

THE PENNSYLVANIA STATE UNIVERSITY  
SCHREYER HONORS COLLEGE

DEPARTMENT OF ASTRONOMY AND ASTROPHYSICS

**BUILDING A WINNING SOCCER TEAM**  
**ANALYSIS OF SOCCER STATISTICS**

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FALL 2009

A thesis  
submitted in partial fulfillment  
of the requirements  
for a baccalaureate degree  
in Science  
with honors in of Astronomy and Astrophysics

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## **ABSTRACT**

Statistics are used in a wide variety of areas and have a broad range of uses. One such area in which statistics is extremely important and useful is in the arena of professional sports, including association football, known better as soccer in the United States. Like other sports, statistics recorded in soccer is often used as a base to evaluate players. This evaluation utilizing statistics is not only used to determine how good the player is, but also how much the player is worth or valued in the market of professional soccer players. The main issue is how the current statistics tracked in soccer contribute to the value of players and whether or not these statistics are accurate and meaningful. Furthermore, there certainly are statistics that are not being tracked that are influential and meaningful to the evaluation of a player's performance and true value. However, the problem is that it needs to be determined how to accurately record these other meaningful statistics because they are not as obvious or as easily recordable.

In addition, statistics are not the only measure or influence upon a player's performance, evaluation, and value. So, the statistics used should be taken in context of other varying forces. There is a wide range of theoretical and other related influences that have an impact including moral hazard, contract incentives, team fitness, cheating, and pay inequality. Some of these affect what and how some statistics should be tracked, while others influence the overall relationship of players to the team.

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**ACKNOWLEDGEMENTS**

I would like to acknowledge the help of Dr. Steinn Sigurdsson and Dr. Jane Charlton with my thesis.

I would also like to thank the support of my Parents and Family, Peter Tombros, Jim Gardner, Cindye Rudy, Mary Fleming, and Susan Knell.

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## **Chapter 1**

### **Introduction**

Soccer, often recognized as the most popular sport in the world, is a fluid and continuously moving game. Players are in constant motion and play is not frequently stopped throughout the hour and a half game. Due to this continuous motion and the simplicity of the game, very limited statistics are kept about the teams and players, especially when compared to other sports. Not only are there fewer statistics, but the statistics kept in soccer simply do not occur very frequently or as often to comparable statistics in other sports. For example, goals are often referred to as rare events in soccer and it is not uncommon to have no goals at all in a game. This is unlike points in American football, goals in hockey, points in basketball, and runs in baseball. Also, individuals in soccer are evaluated on a greater amount of perception than other sports individuals because there are very few statistics that are tracked or that are actually able to be kept accurately. This will be examined in further depth later in the paper.

Furthermore, players are traded and bought in an open market between various leagues that have no salary cap, true about the majority of leagues in the world and more importantly the larger leagues, and no restrictions on transfer fees or player salary. So, more often than not bidding wars occur over players and the best players are worth multiple times the amount of the average player. Just as an example, Cristiano Ronaldo, regularly recognized as the best or at the very least a top five player in the world, was traded during the summer of 2009 from Manchester United to Real Madrid for a staggering £80million. In addition, Ronaldo was quoted as saying that the price “paid for him is a ‘fair price’ and he is more than comfortable with being the most expensive player in the world” (Soccernet Staff). Ronaldo is just one recent example of the high costs of players in the soccer market.

Many teams are willing to pay such high costs for players because they believe that having better players will lead to more wins, a view that makes sense, but that can also be very expensive. The goal of any team sport is to build a team that can win as many games as possible and this is no different in soccer. However, normally the idea is to build the best team with the limited amount of money in the teams control or as small a cost as possible. The question is how a coach, team, or owner can be sure that a given player is worth the transfer fee and salary that they pay. In order to know if the money paid is being spent wisely, the information that needs to be known is what statistics are influences on or at least correlated with these costs and what statistics are important in increasing wins for the team. In addition to these statistics, there are other theories and factors that influence the winning of a team and the value of individual players. These questions and related theories will be discussed throughout the rest of this paper.



## Chapter 2

### A Comparison of Soccer Statistics with Other Sports Statistics

The statistics that are kept in soccer can be compared to other sports statistics and this comparison can give insight into how statistics in soccer should be collected, recorded, and interpreted. In recent years, baseball statistics have gone through a revolutionary change of thought and use. Many of these changes were documented by Michael Lewis in *Moneyball*. A number of comparisons can be made between the realizations made about statistics in baseball and where soccer statistics currently are and about the type of statistics kept in both.

One comparison is how players have been evaluated historically. Much of the evaluation has been based on perception and the “tools” that a player has. Traditionally in baseball, players were evaluated on “five tools: the abilities to run, throw, field, hit, and hit with power” (Lewis, *Moneyball*). Furthermore, if the person did not “look like” a baseball player, then baseball scouts would immediately write that player off as not good, even if the player had all the tools. However, as it turns out, just because a player does not have all the tools and does not look the part, does not actually mean that the player is not good and does not contribute greatly to the winning of the team he plays for.

One player example pointed out by Lewis is Kevin Youkilis. “Youkilis was a fat third baseman who couldn’t run, throw, or field” (Lewis, *Moneyball*). So, Youkilis was looked at as worthless and not a good player. However, Youkilis could draw walks and get on base, which as statistics showed is the most important statistic that contributed to helping the team win. The problem with the traditional system of baseball was that it actually looked down upon walks as a negative and did not even track or record on-base percentage for players. The abilities and statistics that were used to evaluate players were not in actuality as important as they were

thought to be. Advancement in statistics in baseball was able to uncover the truth about walks and that on-base percentage was extremely important in the evaluation of a player.

Similarly in soccer, many players are evaluated on the tools that they have and whether or not they look like a soccer player. These tools for soccer include such things as the player being able to dribble, pass, shoot, shoot with power, tackle, and run. Just as an example, it is widely accepted that in Brazil if a player is not able to play the game with style and flair then the player is considered to not be a very good player. However, if the player is able to greatly contribute to the team winning and does it in such a way that it is not entertaining, the fact is that that player is still worth a lot to the team. As in baseball, the view of evaluating players on such aspects is very misleading and is probably not as accurate as it could be.

Another comparison that can be drawn is between pitchers in baseball and goalies in soccer. Two statistics that have traditionally been kept on pitchers in baseball is ERA (Earned Run Average) and number of hits given up and both of these statistics have a fairly big influence on the evaluation and perceived worth of a pitcher. However, Voros McCracken asked the question “What if the pitcher has no control of whether a ball falls for a hit, once it gets put into play?” (Lewis, Moneyball). As it turns out, both of these statistics are defense dependent and therefore the pitcher does not have full control over these statistics. So, statistically speaking, neither ERA nor number of hits given up was a good measure to evaluate pitchers worth and ability. Furthermore, due to the nature of the position, pitchers are harder to judge and evaluate than other positions. This is mainly due to the fact that the pitching position is more mental and can be greatly influenced by aspects such as learning a new pitch. Instead, as it was found out through the analysis of statistics, pitchers should be evaluated with defense independent statistics, such as the number of strikeouts, walks, and homeruns given up (Lewis, Moneyball).

Goalies in soccer are similar to pitchers in baseball, including the statistics that their worth should be evaluated with. Currently, one of the major statistics that soccer goalies are evaluated on is GAA (Goal Against Average). Just as is the case in baseball, the GAA statistic is dependent on the other players in front of the goalie. However, unlike baseball, there currently are not any very useful or reliable goalie defense independent statistics. So, the question then becomes what defense independent statistic should be used to evaluate the performance and worth of goalies. This is just one example of an area where there needs to be further study into statistics in soccer and where the advancement of statistics in baseball has already proven to be more meaningful.

There are many more comparisons that can be drawn between soccer and other sports as well. However, the general idea can be seen in the comparison of baseball with soccer. Michael Lewis also wrote an article, *The No Stats All-Star*, in the New York Times about statistics in basketball that is similar in ideas and realizations to what *Moneyball* discussed about baseball. This article points out some of the same ideas and problems with how players are evaluated with the current statistics kept in basketball.

The player example used throughout the article is Shane Battier. As Lewis points out, Battier's normal basketball statistics are nothing to be proud of and are not at all impressive. However, if a closer look is taken with a number of more meaningful statistics that are being used by the Houston Rockets, Battier is an all-star player and greatly contributes to the team winning. Not only this, but when he is on the court everyone on his team gets noticeably better and everyone on the opposing team gets noticeably worse. If only traditional basketball statistics were used to evaluate Battier, then he would be extremely undervalued and his performance would not be accurately evaluated (Lewis, *The No Stats All-Star*).

Again this can be compared to players and statistics used in soccer. Just as is the case in basketball and other sports too, there are many players in soccer that statistically are very unimpressive, but that contribute greatly to the team winning. Some of these players can be noticed by simply watching players and teams play; however, most probably cannot be found so easily. So, advancement in soccer statistics would be very beneficial in being able to accurately identify these types of players.

One of the newer statistics that is being kept in soccer in the English Premier League is the Actim Index. The Actim Index is a statistic that tries to take into account the value or contribution of performance of a player to their team that is agnostic of their position. It is based on six different calculations seen below in Table 2-1.

Table 2-1: Calculations in the Actim Index.

1	-	Assesses a player's contribution to a winning team, based on points won by the team when he appeared.
2	-	Assesses a player's performance in each game, by allocating points for actions that positively contribute to a winning performance such as shots, tackles, clearances and saves. It also takes points away from players for negative actions such as yellow/red cards and shots off target.
3	-	Allocates points based on time on the pitch.
4	-	Allocates points for goal scorers.
5	-	Allocates points for assists.
6	-	Allocates points for clean sheets.

(Actim Index)

The Actim Index would be comparable to the QB Rating in the NFL, other than the obvious fact that the Actim Index tries to be position agnostic and rate all players to each other. Just as a note, it could be argued that the Actim Index is skewed to players who score goals and to players on the better teams, but there are arguments for the two sides of this topic. However,

both the Actim Index and the QB Rating are trying to evaluate a player's performance to contributing to the team winning and value to their team compared to other players in the respective leagues. Neither of these statistics are without their faults and problems, but they do appear to do a better job in evaluating player performance than the statistics being used previous to them.

As can be seen there are many comparisons that are able to be made between statistics in soccer and other sports. Even though it could be argued that these comparisons do not correlate perfectly, they still are able to lead to some meaningful insights and realizations. These comparisons are able to highlight some of the areas that there is room for improvement and advancement in soccer statistics. Also, they show some of the potential benefits of having new statistics that are more meaningful and accurate.

## Chapter 3

### Problems with Statistics in Soccer

With the differences and similarities of statistics in soccer compared to other sports pointed out in chapter 2, there are some noticeable problems and gaps with some of the statistics kept in soccer and challenges with how to track new and more individual and team statistics in soccer. These problems add to the difficulty of assessing a good player and their worth to a team. In a sense, these difficulties are what make the assessment of players more subjective in soccer currently. These hindrances are some of the aspects that need to be solved in order to advance to more meaningful statistics in soccer.

Even though many of the statistics that are currently tracked in soccer are straight forward and are able to be accurately kept, such as goals, assists, fouls, games and minutes played, and shots, the problem comes in what is their true importance or significance. “The second kind of bogus numerology is the one found in actual match statistics, and is bogus only to the extent that the officially recognized numbers are not sufficient to describe or clarify what really takes place on the pitch” (Phillips). Are these statistics simply being tracked because they are easy to track? The important question is how significant are these statistics to the value of a player to a team or do these statistics even influence the value of a player. This problem isn’t just seen in soccer either. An example of this can be seen in basketball. “To get at this they need something that basketball hasn’t historically supplied: meaningful statistics. For most of its history basketball has measured not so much what is important as what is easy to measure — points, rebounds, assists, steals, blocked shots — and these measurements have warped perceptions of the game” (Lewis, *The No Stats All-Star*). Just because statistics are easy to track

and plentiful does not mean they are significant, influential, or meaningful, which is much more important.

A correlating statistic example from baseball can be found in *Moneyball*. Runs Batted In (RBIs) were tracked for a very long time and are still tracked to this day and were given a lot of weight in the value of a player. However, after actually analyzing the importance of this statistic, the number of RBIs a player has, it was determined that RBIs really had no large bearing on the player's worth to the team (Lewis, Moneyball). This example also goes to show that even though a statistic might from a high view appear to be important, hitting the baseball so your teammates on base can get to home plate, does not mean that it is meaningful when an analytical eye looks more closely at it.

Some of the more recent statistics being tracked in soccer point out a flaw in the collection of some statistics in soccer. For example, one of the more recently tracked statistics in soccer is passes completed out of the number of passes attempted by a player. However, there is a vital flaw in the collection of the passes completed statistic and this is pointed out in the following quote. "This is as good a description of the problem with existing statistical measures in soccer as any I've read: a visibly poor pass that loses possession is rated as 'accurate' because it hits its man, a brilliant pass goes down as 'inaccurate' for the passer even though it was the intended recipient's lack of imagination that caused it to fail" (Phillips). So, even though one would think that the accuracy of passes in soccer by a player would be a good measure of how efficient that player is with the possession of the ball, which one could assume is a fairly important or of large value to the team, it turns out that this statistic can be misleading and not accurate due to the way it is collected and assigned.

Another problem with statistics in soccer is that they do not take into account what some people would describe as the flair or skill that a player possesses. One example of this problem is evident in the Actim Index. “The Actim Index only includes actions that can be measured objectively. Skill, passion and flair are subjective factors so they are not included in the rating system” (Actim Index). One skill that is not taken into account is the ability of a player to make a dribbling move and be able to get past a player on the other team. Another ability that is not incorporated is being able to make creative and innovative passes that lead to better scoring chances. Some players are able to see and make these passes, while others are not able to. It can be said fairly confidently that these types of “subjective factors” most probably play an important part in the game and the value of a player. Furthermore, with the advancement in statistics over the years, this type of factor could be accounted for in some type of numerical way that could be tracked accurately and meaningfully.

An example of this in another sport can be seen in basketball through the player Shane Battier. “Battier’s game is a weird combination of obvious weaknesses and nearly invisible strengths. When he is on the court, his teammates get better, often a lot better, and his opponents get worse — often a lot worse” (Lewis, *The No Stats All-Star*). Even though Battier’s statistics do not show a contribution or value to the team, whenever he is playing there is an obvious good benefit to the team. “Here we have a basketball mystery: a player is widely regarded inside the N.B.A. as, at best, a replaceable cog in a machine driven by superstars. And yet every team he has ever played on has acquired some magical ability to win” (Lewis, *The No Stats All-Star*). The question then becomes how one tracks this through the use of statistics. The article, *The No Stats All-Star*, suggests that the Houston Rockets have figured out a way to do this. This is



something that also needs to be and most probably can be done in soccer. It is just a matter of how to do it statistically that it is accurate and meaningful.

Being able to take into account these problems discussed above and even being able to correct them will lead to more accurate and meaningful statistics that can be used to evaluate a players performance and therefore value to the team or in the open market.

## Chapter 4

### Related Research and Theories

It should be kept in mind that the analysis of individual player statistics done in this paper is not the only factors influencing the value of a player. There are many other forces acting on the players, team, and league in what the value of players is. Items such as moral hazard and incentive clauses in player contracts influence how players act and in turn the value of the players. There are many theories and related research that directly or indirectly affect the value and worth of a player to the team, but only these two will be discussed here. Also included in this section are a number of results from other research done that is relevant to the Market Value of players.

Moral hazard describes a situation which arises from asymmetric or incomplete information between parties resulting in one party being fully or partially insulated from a risk and so this party acts differently, often inappropriately in the eyes of the other party, than what would be expected if the risk was burdened fully. For the case of viewing moral hazard in soccer, it occurs in a case referred to as the Principal-Agent Problem. Moral hazard occurs in this case when a Principal hires an Agent; in this case, a team hires a soccer player. The team does not have full information into the actions or the interests of the player. The player's interests could include how much effort they give while playing, if they are more concerned with their personal statistics then the team winning, or that they are hiding injury just to ensure playing time. This may cause the interests of the team and the player to be different and misaligned. If the interests of these two parties are dissimilar, then the player will most likely act in a different way than what the team wants them to. Furthermore, if the team does not know how exactly the player affects its interests, winning soccer games is a safe overarching interest in

this case, then the team will not know how to interact with the player in order to align their actions (Mirrlees).

Being able to align the interests of the players with the interests of the teams is extremely important. Probably the largest influence that the team has over aligning the player's interests with their own is through the player contract, the agreement of how and how much the player gets paid, that the player agrees to. This is such a large influence because most players' interests are dominated by what they are going to get paid for; playing soccer is their job. There can be many different parts of a player salary contract including: base salary, incentive salary, player based bonuses, team bonuses, injury clauses, and many more. So, how the team decides to incentivize the player whether it's through a base salary or by scoring goals is very important. "We think about this deeply whenever we're talking about contractual incentives," he says. "We don't want to incent a guy to do things that hurt the team" (Lewis, The No Stats All-Star). Players will more likely do what benefits them personally the most, whatever gets them paid, than always have the team's best interest in mind.

In many sports, individual performance is rewarded through incentives in players' contracts. This is done because trying to get players to maximize or minimize certain individual performances is a direct influence on maximizing the interests of team. Somewhat surprisingly, these types of individual rewards are not really found in soccer. "In German soccer objective individual performance measures for the players' effort are hardly used. There is only a combination of tournament-style incentives and clauses based on team output" (Heubeck and Scheuer). Part of the reasoning behind focusing more on team and overbearing incentives is that it is not know how the statistics kept for individuals in soccer truly impact the team's interest of winning games. "It seems to be a strong argument, that because of the nature of soccer it is

difficult, costly, and maybe not even desirable to define objective performance measures in addition to the subjective performance measures already used” (Heubeck and Scheuer).

However, if there was advancement in the statistics used in soccer, then this could change and have a more positive result aligning the players’ interests to that of the team. Using more accurate and meaningful statistics would not only allow a team have a measure of the true value of a player, but the team would also be able to incentivize the maximization of players’ interests to winning games.

Other research has also been done on a number of other soccer statistics, team and individual, that have produced results that are interesting and pertinent to this paper. The first looked at goal difference between goals scored and goals allowed as an indication of overall team fitness. “The overall fitness, defined via the goal difference, delta G, is to a large extent the only characteristics of a team” (Heuer and Rubner). From this analysis, the only team characteristic or statistic that is meaningful is this goal differential. In addition to this, another important result was found that has implications for the value of players. “A more detailed view on the number of goals reveals that the quality of the offence and that of the defence of a team is strongly correlated. Furthermore, the strength of attack is slightly more important for a successful soccer team than the strength of defence, albeit the difference is not big.” (Heuer and Rubner). This is of importance because it implies that offensive players are worth more than defensive. So, it is slightly more crucial to have better offensive players on the team.

Another research paper looked into how team revenue and performance were related to one another. Once again, even though this is on a team level, it has some bearing on how player value changes based on team performance. This relates to the idea that player worth should be evaluated based on how they contribute to the team’s success.

The question remains, however, as to the direction of causation. In comparing revenue and performance, Dobson and Goddard (1998) use Granger causality tests to discover that high levels of past revenue lead to current on-field success while past performance has only a limited effect on current revenue. The situation is reversed in soccer with high payrolls leading to better performance but performance not causing higher payrolls (Matheson).

However, it appears that what is happening is that the teams that are able to buy established or easily recognizable good players who are already at higher prices are also the ones that are able to succeed. Also of interest here is that a team with increasingly better performance has no bearing on what the players are paid. This is opposite of what should happen if player evaluation of worth is based on their contribution to the team's success.

Also of interest were some of the characteristics found about players who were actually transferred. This is of importance because the market value of these players is actually known because it was paid. Other players' market value can only be estimated.

They find that transfers are more likely among older, more experienced players, when a change in management has occurred, and among players who have been frequently loaned out to other teams as temporary transfers. The transfer received is based upon the age of the player with a peak transfer payment at the age of 23, and other obvious measures of player skill such as goals scored, league appearances, and international appearances. Each goal scored during the previous regular season added between 21,860 and 32,690 to the transfer payment for the player depending on the player's position (Matheson).

The big highlight from this is the added value to the transfer payment, market value of the player, for each goal scored in the previous season. This shows insight into how goals are currently viewed by the “soccer player market”. Further information about influence on the market value of players is given in the following quote.

The skill of the player, as evidenced by goals scored and league appearances, leads to higher transfer fees and greater bargaining power on the part of the current club. Higher team profits, attendance, winning margin, and rank in the standings by the buying club lead to higher transfer fees after adjusting for player skill suggesting that rich and successful teams have less bargaining power in the transfer market. On the selling side, the playing division is the most significant variable with lower division clubs having less bargaining power (Matheson).

So, the market value of players is not only influenced by just the players’ actions and statistics, but it is further influenced by the actual team and league a player is coming from. This may not have actual meaning in the sense of what a player is worth in theory, but it does have impact upon the real world value of that player. However, the question to be raised with these insights is what the true and meaningful worth of a goal, a league appearance, or what team or league a player comes from actually is when it comes to contribution to a team’s success.

There are also a many more influences upon the Market Value of players including: coach efficiency, international and interleague competitions, league structures and rankings, transfer market structure, cheating within soccer, demand for soccer by fans, and many others. However, there are too many to discuss for the purposes of this paper, but it should be noted that they exist.

## Chapter 5

### Analysis

In order to analyze the current or traditional statistics kept in soccer, Principal Component Analysis, Regression, and Correlation were run in SPSS, a computer statistical analysis program, for a number of gathered statistics for players in the English Premier League. Specifically, the statistics were used to try and find if there was any relationship to the market value or worth of a player. The English Premier League was used as a base to run analysis because it is widely regarded as the best soccer league in the world. Another reason that the English Premier League was used is that statistics on players are readily accessible and accurate. These three analyses have different meanings, results, and importance and their results are discussed in the rest of this chapter.

Principal Component Analysis was run on the statistics collected and produced three meaningful components. The purpose of Principal Component Analysis is to extract from a set of variables a reduced set of components that accounts for most of the variance in the set of variables. In the case of the selected variables, three components were reduced from the 16 variables. As can be seen in Table 5-1, these three components account for 76% of the variance in the variables.

Table 5-1: Rotation Sums of Squared Loadings and % of Variance

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	5.021	41.843	41.843
2	2.882	24.017	65.859
3	1.265	10.543	76.403

The loadings of the three components can be seen in Table 5-2. Component 1 has a strong positive loading on Goals, Fantasy Score, Shots on Goal, Shots, Market Value, Actim Index, and Assists. This component could be called Offensive / Value Player. Goals, Shots on Goal, Shots, and Assists are all statistics related to the offensive part of soccer and to a player trying to help the team score a goal. These statistics are major influences on a player's Soccer Fantasy Score and Actim Index and is assumed to be an influence on the player's Market Value. Accepting this explanation leads to an understanding of Component 1.

Component 2 has strong positive loading on Fouls Suffered and Assists and a strong negative loading on Height, Weight, and Age. This component could be called Style / Flair Player. Fouls Suffered and Assists are often a result of a player being able to beat a player on the opposing team or make a very good or creative pass. As a player gets older, the player tends not to be as fast or quick which would result in a decreased ability in Style / Flair. A decrease in Style / Flair would also often tend to occur with taller and heavier players because they are not able to be as fast, quick, or nimble.

Component 3 has only strong positive loading on the number of Substitutions. Since only one variable is heavily loaded on this component, it is not very well defined and is probably not useful or reliable. However, this component could be labeled as Substitute Player, meaning that there are players who are basically used as a substitute for the team and nothing else. This component is probably not loaded towards any other variable due to the fact that substitutes do not accumulate nearly as many other statistics as other players, specifically ones who start.



Table 5-2: Rotated Component Matrix

	Component		
	1	2	3
Goals	.918	.127	.171
Fantasy_Score	.897	.125	-.104
Shots_on_Goal	.883	.314	.186
Shots	.864	.350	.142
Salary_Market_Value	.857	.064	.103
Actim_Index	.820	.046	-.199
Height	.113	-.812	-.382
Weight	.060	-.776	-.315
Fouls_Suffered	.368	.692	-.112
Assists	.451	.671	-.113
Age	-.258	-.644	.029
Sub	.135	.134	.921

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

\*Significance = .000

It is interesting to note that the Offensive / Value Player, Component 1, accounts for the majority, about 42%, of the variance in the statistics. This is followed by the Style / Flair Player, Component 2 accounting for 24% and the Substitute Player only accounting for 10% of the variance in the statistics. Due to these degrees in accounting for variance, it hints at a possibility that offensive players are the most important, followed by style players and then substitutes that come in later during the game. However, there is nothing to confirm this.

Two types of correlation, Pearson and Spearman, were run on the statistics gathered. Spearman's correlation assigns ranks within each variable statistic and then the differences in these ranks are what are used to determine if there is any association. Pearson correlation simply

looks for an association with the given numbers of the variables. Many of the variables are both correlated to Market Value in Pearson and Spearman's correlation

All the correlations for the 15 other variables to Market Value for both Pearson and Spearman correlation can be found in Table 5-1. There are a number of very strongly correlated variables with Market Value. However, there are also no significant negatively correlated variables with Market Value at all, which is somewhat surprising to see. The Actim Index, Fantasy Score, Goals, Shots, and Shots on Goal are all strongly correlated with the Market Value of a player using both types of correlation. This is not surprising given the fact that offensive or attacking players on average have a much higher market value than other players.

Another interesting strong correlation is the .590 Spearman ranking correlation of Fouls Suffered to Market Value. This is a note worthy statistic for the following possible explanation. The number of Fouls Suffered is probably a pretty good indicator of who the best offensive players are. The logic behind this is that the best offensive players will be fouled the most by the opposing team. The reasoning is that these best players are fouled so much either to slow them down in general or because they beat other players, who in turn have to foul them to stop them. So, this result makes Fouls Suffered an appealing possible indicator.

Weight, Height, and number of games Substituted were the only variables that did not significantly correlate with Market Value of players, in either Pearson or Spearman's correlation. In addition, Age was also not correlated to Market Value in the Pearson correlation. This is not too surprising that the physical components, Weight and Height, are not correlated to Market Value because soccer is the type of game in which greater physical stature is not often a great advantage. The number of times a player is Substituted not being correlated to Market Value can

be explained in the fact that whether or not a player starts or is a sub into a game is mainly determined by the will of the coach, not necessarily the value of the player.

It should be noted that a large correlation (in absolute value) does not necessarily imply that a causal relationship exists between the two variables, only that a linear association may exist. Additionally, a small correlation (in absolute value) does not necessarily imply that the two variables are unrelated, only that they are not strongly linearly related

Table 5-3: Correlations and Nonparametric Correlations to Market Value of Players

Correlations			Nonparametric Correlations			
		Salary_Market_Value			Salary_Market_Value	
Salary_Market_Value	Pearson Correlation Sig. (2-tailed) N	1 325	Spearman's rho	Salary_Market_Value	Correlation Coefficient Sig. (2-tailed) N	1.000 325
Actim_Index	Pearson Correlation Sig. (2-tailed) N	.651** .000 77		Actim_Index	Correlation Coefficient Sig. (2-tailed) N	.505** .000 77
Fantasy_Score	Pearson Correlation Sig. (2-tailed) N	.665** .000 243		Fantasy_Score	Correlation Coefficient Sig. (2-tailed) N	.729** .000 243
Age	Pearson Correlation Sig. (2-tailed) N	.007 .900 321		Age	Correlation Coefficient Sig. (2-tailed) N	.135* .015 321
Height	Pearson Correlation Sig. (2-tailed) N	-.018 .743 321		Height	Correlation Coefficient Sig. (2-tailed) N	-.059 .294 321
Weight	Pearson Correlation Sig. (2-tailed) N	.014 .806 320		Weight	Correlation Coefficient Sig. (2-tailed) N	-.027 .631 320
Start	Pearson Correlation Sig. (2-tailed) N	.338** .000 325		Start	Correlation Coefficient Sig. (2-tailed) N	.565** .000 325
Sub	Pearson Correlation Sig. (2-tailed) N	-.027 .630 325		Sub	Correlation Coefficient Sig. (2-tailed) N	.098 .077 325
Goals	Pearson Correlation Sig. (2-tailed) N	.729** .000 325		Goals	Correlation Coefficient Sig. (2-tailed) N	.578** .000 325
Shots	Pearson Correlation Sig. (2-tailed) N	.673** .000 325		Shots	Correlation Coefficient Sig. (2-tailed) N	.615** .000 325
Shots_on_Goal	Pearson Correlation Sig. (2-tailed) N	.700** .000 325		Shots_on_Goal	Correlation Coefficient Sig. (2-tailed) N	.605** .000 325
Assists	Pearson Correlation Sig. (2-tailed) N	.469** .000 325		Assists	Correlation Coefficient Sig. (2-tailed) N	.551** .000 325
Fouls_Committed	Pearson Correlation Sig. (2-tailed) N	.196** .000 325		Fouls_Committed	Correlation Coefficient Sig. (2-tailed) N	.467** .000 325
Fouls_Suffered	Pearson Correlation Sig. (2-tailed) N	.411** .000 325		Fouls_Suffered	Correlation Coefficient Sig. (2-tailed) N	.590** .000 325
Yellow_Card	Pearson Correlation Sig. (2-tailed) N	.233** .000 325		Yellow_Card	Correlation Coefficient Sig. (2-tailed) N	.381** .000 325
Red_Card	Pearson Correlation Sig. (2-tailed) N	.162** .003 325		Red_Card	Correlation Coefficient Sig. (2-tailed) N	.115* .039 325

\*\* . Correlation is significant at the 0.01 level (2-tailed).

\* . Correlation is significant at the 0.05 level (2-tailed).

Three methods, Forward, Backward, and Step-Wise, of Regression were used to analyze the statistics collected to find relationships to the market value of a player. All three of these types of Regression are methods to compute a multiple regression model, which generalizes simple regression to include more than one independent variable. Regression was run to determine an equation for the Market Value of Players given fifteen potential soccer statistic inputs. The inputs included: Actim Index Score, Fantasy Score, Age, Height, Weight, Number of Starts, Number of Subs, Goals, Assists, Shots, Shots on Goal, Fouls Committed, Fouls Suffered, Yellow Cards Received, and Red Cards Received. It should be noted that just because some of these statistics are able to be used to estimate the Market Value of a player, it does not mean that these inputs are the actual causation for increased or decreased Market Value. It simply means that there is some type of correlation between the variables and Market Value.

The regression equations can be found in the figures below. Step-Wise Regression and Forward Regression were very similar in results, only very slight differences in the constants before each of the same variables, therefore only Step-Wise Regression, Figure 5-1, is shown for the purposes of this paper. Backward Regression was noticeably different than the other two methods and is shown in Figure 5-2.

Figure 5-1: Equation for Market Value from Step-Wise Regression

$$\text{Market Value} = -5.951\text{E}+06 + 324996.169 * (\text{Shots on Goal}) + 44915.535 * (\text{Actim Index}) - 2.118\text{E}+05 * (\text{Fouls Committed}) + 1.352\text{E}+06 * (\text{Yellow Cards}) - 5.633\text{E}+05 * (\text{Assists}) + 4.290\text{E}+06 (\text{Red Cards}) - 2.762\text{E}+05 * (\text{Starts})$$

Adjusted R square = .795

Standard Error of the Estimate = 4945162.079

Significance = .000

Figure 5-2: Equation for Market Value from Backward Regression

$$\text{Market Value} = -4.251\text{E}+06 + 46036.854 * (\text{Actim Index}) - 4.335\text{E}+05 * (\text{Age}) + 164465.919 * (\text{Weight}) - 3.599\text{E}+05 * (\text{Starts}) + 196043.599 * (\text{Shots}) - 7.756\text{E}+05 * (\text{Assists}) - 2.290\text{E}+05 * (\text{Fouls Committed}) + 1.520\text{E}+06 * (\text{Yellow Cards}) + 4.025\text{E}+06 * (\text{Red Cards})$$

Adjusted R square = .818

Standard Error of the Estimate = 4665427.719

Significance = .000

Both regression equations had similarities in the size and sign of the constant, Actim Index, Starts, Assists, Fouls Committed, Yellow Cards, and Red Cards. The differences were that Step-Wise included the variable Shots on Goal, while Backward included the variables Age, Weight, and Shots instead. Both equations had a significance of .000 and adjusted R square values close to .8, which means the variables accounted for close to 80% of the variance in the Market Value of a soccer player in the English Premier League. However, a concern is that both equations have a fairly large standard error, 4.6 and 4.9 million dollars.

One of the surprises was that none of the regression equations included Goals as a variable that factored in to the Market Value of players. This was extremely surprising due to the fact of how important goals are in soccer. However, a plausible explanation is that the number of goals that a player accumulates during any given season is largely dependent upon luck and is actually random and therefore does not correlate to the market value of a player. In *The Drunkard's Walk: How Randomness Rules Our Lives*, Leonard Mlodinow discusses just how much of our everyday lives are determined by randomness. "A new theory of accidents, in which is codified the central argument of this chapter: in complex systems (among which I count our lives) we should expect that minor factors we can usually ignore will by chance sometimes

cause major incidents” (Mlodinow). This is in opposite thought of the deterministic view also explained in the book.

“That is the deterministic view of the marketplace, a view in which it is mainly the intrinsic qualities of the person or the product that governs success. But there is another way to look at it, a nondeterministic view. In this view there are many high-quality but unknown books, singers, actors, and what makes one or another come to stand out is largely a conspiracy of random and minor factors – that is luck” (Mlodinow).

This view also applies to athletes, such as soccer players, and even further to the number of goals a player has in any given season. Luck plays a large part in it. In addition, a player may consistently have more than say ten goals each season, but the actual number of goals scored above ten is most likely determined at random. In addition, the number of goals scored by a certain player depends greatly upon the play of other players on their team. Having better and more skilled players on a team could lead to greater benefits, goals, to a less skilled player because the less skilled player could receive better passes and less attention from opposing defenses. Therefore, it would make sense why the number of goals a player accumulates in a season does not show up in the regression equations for the market value of a player.

This is also an explanation for why Assists have a negative sign in the regression equations. Furthermore, there are a number of problems with the assist statistic in soccer. One problem is that after a pass, the player who passed the ball has no control or influence over whether or not the ball ends up in the back of the soccer net for a goal. It is the same concept as a pitcher in baseball who has no control over whether a ball goes for a hit after the ball is put into play. Another problem is that assists can be skewed towards whoever the coach appoints as the

free kick and corner kicker. Most likely, these players will have more assists than other players due to the repetition of chances.

The negative value for Starts and positive values for Yellow Cards and Red Cards are also opposite of what logic would lead one to think. Logic would say that a player who starts more games for a team is more valuable and that players who receive cards, which is looked as a detriment to the team, would be less valuable. However, it may be thought of that Market Value is more dependent on a player's contribution to the team winning and not just on how active the player is, the number of starts the player receives. In addition, whether or not a player starts or substitutes into the game is dependent on the coach's view of the player and so is not a true reflection of the value of the player. An explanation for the values of the Yellow and Red Cards might be that the players who are putting greater effort and are playing more on the edge of fouling people are the same ones that are getting more Yellow and Red Cards. It may be the case that these players are more valued due to their more aggressive playing style.

It is not surprising that the Actim Index, Shots, and Shots on Goal all have a positive value in the regression equations. Offensive players, midfielders and strikers who shoot the ball much more often, on average are paid much more than defensive players, goalies and defenders. These averages by position can be seen in Table 5-1.

Table 5-4: Average Market Value by Position

	Goalie	Defender	Midfielder	Striker
Average Market Value	\$1,747,775	\$2,537,107	\$4,472,478	\$5,433,485

Furthermore, the Actim Index is designed to be a better statistic for the evaluation of the performance of a player. So, it is not surprising that a greater Actim Index value correlates to a higher Market Value for that player.

## Chapter 6

### Significance

Even though there are plausible explanations to the results of the above analyses, it is more likely that these statistics are not the major causations for increased or decreased Market Value of players. The results from the analyses did not provide a convincing enough conclusion that they are meaningful in the determination of a player's Market Value. Too many of the results, even though they could be explained, were opposite or not as strong as would have been expected. Instead, these traditional statistics seem to be simply showing correlation with Market Value. It would be my interpretation that since these results do not follow what basic logic would imply with these statistics, such as goals being included in the regression equations for Market Value, that it points more to the fact that these traditional statistics are not as meaningful as thought to be in the value and evaluation of players.

However, the Principal Component Analysis does help break down important types of players that account for the variance in these statistics. There were also other interesting findings from these analyses. One of these points of interest was the fact of a strong correlation between Market Value and Fouls Suffered. Others included, the lack of Goals being included in the regression equations, Assists and Starts having a negative value in the regression equations, and Yellow and Red Cards having positive values in the regression equations. Even though it is not a basis to establish causation, one is able to come up with plausible reasoning for these results that make for an interesting discussion and further looking into.



## Chapter 7

### Conclusion and Suggestions for Further Research

In conclusion, the current statistics that are recorded in soccer, even though they most likely have some amount of meaning and influence on the value of a player, are not comprehensive enough and are not to a point that they can be used to evaluate players accurately and meaningfully. There are definitely improvements and advancements that can be made in the soccer statistics world that will provide further insight into performance and contribution to winning of players. Some potential improvements have been noted and other problem areas have identified throughout this paper.

Therefore, further research in statistics recorded in soccer needs to be done in order to not only determine what ones are truly representative of the true value of a player, but also what other statistics need to be recorded and tracked in order to do this. This could include ideas such as improving the accuracy of current statistics, breaking the field into smaller sectors to track statistics on a per player basis, tracking statistics such as tackles, one-on-one situations, passing efficiency, dribble distance, balls won in the air, and many more, and creating new statistics such as a goalie defense independent statistic. “The accepted statistical measures aren't good enough. It's possible, however, without going too far into the problem of statistics in fluidly complex sports, to imagine that advances in methodology would lead to new measures that would further our understanding of the sport and help us see it in a fresh way” (Phillips). Many lessons can be taken from the furthering of statistics in other sports and applied to soccer. With these lessons and concepts in mind, the advancement in soccer statistics will lead to a new way of viewing the value and performance of players and with this information will lead to an innovative way of building a winning soccer team.

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## APPENDIX

## Regression – Step-Wise

Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	Shots_on_Goal	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Actim_Index	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Fouls_Committed	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	Yellow_Card	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
5	Assists	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
6	Red_Card	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
7	Start	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.762 <sup>a</sup>	.581	.574	7125254.502
2	.810 <sup>b</sup>	.655	.644	6513281.633
3	.843 <sup>c</sup>	.711	.697	6009044.197
4	.866 <sup>d</sup>	.750	.733	5642980.600
5	.881 <sup>e</sup>	.777	.758	5371683.432
6	.894 <sup>f</sup>	.799	.778	5149480.441
7	.904 <sup>g</sup>	.817	.795	4945162.079

a. Predictors: (Constant), Shots\_on\_Goal

b. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index

c. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed

d. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card

e. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists

f. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists, Red\_Card

g. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists, Red\_Card, Start

h. Dependent Variable: Salary\_Market\_Value

ANOVA<sup>h</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.436E+15	1	4.436E+15	87.369	.000 <sup>a</sup>
	Residual	3.198E+15	63	5.077E+13		
	Total	7.634E+15	64			
2	Regression	5.004E+15	2	2.502E+15	58.977	.000 <sup>b</sup>
	Residual	2.630E+15	62	4.242E+13		
	Total	7.634E+15	64			
3	Regression	5.432E+15	3	1.811E+15	50.141	.000 <sup>c</sup>
	Residual	2.203E+15	61	3.611E+13		
	Total	7.634E+15	64			
4	Regression	5.724E+15	4	1.431E+15	44.935	.000 <sup>d</sup>
	Residual	1.911E+15	60	3.184E+13		
	Total	7.634E+15	64			
5	Regression	5.932E+15	5	1.186E+15	41.114	.000 <sup>e</sup>
	Residual	1.702E+15	59	2.885E+13		
	Total	7.634E+15	64			
6	Regression	6.096E+15	6	1.016E+15	38.316	.000 <sup>f</sup>
	Residual	1.538E+15	58	2.652E+13		
	Total	7.634E+15	64			
7	Regression	6.240E+15	7	8.915E+14	36.454	.000 <sup>g</sup>
	Residual	1.394E+15	57	2.445E+13		
	Total	7.634E+15	64			

a. Predictors: (Constant), Shots\_on\_Goal

b. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index

c. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed

d. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card

e. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists

f. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists, Red\_Card

g. Predictors: (Constant), Shots\_on\_Goal, Actim\_Index, Fouls\_Committed, Yellow\_Card, Assists, Red\_Card, Start

h. Dependent Variable: Salary\_Market\_Value

Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.426E+06	1212093.495		1.176	.244
	Shots_on_Goal	386790.615	41380.561	.762	9.347	.000
2	(Constant)	-1.144E+07	3685778.314		-3.104	.003
	Shots_on_Goal	280761.766	47645.876	.553	5.893	.000
	Actim_Index	34685.550	9477.197	.344	3.660	.001
3	(Constant)	-9.312E+06	3456192.505		-2.694	.009
	Shots_on_Goal	311850.220	44876.050	.615	6.949	.000
	Actim_Index	36378.553	8757.333	.360	4.154	.000
	Fouls_Committed	-1.392E+05	40456.501	-.248	-3.441	.001
4	(Constant)	-1.035E+07	3263683.626		-3.171	.002
	Shots_on_Goal	310882.701	42143.467	.613	7.377	.000
	Actim_Index	35204.688	8232.977	.349	4.276	.000
	Fouls_Committed	-2.176E+05	45975.907	-.387	-4.734	.000
	Yellow_Card	1.061E+06	350366.551	.242	3.028	.004
5	(Constant)	-1.071E+07	3109709.733		-3.445	.001
	Shots_on_Goal	366276.895	45108.505	.722	8.120	.000
	Actim_Index	37116.843	7869.432	.368	4.717	.000
	Fouls_Committed	-2.198E+05	43772.798	-.391	-5.021	.000
	Yellow_Card	1.255E+06	341252.004	.287	3.678	.001
	Assists	-5.519E+05	205485.477	-.214	-2.686	.009
6	(Constant)	-1.231E+07	3049613.073		-4.038	.000
	Shots_on_Goal	348277.370	43842.456	.686	7.944	.000
	Actim_Index	40364.739	7655.816	.400	5.272	.000
	Fouls_Committed	-2.203E+05	41962.613	-.392	-5.250	.000
	Yellow_Card	1.183E+06	328396.154	.270	3.604	.001
	Assists	-5.334E+05	197125.550	-.207	-2.706	.009
	Red_Card	4.350E+06	1746870.937	.151	2.490	.016
7	(Constant)	-5.951E+06	3930283.021		-1.514	.135
	Shots_on_Goal	324996.169	43181.585	.640	7.526	.000
	Actim_Index	44915.535	7587.339	.445	5.920	.000
	Fouls_Committed	-2.118E+05	40447.195	-.377	-5.238	.000
	Yellow_Card	1.352E+06	322923.846	.309	4.187	.000
	Assists	-5.633E+05	189703.569	-.218	-2.969	.004
	Red_Card	4.290E+06	1677741.320	.148	2.557	.013
	Start	-2.762E+05	113780.941	-.150	-2.427	.018

### Regression - Backward

Variables Entered/Removed<sup>b</sup>

Model	Variables Entered	Variables Removed	Method
1	Red_Card, Age, Start, Actim_Index, Fouls_Committed, Weight, Sub, Assists, Yellow_Card, Fouls_Suffered, Shots_on_Goal, Height, Fantasy_Score, Goals, Shots <sup>a</sup>	.	Enter
2	.	Shots_on_Goal	Backward (criterion: Probability of F-to-remove >= .100).
3	.	Sub	Backward (criterion: Probability of F-to-remove >= .100).
4	.	Height	Backward (criterion: Probability of F-to-remove >= .100).
5	.	Goals	Backward (criterion: Probability of F-to-remove >= .100).
6	.	Fantasy_Score	Backward (criterion: Probability of F-to-remove >= .100).
7	.	Fouls_Suffered	Backward (criterion: Probability of F-to-remove >= .100).

a. All requested variables entered.

b. Dependent Variable: Salary\_Market\_Value

## Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.923 <sup>a</sup>	.852	.806	4805799.350
2	.923 <sup>b</sup>	.851	.810	4761867.497
3	.923 <sup>c</sup>	.851	.813	4720681.995
4	.922 <sup>d</sup>	.851	.817	4678499.403
5	.922 <sup>e</sup>	.850	.819	4640578.125
6	.921 <sup>f</sup>	.849	.821	4626926.319
7	.918 <sup>g</sup>	.843	.818	4665427.719

a. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Sub, Assists, Yellow\_Card, Fouls\_Suffered, Shots\_on\_Goal, Height, Fantasy\_Score, Goals, Shots

b. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Sub, Assists, Yellow\_Card, Fouls\_Suffered, Height, Fantasy\_Score, Goals, Shots

c. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Height, Fantasy\_Score, Goals, Shots

d. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Fantasy\_Score, Goals, Shots

e. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card,

Fouls\_Suffered, Fantasy\_Score, Shots

f. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Shots

g. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Shots

h. Dependent Variable: Salary\_Market\_Value

ANOVA<sup>h</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.502E+15	15	4.335E+14	18.770	.000 <sup>a</sup>
	Residual	1.132E+15	49	2.310E+13		
	Total	7.634E+15	64			
2	Regression	6.500E+15	14	4.643E+14	20.476	.000 <sup>b</sup>
	Residual	1.134E+15	50	2.268E+13		
	Total	7.634E+15	64			
3	Regression	6.498E+15	13	4.998E+14	22.429	.000 <sup>c</sup>
	Residual	1.137E+15	51	2.228E+13		
	Total	7.634E+15	64			
4	Regression	6.496E+15	12	5.413E+14	24.731	.000 <sup>d</sup>
	Residual	1.138E+15	52	2.189E+13		
	Total	7.634E+15	64			
5	Regression	6.493E+15	11	5.903E+14	27.409	.000 <sup>e</sup>
	Residual	1.141E+15	53	2.153E+13		
	Total	7.634E+15	64			
6	Regression	6.478E+15	10	6.478E+14	30.259	.000 <sup>f</sup>
	Residual	1.156E+15	54	2.141E+13		
	Total	7.634E+15	64			
7	Regression	6.437E+15	9	7.152E+14	32.859	.000 <sup>g</sup>
	Residual	1.197E+15	55	2.177E+13		
	Total	7.634E+15	64			

a. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Sub, Assists, Yellow\_Card, Fouls\_Suffered, Shots\_on\_Goal, Height, Fantasy\_Score, Goals, Shots

b. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Sub, Assists, Yellow\_Card, Fouls\_Suffered, Height, Fantasy\_Score, Goals, Shots

c. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Height, Fantasy\_Score, Goals, Shots

d. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Fantasy\_Score, Goals, Shots

e. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Fantasy\_Score, Shots

f. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Fouls\_Suffered, Shots

g. Predictors: (Constant), Red\_Card, Age, Start, Actim\_Index, Fouls\_Committed, Weight, Assists, Yellow\_Card, Shots

h. Dependent Variable: Salary\_Market\_Value

Coefficients<sup>a</sup>

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-1.958E+07	2.712E+07		-7.221E-01	.474
Actim_Index	42080.043	10153.419	.417	4.144	.000
Fantasy_Score	34958.508	37251.334	.119	.938	.353
Age	-4.392E+05	196192.226	-1.600E-01	-2.239E+00	.030
Height	7.438E+06	1.665E+07	.047	.447	.657
Weight	168028.989	116044.150	.123	1.448	.154
Start	-3.864E+05	133551.150	-2.105E-01	-2.893E+00	.006
Sub	146863.228	405593.363	.030	.362	.719
Goals	-1.705E+05	309940.772	-1.002E-01	-5.500E-01	.585
Shots	151465.457	126043.878	.508	1.202	.235
Shots_on_Goal	65931.836	219729.076	.130	.300	.765
Assists	-8.201E+05	262207.489	-3.181E-01	-3.128E+00	.003
Fouls_Committed	-2.352E+05	45076.934	-4.183E-01	-5.219E+00	.000
Fouls_Suffered	59748.889	47057.805	.109	1.270	.210
Yellow_Card	1.490E+06	331009.839	.340	4.501	.000
Red_Card	3.986E+06	1.810E+06	.138	2.203	.032
2 (Constant)	-1.686E+07	2.533E+07		-6.658E-01	.509
Actim_Index	42840.664	9742.020	.424	4.398	.000
Fantasy_Score	32795.513	36213.119	.112	.906	.369
Age	-4.552E+05	187048.886	-1.658E-01	-2.434E+00	.019
Height	6.041E+06	1.584E+07	.038	.381	.705
Weight	174849.281	112756.055	.129	1.551	.127
Start	-3.952E+05	129072.741	-2.153E-01	-3.062E+00	.004
Sub	139922.719	401231.611	.028	.349	.729
Goals	-1.357E+05	284866.357	-7.981E-02	-4.764E-01	.636
Shots	186398.804	47860.955	.625	3.895	.000
Assists	-8.379E+05	253096.261	-3.250E-01	-3.311E+00	.002
Fouls_Committed	-2.381E+05	43687.794	-4.233E-01	-5.449E+00	.000



	Fouls_Suffered	56926.601	45686.734	.104	1.246	.219
	Yellow_Card	1.505E+06	323986.786	.344	4.646	.000
	Red_Card	3.883E+06	1.761E+06	.134	2.206	.032
3	(Constant)	-1.240E+07	2.167E+07		-5.723E-01	.570
	Actim_Index	42463.253	9597.984	.421	4.424	.000
	Fantasy_Score	30840.492	35467.124	.105	.870	.389
	Age	-4.471E+05	183968.097	-1.629E-01	-2.430E+00	.019
	Height	3.989E+06	1.458E+07	.025	.274	.786
	Weight	177046.528	111606.176	.130	1.586	.119
	Start	-4.140E+05	116309.750	-2.256E-01	-3.559E+00	.001
	Goals	-9.990E+04	263405.008	-5.875E-02	-3.793E-01	.706
	Shots	185167.521	47317.723	.621	3.913	.000
	Assists	-8.369E+05	250889.205	-3.246E-01	-3.336E+00	.002
	Fouls_Committed	-2.393E+05	43159.026	-4.256E-01	-5.545E+00	.000
	Fouls_Suffered	57247.969	45282.374	.104	1.264	.212
	Yellow_Card	1.490E+06	318209.788	.340	4.682	.000
	Red_Card	3.742E+06	1.699E+06	.129	2.203	.032
4	(Constant)	-6.909E+06	8.089E+06		-8.541E-01	.397
	Actim_Index	42628.878	9493.276	.422	4.490	.000
	Fantasy_Score	31232.145	35121.553	.107	.889	.378
	Age	-4.420E+05	181413.862	-1.610E-01	-2.437E+00	.018
	Weight	195749.643	87426.477	.144	2.239	.029
	Start	-4.061E+05	111653.626	-2.213E-01	-3.637E+00	.001
	Goals	-9.916E+04	261037.567	-5.831E-02	-3.799E-01	.706
	Shots	186255.768	46728.893	.624	3.986	.000
	Assists	-8.523E+05	242262.248	-3.306E-01	-3.518E+00	.001
	Fouls_Committed	-2.390E+05	42759.278	-4.251E-01	-5.590E+00	8.481E-07
	Fouls_Suffered	55162.122	44236.993	.100	1.247	.218
	Yellow_Card	1.476E+06	311550.346	.337	4.739	.000
	Red_Card	3.636E+06	1.639E+06	.126	2.218	.031
5	(Constant)	-6.567E+06	7.974E+06		-8.236E-01	.414

Actim_Index	41427.169	8878.150	.410	4.666	.000
Fantasy_Score	27838.441	33691.027	.095	.826	.412
Age	-4.274E+05	175841.575	-1.557E-01	-2.431E+00	.018
Weight	193251.619	86472.197	.142	2.235	.030
Start	-4.010E+05	109940.655	-2.185E-01	-3.647E+00	.001
Shots	173478.856	32176.463	.582	5.391	.000
Assists	-8.066E+05	208516.361	-3.129E-01	-3.868E+00	.000
Fouls_Committed	-2.421E+05	41660.219	-4.305E-01	-5.811E+00	3.618E-07
Fouls_Suffered	54429.944	43836.765	.099	1.242	.220
Yellow_Card	1.485E+06	308232.598	.339	4.817	.000
Red_Card	3.700E+06	1.617E+06	.128	2.288	.026
6 (Constant)	-7.294E+06	7.902E+06		-9.231E-01	.360
Actim_Index	45882.417	7032.550	.455	6.524	2.436E-08
Age	-4.156E+05	174748.446	-1.514E-01	-2.378E+00	.021
Weight	194935.050	86193.876	.143	2.262	.028
Start	-3.804E+05	106778.132	-2.073E-01	-3.563E+00	.001
Shots	190388.074	24757.277	.638	7.690	3.125E-10
Assists	-8.445E+05	202800.829	-3.276E-01	-4.164E+00	.000
Fouls_Committed	-2.488E+05	40741.334	-4.424E-01	-6.106E+00	1.151E-07
Fouls_Suffered	59864.336	43213.087	.109	1.385	.172
Yellow_Card	1.515E+06	305141.164	.346	4.965	.000
Red_Card	3.650E+06	1.611E+06	.126	2.265	.028
7 (Constant)	-4.251E+06	7.654E+06		-5.554E-01	.581
Actim_Index	46036.854	7090.178	.456	6.493	2.545E-08
Age	-4.335E+05	175723.495	-1.579E-01	-2.467E+00	.017
Weight	164465.919	84034.006	.121	1.957	.055
Start	-3.599E+05	106624.458	-1.961E-01	-3.375E+00	.001
Shots	196043.599	24621.551	.657	7.962	1.005E-10
Assists	-7.756E+05	198238.888	-3.008E-01	-3.912E+00	.000
Fouls_Committed	-2.290E+05	38485.189	-4.073E-01	-5.951E+00	1.928E-07
Yellow_Card	1.520E+06	307664.030	.347	4.939	.000
Red_Card	4.025E+06	1.602E+06	.139	2.513	.015

Correlations

	Salary_Market_Value	Pearson Correlation	Actim_Index	Fantasy_Score	Age	Height	Weight	Start	Sub	Goals	Shots	Shots_on_Goal	Assists	Fouls_Committed	Fouls_Suffered	Yellow_Card	Red_Card
	1		.651**	.665**	.007	-.018	.014	.338**	-.027	.729**	.673**	.700**	.469**	-.196**	.411**	.233**	.162**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.920	.743	.806	.000	.630	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	77	243	321	320	320	325	325	325	325	325	325	325	325	325	325
	.651**		1	.749**	-.255**	.005	-.030	.140**	.051**	.679**	.601**	.622**	.464**	.201**	.285**	.080**	-.022**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.012	.958	.770	.169	.615	.000	.000	.000	.000	.048	.004	.435	.832
	77	N	98	78	96	96	96	98	98	98	98	98	98	98	98	98	98
	.665**		.749**	1	.161**	-.053	-.016	.856**	.059	.772**	.803**	.800**	.674**	.627**	.743**	.622**	.170**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.001	.274	.743	.000	.230	.000	.000	.000	.000	.000	.000	.000	.000
	243	N	78	421	420	419	421	421	421	421	421	421	421	421	421	421	421
	.007		-.255**	.161**	1	.065	.110**	.245**	-.061	.003	-.009	-.021	-.034	.125**	.118**	.143**	.048**
		Pearson Correlation Sig. (2-tailed)	.000	.012	.001	.115	.008	.000	.142	.938	.836	.614	.413	.002	.004	.001	.244**
	321	N	96	420	590	589	589	590	590	590	590	590	590	590	590	590	590
	.743		.958	.274	.115	.000	.989	.001	.000	.251	.000	.002	.000	.021	.000	.001	.861**
		Pearson Correlation Sig. (2-tailed)	.000	.005	.065	.1	.719**	.001	-.206**	-.047	-.143**	-.130**	-.173**	-.095**	-.151**	-.134**	-.007**
	321	N	96	420	590	589	589	590	590	590	590	590	590	590	590	590	590
	.014		-.030	-.016	.110**	.719**	1	.044	-.182**	-.047	-.115**	-.113**	-.125**	-.051**	-.105**	-.054**	.066**
		Pearson Correlation Sig. (2-tailed)	.006	.770	.743	.008	.000	.290	.000	.260	.005	.006	.002	.219	.011	.189	.112**
	320	N	96	419	589	589	589	589	589	589	589	589	589	589	589	589	589
	.338**		.140	.856**	.245**	.001	.044	1	-.100	.409**	.531**	.498**	.504**	.688**	.753**	.652**	.213**
		Pearson Correlation Sig. (2-tailed)	.000	.169	.000	.989	.290	.000	.014	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	-.027		.051	.059	-.061	-.206**	-.182**	-.100**	1	.172**	.211**	.211**	.099**	.142**	.050**	.042**	-.018**
		Pearson Correlation Sig. (2-tailed)	.630	.615	.230	.142	.000	.014	.000	.000	.000	.000	.015	.000	.215	.300	.661**
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.729**		.679**	.772**	.003	-.047	-.047	.409**	.172**	1	.825**	.872**	.553**	.454**	.511**	.256**	.075**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.938	.251	.260	.000	.000	.000	.000	.000	.000	.000	.000	.000	.064**
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.673**		.601**	.803**	-.009	-.143**	-.115**	.531**	.211**	.825**	1	.977**	.727**	.607**	.672**	.416**	.145**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.836	.000	.005	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.700**		.622**	.800**	-.021	-.130**	-.113**	.498**	.211**	.872**	.977**	1	.705**	.574**	.638**	.384**	.118**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.614	.002	.006	.000	.000	.000	.000	.000	.000	.000	.000	.000	.004**
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.469**		.464**	.674**	-.034	-.173**	-.125**	.504**	.099**	.553**	.727**	.705**	1	.500**	.628**	.425**	.104**
		Pearson Correlation Sig. (2-tailed)	.000	.000	.413	.000	.002	.000	.015	.000	.000	.000	.000	.000	.000	.000	.010**
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.196**		.201**	.627**	.125**	-.095**	-.051**	.688**	.142**	.454**	.607**	.574**	.500**	1	.758**	.763**	.226**
		Pearson Correlation Sig. (2-tailed)	.000	.048	.002	.021	.219	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.411**		.285**	.743**	.118**	-.151**	-.105**	.753**	.050**	.511**	.672**	.638**	.628**	.758**	1	.660**	.198**
		Pearson Correlation Sig. (2-tailed)	.000	.004	.004	.000	.011	.000	.215	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.233**		.080**	.522**	.143**	-.134**	-.054**	.652**	.042**	.256**	.416**	.384**	.425**	.763**	.660**	1	.219**
		Pearson Correlation Sig. (2-tailed)	.000	.435	.001	.189	.000	.000	.300	.000	.000	.000	.000	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608
	.162**		-.022**	.170**	.048	-.007	.066	.213**	-.018**	.075**	.145**	.118**	.104**	.226**	.198**	.219**	1
		Pearson Correlation Sig. (2-tailed)	.003	.832	.000	.861	.112	.000	.661	.064	.000	.004	.010	.000	.000	.000	.000
	325	N	98	421	590	590	589	608	608	608	608	608	608	608	608	608	608

\*\* Correlation is significant at the 0.01 level (2-tailed).

\* Correlation is significant at the 0.05 level (2-tailed).

Nonparametric Correlations

	Salary_Market_Value	Acim_Index	Fantasy_Score	Age	Height	Weight	Start	Sub	Goals	Shots	Shots_on_Goal	Assists	Fouls_Committed	Fouls_Suffered	Yellow_Card	Red_Card
Spearman's rho	1.000	-.505	.729	-.135	-.059	-.027	.565	-.098	-.578	.615	.605	.551	.467	.590	.381	.115
Correlation Coefficient		.000	.015	.294	.631	.000	.077	.000	.000	.000	.000	.000	.000	.000	.000	.039
Sig. (2-tailed)		.325	.771	.243	.321	.320	.325	.325	.325	.325	.325	.325	.325	.325	.325	.325
N		505	1,000	623	-.202	-.003	.049	-.011	.335	.324	.333	.318	.208	.144	.098	-.039
Correlation Coefficient		.000	.000	.049	.976	.635	.021	.914	.001	.001	.001	.001	.040	.156	.335	.702
Sig. (2-tailed)		.771	.98	.78	.96	.96	.98	.98	.98	.98	.98	.98	.98	.98	.98	.98
N		.729	.623	1,000	.254	-.108	.068	.917	.202	.795	.788	.725	.765	.846	.668	.180
Correlation Coefficient		.000	.000	.000	.027	.167	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Sig. (2-tailed)		.421	.243	.421	.420	.419	.421	.421	.421	.421	.421	.421	.421	.421	.421	.421
N		.135	-.202	.254	1,000	.046	.084	-.021	.070	.084	.066	.056	.176	.194	.195	.054
Correlation Coefficient		.015	.049	.000	.260	.022	.000	.604	.088	.042	.107	.171	.000	.000	.000	.191
Sig. (2-tailed)		.321	.96	.420	.590	.589	.590	.590	.590	.590	.590	.590	.590	.590	.590	.590
N		-.059	-.003	-.108	1,000	.738	-.021	-.289	-.157	-.252	-.251	-.229	-.171	-.176	-.177	-.016
Correlation Coefficient		.294	.976	.027	.260	.022	.000	.604	.000	.000	.000	.000	.000	.000	.000	.691
Sig. (2-tailed)		.321	.96	.420	.590	.589	.590	.590	.590	.590	.590	.590	.590	.590	.590	.590
N		-.027	.049	-.068	.084	.738	1,000	-.009	-.112	-.204	-.217	-.171	-.106	-.124	-.084	.039
Correlation Coefficient		.631	.635	.167	.022	.000	.826	.000	.006	.000	.000	.000	.010	.003	.041	.341
Sig. (2-tailed)		.320	.96	.419	.589	.589	.589	.589	.589	.589	.589	.589	.589	.589	.589	.589
N		.565	.234	.917	.278	-.021	1,000	.017	.506	.646	.620	.583	.762	.848	.727	.222
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.088	-.011	.202	-.289	-.245	.017	1,000	.329	.456	.453	.273	.320	.247	.159	.009
N		.077	.914	.000	.604	.000	.677	.608	.608	.608	.608	.608	.608	.608	.608	.829
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.578	.335	.760	.070	-.112	.508	.329	1,000	.795	.813	.627	.615	.618	.456	.094
N		.000	.001	.000	.088	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.021
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.615	.324	.795	.084	-.204	.646	.458	.795	1,000	.974	.732	.826	.810	.620	.174
N		.000	.001	.000	.042	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.605	.333	.788	.086	-.251	.620	.453	.813	.974	1,000	.712	.797	.782	.592	.158
N		.000	.001	.000	.107	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.551	.318	.725	.056	-.229	.583	.273	.627	.732	.712	1,000	.639	.679	.502	.139
N		.000	.001	.000	.171	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.001
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.467	.208	.765	.176	-.171	.762	.320	.615	.826	.797	.639	1,000	.876	.799	.256
N		.000	.040	.000	.000	.010	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.690	.144	.846	.194	-.176	.848	.247	.618	.810	.782	.673	.876	1,000	.754	.237
N		.000	.156	.000	.003	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.381	.098	.668	.195	-.177	.727	.159	.456	.620	.592	.502	.799	.754	1,000	.258
N		.000	.335	.000	.000	.041	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)		.115	-.039	.180	.054	-.016	.039	.009	.094	.174	.168	.139	.256	.237	.256	1,000
N		.039	.702	.000	.191	.691	.000	.829	.021	.000	.000	.001	.000	.000	.000	.000
Correlation Coefficient		.325	.98	.421	.590	.589	.608	.608	.608	.608	.608	.608	.608	.608	.608	.608
Sig. (2-tailed)																
N																

\*\* . Correlation is significant at the 0.01 level (2-tailed).  
 \* . Correlation is significant at the 0.05 level (2-tailed).

## Principal Component Analysis

### KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.781
Bartlett's Test of Sphericity	Approx. Chi-Square	717.987
	df	66
	Sig.	.000

### Communalities

	Initial	Extraction
Salary_Market_Value	1.000	.749
Actim_Index	1.000	.714
Fantasy_Score	1.000	.830
Age	1.000	.482
Height	1.000	.818
Weight	1.000	.705
Sub	1.000	.884
Goals	1.000	.888
Shots	1.000	.890
Shots_on_Goal	1.000	.913
Assists	1.000	.667
Fouls_Suffered	1.000	.627

Extraction Method: Principal Component Analysis.

### Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.852	48.767	48.767	5.852	48.767	48.767	5.021	41.843	41.843
2	2.285	19.038	67.805	2.285	19.038	67.805	2.882	24.017	65.859
3	1.032	8.597	76.403	1.032	8.597	76.403	1.265	10.543	76.403
4	.664	5.530	81.933						

5	.542	4.513	86.446					
6	.466	3.886	90.332					
7	.426	3.549	93.882					
8	.309	2.578	96.460					
9	.199	1.660	98.119					
10	.156	1.303	99.422					
11	.060	.499	99.921					
12	.009	.079	100.000					

Extraction Method: Principal Component Analysis.

**Component Matrix<sup>a</sup>**

	Component		
	1	2	3
Shots_on_Goal	.942	.096	.130
Shots	.938	.075	.074
Goals	.883	.267	.190
Fantasy_Score	.834	.362	-.064
Salary_Market_Value	.793	.314	.147
Actim_Index	.719	.425	-.128
Assists	.697	-.280	-.319
Fouls_Suffered	.634	-.337	-.334
Age	-.524	.381	.249
Height	-.322	.845	-.033
Weight	-.344	.766	.010
Sub	.281	-.389	.809

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

**Rotated Component Matrix<sup>a</sup>**

	Component		
	1	2	3
Goals	.918	.127	.171
Fantasy_Score	.897	.125	-.104

Shots_on_Goal	.883	.314	.186
Shots	.864	.350	.142
Salary_Market_Value	.857	.064	.103
Actim_Index	.820	.046	-.199
Height	.113	-.812	-.382
Weight	.060	-.776	-.315
Fouls_Suffered	.368	.692	-.112
Assists	.451	.671	-.113
Age	-.258	-.644	.029
Sub	.135	.134	.921

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Analysis was run on statistics compiled from ESPN (ESPN).

## ACADEMIC VITA of Jon W. Schultz

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Education: Bachelor of Science Degree in Science, Penn State University, Fall 2009  
Focus in Mathematics  
Honors in Astronomy and Astrophysics  
Thesis Title: Building a Winning Soccer Team – Analysis of Statistics in Soccer  
Thesis Supervisor: Dr. Steinn Sigurdsson

Related Experience:  
Co-op with Lockheed Martin Corporation (used statistics to analyze various business situations)  
Supervisor: Joseph Ferrara  
Summer 2008 and Spring/Summer 2009

Awards:  
Dean's List  
Balog Scholar  
Eagle Scout of Boy Scouts of America

Presentations/Activities:  
Smeal MBA Finance Association  
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Junior Assistant Scout Master for Boy Scouts of America