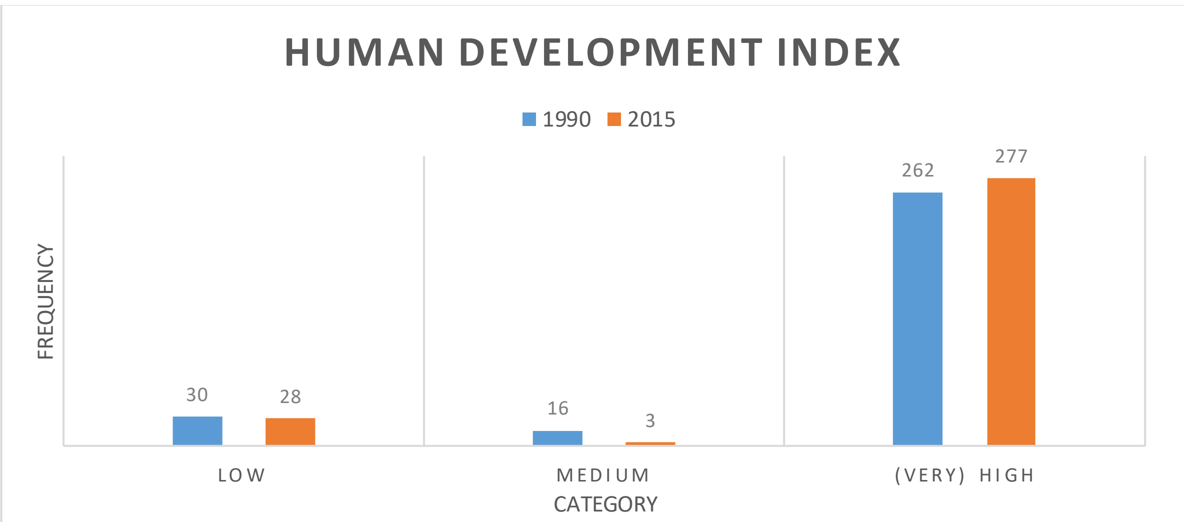


*Figure 2: The Allocation of the Sample over the Human Development Index Categories*

# Chapter 4: Results

In this chapter, I present the main findings. First, I investigate whether the level of human development in a football player's country of birth should be considered as an uninformative performance cue. Thereafter, I test whether the underdog bias is detected in the crowds' valuation of football players in English top-tier football league. Finally, to determine the robustness and external validity of the findings, I check whether the results in the Premier League hold in the German Bundesliga as well.

## 4.1 Main Findings

Before I actually test for the underdog bias in the crowds' valuation of football players in the Premier League, I first show that the Human Development Index in a players' native country can indeed be regarded as an uninformative performance cue. To capture a player's performance, I use the WhoScored player performance rating. These ratings are based on over two hundred performance statistics and they are calculated by means of a unique algorithm. The WhoScored ratings are considered as the most accurate performance indicator in the football world and they are frequently used by bookmakers, media giants and football clubs (WhoScored, 2017). I employ the WhoScored ratings over the 2015/2016 season (Performance 1) and over the last thirty-eight (equal to a full season) Premier League matches played by a footballer (Performance 2).

It turns out that the HDI score is not normally distributed in both 1990 and 2015 (see Appendix 3). As the Pearson correlation requires a normal distribution, I use Kendall's Tau and Spearman's Rho to determine the correlation. In Table 3, it appears that none of the performance indicators are significantly correlated with the Human Development Index of 2015 or 1990. Even if the correlation would have been significant, the coefficients are still very low, suggesting a weak correlation. The insignificance of the correlation indicates that the performance of a player is independent of the Human Development Index in his native country. For that reason, I conclude that being born in an underprivileged country should be considered as an uninformative performance cue.

| | | HDI (1990) | | HDI (2015) | |
|---|---|---|---|---|---|
| | | *Kendall's Tau* | *Spearman's Rho* | *Kendall's Tau* | *Spearman's Rho* |
| **Performance 1** | ***Coefficient*** | -0.008 | -0.013 | -0.024 | -0.037 |
| | ***Significance*** | 0.848 | 0.817 | 0.548 | 0.520 |
| **Performance 2** | ***Coefficient*** | -0.003 | -0.006 | -0.021 | -0.031 |
| | ***Significance*** | 0.939 | 0.922 | 0.607 | 0.593 |

*Table 3: Correlation between Performance and Human Development Index*

As mentioned earlier, I perform a natural logarithmic transformation on the dependent variable. Before I introduce the regression results, I first want to discuss why I did so. The natural logarithmic transformation has a so called '*variance-stabilizing*' effect. It is a valid method to tackle the non-normal distribution of the residuals, especially when it is right skewed (Garson, 2012; Stafford & Sabin, 1990). In Appendix 4, I present the histograms of the distribution of the residuals in Model 2. The first histogram contains the residuals in case I do not transform the dependent variable. As can be seen, the distribution is skewed to the right, which means that the normality assumption is harmed. However, if I replace the dependent variable by the (natural) log transformed collective value, the skewness disappears in the second histogram. This is supported by the Kolmogorov-Smirnov test ($\alpha = 0.10$) and the Shapiro-Wilk test ($\alpha = 0.01$). Other researchers who investigated the determinants of the market value of football players or their salaries used a natural logarithmic transformation as well (Bryson et al. 2013; Franck & Nüesch, 2012; Lucifora & Simmons, 2003; Müller et al. 2017).

A logarithmic transformation of the dependent variable makes the interpretation of the results slightly more complicated. A non-transformed model is about the effect of independent variables on the dependent variable in absolute numbers. However, the transformed '*log-linear model*' can be used to calculate the effects of the independent variables in relative terms. Keep in mind the following model:

$$ln(y) = b_0 + b_n x_n + \varepsilon$$

To calculate the effect of $x_n$ on $y$, I use the inverse of the natural logarithm, which is called the exponential function $e$ (Benoit, 2011; Halvorsen & Palmquist, 1980). In formula, the effect of a one unit change in $x_n$ on $y$ (in %) can be calculated as follows:

$$y = (e^{b_n} - 1) \times 100\%$$

In the remainder of this chapter, I discuss the results for each model individually. I first check whether the models are meaningful by looking at the ANOVA analysis and the explanatory power (Adjusted R-Square). In the ANOVA analysis, I simply test whether the null hypothesis of *'$b_0 = b_1 = b_2 = \ldots = b_n = 0$'* should be rejected. In case this hypothesis is not rejected, the variance that is explained by the model would not be significant and so fit between the model and the data would be insufficient. In other words, the explanatory power would be nil, which means that the model is not meaningful (Janssens et al. 2008). After judging the meaningfulness and explanatory power, I interpret the regression coefficients of the models and determine whether the underdog bias is present.

### 4.1.1 Results Model 1

In Model 1a, I include the Human Development Index classification of 2015, whereas I do so for 1990 in Model 1b. Recall that I capture the average, minimum and maximum objective value that is calculated by the Transfer Value Calculator in both models separately. In other words, I run three regressions for Model 1a and three regressions for Model 1b; one that contains the average objective value, one that contains the minimum objective value and one that contains the maximum objective value. Unless major differences occur, I only explicitly interpret the results of the models that include the average objective value. I mention the effects that are obtained when including the minimum or maximum objective value in parentheses in case they differ from the regression in which the average objective value is captured.

I first check whether the models are meaningful. To start with, the ANOVA analysis shows that there is a good fit between the models and the data (0.01 level). However, the Adjusted R-Square is only 0.403 (min: 0.392, max: 0.413) for Model 1a and 0.413 (min: 0.402, max: 0.423) for Model 1b. In other words, the independent variables explain 40.3% (min: 39.2%, max: 41.3%) and 41.3% (min: 40.2%, max: 42.3%) of the variation in the collective player value in Model 1a and 1b respectively. As the lower bound for a good model is 0.500, the explanatory power of both models is relatively limited (Janssens et al. 2008). Although one should keep this in mind, I still interpret the results.

Table 4 contains the regression coefficients of Model 1a and 1b. As predicted in Chapter 3.1.1, the objective value as calculated by the Transfer Value Calculator (*OBV*) has a significant and positive impact on the collective player value by the crowds. In both models, the collective value is 2.1% (min: 2.1%, max: 2.0%) higher in case the objective value increases by one million euros. To the best of my knowledge, the objective value as obtained from the Transfer

| ***Coefficients*** | ***Objective Value*** | ***Adjusted R-Square*** | ***Constant*** | ***OBV*** | ***OBV²*** | ***FANS*** | ***FANS²*** | ***OBV_ FANS*** | ***HDI*** |
|---|---|---|---|---|---|---|---|---|---|
| ***Model 1a (HDI 2015)*** | AVG | 0.403 | 1.671*** (0.051) | 0.021*** (0.002) | - | 0.098*** (0.015) | - | - | 0.154 (0.133) |
| | MIN | 0.392 | 1.685*** (0.051) | 0.021*** (0.002) | - | 0.100*** (0.015) | - | - | 0.150 (0.134) |
| | MAX | 0.413 | 1.657*** (0.051) | 0.020*** (0.002) | - | 0.096*** (0.015) | - | - | 0.156 (0.131) |
| ***Model 1b (HDI 1990)*** | AVG | 0.413 | 1.641*** (0.052) | 0.021*** (0.002) | - | 0.097*** (0.015) | - | - | 0.290*** (0.111) |
| | MIN | 0.402 | 1.656*** (0.052) | 0.021*** (0.002) | - | 0.099*** (0.015) | - | - | 0.287** (0.112) |
| | MAX | 0.423 | 1.628*** (0.052) | 0.020*** (0.002) | - | 0.095*** (0.015) | - | - | 0.292*** (0.110) |
| ***Extended Model 1a (HDI 2015)*** | AVG | 0.588 | 1.347*** (0.052) | 0.044*** (0.003) | -0.0001*** (0.000) | 0.299*** (0.037) | -0.006*** (0.001) | -0.003*** (0.000) | 0.207* (0.110) |
| | MIN | 0.585 | 1.354*** (0.051) | 0.046*** (0.004) | -0.0001*** (0.000) | 0.302*** (0.038) | -0.006*** (0.001) | -0.003*** (0.000) | 0.209* (0.111) |
| | MAX | 0.591 | 1.340*** (0.052) | 0.042*** (0.003) | -0.0001*** (0.000) | 0.296*** (0.037) | -0.005*** (0.001) | -0.003*** (0.001) | 0.206* (0.110) |
| ***Extended Model 1b (HDI 1990)*** | AVG | 0.594 | 1.332*** (0.051) | 0.044*** (0.003) | -0.0001*** (0.000) | 0.289*** (0.037) | -0.005*** (0.001) | -0.003*** (0.000) | 0.262*** (0.092) |
| | MIN | 0.591 | 1.339*** (0.051) | 0.047*** (0.003) | -0.0001*** (0.000) | 0.292*** (0.037) | -0.005*** (0.001) | -0.003*** (0.000) | 0.263*** (0.092) |
| | MAX | 0.597 | 1.324*** (0.051) | 0.042*** (0.003) | -0.0001*** (0.000) | 0.286*** (0.037) | -0.005*** (0.001) | -0.003*** (0.000) | 0.261*** (0.092) |

*Table 4: Regression Coefficients Model 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

Value Calculator has never been used as a predictor of market value before. For that reason, it is impossible to compare the size of the effect with other studies.

Additionally, the number of followers on social media (*FANS*) has a significant and positive effect on the collective value, which is in accordance with the predictions in Chapter 3.1.1. A million extra followers on social media leads to an increase in collective value of 10.3% (min: 10.5%, max: 10.1%) in Model 1a and 10.2% (min: 10.4%, max: 10.0%) in Model 1b. It is hard to compare the size of the effect with the findings by other researchers, as the popularity of football players has been captured in a variety of ways. However, I am not aware of any related studies that include the popularity of a football player by the amount of followers on social media. For that reason, the only statement I could make is that the positive and significant effect of popularity on the crowds' market valuation of football players is supported by other scientists (Franck & Nüesch, 2012; Herm et al. 2014; Müller et al. 2017).

More interesting, the effect of the underdog variable (*HDI*) is significant in case I consider the Human Development Index allocation of 1990 only. All else being equal, the player value on *Transfermarkt* is 33.6% (min: 33.2%, max: 33.9%) higher for underdogs than for non-underdogs in Model 1b. However, in Model 1a, the effect of *HDI* is insignificant and smaller; 16.6% (min: 16.2%, max: 16.9%). This may be caused by the fact that the underdog variable is highly unbalanced, especially in Model 1a. Based on the HDI classification of 2015, the ratio underdogs to non-underdogs is 1:10, whereas it is 1:7 in case I consider the Human Development Index allocation of 1990. I will elaborate on the effect of unbalanced group sizes on OLS regression in the *Limitations* and *Recommendations* chapters.

An important drawback of Model 1 is that some OLS regression assumptions are being harmed (see Appendix 5). The model may be wrongly specified, the linear and additive relationships are doubted, and the residuals are not normally distributed, nor homoscedastic. As violations of the assumptions may result in biased regression coefficients and errors in the significance, one should be careful when drawing conclusions based on Model 1. Since it solves some of the issues with regard to the OLS assumptions, I include the quadratic term of *OBV* and *FANS*, and the interaction between *OBV* and *FANS* in Extended Model 1a and Extended Model 1b. In the *Limitations* and *Recommendations* chapters, I will elaborate on the effects of violating OLS assumptions in more detail.

#### 4.1.1.1 Results Extended Model 1

The ANOVA analysis indicates that there is still a good fit between the models and the data (0.01 level), which suggests that they are meaningful. Besides, the explanatory power of Extended Model 1a increases to 0.588 (min: 0.585, max: 0.594), whereas it improves to 0.594 (min: 0.591, max: 0.597) for Extended Model 1b. This means that the lower bound of 0.500 is met (Janssens et al. 2008). So, expanding Model 1 with $OBV^2$, $FANS^2$ and *OBV_FANS* solves the limited explanatory power. Again, the exact regression coefficients and their significance are presented in Table 4.

In accordance with Model 1, the effect of *OBV* is significant and positive. In case the objective value increases by one million euros, the collective value grows by 4.5% (min: 4.7% (1a), 4.8% (1b); max: 4.3%). However, the size of the effect is weakened by the negative impact of $OBV^2$ (-0.01%), suggesting a diminishing effect of the objective player value. Again, since the objective value by the Transfer Value Calculator has not been used in related studies before, I cannot compare the size of the effect.

The impact of *FANS* is significant and positive as well. In Extended Model 1a, one million extra followers on social media results in an increase in collective value by 34.5% (min: 35.3%, max: 34.4%), whereas the impact is 33.5% (min: 33.9%, max: 33.1%) in Extended Model 1b. On the other hand, the influence of $FANS^2$ is significant and negative; -0.6% (min: -0.6%, max: -0.5%) in Extended Model 1a and -0.5% in Extended Model 1b. Overall, this suggests a diminishing effect of the number of followers on social media on the collective value of football players on *Transfermarkt*.

The effect of the interaction between *OBV* and *FANS* is significant as well. This means that the variables strengthen each other. Since the impact of *OBV_FANS* is negative (-0.3%), the collective value is lower for players with a high objective value and a large number of followers on social media. Intuitively this does not make sense, as players who perform well and represent a large marketing potential should be most valuable for football clubs.

More important, the impact of *HDI* is significant and positive. In Extended Model 1a, crowds value players who are born in countries that are in the low or medium Human Development Index category 23.0% (min: 23.2%, max: 22.9%) higher than those who are not ($\alpha = 0.10$). In case I use the HDI classification of 1990, underdogs are valued 30.0% (min: 30.1%, max: 29.8%) higher than non-underdogs ($\alpha = 0.01$). Again, the differences between Extended Model 1a and Extended Model 1b may be explained by the small proportion of underdogs in the sample. I will clarify this in the *Limitations* and *Recommendations* chapters.

Although some violations of the OLS regression assumptions are tackled by expanding Model 1, others are still present (see Appendix 5). Extended Model 1 is still wrongly specified, which means that some variables may be missing. Besides, the residuals are not homoscedastic across all the predicted values. Since these violations weaken the reliability of the results (see *Limitations* and *Recommendations*), it is tricky to make some valid statements about the presence and the size of the underdog bias in the collective player valuation by the crowds. For that reason, I capture all the variables of the Transfer Value Calculator separately in Model 2 and test whether the violations are solved.

### 4.1.2 Results Model 2

In accordance with Model 1, I distinguish between the Human Development Index classification of 2015 (Model 2a) and 1990 (Model 2b). The ANOVA analysis indicates that there is a good fit between the models and the data (0.01 level) and so they are relevant. Besides, the explanatory power of Model 2a and 2b is 0.592 and 0.599 respectively, which means that the lower bound of 0.500 for a good model is met (Janssens et al. 2008).

The regression coefficients of Model 2a and 2b are presented in Table 5. Except for the position dummies, the control variables all have a significant effect on the estimated player value by the crowds. The signs of the variables meet the expectations that are presented in Chapter 3.1.1. To start with, the effect of the *AGE* and $AGE^2$ variable is significant in Model 2a and Model 2b. The impact of the former is positive, whereas the influence of the latter is negative in nature. This suggests a diminishing effect of age (Carmichael et al. 1999). The collective value by the crowds is maximized for football players at the age of 25 to 26 years, which is comparable to the findings of Franck and Nüesch (2012) and Bryson, Frick and Simmons (2013).

Regarding the position dummy variables (*GK*, *MID* and *FW*), it turns out that only the impact of *FW* is significant in Model 2a ($\alpha = 0.10$). All else being equal, crowds value forwards 18.2% higher than players on other positions. Although other researchers confirm the higher value and salary of forwards, some of them also found that midfielders are valued higher than defenders and goalkeepers (Bryson et al. 2013; Frick, 2007; Müller et al. 2017). Model 2a only supports the former. In Model 2b, none of the position variables are significant, suggesting that there is no direct effect. However, this is not so uncommon. In some studies, it is argued that the higher value of forwards (and midfielders) is established indirectly through the positive

| *Coefficients* | *Constant* | *AGE* | *AGE²* | *GK* | *MID* | *FW* | *CY* | *M* |
|---|---|---|---|---|---|---|---|---|
| ***Model 2a (HDI 2015)*** | $-8.248^{***}$ (1.702) | $0.623^{***}$ (0.132) | $-0.013^{***}$ (0.003) | 0.108 (0.149) | 0.088 (0.088) | $0.167^{*}$ (0.099) | $0.154^{***}$ (0.034) | $0.070^{***}$ (0.019) |
| ***Model 2b (HDI 1990)*** | $-8.164^{***}$ (1.685) | $0.615^{***}$ (0.131) | $-0.012^{***}$ (0.002) | 0.118 (0.148) | 0.067 (0.087) | 0.148 (0.098) | $0.155^{***}$ (0.034) | $0.068^{***}$ (0.019) |
| ***Extended Model 2a*** | $-8.157^{***}$ (1.567) | $0.627^{***}$ (0.121) | $-0.013^{***}$ (0.002) | 0.024 (0.138) | -0.050 (0.095) | $0.174^{*}$ (0.092) | $0.143^{***}$ (0.031) | $0.060^{***}$ (0.018) |
| ***Extended Model 2b*** | $-8.038^{***}$ (1.555) | $0.618^{***}$ (0.120) | $-0.012^{***}$ (0.002) | 0.033 (0.137) | -0.063 (0.094) | $0.168^{*}$ (0.091) | $0.143^{***}$ (0.031) | $0.058^{***}$ (0.018) |
| ***Coefficients (Continued)*** | ***M²*** | ***G*** | ***G_MID*** | ***PM*** | ***CAPS*** | ***FANS*** | ***FANS²*** | ***HDI*** |
| ***Model 2a (HDI 2015)*** | $-0.001^{**}$ (0.000) | $0.031^{**}$ (0.012) | - | $0.563^{***}$ (0.077) | $0.034^{***}$ (0.008) | $0.079^{***}$ (0.013) | - | 0.122 (0.113) |
| ***Model 2b (HDI 1990)*** | $-0.001^{**}$ (0.000) | $0.031^{***}$ (0.012) | - | $0.562^{***}$ (0.076) | $0.034^{***}$ (0.008) | $0.079^{***}$ (0.013) | - | $0.240^{**}$ (0.094) |
| ***Extended Model 2a*** | $-0.001^{**}$ (0.000) | 0.015 (0.011) | $0.055^{**}$ (0.024) | $0.496^{***}$ (0.072) | $0.025^{***}$ (0.007) | $0.256^{***}$ (0.028) | $-0.008^{***}$ (0.001) | $0.186^{*}$ (0.105) |
| ***Extended Model 2b*** | $-0.001^{*}$ (0.000) | 0.015 (0.011) | $0.055^{**}$ (0.024) | $0.498^{***}$ (0.071) | $0.025^{***}$ (0.007) | $0.250^{***}$ (0.027) | $-0.007^{***}$ (0.001) | $0.226^{***}$ (0.087) |

*Table 5: Regression Coefficients Model 2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

impact of goals scored. Since most goals are scored by forwards[1], the positive effect of goals automatically results in a higher value of forwards. As midfielders score more goals than defenders and goalkeepers, the same applies to the value of midfielders compared to that of players on those two positions (Carmichael & Thomas, 1993; Carmichael et al. 1999).

The remaining contract years at the current club (*CY*) has a positive and significant influence on the player value by the crowds. An additional contract year increases the collective value by 16.7% in Model 2a and 16.8% in Model 2b. The positive effect is supported by Frick (2007). However, since he does not present the exact numbers, it is impossible to compare the size of the effect.

Additionally, the amount of matches played during the 2015/2016 season significantly affects the value on *Transfermarkt* as well. In accordance with Frick (2007), the linear variable (*M*) is positive, whereas the squared term ($M^2$) is negative. In Model 2a and Model 2b, the collective value is optimized for footballers who played thirty-four matches. Although Lucifora and Simmons (2003) support the diminishing impact of appearances, they do not so for the optimal amount of matches played. In their research, the optimal number of matches exceeds the maximum amount of matches that a player could have played during the season. In other words, the squared term only captures the non-linearity of the effect.

Another important determinant of the market value of football players is the number of goals scored (*G*). In Model 2a and 2b, the collective player value significantly increases by 3.1% for each goal scored during the 2015/2016 season. Many researchers confirm the positive impact of goals on the market value of a football player (Carmichael & Thomas, 1993; Frick, 2007; Herm et al. 2014; Lucifora & Simmons, 2003). Besides, the size of the effect is more or less comparable to what is found by Müller, Simons and Weinmann (2017), who established an impact of 2.7% per goal scored.

The average amount of points per match played by a footballer (*PM*) in the 2015/2016 season has a significant and positive impact on the market value as well. In case the average amount of points per match increases by one, the collective value of a player on *Transfermarkt* grows by 75.6% in Model 2a and 75.4% in Model 2b. The influence of team effects is confirmed in other studies before, however the size of the effect is not explicitly stated (Bryson et al. 2013; Franck & Nüesch, 2012; Lucifora & Simmons, 2003).

Also, the number matches played for the national team (*CAPS*) during the 2015/2016 season significantly improves the market value of a football player. For each international cap,

[1] The correlation between *G* and *FW* is significant ($\alpha = 0.01$). In case I use Kendall's tau it is 0.446, whereas it is 0.506 if I look at Spearman's rho. This means that most goals are scored by forwards.

the collective value increases by 3.5% in Model 2a and 2b. In previous studies, researchers distinguished between countries and included dummy variables to capture impact international status rather than the amount of caps played (Bryson et al. 2013; Carmichael et al. 1999; Lucifora & Simmons, 2003). Since I do not so to limit the number of variables in the model, it is impossible to compare the size of the effect.

The amount of followers on social media (*FANS*) has a significant and positive effect in Model 2 as well. The market value by the crowds increases by 8.2% per million followers. As is the case for Model 1, it is not possible to compare the size of the effect. Although the popularity of football players has been captured in a variety of ways, I am not aware of any studies that use the amount of followers on social media. For that reason, all I can conclude is that this thesis confirms the positive effect of popularity and marketing potential on the market value of a football player (Franck & Nüesch, 2012; Herm et al. 2014; Müller et al. 2017).

In accordance with Model 1, the impact of *HDI* is significant in case I use the Human Development Index classification of 1990 only. Crowds value underdogs 27.1% higher than non-underdogs in Model 2b. In Model 2a, the effect of *HDI* would be 13.0% in case it were significant. As in Model 1a, the insignificance of the Human Development Index Category in Model 2a may be explained by the small number of underdogs in the sample (see *Limitations* and *Recommendations*). Overall, I conclude that the underdog bias in Model 2 is a bit smaller than in Model 1.

Unfortunately, some assumptions of OLS regression are harmed (see Appendix 5.1). In line with (Extended) Model 1, Model 2 is still wrongly specified. Besides, some quadratic and interaction effects are missing. The consequences of these violations are discussed in the *Limitations* and *Recommendations* chapters. Since adding $FANS^2$ and the interaction effect between the number of goals scored and the midfielder dummy variable (*G_MID*) significantly improves the model, I do so in Extended Model 2.

#### 4.1.2.1 Results Extended Model 2

Extended Model 2a contains the HDI classification of 2015, whereas the allocation of 1990 is included in Extended Model 2b. The ANOVA analysis shows that the models are meaningful. Besides, the explanatory power of Extended Model 2a enhances to 0.655, whereas that of Extended Model 2b increases to 0.659. This suggest that the lower bound of 0.500 is met (Janssens et al. 2008). The regression coefficients can be found in Table 5.

To start with, the impact of *AGE* is positive, while that of $AGE^2$ is negative. Both variables are significant, suggesting a diminishing effect of age on the collective player values on *Transfermarkt*. In accordance with Model 2, the market value of footballers is maximized for players at the age of 25 to 26. This finding is supported by previous studies about the valuation of football players (Franck & Nüesch, 2012; Bryson et al. 2013).

In accordance with Model 2a, *FW* is the only position dummy variable that significantly affects the collective player value. In Extended Model 2a, forwards are valued 19.0% higher than football players on other positions ($\alpha = 0.10$). The size of the effect is slightly larger than in Model 2a. However, in contrast with Model 2b, the impact of *FW* is significant and positive in Extended Model 2b as well ($\alpha = 0.10$). In this model, crowds value forwards 18.3% higher than midfielders, defenders and goalkeepers. The increased size of the effect in Extended Model 2a and the significance of *FW* in Extended Model 2b can be explained in combination with some other variables. Unlike Model 2, the effect of goals (*G*) is insignificant in Extended Model 2. Since most goals are scored by forwards and *FW* is the only significant position variable, one could argue that the impact of goals scored by forwards is captured in the forward position dummy. This means that forwards get a premium in value automatically, because they are expected to score goals. At the same time, the second most goals are scored by midfielders. Their value significantly increases by 5.7% for each goal scored (*G_MID*), which suggests that goal-scoring midfielders are valued higher than defenders and goalkeepers. This theory is supported by Carmichael and Thomas (1993). They found that the impact of goals on the market value of football players decreases when position dummies are added, which is caused by the high correlation between *FW* and *G*.

As expected in chapter 3.1.1, the effect of the amount of years remaining on a player's contract with his current club (*CY*) is significant as well (Frick, 2007). The collective value by the crowds increases with 15.4% per contract year in Extended Model 2a and 2b. The size of the effect is a little lower than in Model 2.

In accordance with Model 2, the impact of matches played (*M* and $M^2$) is significant and diminishing. The market value of a football player is optimized in case he played thirty-eight matches during the 2015/2016 season. Since the Premier League consists of twenty teams, this is the maximum number of matches a footballer could have possibly played. So, $M^2$ is included just to capture the non-linearity, which is supported by Lucifora and Simmons (2003).

The influence of the *PM* variable is significant as well. In case the average amount of points per match played by a footballer increases by one, the collective player value on *Transfermarkt* grows by 64.2% in Extended Model 2a and 64.5% in Extended Model 2b. The size of the effect is lower than in Model 2. The same applies to the amount of games played for the national team (*CAPS*) during the 2015/2016 season. In Extended Model 2a and 2b, the crowds' estimation of the market value of a football player increases by 2.5% for each match played in the national team.

In line with Model 2, the impact of *FANS* is significant and positive. However, the quadratic term ($FANS^2$) significantly affects the market value of football players in a negative direction, which means that the overall effect of followers on social media is diminishing. In Extended Model 2a and 2b, the collective value is maximized for players who have around seventeen million followers on social media.

More important is the effect of the underdog variable. In contrast to Model 2a, the impact of *HDI* is significant and positive in Extended Model 2a ($\alpha = 0.10$). Based on the Human Development Index classification on 2015, crowds value players who are born in the low or medium category 20.4% higher than players whose native country is in one of the other classes. Besides, the value of underdogs is 25.4% larger than that of non-underdogs in Extended Model 2b ($\alpha = 0.01$). So, Extended Model 2 detects an underdog bias in the collective valuation of football players in case I use the HDI allocation of either 2015 or 1990. Again, the proportion of underdogs in the sample is relatively limited, especially in Extended Model 2a. For that reason, the estimated effect of *HDI* may be incorrect (see *Limitations* and *Recommendations*).

Based on the assumptions of Ordinary Least Squares regression, Extended Model 2 is the best model in this thesis. Unfortunately, it remains wrongly specified (see Appendix 5.2). Since violating the specification assumption may result in biased regression coefficient (Bera & Jarque, 1982), one should be careful when drawing firm conclusions. For more information, I refer to the *Limitations* and *Recommendations* chapters.

The next step is to investigate the external validity of the results. I do so by applying the exact same models to the Bundesliga, the top-tier football league in Germany. In the next chapter, I briefly describe the results. A schematic overview of the descriptive statistics, the regression coefficients and the OLS regression assumptions can be found in Appendix 6.

## 4.2 Robustness Checks

In this chapter, I present the results in de Bundesliga. The sample consists of 278 football players who are suitable for the analysis. In accordance with the players in the Premier League, the average age of a footballer in the Bundesliga is 26 years. So, I distinguish the underdogs from the non-underdogs based on the Human Development Index classification of 2015 and 1990 again. The correlation between performance and HDI is insignificant (see Appendix 6.1), which suggests that the degree of human development in the country of birth may be approached as an uninformative performance cue.

When I look at the Human Development Index allocation of 2015 (1990), the sample contains six (eighteen) underdogs (see Appendix 6.2). This means that the proportion of underdogs in the sample is very small, which may have some negative consequences for the reliability of the regression results. I will elaborate on this in the *Limitations* and *Recommendations* chapters.

In accordance with the Premier League, it will appear that some of the OLS regression assumptions are harmed in case I test for the underdog bias in the valuation of football players in the Bundesliga. This may reduce the validity of the results even further. I will discuss these issues and the possible solutions in the *Limitations* and *Recommendations* chapters as well.

### 4.2.1 Results Model 1 - Bundesliga

Although the explanatory power of Model 1a (0.396) and 1b (0.398) is limited, the ANOVA analysis suggests that there is a good fit between the model and the data. The effects of *OBV* and *FANS* are significant and positive (see Appendix 6.3). In Model 1a, the collective value of a footballer increases by 5.5% (min: 6.1%, max: 5.2%) in case the objective value grows by one million euros. Besides, the crowds' valuation of a football player rises by 15.6% per million followers on social media. In Model 1b, the impact is *OBV* is 5.7% (min: 6.1%, max: 5.2%), whereas that of *FANS* is 15.5%. So, the influence of both variables is larger in the Bundesliga sample than in the Premier League sample.

| | ***Objective Value*** | ***Model 1a*** | ***Model 1b*** | ***Extended Model 1a*** | ***Extended Model 1b*** |
|---|---|---|---|---|---|
| ***Human Development Index*** | AVG | 0.262<br>(0.342) | 0.243<br>(0.202) | 0.271<br>(0.278) | 0.207<br>(0.164) |
| | MIN | 0.262<br>(0.342) | 0.243<br>(0.202) | 0.272<br>(0.278) | 0.206<br>(0.164) |
| | MAX | 0.262<br>(0.342) | 0.244<br>(0.202) | 0.271<br>(0.278) | 0.207<br>(0.164) |

*Table 6: The Regression Coefficients of the Underdog Variable in Model 1*

More important, as presented in Table 6, the effect of *HDI* is insignificant, which means that the collective valuation by the crowds is not significantly affected by the Human Development Index category in a player's country of birth. This contradicts the findings in the Premier League, since Model 1b detects an underdog bias in the crowds' valuation of football players in the top-tier football league in England. In case I neglect the insignificance of the effect, crowds would value the underdogs 31.1% higher than the non-underdogs in Model 1a. The impact of *HDI* would be 27.5% (min: 27.5%, max: 27.6%) in Model 1b.

An explanation for the different results may be the smaller proportion of underdogs in the Bundesliga sample. Besides, some of the OLS assumptions are harmed (see Appendix 6.5), which lowers the reliability of the results. In case I expand Model 1 with $OBV^2$, $FANS^2$ and *OBV_FANS*, most of these violations are resolved. For that reason, I do so in Extended Model 1. The explanatory power of Extended Model 1a (1b) improves to 0.603 (0.604) and the ANOVA analysis shows that there is a good fit between the model and the data. I report the exact regression coefficients in Appendix 6.3.

The collective player value grows by 13.8% (min: 15.0%, max: 12.9%) in Extended Model 1a and 13.9% (min: 15.1%, max: 12.9%) in Extended Model 1b if the objective value of a footballer increases by one million euros. However, in the latter model, $OBV^2$ has a significant effect of -0.1% on the collective value ($\alpha = 0.10$). This means that the overall impact of the objective value on the crowds' valuation of football players in the Bundesliga is diminishing. However, the influence of $OBV^2$ is insignificant in Extended Model 1a.

One million extra followers on social media results in an increase in collective value of 55.9% (min: 56.0%, max: 55.7%) in Extended Model 1a and 54.2% (min: 54.3%, max: 54.0%) in Extended Model 1b. However, the effect of $FANS^2$ is -2.0% and -1.9% respectively, which suggests a diminishing impact. Since the influence of *OBV_FANS* is -0.8% (min: -0.8%, max: -0.7%) in Extended Model 1a and 1b, the diminishing effect of *OBV* and *FANS* is strengthened. This supports the findings in the Premier League.

More important, the impact of the underdog variable is insignificant, suggesting that the Human Development Index in a player's country of birth does not affect the collective valuation by the crowds. This contradicts the results in the Premier League, which is probably caused by the limited amount of underdogs in the Bundesliga sample. In case *HDI* were significant, crowds would value the underdogs 31.1% (min: 31.3%, max: 31.1%) higher than the non-underdogs in Extended Model 1a, whereas the size of the effect would be 23.0% (min: 22.9%, max: 23.0%) in Extended Model 1b. Nonetheless, it turns out that Extended Model 1 is still wrongly specified (see Appendix 6.3), which weakens the reliability of the findings.

### 4.2.2 Results Model 2 - Bundesliga

Model 2a and 2b contain each component of the Transfer Value Calculator individually. The ANOVA analysis shows that there is a good fit between the model and the data, whereas the explanatory power improves to 0.681. It turns out most of the estimated regression coefficients are equal for Model 2a and 2b. The exact coefficients can be found in Appendix 6.4.

The impact of *AGE* and *AGE*$^2$ is significant and diminishing. The collective value on *Transfermarkt* is optimized for football players at the age of 24. Although this is two years younger than in the Premier League sample, Carmichael, Forrest and Simmons (1999) argue that the market value is maximized for even younger players.

In contrast with the findings in the Premier League, the effect of *FW* is negative in Model 2 ($\alpha = 0.10$). All else being equal, crowds value forwards 25.6% lower than football players on other positions. However, since forwards score most goals, the negative influence of *FW* may be compensated by the larger effect of *G*. The collective value increases by 4.8% (2b: 4.7%) for each goal scored. This means that forwards who score more goals than players on other positions may still be valued higher by the crowds. As is the case in the Premier League, the impact of the other position dummy variables is insignificant.

In contrast with the findings in the Premier League, the insignificance of *M*$^2$ suggests that the effect of matches played is linear in Model 2. The estimated player value by the crowds grows by 8.7% per domestic match played. All the other control variables confirm the results in the Premier League when it comes to the significance and the sign of the impact. The collective value increases by 24.4% per remaining contract year; by 112.8% in case the average amount of points per match grows by one; by 4.3% per cap; and by 11.3% per million followers on social media. The size of the effects is larger in the Bundesliga than in the Premier League.

| | ***Model 2a*** | ***Model 2b*** | ***Extended Model 2a*** | ***Extended Model 2b*** |
|---|---|---|---|---|
| ***Human Development Index*** | -0.045<br>(0.254) | 0.002<br>(0.152) | 0.007<br>(0.244) | 0.0002<br>(0.147) |

*Table 7: Regression Coefficients of the Underdog Variable in Model 2*

More interesting, the impact of being born in a country that is in the low or medium Human Development Index category is insignificant. This contradicts the previous findings, since Model 2b detects an underdog bias in the collective valuation of football players in the

Premier League. In case I ignore the insignificance, the effect of *HDI* would be -4.4% in Model 2a and 0.2% in Model 2b. This suggests that crowds would value the non-underdogs higher than the underdogs in Model 2a, whereas the difference would be very small in Model 2b, which conflicts the findings in Premier League sample even more.

These contradictory results may be caused by the limited amount of underdogs in the Bundesliga sample. Additionally, some of the OLS regression assumptions are being harmed in Model 2 (see Appendix 6.5), which decreases the validity of the results. Since adding $FANS^2$ and *G_MID* partly solves these violations, I do so in Extended Model 2. The ANOVA analysis shows that Extended Model 2 is meaningful, whereas the explanatory power improves to 0.704. As is the case for Model 2, the regression coefficients of Extended Model 2a and 2b are roughly the same (see Appendix 6.4).

In accordance with the previous findings in this thesis, the effect of age is diminishing. The valuation by the crowds is maximized for players who are 23 years old, which is supported by Carmichael, Forrest and Simmons (1999).

Regarding the position dummies, it turns out that crowds value forwards (midfielders) 19.6% (16.4%) lower than defenders and goalkeepers ($\alpha = 0.10$). The significance of *MID* contradicts the previous findings in this thesis. The explanation of the negative effect of *FW* (and *MID*) is equal to that in Model 2. Since most goals are scored by forwards, the positive impact of goals can compensate the negative influence of *FW*. It turns out that the market value by the crowds increases by 3.6% per goal scored. However, there is a position specific effect of goals scored as well. Midfielders, who score the second most goals, earn an extra premium in value per goal scored. Next to the impact of *G*, *G_MID* indicates that there is an extra increase in collective value of 6.6% per goal scored by midfielders. For that reason, midfielders have to score fewer goals to compensate the negative effect of the position dummy.

In contrast to Model 2, the impact of $M^2$ is significant ($\alpha = 0.10$), suggesting a diminishing impact of matches played. It turns out that the optimal number of matches exceeds the overall amount of matches played by a club. This means that the optimal number of matches cannot be achieved, which suggests that $M^2$ is only included to capture the non-linearity of the effect (Lucifora and Simmons, 2003). This confirms the findings in the Premier League.

In accordance with Model 2, the effects of *CY*, *PM* and *CAPS* support the findings in the Premier League when it comes to the significance and the sign of the effect. The collective value increases by 24.1% per remaining contract year; by 88.9% in case the average amount of points per match grows by one; and by 2.8% per cap. Compared to the Premier League, the size of the effect is larger in the Bundesliga.

In Extended Model 2, the impact of *FANS* and *FANS*$^2$ is significant. Since the effect of the former is positive and that of the latter is negative, the amount of followers has a diminishing influence on the collective player value on *Transfermarkt*. The market valuation by the crowds is optimized for players who have around 7.5 million followers on social media. This number is much lower than in the Premier League, which may be explained by the fact that Bundesliga players are much less popular on social media (see Appendix 6.2).

More important, the effect of the Human Development Index category in a football player's country of birth is insignificant. This means that the underdog bias is not detected in the collective valuation of Bundesliga players, which contradicts the findings in the Premier League. Again, this may be caused by the lower proportion of underdogs in the Bundesliga sample. In case I overlook the insignificance, the impact of *HDI* would be 0.7% in Extended Model 2a and 0.02% in Extended Model 2b. The limited size of the effect would conflict the results in the Premier League even further. However, one should keep in mind that Extended Model 2 is still wrongly specified, which may reduce the reliability of the estimated regression coefficients.

Overall, I conclude that the presence of the underdog bias is not demonstrated in the Bundesliga. In none of the models, the effect of the *HDI* variable is significant. This means that the findings in the Premier League are not supported by the results in the Bundesliga.

# Chapter 5: Discussion

## 5.1 Conclusions

In this thesis, I study the impact of uninformative performance cues on collective judgements in the field of football. More specifically, I test for the presence of an underdog bias in the crowds' valuation of football players in the Premier League. I distinguish the underdogs from the non-underdogs based on the Human Development Index in a footballer's native country. This is a composite measure of health, education and income by the United Nations. In case players are born in a country that is in the low or medium HDI category, I define them as underdogs. These football players started their lives in a disadvantaged position and therefore people would feel sympathy for them.

The crowds' valuation of football players is obtained from a football statistics website called *Transfermarkt*. On this website, community members may suggest market valuations of football players. Based on these suggestions and their own opinions, some authorized members determine the collective market values. Those values accurately predict the actual transfer fees paid and so they are referred to in many other scientific papers.

In Model 1, I include the valuation of football players as obtained from the Transfer Value Calculator by the CIES Football Observatory. This calculator captures some objective player and performance statistics, like age, contract length, matches played, goals scored and international appearances. The individual impact of those factors on the market value of footballers has been proven in other studies before. In Model 2, I include all the components of the Transfer Value Calculator separately, which allows me to determine the exact effect of each factor. Additionally, I incorporate the popularity of a football player in both models.

The underdog bias is detected in Model 1 and Model 2 in case I consider the HDI classification of 1990, the year in which the average player in the sample is born. It turns out that crowds value players whose native country is in the low or medium HDI category higher than players to whom this does not apply. However, if I use the most recent Human Development Index classification (2015), the crowds' favourable attitude towards underdogs is only detected in the extended models ($\alpha = 0.10$). As the Human Development Index category is uncorrelated with player performance, I conclude that these findings suggest that crowds include uninformative performance cues in the way they value others.

To check the generalizability of the results, I apply the exact same models to the collective valuation of football players in the German Bundesliga. However, it turns out that the findings in the Premier League are not supported by the results in the Bundesliga. None of the models provide evidence for the existence of an underdog bias in crowds' valuation of football players. For that reason, the findings in the Premier League may not be applicable to other football competitions. So, this thesis provides initial evidence for the presence of the underdog bias in the valuation of football players, however more research is needed.

## 5.2 Limitations

As is the case for almost every research, this thesis deals with some limitations. Most important, the proportion of underdogs in the sample is very low. In case I use the HDI classification of 2015, the proportion is 1:10, whereas it improves 1:7 if I distinguish the underdogs from the non-underdogs based on the HDI of 1990. Remember that the regression coefficients are estimated in such a way that sum of square of the residuals is as small as possible. If the proportion of underdogs is too small, the best way to estimate the regression coefficients is to assume that all players are non-underdogs. By doing so, the other regression coefficients can be optimized, which would result in optimal estimates for 90% (the non-underdogs) of the sample in case I use the HDI classification of 2015. For that reason, the size of the effect and the significance of the underdog variable may be incorrect in case the sample is too imbalanced (Chawla, Bowyer, Hall, Kegelmeyer, 2002; He & Garcia, 2009). Since $HDI_{2015}$ is more imbalanced than $HDI_{1990}$, this could be an explanation of why the significance of the *HDI* variable differ between (Extended) Model 1a and (Extended) Model 1b. The same applies to (Extended) Model 2a and (Extended) Model 2b.

Additionally, a major limitation in this thesis is the fact that not all the OLS assumptions are met, especially in Model 1 and 2. In Extended Model 1 and 2, I add some quadratic and interaction effects, which solves most of the violations. However, both models are still wrongly specified, which may result in incorrect regression coefficients. The specification error may be caused by missing predictor variables (omitted variable bias), the inclusion of irrelevant variables or the violation of the assumptions about normal and homoscedastic residuals (Bera & Jarque, 1982). Next to the specification assumption, the null hypothesis of homoscedastic residuals is rejected in Extended Model 1 as well. Although this does not affect the estimators, it does influence the significance of the effect (Long & Ervin, 2000). This may lead to erroneous conclusions about the effect of a variable on the collective market value of football players.

Next to the limitations that are related to statistics, there are some practical drawbacks as well. To start with, Wolff, Chong and Auffhammer (2011) argue that the Human Development Index may suffer from data error, which results in countries being misclassified. If this is the case, it may be that some football players are incorrectly labelled as underdogs or non-underdogs. This would undesirably impact the results.

Besides, as I lack financial resources for this thesis, I use the free version of the Transfer Value Calculator that is publicly available on the CIES Football Observatory website. Although this free edition provides some rough estimates of the market value of football players, the more sophisticated edition will undoubtedly offer more detailed and thus more reliable estimates. So, in case I had an actual budget for this research, I would use the more sophisticated Transfer Value Calculator.

Finally, I might have misinterpreted the *PM* variable in the Transfer Value Calculator. I consider it as a team performance variable and include the average amount of points per match played by the football player. So, I do not consider the matches in which a footballer did not play. Alternatively, I could approach it as an indicator of club success or strength and incorporate the average number of points per match achieved by the team, irrespective of whether a player performed in a match. As the algorithm of the Transfer Value Calculator is already adjusted based on the player transfers during the most recent transfer period, it is impossible to recalculate the objective player value based on the data of the 2015/2016 season. Nonetheless, in Appendix 7, I present the regression coefficients of the *PM* and *HDI* in case I define PM on club level. It turns out that there are no major changes in the size or the significance of the effects. I also tested whether the new PM variable would solve the model specification issues, however this is not the case.

## 5.3 Recommendations

In this thesis, I provide some initial evidence for existence of an underdog bias in the crowds' valuation of football players. However, because of the statistical limitations, the exact size of the underdog bias may not be very reliable. The lowest (significant) effect is 20.4% in Extended Model 2a up to even 33.6% in Model 1b. Intuitively, these impacts seem rather large. For that reason, it may be good to do the analysis again and correct for the statistical limitations. By doing so, more reliable conclusions about the underdog bias can be drawn.

To solve issue of imbalanced group sizes, one could use the oversampling method. The easiest way to do so is to replicate (some of) the existing underdogs and add the newly created, artificial underdogs to the sample. However, as this technique may lead to overfitting, it may be better to use more sophisticated procedures, like the Synthetic Minority Over-sampling Technique (Chawla et al. 2002; He & Garcia, 2009).

Additionally, one should correct for the heteroskedasticity of the residuals in Extended Model 1. One way to do so would be to weigh the observations by the inverse of the standard deviation of the residuals or by transforming some (of the) independent variable(s). As it is not always possible to do so correctly, more complex methods are available as well. A well-known technique is to use tests that are based on heteroscedasticity consistent covariance matrixes (Long & Ervin, 2000).

The specification problems in the current models could be solved by using a model whose accuracy has been proven by other studies in highly regarded journals. By doing so, one could avoid that there are some variables missing in the model. A good example may be the paper of Franck and Nüesch (2012). To a large extent, they agree with (Extended) Model 2 in this thesis. The main difference is that Frank and Nüesch (2012) use more detailed performance statistics to capture the capabilities of a football player. An interesting direction for further research would be to expand this model with the HDI variable to test for the underdog bias.

After these adjustments are made, one could test for the underdog bias in the crowds' valuation of football players in the Premier League again. As the statistical limitations of the current thesis are solved, this expanded research would result in better estimates of the regression coefficients. For that reason, more reliable conclusions about the presence and the size of the underdog bias could be drawn. For robustness issues, one should apply the newly created model to other football competitions as well. In thesis it turns out that there are only very few underdogs in the Bundesliga. Although oversampling could correct for this, it may be better to use another competition to judge the external validity of the results.

To finalize, this thesis provides a good starting point for other researchers who want to invest the underdog bias in the crowds' valuation of football players based on the living conditions in their countries of birth. Initial evidence for the existence of the underdog bias in the field of football is presented. In case the statistical limitations are solved in follow-up research, more specific and reliable conclusions could be drawn. If the underdog bias would still be detected, one could conclude that uninformative cues are used in aggregated group behavior.

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# Appendix

## Appendix 1 – Discussion Thread *Transfermarkt*

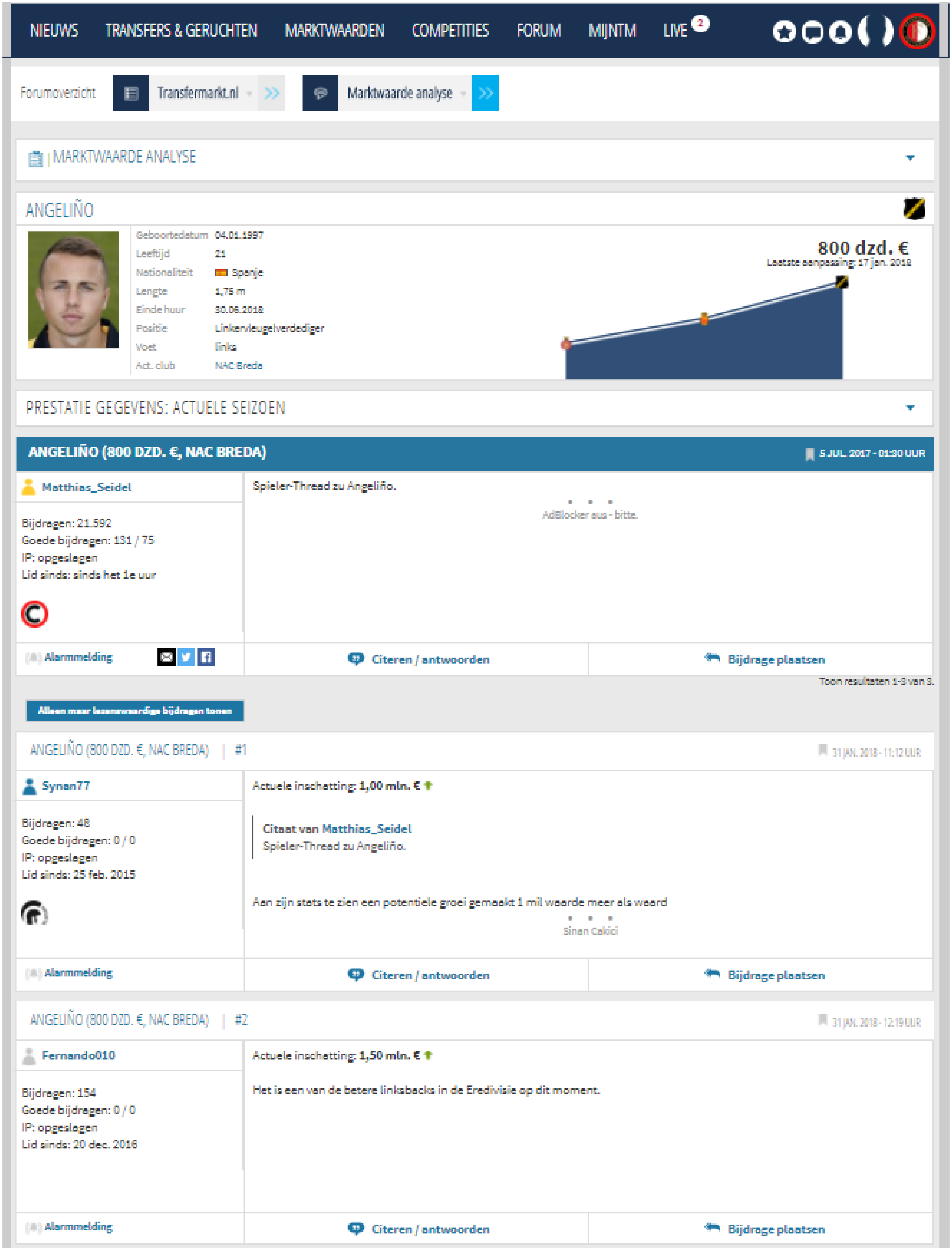


*Figure 3: Discussion Thread Transfermarkt*

# Appendix 2 – The Transfer Value Calculator and the Resulting Output

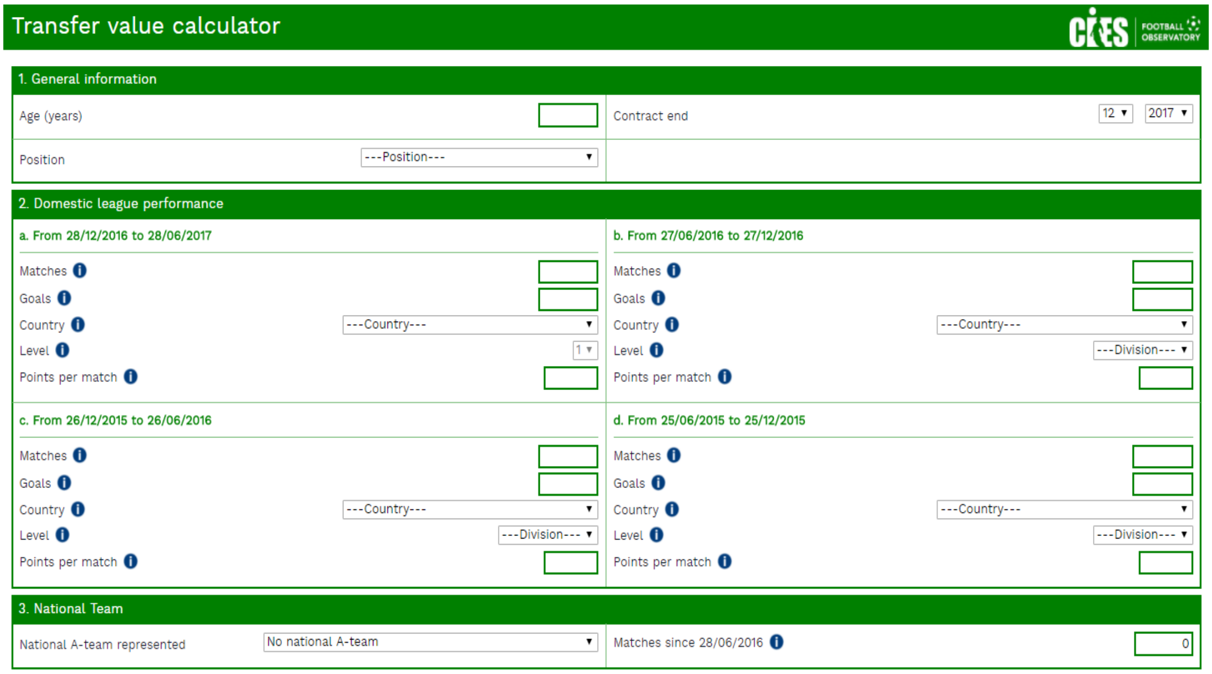


*Figure 4: Transfer Value Calculator*

## Player transfer value calculator

Dear user,

According to the information provided, the transfer market value of the player is between **€ 5.0 million** and **€ 5.8 million**. The CIES Football Observatory academic team is at your disposal for more detailed analysis and market value scenarios. For more information about our products and services, please contact us at football.observatory@cies.ch

### About CIES Football Observatory

The CIES Football Observatory is a research group within the International Centre for Sports Studies (CIES), which is an independent study centre located in Neuchâtel, Switzerland. Created in 2005 by Dr. Raffaele Poli and Dr. Loïc Ravenel, the CIES Football Observatory currently comprises a staff of four full-time permanent researchers who specialise in the statistical analysis of football. Click here for more information.

### About the CIES

The International Centre for Sports Studies (CIES) is an independent study centre located in Neuchâtel, Switzerland. It was created in 1995 as a joint venture between the Fédération Internationale de Football Association (FIFA), the University of Neuchâtel, the City and State of Neuchatel. Click here for more information.

*Figure 5: Output Transfer Value Calculator*

## Appendix 3 – Normal Distribution HDI and Performance

| | Kolmogorov-Smirnov | | Shapiro-Wilk | |
|---|---|---|---|---|
| | *Statistic* | *Significance* | *Statistic* | *Significance* |
| ***HDI (1990)*** | 0.405 | 0.000* | 0.487 | 0.000* |
| ***HDI (2015)*** | 0.356 | 0.000* | 0.597 | 0.000* |
| ***Performance 1*** | 0.035 | 0.200 | 0.992 | 0.121 |
| ***Performance 2*** | 0.035 | 0.200 | 0.994 | 0.321 |

*Table 8: Normal Distribution Tests for HDI and Performance*

* The null hypothesis of a normal distribution is rejected for HDI (1990) and HDI (2015).

# Appendix 4 – Natural Logarithmic Transformation Dependent Variable

## Historgram 1:

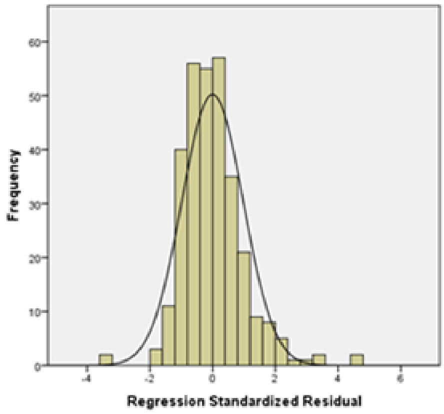


*Figure 6: Distribution of the residuals in case the dependent variable is Collective Value*

Dependent Variable:
Collective Value

| **Kolmogorov-Smirnov** | | **Shapiro-Wilk** | |
|---|---|---|---|
| ***Statistic*** | ***Sig.*** | ***Statistic*** | ***Sig.*** |
| 0.077 | 0.000 | 0.931 | 0.000 |

The null hypothesis of a normal distribution is rejected

## Histogram 2:

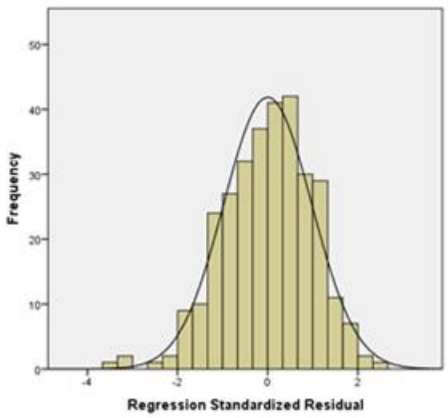


*Figure 7: Distribution of the residuals in case the dependent variable is LN (Collective Value)*

Dependent Variable:
LN (Collective Value)

| **Kolmogorov-Smirnov** | | **Shapiro-Wilk** | |
|---|---|---|---|
| ***Statistic*** | ***Sig.*** | ***Statistic*** | ***Sig.*** |
| 0.039 | 0.200** | 0.931 | 0.031* |

The null hypothesis of a normal distribution is not rejected in case α = 0.01 (*) or α = 0.10 (**)

## Appendix 5 – Assumptions OLS Regression

To test whether the assumptions of multiple regression hold, I use the methods that are described by Janssens, Wijnen, De Pelsmacker and Van Kenhove (2008, p.150-168). In Table 9 and 10, I present a schematic overview. I shortly describe the analysis for each assumption afterwards.

### Appendix 5.1 – Assumptions OLS Regression Model 1

| *Assumptions* | *Model 1a* | *Model 1b* | *Extended Model 1a* | *Extended Model 1b* |
|---|---|---|---|---|
| *1. Causality* | + | + | + | + |
| *2. All Variables Included* | - | - | - | - |
| *3. Interval Scale* | + | + | + | + |
| *4. Linear Relationship* | - | - | + | + |
| *5. Additive Relationship* | - | - | + | + |
| *6A. Residuals: Independence* | + | + | + | + |
| *6B. Residuals: Normality* | - | - | +/- | +/- |
| *6C. Residuals: Homoscedasticity* | - | - | - | - |
| *7. Number of Observations* | + | + | + | + |
| *8. No Multicollinearity* | + | + | + | + |
| *9. Outliers* | + | + | + | + |

*Table 9: Assumptions Multiple Regression Model 1*

**Assumption 1: Causality**

All the variables in Model 1 are obtained from previous research or from the CIES Football Observatory. For that reason, I assume that the causality assumption holds.

**Assumption 2: All relevant variables are included**

Ramsey's Reset test indicates that some variable(s) is (are) missing in Model 1. The same applies to Extended Model 1. This means that the models may be wrongly specified.

**Assumption 3: Dependent and independent variables are at least interval scaled**

*COLV*, *OBV* and *FANS* are ratio scaled. *HDI* is added as a dummy variable.

**Assumption 4: Linear relationship between the dependent and independent variables**

In case I add the quadratic term of *OBV* and *FANS*, the Adjusted R-Square significantly increases. For that reason, I include those variables in Extended Model 1.

**Assumption 5: Additive relationship between dependent and independent variables**

Model 1 does not contain any interaction effect. However, if I add the interaction effect between *OBV* and *FANS*, the explanatory power improves significantly. I do so in Extended Model 1.

**Assumption 6: Residuals**

A. **Independence**

   Each observation is made independently of the others.

B. **Normality**

   For Model 1, the normality assumption is harmed. For Extended Model 1, the Kolmogorov-Smirnov test supports the assumption, whereas the Shapiro-Wilk test rejects it. So, the evidence of normally distributed residuals is mixed for Extended Model 1.

C. **Homoscedasticity**

   The White test rejects the null hypothesis of homoscedastic residuals for Model 1 and Extended Model 1.

**Assumption 7: Sufficient number of observations**

There is no generally accepted rule of thumb to determine the required sample size. I assume that the number of observations in this thesis is sufficiently high.

**Assumption 8: No multicollinearity**

Except for the squared terms, the Variance Inflation Factor (VIF) of each variable is lower than four, the strictest rule of thumb that is discussed by O'Brien (2007). For that reason, I conclude that there is no multicollinearity problem in the data.

**Assumption 9: Outliers**

The number of outliers in Model 1 (nine) and Extended Model 1 (ten) is very limited. Besides, the standardized residual of most outliers is only slightly larger than two. As removing the outliers does not lead to major differences in the results, I decide to keep them in.

## Appendix 5.2 – Assumptions OLS Regression Model 2

| *Assumptions* | *Model 2a* | *Model 2b* | *Extended Model 2a* | *Extended Model 2b* |
|---|---|---|---|---|
| ***1. Causality*** | + | + | + | + |
| ***2. All Variables Included*** | - | - | - | - |
| ***3. Interval Scale*** | + | + | + | + |
| ***4. Linear Relationship*** | - | - | + | + |
| ***5. Additive Relationship*** | - | - | + | + |
| ***6A. Residuals: Independence*** | + | + | + | + |
| ***6B. Residuals: Normality*** | +/- | $+^{*}$ | $+^{*}$ | $+^{*}$ |
| ***6C. Residuals: Homoscedasticity*** | $+^{**}$ | $+^{**}$ | $+^{**}$ | $+^{**}$ |
| ***7. Number of Observations*** | + | + | + | + |
| ***8. No Multicollinearity*** | + | + | + | + |
| ***9. Outliers*** | + | + | + | + |

*Table 10: Assumptions Multiple Regression Model 2. * Shapiro-Wilk test (α = 0.01), ** White test (α = 0.01)*

**Assumption 1: Causality**

All the variables in Model 2 are obtained from previous research or from the CIES Football Observatory. For that reason, I assume that the causality assumption holds.

**Assumption 2: All relevant variables are included**

Ramsey's Reset test indicates that some variable(s) is (are) missing in Model 2a and 2b. The same applies to Extended Model 2a and 2b, which means that the models may be wrongly specified.

**Assumption 3: Dependent and independent variables are at least interval scaled**

*AGE*, $AGE^2$, *CY*, *M*, $M^2$, *G*, *PM*, *CAPS* and *FANS* are all ratio scaled. The position variables (*GK*, *MID* and *FW*) and *HDI* are included as dummy variables.

**Assumption 4: Linear relationship between the dependent and independent variables**

If I add the quadratic term of *FANS*, the explanatory power of Model 2 increases significantly. For that reason, I include $FANS^2$ in the Extended Model 2.

**Assumption 5: Additive relationship between dependent and independent variables**

In Model 2, I did not include any interaction term. As adding the interaction effect between the amount of goals scored and the midfielder dummy significantly increases the Adjusted R-Square, I include the *G_MID* variable in the Extended Model 2.

**Assumption 6: Residuals**

A. **Independence**

   Each observation is made independently of the others.

B. **Normality**

   The Kolmogorov-Smirnov test supports the normality assumption for Model 2 and Extended Model 2. The Shapiro-Wilk test rejects the normal distribution of the residuals for Model 2a, whereas it accepts the assumption for Model 2b and Extended Model 2 ($\alpha = 0.01$). For that reason, the evidence of normally distributed residuals is mixed for Model 2a, whereas it holds for the other regression models.

C. **Homoscedasticity**

   The White test does not reject the null hypothesis of homoscedastic residuals for Model 2 and Extended Model 2 ($\alpha = 0.01$).

**Assumption 7: Sufficient number of observations**

There is no generally accepted rule of thumb to determine the required sample size. I assume that the number of observations in this thesis is sufficiently high.

**Assumption 8: No multicollinearity**

Except for the squared terms, the Variance Inflation Factor (VIF) of each variable is lower than four, the strictest rule of thumb that is discussed by O'Brien (2007). For that reason, I conclude that there is no multicollinearity problem in the data.

**Assumption 9: Outliers**

The amount of outliers in Model 2 and Extended Model 2 is very limited (nine, ten or eleven). Besides, the standardized residuals of most outliers are only slightly higher than two. Removing them leads to minor changes in the significance level of some control variables (*FW, MID, G*), but the effect of the underdog variable is still significant and relatively stable. For that reason, I keep the outliers in as removing them may bias the results.

## Appendix 6 – Robustness Checks – German Bundesliga

### Appendix 6.1 – Correlation HDI and Performance

| | | HDI (1990) | | HDI (2015) | |
|---|---|---|---|---|---|
| | | *Kendall's Tau* | *Spearman's Rho* | *Kendall's Tau* | *Spearman's Rho* |
| Performance 1 | *Coefficient* | -0.002 | -0.003 | -0.065 | -0.087 |
| | *Significance* | 0.968 | 0.963 | 0.138 | 0.147 |
| Performance 2 | *Coefficient* | 0.006 | 0.005 | -0.053 | -0.072 |
| | *Significance* | 0.899 | 0.930 | 0.223 | 0.233 |

*Table 11: Correlations HDI and Performance*

As HDI and performance are not normally distributed, I look at Kendall's Tau and Spearman's Rho. The correlation between performance and HDI turns out to be insignificant.

### Appendix 6.2 – Descriptive Statistics Bundesliga Sample

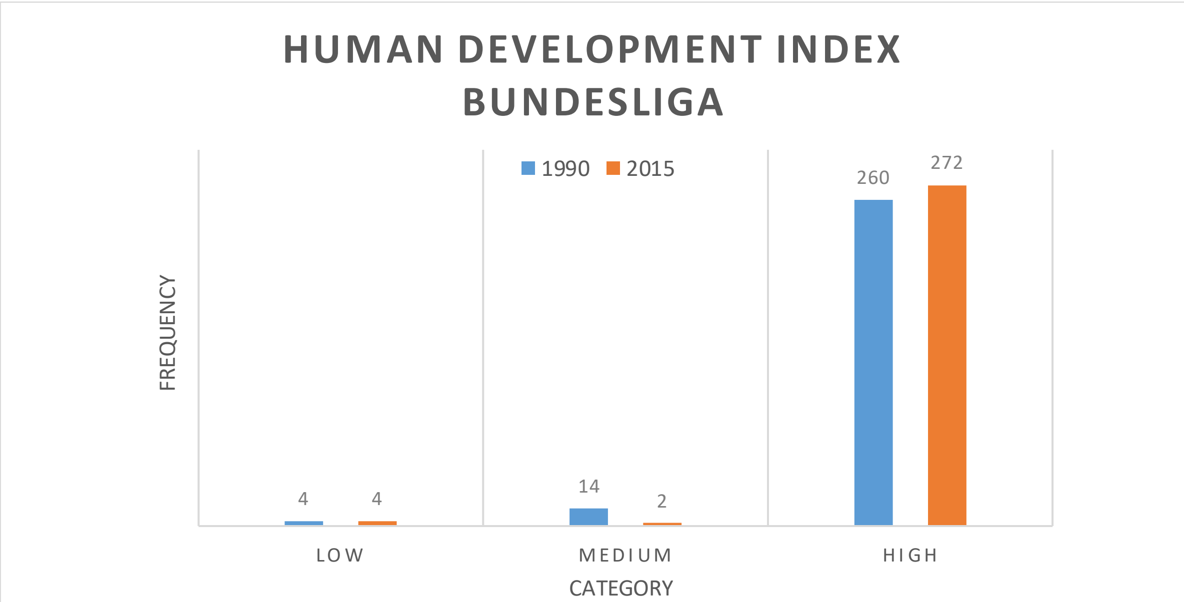


*Figure 8: Human Development Index Bundesliga*

| | *Mean* | *Median* | *St. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|---|
| ***Collective Value (x 1,000,000 €)*** | 7.637 | 3.500 | 10.504 | 0.250 | 75.000 |
| ***Objective Value (x 1,000,000 €)*** | 5.670 | 3.050 | 9.420 | 0.180 | 100.950 |
| ***Fans (x 1,000,000)*** | 0.523 | 0.046 | 1.586 | 0.001 | 13.587 |
| ***Age*** | 25.597 | 26.000 | 3.311 | 19.000 | 33.000 |
| ***Contract Years*** | 2.935 | 3.000 | 1.076 | 1.000 | 6.000 |
| ***Matches*** | 23.155 | 24.000 | 7.974 | 4.000 | 34.000 |
| ***Goals*** | 2.435 | 1.000 | 3.942 | 0.000 | 30.000 |
| ***Average Points per Match*** | 1.439 | 1.333 | 0.533 | 0.000 | 3.000 |
| ***Caps*** | 2.705 | 1.000 | 3.917 | 0.000 | 14.000 |

*Table 12: Descriptive Statistics Bundesliga*

## Appendix 6.3 – Regression Coefficients Model 1

| ***Coefficients*** | ***Objective Value*** | ***Adjusted R-Square*** | ***Constant*** | ***OBV*** | ***$OBV^2$*** | ***FANS*** | ***$FANS^2$*** | ***OBV_FANS*** | ***HDI*** |
|---|---|---|---|---|---|---|---|---|---|
| ***Model 1a (HDI 2015)*** | AVG | 0.396 | $1.043^{***}$ (0.059) | $0.054^{***}$ (0.007) | - | $0.145^{***}$ (0.040) | - | - | 0.262 (0.342) |
| | MIN | 0.396 | $1.043^{***}$ (0.059) | $0.059^{***}$ (0.007) | - | $0.145^{***}$ (0.040) | - | - | 0.262 (0.342) |
| | MAX | 0.396 | $1.043^{***}$ (0.059) | $0.051^{***}$ (0.006) | - | $0.145^{***}$ (0.040) | - | - | 0.262 (0.342) |
| ***Model 1b (HDI 1990)*** | AVG | 0.398 | $1.032^{***}$ (0.060) | $0.055^{***}$ (0.007) | - | $0.144^{***}$ (0.040) | - | - | 0.243 (0.202) |
| | MIN | 0.398 | $1.032^{***}$ (0.060) | $0.059^{***}$ (0.007) | - | $0.144^{***}$ (0.040) | - | - | 0.243 (0.202) |
| | MAX | 0.398 | $1.032^{***}$ (0.060) | $0.051^{***}$ (0.006) | - | $0.144^{***}$ (0.040) | - | - | 0.244 (0.202) |
| ***Extended Model 1a (HDI 2015)*** | AVG | 0.603 | $0.699^{***}$ (0.057) | $0.129^{***}$ (0.011) | -0.001 (0.000) | $0.444^{***}$ (0.089) | $-0.020^{***}$ (0.007) | $-0.008^{**}$ (0.003) | 0.271 (0.278) |
| | MIN | 0.603 | $0.699^{***}$ (0.057) | $0.140^{***}$ (0.012) | -0.001 (0.000) | $0.445^{***}$ (0.089) | $-0.020^{***}$ (0.007) | $-0.008^{**}$ (0.003) | 0.272 (0.278) |
| | MAX | 0.604 | $0.669^{***}$ (0.057) | $0.121^{***}$ (0.010) | -0.0004 (0.000) | $0.443^{***}$ (0.089) | $-0.020^{***}$ (0.007) | $-0.007^{**}$ (0.003) | 0.271 (0.278) |
| ***Extended Model 1b (HDI 1990)*** | AVG | 0.604 | $0.661^{***}$ (0.058) | $0.130^{***}$ (0.011) | $-0.001^{*}$ (0.000) | $0.433^{***}$ (0.089) | $-0.019^{***}$ (0.007) | $-0.008^{**}$ (0.003) | 0.207 (0.164) |
| | MIN | 0.604 | $0.661^{***}$ (0.058) | $0.141^{***}$ (0.012) | $-0.001^{*}$ (0.000) | $0.434^{***}$ (0.089) | $-0.019^{***}$ (0.007) | $-0.008^{**}$ (0.003) | 0.206 (0.164) |
| | MAX | 0.605 | $0.660^{***}$ (0.058) | $0.121^{***}$ (0.010) | $-0.0005^{*}$ (0.000) | $0.432^{***}$ (0.089) | $-0.019^{***}$ (0.007) | $-0.007^{**}$ (0.003) | 0.207 (0.164) |

*Table 12: Regression Coefficients Model 1. ***p < 0.01, **p < 0.05, *p < 0.10*

## Appendix 6.4 – Regression Coefficients Model 2

| Coefficients | Constant | AGE | $AGE^2$ | GK | MID | FW | CY | M |
|---|---|---|---|---|---|---|---|---|
| Model 2a (HDI 2015) | -5.000*** (1.862) | 0.286** (0.145) | -0.006** (0.003) | 0.058 (0.167) | -0.064 (0.089) | -0.296** (0.120) | 0.218*** (0.039) | 0.083*** (0.027) |
| Model 2b (HDI 1990) | -5.003*** (1.863) | 0.287** (0.145) | -0.006** (0.003) | 0.059 (0.168) | -0.064 (0.089) | -0.296** (0.120) | 0.218*** (0.039) | 0.083*** (0.027) |
| Extended Model 2a | -5.011*** (1.792) | 0.296** (0.139) | -0.007** (0.003) | 0.108 (0.161) | -0.179* (0.099) | -0.218* (0.120) | 0.216*** (0.037) | 0.094*** (0.026) |
| Extended Model 2b | -5.011*** (1.792) | 0.296** (0.139) | -0.007** (0.003) | 0.108 (0.162) | -0.179* (0.099) | -0.218* (0.120) | 0.216*** (0.037) | 0.094*** (0.026) |

| Coefficients (Continued) | $M^2$ | G | G_MID | PM | CAPS | FANS | $FANS^2$ | HDI |
|---|---|---|---|---|---|---|---|---|
| Model 2a (HDI 2015) | -0.001 (0.001) | 0.047*** (0.013) | - | 0.755*** (0.083) | 0.042*** (0.011) | 0.107*** (0.029) | - | -0.045 (0.254) |
| Model 2b (HDI 1990) | -0.001 (0.001) | 0.046*** (0.013) | - | 0.755*** (0.083) | 0.042*** (0.011) | 0.107*** (0.029) | - | 0.002 (0.152) |
| Extended Model 2a | -0.001* (0.001) | 0.035** (0.014) | 0.064** (0.026) | 0.636*** (0.086) | 0.028*** (0.011) | 0.389*** (0.075) | -0.026*** (0.007) | 0.007 (0.244) |
| Extended Model 2b | -0.001* (0.001) | 0.035** (0.014) | 0.064** (0.026) | 0.636*** (0.086) | 0.028*** (0.011) | 0.389*** (0.074) | -0.026*** (0.007) | 0.0002 (0.147) |

*Table 13: Regression Coefficients Model 2. ***p < 0.01, **p < 0.05, *p < 0.10*

**Appendix 6.5 – OLS Assumptions Model 1**

| | Model 1a | Model 1b | Extended Model 1a | Extended Model 1b |
|---|---|---|---|---|
| 1. Causality | + | + | + | + |
| 2. All Variables Included | - | - | - | - |
| 3. Interval Scale | + | + | + | + |
| 4. Linear Relationship | - | - | + | + |
| 5. Additive Relationship | - | - | + | + |
| 6A. Residuals: Independence | + | + | + | + |
| 6B. Residuals: Normality | +/-* | +/-* | + | + |
| 6C. Residuals: Homoscedasticity | - | - | + | + |
| 7. Number of Observations | + | + | + | + |
| 8. No Multicollinearity | + | + | + | + |
| 9. Outliers | + | + | + | + |

*Table 14: Assumptions Multiple Regression Model 1. * Supported by Kolmogorov-Smirnov test, rejected by Shapiro-Wilk test*

**Appendix 6.6 – OLS Regression Assumptions Model 2**

| | Model 2a | Model 2b | Extended Model 2a | Extended Model 2b |
|---|---|---|---|---|
| 1. Causality | + | + | + | + |
| 2. All Variables Included | - | - | - | - |
| 3. Interval Scale | + | + | + | + |
| 4. Linear Relationship | - | - | + | + |
| 5. Additive Relationship | - | - | + | + |
| 6A. Residuals: Independence | + | + | + | + |
| 6B. Residuals: Normality | + | + | + | + |
| 6C. Residuals: Homoscedasticity | +* | +* | + | + |
| 7. Number of Observations | + | + | + | + |
| 8. No Multicollinearity | + | + | + | + |
| 9. Outliers | + | + | + | + |

*Table 15: Assumptions Multiple Regression Model 2. * White test ($\alpha = 0.01$)*

## Appendix 7 – The Underdog Variable in Case of a New Interpretation of PM

| | *Model 2a* | *Model 2b* | *Extended Model 2a* | *Extended Model 2b* |
|---|---|---|---|---|
| ***PM*** | 0.744*** (0.086) | 0.739*** (0.085) | 0.669*** (0.080) | 0.667*** (0.080) |
| ***HDI*** | 0.132 (0.110) | 0.229** (0.091) | 0.191* (0.101) | 0.214** (0.084) |
| ***Adjusted R-Square*** | 0.614 | 0.620 | 0.673 | 0.677 |

*Table 16: HDI and Adjusted R-Square in case the points per match variable is approached on club level (PMC). ***p < 0.01, **p < 0.05, *p < 0.10*