PERCEPTION VERSUS REALITY - COMPETITIVE BALANCE IN MAJOR LEAGUE SOCCER FROM 1996 – 2016

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Abstract

For different sports leagues, studies show the positive effect of competitive balance on fan interest and consequently revenues. Particularly for Northern American leagues, competitive balance is a core concept in the construction of such, also to ensure financial stability of teams. Nevertheless, most studies in the literature concentrate on measuring competitive balance in European football leagues. To enhance the existing literature, our paper analyzes competitive balance in Major League Soccer (MLS), a comparatively young and therefore still developing league. To encompass ex-post results, as well as the ex-ante perception of fans if a league or match is uncertain in its outcome, we distinguish between ´actual´ and ´perceived´ competitive balance. Based on compiled data for MLS from 1996 until 2016 we measure the ´actual´ level of competitive balance in MLS with several commonly used competitive balance measures. Considering the corresponding decimal odds predictions and team wage bill information from 2006 until 2016, the ´perceived´ competitive balance is measured using a seemingly unrelated regression and further explanatory statistics. While the results of the ´actual´ competitive balance measurements indicate a league that becomes more balanced over time, the perception points towards an imbalanced league with clear favorites and reduced uncertainty of outcome.

Keywords: Competitive Balance, Major League Soccer, Football.

JEL Classification*: D40, L10, L83, Z21*

1. Introduction

Competitive balance is a key concept for all North American professional leagues due to its supposed positive effects on (ticket) demand. Also for Major League Soccer (MLS) competitive balance caters to their mission. MLS strives to maximize turnover, profits and to achieve a steady growth for the league grounded in strong and financially viable teams. Competitive balance has varying degrees of influence on those different goals. On a broad level, the term competitive balance reflects the degree of equality in match or championship outcomes of professional sporting events (compare Owen, Ryan, & Weatherston, 2007). Under perfect balance conditions, all teams at the start of the season should have the same expectation to win the championship or at least to perform well and end up high in the final ranking. Thus, no team should be constantly ranked at the top or at the bottom of the league. The unpredictability of the final competition winner is called seasonal uncertainty which is separate from prize concentration, number of wins of teams across seasons, and match unpredictability (compare Sloane, 2015). According to Sloane (2015, p. 2), "uncertainty of outcome creates interest" along the lines of the original uncertainty of outcome hypothesis (UoO) formulated by Rottenberg (1956). Hence, in a balanced league the UoO is high which in turn attracts fans. With regards to fans, Pawlowski and Budzinski (2012, p. 5) explain that "it is helpful to distinguish between objective competitive balance and perceived competitive balance". Whereas objective competitive balance is measured with statistics based on actual results, perceived competitive balance is a subjective impression of how uncertain and balanced a league is. Empirical findings to test the effect of UoO and competitive balance are mixed. In Major League Baseball, Schmidt and Berri (2001) found a difference between the 'actual' and 'perceived' competitive balance on attendance which is then later explained by Paul, Weinbach, Borghesi, and Wilson (2008) with ex-ante and ex-post measures. Here, both types have positive effects on the relevant league indicators mentioned before. In contrast, Sung and Mills (2017) propose, based on their regression results, that MLS fan attendance is not sensitive to changes in the competitive balance in the sense of match UoO. They present evidence that "superior teams and superstars may be particularly important to the growth and popularity of MLS, at least in terms of attendance" (p. 12). Paul and Weinbach (2013), for example, explain the positive impact that uncertainty of outcome, hence a 'perceived' competitive balance for fans, has on TV ratings in MLS and NHL. The contrasting findings are in line with previous research finding that stadium attendance and TV viewership is not necessarily driven by the same factors (Coates et al., 2014). Coates et al. (2014) also explain a multi-layered effect from

UoO on attendance with reference-dependent preferences. According to Coates et al. (2014) the relevance of UoO on game attendance depends upon „whether fans' preference for tighter games dominates their preference for home team wins" (p. 963). Hence, the UoO hypothesis is important once fans' preference for a home win is not stronger than their utility from, e.g., a win of their home team when they expect a home loss and loss aversion is not present. This might explain the different findings by Sung and Mills who do not control for all type of reference-dependent preferences. Also, Sung and Mills (2017) leave out cross-season uncertainty and focus on in-season balance which present an incomplete picture. With the mixed results in mind, some fans prefer at least seasonal unpredictability when deciding to attend a game live or watch/listen/follow via another medium. In turn, more interest in matches and the league translates into higher income via stadium revenues (tickets, merchandizing, and other stadium sales), merchandizing, and broadcasting rights. Or to rephrase it, greater competitive balance leads to greater demand and in consequence, less competitive balance results in less income. This relation also supports the interest of single teams trying to maximize their own revenue but in addition, and in contrast to the league, also try to maximize wins. Win maximization is in stark contrast to MLS's focus on competitive balance which hinders single teams to dominate the league constantly. And from the beginning, MLS has introduced rules and regulations like revenue sharing, salary caps, transfer approvals and centralized contracts that all foster competitive balance. This is only balanced partly by the MLS Players Association. Coates et al. (2016) also explain the, sometimes, conflicting priorities along the introduction of the Designated Player Rule and the resulting greater wage inequality. Greater wage inequality impacts performance negatively which is a concern for win maximizing teams. But, the intention behind the league was to generate higher revenue from increased merchandizing and ticket sales due to an increased fan interest in superstars like David Beckham. In line with this intention, the average value of MLS teams increased indeed, according to Forbes, from 2007 until 2016 by a factor of 5. And average team revenue increased from $37 to $223 million with eight teams generating a positive operating income. Despite the initial fee of $150 million that new owners face, a whopping 275% increase from just five years ago when the Montreal Impact paid $40 million, prospective MLS team owners across the country clamor for being part of the growing league. After adding Atlanta United FC and Minnesota United FC in 2017 and Los Angeles FC in 2018, Miami and Nashville, plus one additional city, are supposed to fill the 26 MLS team spots for 2020. Then again, the introduction of the Designated Player Rule was a first step towards opening the tight salary cap system which ensured equality among all teams, from a resource perspective. Nevertheless, MLS still claims to be a league of parity despite changes in the roster sizes towards more players in the final roster, allowing MLS teams to compete for star players in the international soccer market, tendencies towards free agency, and continuous expansion. In contrast, according to the level of competitive balance in the top European soccer leagues, Pawlowski et al. (2010, p. 199) find "clear evidence of a persistent decline of competitive balance in the five domestic leagues analyzed since the turn of the millennium". Thus, can this decrease in competitive balance also be observed in MLS or is the league as balanced as it claims? Moreover, is the fight for playoffs spots throughout the regular season highly competitive and unpredictable? Has each team in different seasons the same chance to win the championship? And even if the competition in MLS between the teams is equally balanced, do consumers perceive MLS in this way? Is the 'perceived' balance or imbalance reflected by the actual situation? These are the research questions that we address in this paper. Answers to these questions will, first, help to clarify the discussion about MLS's league parity. Secondly, advance research by generating an understanding for competitive balance in a specialized league in the long-run and contrast it to European leagues that operate under an open system with relegation and promotion. And thirdly, answers will help MLS officials to draw conclusions to support decision making around league size or necessary regulations based on the 'perceived' versus 'actual' situation around competitive balance or imbalance in MLS.

2. Measuring competitive balance in MLS

The concept of competitive balance plays a major role in the existing literature. Initially, the theoretical developments concerning competitive balance all follow the ideas of Rottenberg (1956) as well as El-Hodiri and Quirk (1971; 1974). The empirical literature on competitive balance follows two distinct lines. The first line focuses on what has happened to competitive balance over time or as a result of changes in the business practices of pro sports leagues (e.g., Quirk & Fort, 1997). These studies include general overviews of changes in competitive balance over time in single leagues, as well as comparisons to other leagues (see e.g., Evans, 2014) based on ex-post results. The second line of literature on competitive balance analyzes its effect on fan welfare and tests the longstanding UoO hypothesis (e.g., Humphreys, 2002). In this line, betting odds are used to proxy the ex-ante perception of fans and interested media (compare Paul et al., 2008). In the following, we conduct empirical tests for both areas, 'actual' and 'perceived' competitive balance, to determine competitive balance in MLS over time.

2.1. ´Actual´ competitive balance

The measurement of competitive balance, in terms of ex-post measures, is complicated by its multidimensional nature related to the type of unpredictability as mentioned in the introduction. The different dimensions include the evenness of teams in individual matches, the distribution of wins or points across teams at the end of a season, the persistence of team records of wins or points across successive seasons, and the degree of concentration of championship wins over a number of seasons (Kringstad & Gerrard, 2007). Out of those, prize concentration in the MLS history provides a first simple measure for the degree of competitive balance in the league (see Table 1 below).

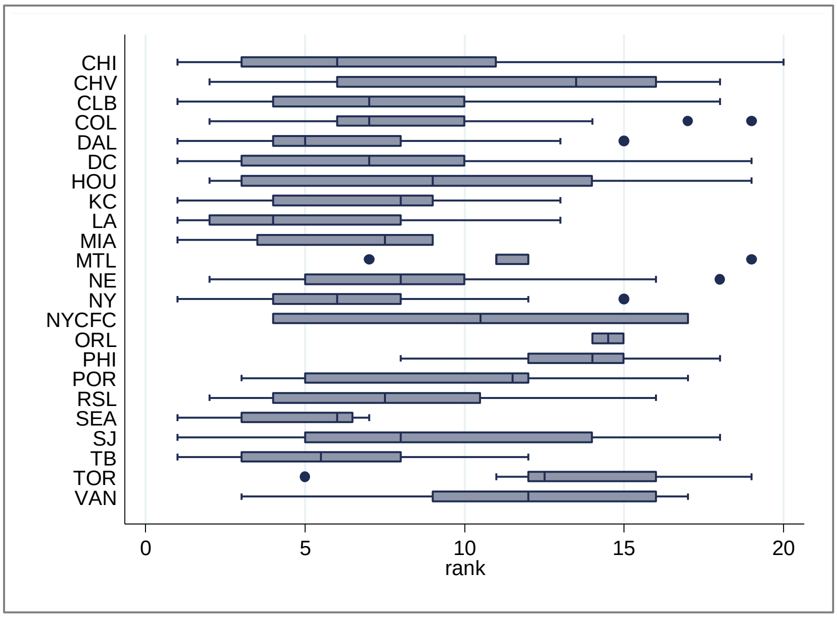
Table 1 MLS Cup Champions, 1996 - 2016

Team	Number of MLS Cup	Years
Los Angeles Galaxy	5	2002, 2005, 2011, 2012, 2014
DC United	4	1996, 1997, 1999, 2004
Houston Dynamo	2	2006, 2007
Sporting Kansas City	2	2000, 2013
San Jose Earthquakes	2	2001, 2003
Chicago Fire	1	1998
Columbus Crew	1	2008
Colorado Rapids	1	2010
Portland Timbers	1	2015
Real Salt Lake	1	2009
Seattle Sounders	1	2016
	21	*1996-2016*

The concentration of championship winners is an indication of the level of turnover of top teams in a league. While high concentration of championship winners is an indicator for low turnover and thus for competitive imbalance, low concentration of championship winners indicates higher turnover and a more equal competition. From 1996 until 2016, MLS crowned 11 different champions (out of 23 teams that participated in MLS until 2016). This number is high, compared to the distribution in the five major European top-division soccer leagues between the 1995/1996 and 2015/2016 seasons. La Liga (or under the name Primera División), the Serie A and the EPL had five different champions in the observed time frame, the German Bundesliga six and only the Ligue 1, in France (until 2002 called Division 1), had an MLS-similar low concentration with 10 different winners. Despite the overall variety of championship winners in France, Olympique Lyon (2002-2008) and Paris St. Germain (2013-

2016) dominated the national championships in two time periods. To a weaker extent in MLS, Los Angeles Galaxy is the most successful team that won close to a quarter of all championships in the last 21 years, followed by DC United that won four championships over the whole period. Three teams (DC United, Houston Dynamo, and Los Angeles Galaxy) managed to defend their title once. The longest stretch different teams have won the title was five season, only in six cases the supporters shield winner (the team with the most points in the regular season) became MLS Cup champion later on which illustrates the ‘own rules’ of MLS playoffs. The ups and downs of teams over time are also displayed in Figure 1.

Figure 1 MLS Team Performance, 1996 – 2016



Most teams display a wide range of ranks that they achieved at the end of each regular season. In this regard, the best teams over time were Seattle and LA Galaxy, the worst Montreal, Toronto, Philadelphia and Orlando[1]. While Seattle and all of the latter are expansion teams and therefore have not as many seasons yet to fail/prove themselves, there is a difference in the strength between the two conferences. The best teams are in the West Coast division while the worst teams are in the East Coast. Using a dataset with all MLS results from 2004 until 2016 we apply a series of Chi-square tests to determine if the observed performance differences are statistically significant. The findings support the general impression that the West Coast is the stronger conference. West Coast teams win statistically more often at home ($p<0.1$). They win 51% of all home matches compared to the East Coast teams that win 48% of their home

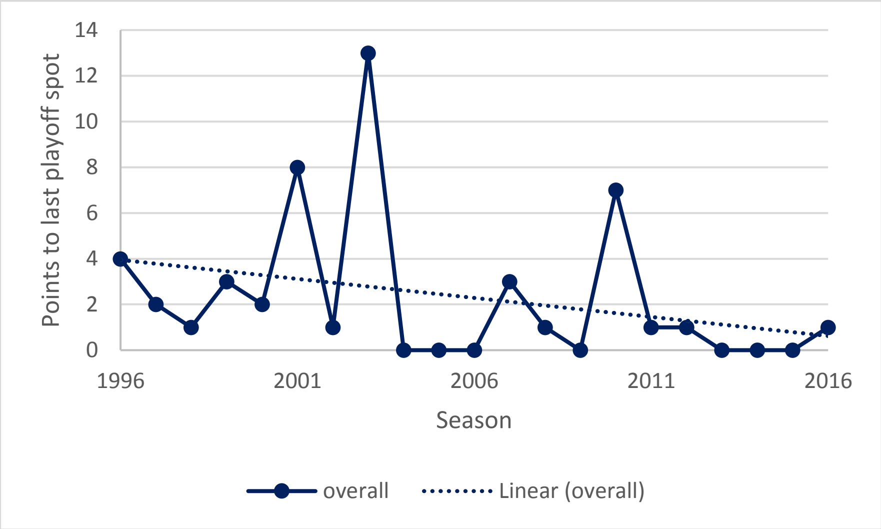
[1]A detailed list of average ranks for all teams can be found in the Appendix (Table 4).

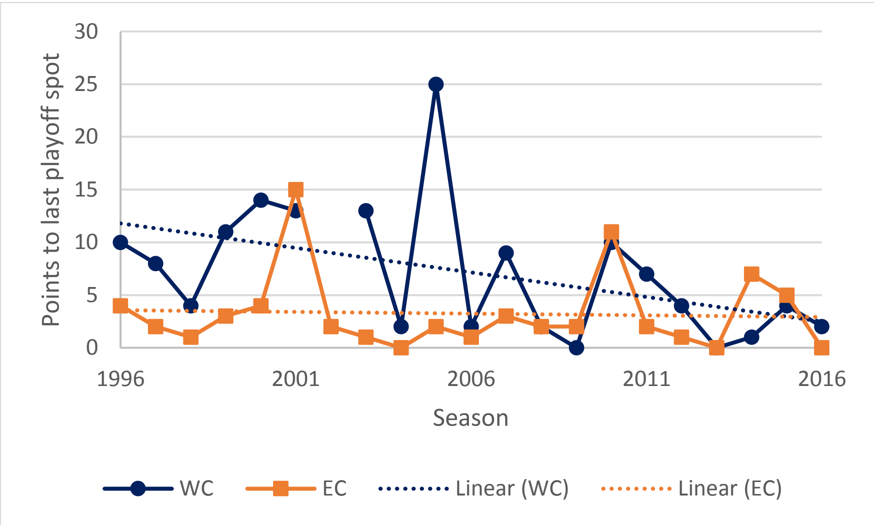
matches. Furthermore, West Coast teams traveling to the East Coast for an inter-conference match are more successful to win ($p<0.05$). West Coast teams win 27% of matches they play against East Coast home teams. East Coast teams only win 22% of matches that they play on the West Coast. An explanation for the differences between West and East Coast teams needs to consider the unbalanced schedule in MLS[2]. For example, in 2016 the 20 teams played two or three times against their own conference opponents (at least once at home and once away against each opponent and six additional games as set by the scheduling board), hence intra-league, and 10 inter-conference games (5 away, 5 home). On the one hand, it means that the schedule strength of each team is different as not everyone faces the same opponents equally often. On the other hand, it also means that special MLS features like Rivalry Week, which draws additional interest in the league, can be planned for and adjusted into the schedule (for an introduction to MLS rivalries see Cobbs & Tyler, 2017). Another aspect of inter-conference games is the increased travel load for the players. So, one explanation for more home wins of Western teams against East Coast teams might be a late game time - a 7pm match on the west coast translates to 10pm for Eastern teams - in inter-conference matches for one side. The Eastern teams jump across two time-zones when traveling West. Medical research has shown that athletes perform better in the afternoon than in the late evening due to our circadian rhythm (Winget, Deroshia, & Holley, 1985). In contrast, Western teams traveling to the East Coast often get to play in “their afternoon”. Draws, which can be also seen as a direct measure of ex-post balance in a game, occur in all games, intra- or inter-conference equally often with 27% of times. This is also reflected by the result distribution over the last 13 seasons. The most frequent outcome in the regular MLS season is a draw with the result 1:1 (12.1%). This is followed by home team wins ending 1:0 (11.9%) and 2:1 (10.6%).

When analyzing competitive balance in a North American sports league like MLS, it can be useful to examine the point differences between the last playoff spot[3] and the first non-playoff spot in order to account for possible changes in the evenness in the middle or at the bottom of the league. The point differences in MLS, and also for both conferences, over the different seasons are displayed in the following Figure.

[2] The exception were the seasons 2010 and 2011 with a double round robin creating a balanced schedule.
[3] Considering all teams who qualified at least for the knockout round.

Figure 2 Points to Last Playoff Spot in MLS, 1996 – 2016, Overall and by Division





As presented in the upper half of Figure 2, the point difference between the last playoff spot and the first non-playoff sport decreases over time. Especially since the 2011 season, the point difference in the overall standings does not exceed one point. With regard to the conferences, the decrease in point differences can only be confirmed for the Western Conference[4], whereas the point difference in the Eastern Conference remains stable over time. The outlier in the Western Conference (2005) is due to the relatively poor performance of the expansion teams Real Salt Lake and Chivas USA. Furthermore, expansion teams perform in general rather poorly in their first season but improve afterwards.

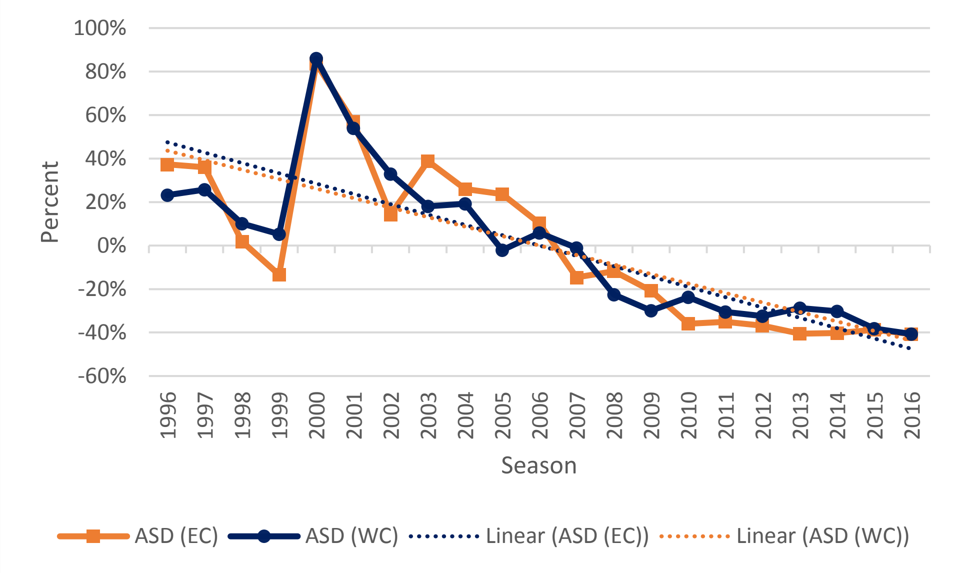
[4] In MLS season 2002 all five teams in the Western conference reach the playoffs. Thus, the value for the point difference in this season is missing in the presented figure.

Using these straightforward measures, MLS appears to be relatively balanced over time, but in general West Coast teams perform better than teams from the East Coast. As mentioned before, the literature is full of alternative measure for competitive balance (see for an overview Evans, 2014) from which some are more sophisticated than others. Considering the different advantages and disadvantages of these measures, it seems impossible to construct one perfect measure of competitive balance. However, standard measures of dispersion, inequality and concentration, applied to end-of season league outcomes such as win percentages or point percentages, are equally good instruments to measure competitive balance according to King and Owen (2012). To further examine competitive balance in MLS over time, we emphasize standard-deviation-based measures because of their popularity and acceptance in practice. But, using a winning percentage does not fully reflect team success in leagues with many ties (Humphreys, 2002). Therefore, the use of point percentages is more appropriate in MLS. Moreover, an advantage of this is that changes in the number of teams and changes in the point system can be reflected by adjusting seasonal mean points received by the teams, i.e. the coefficient of variation. The point scheme that assigns three points for a win, one point for a draw, and zero for a loss is denoted (3,1,0) and represents the current scheme in many world soccer leagues – including MLS (Fort, 2007). In order to consider point ratios and the point assignment scheme used, "the 'actual' standard deviation of points ratios (ASD) provides a simple, natural measure of the ex post variation in end-of-season points ratios across the teams in a league" (Owen & King, 2015, p. 732). Analyzing the distribution of points on season level is useful to understand competitive balance within the league. Therefore, the ASD can be calculated as

$$ASD = \sqrt{\sum_{i=1}^{N} [p_i - \bar{p}]^2 / (N-1)}.$$

N equals the number of teams in the league $p_i = \frac{P_i}{T_i}$, where Pi and Ti are, respectively, the actual number of points accumulated and the maximum possible points total attainable by team i in a season, and $\bar{p} = \sum_{i=1}^{N} p_i / N$ is the league's mean points ratio. We calculate ASD separately for the Western and the Eastern Conference to see if one league drives the trend of MLS of getting more balanced over the years. For the seasons 1996 – 2016, the deviation from the mean (in percent) is presented in the following Figure. Absolute values for ASD and the dispersion of point ratios around the league mean can be found in the Appendix (Table 5).

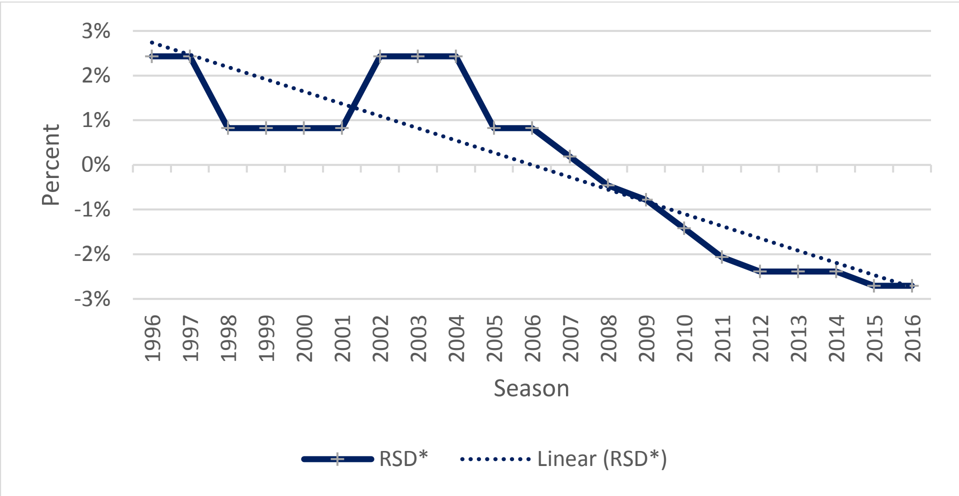
Figure 3 ASD for Competitive Balance in MLS (EC and WC), 1996 - 2016



Other things equal, the larger the dispersion of points ratios around the league mean in any season, the more unequal is the competition. For the interpretation of the results it has to be noted that the number of games played by each team in a regular season (G) is not taken into account by the ASD formula. Sensitivity to season length is of concern, because comparing the values for the dispersion of points ratios around the league mean between seasons with different G can lead to biased results. Thus, ASD tends to decrease if teams play more games because the extent of random noise in the final outcomes is reduced (Leeds & Allmen, 2008). Because G is constant for the seasons 2011-2016 (34 games in the regular season), the results only confirm the previous descriptive findings that MLS is quite balanced over this period. Irrespective of the possibility of bias because of different values for G (range from 30 to 34 games in the regular season), the dispersion of point ratios around the league mean decreases over the period from 1996 until 2016. Until 2011, the teams played between 26 and 32 games which could be, again, a source for potential bias in the presented results. To overcome this bias and with reference to Noll (1988) and Scully (1989), the most commonly used measure of competitive balance in the sports economics literature, the ´relative´ standard deviation (RSD), is applied. The RSD is also considered to be the most useful measure of competitive balance, "because it controls for both season length and the number of teams, facilitating a comparison of competitive balance over time and between leagues" (Fort, 2007, p. 643). In the following we use the normalized measure RSD* as used by Owen (2010), the derivation of which can be found at the end of the Appendix. The normalized measure RSD* serves as a supplement to the examination of the 'actual' standard deviation in our analysis.

This normalized measure RSD* lies in the interval [0, 1], with 0 representing perfect parity and 1 representing maximum imbalance. This normalized measure serves as a measure of competitive balance that can be applied to compare ´open´ (or ´closed´) leagues of any size or number of games per team (Evans, 2014). The deviation from the mean (in percent) is presented in Figure 4. Absolute values for RSD* can be also found in the Appendix (Table 6).

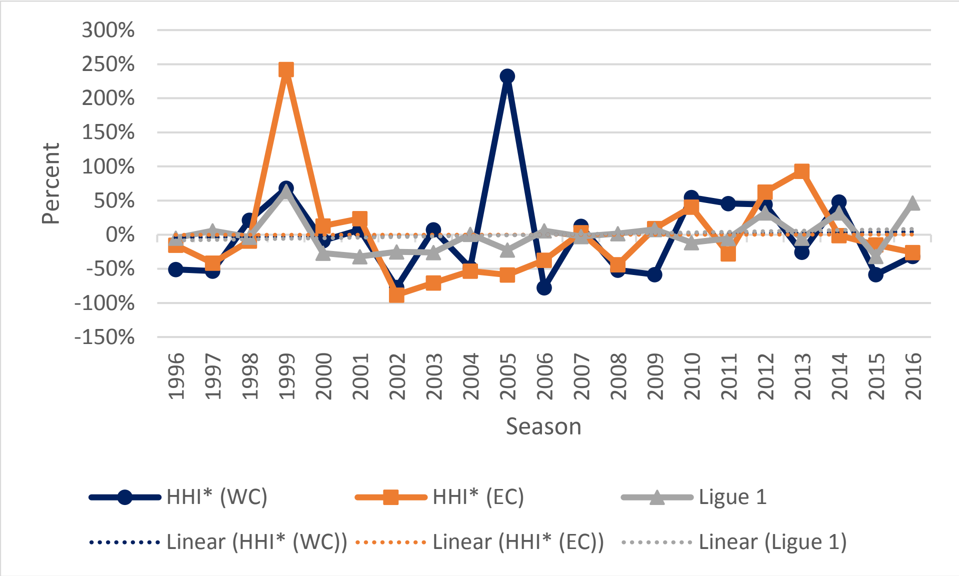
Figure 4 RSD* for Competitive Balance in MLS, 1996 - 2016



As presented in Figure 4, RSD* decreases from 1996 (for N=10; G=32) to 2016 (for N=20; G=34). The presented results from ASD and RSD* imply that the league shows no clear upward or downward trend from the start of MLS in 1996 until the early years of the new millennium. After this period, ASD and RSD* decrease constantly. Taken together, in the early years the level of competitive balance fluctuates in MLS, while in the mid-2000s, the measures suggest a more equal league overall. But, the statement that competitive balance in MLS increased can only be confirmed with confidence for the years since 2011, once the number of games and teams remained identical.

The static competitive balance measures like ASD and RSD have one important limitation, they do not reflect relative changes in standings over time. To overcome this problem, Humphreys (2002) introduced the Competitive Balance Ratio (CBR). The CBR scales average team-specific variation in won-loss ratio during a number of seasons by the average within-season variation in won-loss percentage during the same period (Humphreys, 2002). However, as the number of teams in MLS doubled over time (from 10 teams in 1996 to 20 teams in 2016) which cannot be reflected in the ASD formula, an application of the CBR for MLS would produce bias in the results. To allow for changes in the number of teams in the league over time, Owen et al. (2007) used a normalized Herfindahl-Hirschmann Index (HHI) as a measure of inequality in sports leagues. Once the varying upper and lower bounds of HHI are considered, the normalized HHI is an appropriate measure of competitive balance that is useful for comparisons over time or across different leagues and varying numbers of teams (Owen et al., 2007). To consider the expansion activities of MLS, we used the normalized HHI as a further measure of competitive balance in this league. Similar to RSD*, the normalized HHI lies in the interval [0, 1], with 0 indicating perfect parity and 1 representing the highest level of imbalance. In contrast to standard HHI calculations for leagues like MLB, e.g. (Depken, 1999,), with clear win/loss results, we need to include draws as a further potential outcome of MLS games. Therefore, we include a draw with 1/3 in the calculation. Based on the findings from the European championship distributions, the normalized HHI is also calculated for Ligue 1, French primary football competition. Ligue 1 serves as a good benchmark due to its similarly low concentration of championship teams compared to MLS. Figure 5 shows the deviation from the mean for the calculated HHI*-values (in percent).

Figure 5 HHI* for Competitive Balance in MLS (EC and WC), 1996 - 2016



Overall, the results demonstrate no improvement of competitive balance in the observed leagues and no difference in the strength of the two conferences in MLS. According to the HHI*-values (Table 7 in the Appendix), the values are quite close to parity for MLS and Ligue 1. Apart from the outliers for the Eastern Conference in 1999 and the Western Conference in 2005[5], the volatility of the HHI*-values remains low over time. In contrast to the findings of ASD and RSD as well as the examination of point differences in the Western Conference, the HHI*-values show no increase in competitive balance in MLS since their inaugural season in 1996.

While some measures of 'actual' competitive balance show that MLS became more balanced after the first years of the new millennium, others confirm only a stable development of an already balanced league. In conclusion, once taking the multidimensional nature of the 'actual' competitive balance measurements into account, the presented competitive balance measures indicate that MLS appears to be rather balanced over time.

[5] The outlier in the EC in 1999 is strongly driven by D.C. United, who won three of their four MLS Cups in the late 90´s and played an overall dominant role in the EC during that time. In 2005, the outlier in the WC is due to the strong performance of San Jose Earthquakes, especially in regular season. San Jose belonged to the top teams in MLS after the start of the new millennium (MLS Cup Champion in 2001 and 2003).

2.2. ´Perceived´ competitive balance

According to Paul et al. (2008), the perception of fans if a league or a match is uncertain in its outcome influences various actions that result, irrespectively of the later game outcome, in substantial income for the league and teams. Among those are the decision to buy a ticket, merchandise products, and packages, to watch games on TV or, more recently, online. Obviously, all actions might also be influenced by previous experience, hence previous match results, and are therefore not necessarily on-the-spot activities. The same is true for betting odds in an efficient market. They incorporate all available information up till the game starts and are therefore, according to Buraimo and Simmons (2009), an excellent proxy for 'perceived' competitive balance of fans. Furthermore, "bookmakers have an obvious financial incentive to set accurate odds to the extent that, especially given falling margins in the era of string competition for internet wagering, any errors may result in providing professional bettors with opportunities for positive expected returns." (Buraimo, Forrest, & Simmons, 2007, p. 170). Therefore, we compiled MLS data for the results and the corresponding decimal odds for home win, away team win and draw from 2004 until 2016 and team wage bill information from 2006[6] until 2016. A first overview on the descriptives can be found below in Table 2.

[6] 2006 is the first season where salary information for players were reported officially.

Table 2 MLS Betting Market Descriptives

	count[7]	mean	sd	min	max
year	2732			2006	2016
team	2732			1	21
AvailBookmakers	2732	9.88	3.72	1	17
OddHome	2732	2.10	0.50	1.24	8.38
OddAway	2732	3.89	1.27	1.40	12.1
OddDraw	2732	3.46	0.32	2.90	5.93
OddsRight	2732	0.49	0.50	0	1
pHW	2732	49.9	9.74	11.9	80.6
pD	2732	29.1	2.34	16.9	34.5
pAW	2732	28.2	8.28	8.28	71.4
AT_TimeDif (abs.)	2732	1.15	1.01	0	3
AttDiff	2732			-35672	35672
RunppgHT	2732	1.31	0.52	0	3
RunppgAT	2732	1.35	0.54	0	3
HT_LsRank	2732	8.84	5.09	1	20
AT_LsRank	2732	8.85	5.09	1	20
HT_logwage	2732	15.2	0.57	14.3	16.8
AT_logwage	2732	15.2	0.57	14.3	16.8

The odds are given in the European decimal system from which probabilities are calculated. The implied probabilities equal 1 divided by the decimal odd times 100, hence are corrected for the bookmaker's margin. We prefer the use of probabilities over odds as the interpretation is straightforward while odds follow a reverse scale. *AttDiff* gives the difference in attendance from the previous season, as a proxy for differing fan support, for the two teams competing. The abbreviation HT refers to home team and AT for away team. Time difference, *AT_TimeDif*, is given in absolute hours for the away team traveling (e.g. |-3| for NYCFC traveling to LA). *Runppg* is the running point per game score for the team that is calculated for each gameday. The *LsRank* represents the rank the team finished at in the previous regular season, hence for 2016 the 2015 ranks for all teams are referred to. The odd for each game is an average of the closing odds offered by a varying number of bookmakers. In 2004, only one to five bookmakers offered odds on MLS games while in 2016 on average 16 bookmakers offered MLS odds. This led to a decrease in margin from more than 12% in 2004 to 6% on average for bookmakers in 2016. This prompts the question for efficiency in the early years of the dataset. An efficient betting market would increase the confidence for using the betting data as a suitable proxy for expected match outcomes. Also, the number of correct predictions from the average bookmaker odds is quite low with less than 50% before 2012 (the 2010 season is an outlier with over 50%).

[7] Descriptives for the full sample (2004 - 2016) do not differ substantially and can be found in the Appendix (Table 8) for reference.

The number of correct predictions improves slightly until 2016, but, no clear trend is visible. Also, no trend is observable within seasons even if that can usually be expected. The longer the season runs, the more information on the teams' roster and performance is available which should improve predictions. Anyhow, the prediction quality of the playoff games, after the regular season, fluctuates even more. In some seasons over 60% of games are predicted correctly while in others less than 40%. As before in the ex-post competitive balance measures, this leads us to believe that the MLS playoffs have "different rules" and are somewhat detached from regular season performances. Hence, the chances for each team to succeed here are more equal and this in turn increases the competitive balance of the league. These findings might imply two matters. First, the league is extremely competitive in the sense that bookmakers in general have a hard time to predict the outcomes as favorites are rare. Or second, the betting market is not efficient, e.g. in using available information, and therefore the predictions are bad. With reference to Buraimo et al. (2007) we conduct a short market efficiency test. Using an ordered probit model we regress the implied probabilities on match outcomes for home and away win respectively, while including *AttDiff*.[8] "If the market were efficient, the odds would capture all information relevant to match outcome and additional variables would be redundant in the model" (Buraimo et al., 2007, p. 172). For MLS, the implied probabilities are each highly significant with a positive coefficient as expected, while *AttDiff* is insignificant for the outcome of a home or away win. This means that we do not find evidence, like Buraimo et al. (2007), of an additional uncaptured effect for big or small market teams.

To understand the drivers of MLS odds better, a regression with the respective implied probabilities as dependent variables is estimated. For this, we use Zellner's (1962) seemingly unrelated regression (SUR), as the probability for a home and away win can be estimated as separate models, but the error terms are allegedly correlated across the equations. The results can be found in Table 3 below.

[8] The results of the auxiliary probit regression are available upon request.

Table 3 Probability Determination in MLS with SUR, 2006 – 2016

	SUR (1) Prob. Home Win	SUR (2) Prob. Away Win
RunppgTeam	5.6462***	-4.8606***
	(0.2503)	(0.2114)
RunppgOpponent	-5.4759***	4.6011***
	(0.2410)	(0.2035)
HT_LsRank	-0.4685***	0.3869***
	(0.0289)	(0.0244)
AT_LsRank	0.4622***	-0.3849***
	(0.0289)	(0.0244)
HT_logwages	1.7851***	-1.6409***
	(0.4791)	(0.4045)
AT_logwages	-1.3966**	1.0683**
	(0.4804)	(0.4056)
EC-EC	*Reference Category*	
EC-WC	-0.0563	0.2811
	(0.8694)	(0.7355)
WC-EC	0.6358	-0.3588
	(0.8632)	(0.7303)
WC-WC	-1.3811	1.4178
	(1.1994)	(1.0127)
AttDiff	0.0003***	-0.0003***
	(0.0000)	(0.0000)
AvailBookmakers	0.2514	-0.0850
	(0.1348)	(0.1138)
AT_TimeDif (absolute)		-0.1459***
		(0.0334)
Home & away team fixed effects included (details in the Appendix Table 9)		
Season fixed effects included		
Constant	41.2749***	40.7565***
	(10.1323)	(8.5550)
Observations	2732	
RMSE	6.38	5.41
R2*100	57.02	57.38
Chi-Square	3625.1***	3710.4***
Breusch-Pagan independence	2576.71***	
Correlation of errors	-0.9712	

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We exclude the estimation of the draw probability here, as the process for bookmakers to determine the draw odds is quite different from that of a win (Buraimo et al., 2007). The small variation across matches for the draw probability confirms this as well[9].

The presented regression model shows a medium fit[10] and explains about 57% of the variance in the perceived probability of a home win and away win. This leaves room for unobservable factors in the odd setting process either driven by specific bookmaker strategies or inefficiencies which cannot be controlled for by the available data. The basic results of the SUR are as expected. The better the home team currently is and has been in the last season, the higher the implied probability for a home team win. The opposite is true for the away team performance. Interestingly, team performance[11] in the current season has a 10-time higher influence on bookmakers' odds in MLS than last season's performance. This supports the previous findings that all teams start each season from "zero" with equal chances to win games. The number of bookmakers offering odds has no significant impact on the home or the away team's win probability. As further variables, the teams' wage bills are included to control for overall team quality in the season. This includes designated player salaries paid above the salary cap. As robustness check, the inclusion of the number of designated players on the team and a binary dummy variable (DP yes/no) were tested, both models yield no different or better results. The *HT_logwages* coefficient is positive and significant. The more the team costs, the higher is the implied probability of a home team win. A 1% increase in the home team wage bill is expected to increase the probability for the home team to win by 0.0179 points. This influence is merely gradual. Likewise, the away team's quality has a negative influence on the probability for a home team win. In turn, the away team's win probability is negatively impacted by a better home team and on a similar scale positively by their own quality. As expected, the better the home team, in terms of overall quality proxied by the team's wage bill, the higher is the probability of a home win. The better the away team, the higher is the probability of an away team win. The different conference match-ups were included as further control but show no significant coefficients. In contrast, an away team's prediction to win are

[9] Standard deviations for probD of 2.39 compared to 9.7 and 8.32 for probHW and probAW respectively.

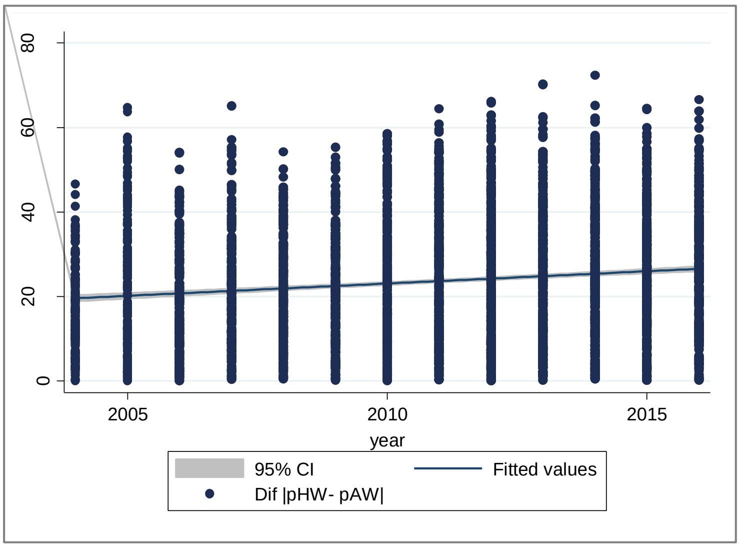
[10] Different model specifications, including OLS, have been tested and the best model was chosen according to statistical tests (e.g. AIC/BIC scores). Across all models, the team performance and quality coefficients remained stable in terms of the magnitude of coefficient and significance and can therefore be deemed as robust.

[11] Different scores for current season performance, e.g. points received in last three games or in the last game, were tested with the running point per game score producing the most coherent model. Adding further explanatory performance variables to the model increases the explanatory power not significantly but increases the risk for multicollinearity due to the high correlation of the variables and therefore have not been shown here. In the Appendix (Table 10), we present a model with alternative performance measures as robustness check.

reduced when they travel across time zones. For each hour of time difference the probability is reduced by 0.15 percent. An explanation for this is the strain on athletes' health once they jump time zones and play against the inner clock. Furthermore, the difference in attendance between the teams in the previous season yields significant but small results. If the home team had a larger attendance in the previous season (positive *AttDiff* value), hence more fan support, this increases the probability of a win (positive coefficient) while the opposite is true for the away win probability (negative coefficient). This is an initial indication for home team biases. Furthermore, we use team fixed effects to control for factors that are present at the team level and that bookmakers might consider, e.g. popularity of a team, the influence of a specific coach, previous success not captured by our performance variables. From the full results (which can be found in the Appendix Table 10) we conclude that those factors do indeed play a role. As reference team we chose New England Revolution because their mean probability is closest to the mean of the overall group. Based on this, teams like Chivas, New York City FC, Orlando, Seattle, and Toronto are perceived to perform worse than the rest of the group at home while teams like Dallas, Kansas City, and New York Red Bull, are perceived to perform better at home by the bookmakers. Notably, Seattle has probably the strongest fan crowd behind them and play constantly in front of a sold-out stadium which is covered by the *AttDiff* variable. Consistently, the described impact is flipped for the away games for those teams. Overall, the results from the probability regression suggest parity among teams across seasons based on the marginal impact of last season performance. In contrast, during a season, bookmakers appear to favor (or underestimate) certain teams which is not warranted by team quality, performance levels, travelling time zone's strain, or fan support. This suggests imbalance in the league. The other explanation, inefficiency in the bookmakers' odds setting process, was tested for and should be rejected.

After discussing the main determinants for implied home and away win probabilities, we now take a detailed look at another common measure for perceived UoO (for application see Buraimo et al., 2007; Meehan, Nelson, & Richardson, 2007; Rascher & Solmes, 2007), i.e. the absolute difference in probabilities of home and away win. Over time, see Figure 6, the absolute difference increased constantly. With the increasing differences of home and away win probabilities the perception of favorites became more pronounced in MLS over the years. This imbalance lowers UoO in turn and hence might lead certain fans to lose interest.

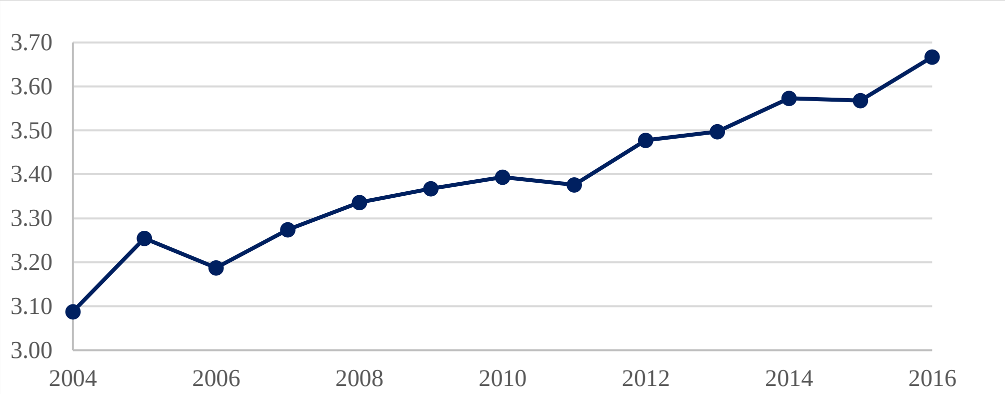
Figure 6 Difference Home and Away Win Probabilities for the Regular Season, 2004 - 2016



Also, unpredictability of MLS results is a conclusion that can be drawn from the high volatility in the probabilities visible in the above Figure. Additionally, a potential sentiment bias in that fans always bet on the home team, no matter what, should be taken into account. This might decrease the odds for a home team win and related arbitrage options. Bookmakers might in turn offer lower odds on the home team than would be justified by the fact-based insights on teams.

As a final check, we follow the example of Paul and Weinbach (2013) and use the absolute odds values on a tie over time as an indication for UoO and balance. “High odds on a tie implies that a draw is unlikely” (Paul & Weinbach, 2013, p. 57) as more money would be paid out once the draw occurs. This result would also suggest that, in perception, a clear favorite exists. Figure 7 shows that the odds on ties increased constantly over time while the percentage of draws (as outcome) remained quite stable.

Figure 7 Average Odds on Ties from 2004 - 2016



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
# ties	47	47	57	53	61	71	59	106	80	84	93	74	107
In % of games	29	23	28	26	28	30	24	33	24	25	28	21	30

Over the last 13 seasons, close to one third, between 21 and 33 percent over the years, of all games ended in a tie. Nevertheless, for the bookmakers the draw became less likely. As mentioned before, the odd setting process for draws is different from home and away wins and drives these outcomes. Bookmakers quote high draws as they generally consider a team's strength and rarely their style of play, e.g. low scoring teams, which would sometimes favor the draw (Pullein, 2009). Also, the American sport fans are rather unfamiliar with a tie as result. For the other large North American leagues, games end in win or loss. With the growing interest in the league, probably also more non-soccer fans are attracted where this unfamiliarity plays a role. All in all, high volatility in the odds are evidence for the unpredictability of MLS overall. Yet, a slow trend towards more 'perceived' imbalance and less UoO was seen in the analysis.

3. Conclusions

The first key finding for this study can be summarized as follows: Each MLS season starts almost from zero for all teams. This can be based on the actual and perceived competitive balance measures applied. For example, the regression results show a robust 10-times lesser impact of last-season results on the probability for a home or away win than current season performance. Turning to the actual outcome measures, prize concentration and seasonal unpredictability is high in MLS. This is partly guaranteed by penalties for the best teams in form of bad draft-slots and less allocation money, while the worst teams from the previous season are rewarded to support future equality. On the contrary, apart from the French first division, other European leagues are far less balanced across seasons. This might be due to the so-called "legacy league" approach. Teams in Europe build their reputation, quality and performance over time (e.g. Pawlowski et al., 2010). Also, team success is rewarded, e.g., the best teams receive the highest shares of broadcasting money. This is important to foster the international competitiveness of the best teams in a country for inter-country competitions like the UEFA Champions League. This is in stark contrast to the penalty system that is mainly in place to foster competitive balance in Northern American leagues. Based on the findings, this system appears to work for MLS in order to keep competitive balance at a high level. To support this, Vrooman (2000) provides theoretical explanations that a profit maximizing league, like MLS, is in general more balanced than a win maximizing league, like the European leagues.

Further result-oriented findings from the standard deviation measurements even indicate that the MLS became constantly more balanced from its inauguration in 1996 up until 2016. We also find indications that the Western Conference is stronger. In the middle of the table, measured by the difference between the last play-off and the first non-playoff spot, the trend towards more balance is strongly driven by the Western Conference with three big outliers. In the lower and upper part of the table the trend towards balance is similar for Western and Eastern Conference. Hence, the differences at the top, middle, and bottom of the table revoke opposing trends, but they leave the overall high level of competitiveness untouched. Furthermore, the normalized HHI*-measure was applied as a superior measure that controls for changes in teams across seasons. The calculated values remain on a relatively low level over time and are much closer to parity than to competitive imbalance. They indicate no differences regarding the strength of the conferences and show no increase in competitive balance in MLS over time. Overall, we conclude that the actual competitive balance was, since its inauguration, and is on a high level in MLS and some statistics even suggest a trend towards more parity over time.

The other key finding is that the results from the betting market with implied probabilities and odds point towards an imbalance and less UoO than the actual results suggested. This is in line with differing findings for perceived and actual competitive balance in MLB (Schmidt and Berry, 2001). The regression shows that across seasons the imbalance is not as strong but the team effects illustrate that not every team receives the same probabilities. These findings stand also after controlling for their performance, team quality, away team’s stress from time differences jumps, and fan support. Furthermore, in the perception ties became less likely, and the difference between home and away win probabilities increased over time. This leads to the conclusion that in the perception of the market clear favorites emerged, the league lost parity, and uncertainty of outcome was reduced. The perception of imbalance might be induced by

MLS's regulation changes and expansion activities even if we do not find support in the actual outcomes which is not unusual. For the NBA, Fort and Lee (2007, p. 1) also find "no break points in competitive balance time series corresponding to rule changes, the draft, free agency, salary caps, or labor disputes". Hence, the changes kept the balance intact but they supposedly lead the market to believe that balance was harmed. While perceived UoO is maybe not as relevant for stadium attendance in MLS (see Sung & Mills, 2017), it is still important for fan attention in the media (TV ratings improve according to Paul & Weinbach, 2013). Considering that the market is growing, especially for online consumption, and revenue sources are shifting, the impression the league makes in the (online) media might be even more relevant to MLS in the near future. Future research should therefore study the difference in impact of perceived versus actual competitive balance and UoO on relevant economic measures like attendance, merchandizing sales, TV ratings and especially online interest (e.g. online game viewership).

One limitation of this study is the application of averages for betting odds across various bookmakers. Ideally, future research should also test implied probabilities with best odds as those would complete the picture of the market. Further limitations for the analysis on the betting market were the unknown volumes of bets placed and origin of bettors. To discuss efficiency and the state of the MLS betting market in full, these data points would be central. Another limitation of this study is the absence of a perfect actual competitive balance measure. Researchers have investigated multiply different measures in extend, but so far, none captures all, or takes different scenarios into account. Especially, a valid measure to compare leagues with different set-ups would be helpful.

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Appendix

Table 4 Team's League Participation in MLS since Inauguration

Team	Abbre-viation	League Participation	Conference	# of Seasons	# of Playoffs	Rank Average	Comments
Chicago Fire	CHI	since 1998	15xEC, 2xWC, 2xCD	19	12	7.7	
Chivas USA	CHV	2005 - 2014	WC	10	4	11.3	
Columbus Crew SC	CLB	since 1996	19xEC, 2xCD	21	13	7.3	
Colorado Rapids	COL	since 1996	WC	21	13	8.3	
FC Dallas	DAL	since 1996	19xWC, 2xCD	21	15	6.2	
D.C. United	DC	since 1996	EC	21	13	7.0	
Houston Dynamo	HOU	since 2006	6xWC, 5xEC	11	7	8.8	*team transferred from San Jose*
Sporting Kansas City	KC	since 1996	10xWC, 11xEC	21	15	6.8	*until 2010 Kansas City Wizards*
LA Galaxy	LA	since 1996	WC	21	18	5.0	*formerly Los Angeles Galaxy*
Miami Fusion	MIA	1998-2001	EC	4	3	6.3	
Montreal Impact	MTL	since 2012	EC	5	3	12.0	
New England Revolution	NE	since 1996	EC	21	13	8.3	
New York Red Bulls	NY	since 1996	EC	21	17	6.4	*until 2005 Metro Stars*
New York City FC	NYCFC	since 2015	EC	2	1	10.5	
Orlando City SC	ORL	since 2015	EC	2	0	14.5	
Philadelphia Union	PHI	since 2010	EC	7	2	13.4	
Portland Timbers	POR	since 2011	WC	6	2	10.0	
Real Salt Lake	RSL	since 2005	WC	12	8	7.6	
Seattle Sounders FC	SEA	since 2009	WC	8	8	4.9	
San Jose Earthquakes	SJ	1996-2005, since 2008	WC	19	8	8.9	
Tampa Bay Mutiny	TB	1996-2001	4x EC, 2xCD	6	4	5.8	
Toronto FC	TOR	since 2007	EC	10	2	13.0	
Vancouver Whitecaps FC	VAN	since 2011	WC	6	3	11.5	

Table 5 ASD Calculation from 1996 - 2016

Western Conference (ASD)	Dispersion of point ratios around the league mean	Eastern Conference (ASD)	Dispersion of point ratios around the league mean
44.0343	4.2343	47.1322	4.5322
44.9194	4.3194	46.6896	4.4896
48.7818	3.7818	43.3615	3.3615
46.6137	3.6137	36.8575	2.8575
51.1925	6.3925	48.5637	6.0637
43.0891	5.2891	42.1765	5.1765
48.1660	4.5660	39.7701	3.7701
42.4556	4.0556	47.9836	4.5836
45.4984	4.0984	43.5612	4.1612
43.3618	3.3618	52.6834	4.0834
46.9383	3.6383	46.9384	3.6384
44.1973	3.3973	44.2200	2.8200
41.7631	2.6631	45.6087	2.9087
44.5065	2.4065	41.0157	2.6157
48.4190	2.6190	39.1153	2.1153
49.8870	2.3870	44.7405	2.1405
48.5220	2.3220	49.6831	2.0831
51.1482	2.4482	46.8649	1.9649
50.0980	2.3980	47.0736	1.9736
50.7267	2.1267	48.2217	2.0217
48.6392	2.0392	46.6561	1.9561

Table 6 RSD* for Competitive Balance in MLS, 1996 - 2016

Season	N	G	$RSD*$
1996	10	32	0.319
1997	10	32	0.319
1998	12	32	0.314
1999	12	32	0.314
2000	12	32	0.314
2001	12	26	0.314
2002	10	28	0.319
2003	10	30	0.319
2004	10	30	0.319
2005	12	32	0.314
2006	12	32	0.314
2007	13	30	0.312
2008	14	30	0.310
2009	15	30	0.309
2010	16	30	0.307
2011	18	34	0.305
2012	19	34	0.304
2013	19	34	0.304
2014	19	34	0.304
2015	20	34	0.303
2016	20	34	0.303

Note: *N* is the number of teams in the league and *G* is the number of games played by each team in a regular season.

Table 7 HHI* for Competitive Balance in MLS, 1996 - 2016

Year	Eastern Conference	Western Conference	Ligue 1
1996	0.0849	0.0517	0.0905
1997	0.0586	0.0493	0.1005
1998	0.0909	0.1284	0.0918
1999	0.3419	0.1777	0.1556
2000	0.1129	0.0963	0.0692
2001	0.1236	0.1133	0.0648
2002	0.0117	0.0242	0.0712
2003	0.0296	0.1132	0.0706
2004	0.0467	0.0544	0.0960
2005	0.0409	0.3513	0.0737
2006	0.0627	0.0238	0.1008
2007	0.1030	0.1188	0.0926
2008	0.0560	0.0509	0.0966
2009	0.1090	0.0439	0.1025
2010	0.1406	0.1632	0.0843
2011	0.0720	0.1540	0.0899
2012	0.1625	0.1527	0.1256
2013	0.1927	0.0788	0.0906
2014	0.0986	0.1566	0.1255
2015	0.0853	0.0441	0.0648
2016	0.0737	0.0722	0.1396

Table 8 MLS Betting Market Descriptives for Regression Sample, 2006 - 2016

	count	mean	sd	min	max
year	2732			2006	2016
team	2732			1	21
AvailBookmakers	2732	9.88	3.72	1	17
OddHome	2732	2.10	0.50	1.24	8.38
OddAway	2732	3.89	1.27	1.40	12.1
OddDraw	2732	3.46	0.32	2.90	5.93
OddsRight	2732	0.49	0.50	0	1
pHW	2732	49.9	9.74	11.9	80.6
pD	2732	29.1	2.34	16.9	34.5
pAW	2732	28.2	8.28	8.28	71.4
AT_TimeDif (abs.)	2732	1.15	1.01	0	3
AttDiff	2732			-35672	35672
RunppgHT	2732	1.31	0.52	0	3
RunppgAT	2732	1.35	0.54	0	3
HT_LsRank	2732	8.84	5.09	1	20
AT_LsRank	2732	8.85	5.09	1	20
HT_logwage	2732	15.2	0.57	14.3	16.8
AT_logwage	2732	15.2	0.57	14.3	16.8

Table 9 Probability Determination in MLS with SUR, 2006 – 2016: Team Effects

	SUR (1) Prob. Home Win	SUR (2) Prob. Away Win
See Table 3 for other coefficients included		
Home Team: CHI	-0.5195	0.2496
	(0.7108)	(0.6001)
Home Team: **CHV**	-3.0950**	3.3835***
	(1.1247)	(0.9497)
Home Team: CLB	1.1762	-1.0391
	(0.7031)	(0.5937)
Home Team: COL	2.1227*	-2.0659*
	(1.0806)	(0.9124)
Home Team: DAL	2.5190*	-2.2094*
	(1.0826)	(0.9141)
Home Team: DC	-1.3666	1.2486*
	(0.7039)	(0.5943)
Home Team: HOU	1.3605	-1.3722
	(0.8720)	(0.7363)
Home Team: **KC**	2.4959***	-2.1146***
	(0.7197)	(0.6077)
Home Team: LA	1.5334	-0.2746
	(1.2155)	(1.0264)
Home Team: MTL	-1.8354	1.6814*
	(0.9683)	(0.8176)
Home Team: NE	0.0000	0.0000
	(.)	(.)
Home Team: **NY**	2.1961**	-1.2221
	(0.7743)	(0.6538)
Home Team: **NYCFC**	-7.4698***	7.4054***
	(1.8747)	(1.5829)
Home Team: **ORL**	-10.9615***	9.5641***
	(1.8284)	(1.5438)
Home Team: PHI	-0.4264	0.1241
	(0.8479)	(0.7159)
Home Team: POR	2.0711	-1.6423
	(1.2060)	(1.0182)

Home Team: RSL	0.3593	-0.1890
	(1.0880)	(0.9186)
Home Team: **SEA**	-5.1548***	4.4011***
	(1.5493)	(1.3081)
Home Team: SJ	1.3546	-1.3311
	(1.1261)	(0.9508)
Home Team: **TOR**	-2.9394***	2.7947***
	(0.8629)	(0.7286)
Home Team: VAN	-0.7741	0.4277
	(1.2086)	(1.0204)
Home Team: CHI	-0.3103	0.2309
	(0.7102)	(0.5996)
Away Team: **CHV**	3.6837**	-2.7989**
	(1.1224)	(0.9478)
Away Team: CLB	-1.1116	0.7732
	(0.7015)	(0.5923)
Away Team: COL	0.5892	-1.1299
	(1.0841)	(0.9153)
Away Team: DAL	-0.5640	0.1741
	(1.0880)	(0.9186)
Away Team: DC	1.3177	-1.0124
	(0.7036)	(0.5941)
Away Team: HOU	-0.0255	-0.1900
	(0.8723)	(0.7365)
Away Team: **KC**	-3.0717***	2.2154***
	(0.7195)	(0.6075)
Away Team: LA	-1.4431	1.7421
	(1.2250)	(1.0344)
Away Team: **MTL**	3.1883***	-2.7043***
	(0.9689)	(0.8181)
Away Team: NE	0.0000	0.0000
	(.)	(.)
Away Team: NY	-1.1906	1.0795
	(0.7723)	(0.6520)

Away Team: NYCFC	4.6340*	-2.8600
	(1.8606)	(1.5709)
Away Team: **ORL**	12.5728***	-9.1574***
	(1.8435)	(1.5565)
Away Team: PHI	1.4360	-1.4509*
	(0.8456)	(0.7139)
Away Team: POR	0.7695	-0.9420
	(1.2139)	(1.0250)
Away Team: **RSL**	3.2577**	-3.0495***
	(1.0886)	(0.9191)
Away Team: **SEA**	7.4486***	-6.6126***
	(1.5593)	(1.3166)
Away Team: SJ	0.5614	-0.7935
	(1.1321)	(0.9559)
Away Team: **TOR**	3.9402***	-3.1656***
	(0.8645)	(0.7299)
Away Team: **VAN**	3.8995**	-3.9777***
	(1.2133)	(1.0244)
Constant	629.4772***	454.5865***
	(104.0332)	(88.7878)
Test Statistics as seen in Table 3		

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10 Robustness Check: Probability Determination with Alternative Performance Measures - points from last three matches

	SUR (3) Prob. Home Win	SUR (4) Prob. Away Win
HT_3Gpoi	0.9060***	-0.7789***
	(0.0638)	(0.0541)
AT_3Gpoi	-0.9626***	0.7926***
	(0.0627)	(0.0531)
HT_LsRank	-0.4658***	0.3836***
	(0.0328)	(0.0278)
AT_LsRank	0.4488***	-0.3750***
	(0.0328)	(0.0278)
HT_logwages	2.3066***	-2.1288***
	(0.5403)	(0.4579)
AT_logwages	-2.4210***	1.9615***
	(0.5496)	(0.4658)
AttDiff	0.0004***	-0.0003***
	(0.0000)	(0.0000)
AvailBookmakers	0.2965	-0.0990
	(0.1627)	(0.1379)
Conference, season, home team and away team fixed effects included		
Constant	48.7373***	34.4994***
	(11.5501)	(9.7886)
Observations	2464	
R2 *100	50.8	50.7
RMSE	6.89	5.85
Breusch-Pagan independence	2345.5***	
Correlation of errors	-0.9757	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The derivation of $RSD*$

While as mentioned before, SD tends to decrease as G increases, other things equal, it is common to compare the ‘actual’ standard deviation to a benchmark called the ´idealized´ standard deviation (ISD). The ISD corresponding to game or match outcomes at the end of a season for a league in which each team has an equal probability of winning each game.

Considering balanced schedules of games in which each of the N teams plays every other team the same number of times, K, with draws treated as half a win. Each team plays $G_i = G = K(N-1)$ games. This format is very common in sports leagues (typically with K= 2). Therefore, ISD is given by:

$ISD = 0.5/[K(N-1)]^{0.5} = 0.5/G^{0.5}$.

ASD is the actual observed standard deviation of end-of-season outcomes and can be calculated as

$ASD = [(N+1)/12(N-1)]$.

Taking the square root, the upper bound for ASD, denoted ASD^{ub}, is given by:

$ASD^{ub} = [(N+1)/12(N-1)]^{0.5}$.

If ASD is the actual standard deviation of end-of-season outcomes, then the measure commonly used is the ratio

$RSD = \frac{ASD}{ISD}$.

Moreover, it must be added that the league's playing schedules impose an upper bound on the value of the relative standard deviation, which is also sensitive to season length and the number of teams. Ignoring its feasible range of outcomes limits the usefulness of the relative standard deviation for comparing within-season competitive balance over time if the numbers of teams and/or games played are not constant, which in practice is usually the case (Owen, 2010, 38). Also, using RSD, but ignoring its upper bound, provides at best a partial view of competitive balance that emphasizes the scale effects of different values of N and/or G (Owen and King, 2010, 41). RSD^{ub} is given by:

$RSD^{ub} = \frac{ASD^{ub}}{ISD}$.

Variation in the upper bounds can be explicitly incorporated in a normalized measure of competitive balance, calculated as

$RSD^* = \frac{RSD}{RSD^{ub}}$.