Dancing with the Stars: Does Playing in Elite Tournaments Affect Performance?

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This paper documents spillover effects using participation in an elite international football tournament as a laboratory. Using a novel dataset from top 5 European football leagues, we find that participation in highly selective UEFA Champions League (UCL) generates large performance gains to participating teams in their domestic leagues. More precisely, UCL participation improves goal difference (goals scored minus goals conceded) by approximately 0.3 goals per game and probability margin (probability of winning minus probability of losing) by approximately 10 percentage points. By investigating causal channels through which participation in the UCL might affect performance, we argue that our results suggest the importance of spillover effects in sports.

Keywords: Spillover effect; Sport economics; Regression discontinuity design; Betting odds.

JEL Classification: L83, Z2, D83, J44.

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1 Introduction

Economists and other social scientists have long sought to understand how interaction with elite peers affects performance, a mechanism referred to as "spillover effects".[1] Any identification strategy that aims at isolating such *causal* effects needs to address the endogeneity problem due to non-random selection into treatment groups, so suitable control groups might not be available. Furthermore, in many work settings an agent's payoff depends on performance, making it extremely difficult to disentangle the spillover effects from the agent's response to other incentives. In this paper, we use a quasi-experimental design that takes advantage of eligibility cutoffs for an elite sport tournament to estimate spillovers effects that is net of unobserved characteristics and financial incentives.

In this paper, we use a regression discontinuity (RD) design that exploits eligibility cutoffs for participation in the most prestigious club football tournament to identify the spillover effects on team performance. Elite sport tournaments offer three important advantages for studying spillover effects.[2] First, elite sports tournaments sharply increase exposure to elite peers, providing a valuable laboratory to measure the causal impact of exposure to high quality peers. Second, extensive data can be gathered for most countries over long time periods. For this project, we have gathered data on teams playing in the top 5 European leagues, i.e. English Premier League (EPL), Spanish La Liga, German Bundesliga, Italian Serie A, and French Ligue 1. We have collected match-level data on betting odds and match scores, and team-level data on end of the season points and rankings from 2000 to 2019. We have also collected exhaustive data on salaries of football players, transfer fees and managerial changes. Third, a unique feature of our

[1] Among others, see Azoulay, Graff Zivin, and Wang (2010), Akcigit, Caicedo, Miguelez, Stantcheva, and Sterzi (2018), Zimmerman (2019), Abdulkadiroğlu, Angrist, and Pathak (2014), Guryan, Kroft, and Notowidigdo (2009).

[2] Similar sports settings have been used as a laboratory for testing and developing economic theories, including mobility responses to tax rates (Kleven, Landais, and Saez, 2013), market efficiency (Gray and Gray, 1997), and peer effects (Gould and Winter, 2009).

research design is the clear distinction between payoffs from performance in the elite tournament and the domestic league performance, where we estimate performance gains. This distinction makes it possible to disentangle the performance gain which is due to spillover from elite peers.

The Union of European Football Associations (UEFA) organizes the UEFA Champions League (UCL), which is considered to be the crown jewel of club football. Each season UCL brings together the best teams from across Europe in a highly competitive tournament.[3] Eligibility status is determined on the basis of total number of points that teams collect in their corresponding national leagues at the end of each season. We then use an RD design that compares performance among teams that narrowly qualified to participate in the UCL and teams that narrowly lost the opportunity.

An empirical challenge when estimating the spillover effects in our setting is to appropriately measure performance (or output). Our first measure of performance is goal difference within a match, defined as the number of goals scored minus the goals conceded. However, since the outcome of a match is only determined by the sign of the goal difference, independent of the magnitude of the goal difference, one might argue that teams might not exert costly effort to improve goal difference if they are confident of the match outcome. As a result, the goal difference might inaccurately reflect the true performance.

One contribution of our paper is to use betting odds to construct an *ex-ante* measure of performance at the match level. Analogues to stock prices, the betting odds aggregate all the public and private information from different sources. They represent the current balance of opinions about the likelihood of different events as expressed by the amounts of money wagered for and against them. From the betting odds, we extract the probability of winning, losing, and getting a draw. The probability margin of winning, defined as the probability of winning minus the probability of losing, is an *ex-ante* measure of

[3]Notice that the UCL does not replace national leagues. Teams participating in the UCL keep competing in their national leagues.

performance and therefore is unlikely to be affected by the dynamics of the match.

As it is standard in the studies using RD design, we perform various validity checks; all but one of these checks support the validity of our design. As Lee and Lemieux (2010) point out, the key condition for the validity of the RD design is that individuals do not have precise control over the assignment variable. In our design, because the ranking of a team on the league table depends on its performance against equally motivated teams, a team cannot fully control its position on the league table. Similarly, the ranking of a team depends on other teams' games among themselves, making it impossible for a team to fully determine its location on the league table. The McCrary test also fails to reject the null hypothesis of no difference in the density of running variable at the cutoff. Moreover, tests with pre-determined transfer fees and wage bills support the validity of our design.

Tests with pre-determined performance measures, on the other hand, do not support the validity of our RD design. When goal difference and probability margin of winning at $t-1$ are regressed on UCL participation in the following year in an RD, the coefficients turn out be statistically significant and positive. The significant and positive coefficients on the backward-looking regressions suggest that the selection into the treatment problem is not fully solved with the RD design, which in turn could lead to an upward bias in our results.

Using a regression discontinuity design that compares performance among teams that narrowly qualified to participate in the UCL and teams that narrowly lost the opportunity, we find that participation in the UCL generates large performance gains to participating teams in their domestic leagues. More precisely, we find that participation in the UCL increases the probability of winning a game by about 10 percentage points, and the within game goal difference by about 0.3 goals. These estimates are statistically significant and robust across different specifications.

As argued above, the results from the regressions on the pre-determined performance measures suggest that the teams on the right side of the threshold could be inherently better than the teams on the left side of the threshold, even after controlling for the running variable. To deal with this problem, we repeat our main regressions while controlling for lagged UCL participation. To the extent that controlling for the lagged UCL participation can deal with the selection problem, the discontinuity estimates in this RD regression could be interpreted as causal effects of UCL participation on team performance. As Table 5 shows, the parameter estimates are about 70% of the original estimates and significant, suggesting that our main findings are robust.

Next, we investigate the causal channels through which participation in the UCL might have affected team performance. There are at least two reasons that the UCL participation might affect performance. First, participation in the UCL is associated with sharp increases in peer quality. Taking player valuations as a proxy for quality, Figure 1 clearly shows that the average quality of players in the UCL is dramatically higher than the average quality of players in national leagues. Thus, the UCL provides a setting in which participants might learn from their elite peers or be motivated by them. We refer to this as "spillover channel".[4] Second, the UCL participation is associated with significant financial rewards.[5] Clubs might use these financial resources to improve their performance by keeping better players in the team, or signing better players and managers,[6] which we refer to as "team composition channel".

Although our identification strategy does not allow us to directly measure the spillover effects, we provide credible evidence that the team composition channel does not account for the improved performance. More precisely, we apply the same regression discontinuity idea to our preferred wage data and do not find strong evidence that narrowly qualified teams have higher wage bills, compared to the teams that narrowly miss the opportunity

[4]By spillover effect we mean any change in performance as a result of social interaction, in contrast to economic incentives.

[5]For instance, according to UEFA, the 32 clubs that played in the 2018/19 UCL group stage have shared about €2 billion in payments from UEFA.

[6]By manager we mean a person who is in charge of training and performance of a team, not an executive manager.

to play in the UCL. Relatedly, we show that transfer fees are balanced at the cutoff, so it is not the case that narrowly qualified teams spend significantly more money to sign better players, compared to the teams that narrowly miss the opportunity. Therefore, our findings suggest that the improved performance is not due to teams employing better players. Moreover, the improvement in team performance persists even when we account for managerial changes before the start of the season, so managerial changes are unlikely to explain the jump in team performance at the eligibility cutoff. This evidence rules out team composition as an explanation of our findings and suggests that spillover effects contribute to the team performance in ways that are hard to reconcile with team composition.

Our paper contributes to a large literature on spillover effects. Perhaps surprisingly, one of the first studies in this literature was conducted in a sport setting. Triplett (1898) observed that cyclists ride faster when competing with other cyclist, compared to when they race alone or against a pace-maker, and concluded that the presence of others affects performance. Consequently, many studies examined whether and how one's performance is influenced by the performance of others in various settings. Examples include education (Carrell, Fullerton, and West, 2009, Sacerdote, 2001), controlled laboratory experiment (Falk and Ichino, 2006), workers in the workplace (Mas and Moretti, 2009, Bandiera, Barankay, and Rasul, 2010), sports (Guryan, Kroft, and Notowidigdo, 2009, Gould and Winter, 2009), and scientists (Azoulay, Graff Zivin, and Wang, 2010, Waldinger, 2012), among many others. The standard approach in this literature consists of estimating an outcome-on-outcome specification. However, as Angrist (2014) points out, outcome-on-outcome regressions are likely to produce biased estimates, with both the sign and the size of the bias depending on the true underlying data generating process.

Several studies attempt to solve these problems by exploiting quasi-experimental variation that comes close to the ideal experiment. Closely related to our paper are Abdulkadiroğlu, Angrist, and Pathak (2014) and Zimmerman (2019) who exploit the regression discontinuity in selective school admissions on academic performance and social mobility. Similar to selective schools, participation in the UCL is associated with sharp increases in peer quality, which we exploit to investigate spillover effects. As Abdulkadiroğlu et al. (2014) argue, RD estimates of the spillover effects rely on assumptions that are weaker in general than outcome-on-outcome regression, though in our setting it comes at the cost of requiring further investigation of plausible causal channels.

The rest of the paper proceeds as follows. Section 2 provides more details about our research design and the UEFA Champions League, and Section 3 describes the data used in this analysis. Section 4 outlines the empirical strategy and its application to the analysis of the UCL program. Section 5 reports the relevant identification checks. Section 6 shows and discusses the main results and some extensions. Section 7 concludes.

2 Institutional Background

European football (soccer) is structured around national football associations. Each national football association organizes (or oversees) many hierarchical divisions of football leagues. At the end of each season, the top ranked teams in a division are promoted to the next upper division, whereas the lowest ranked teams are relegated to the next lower division. Throughout this paper, we will focus only on the top divisions from England (EPL), Spain (La Liga), Germany (Bundesliga), Italy (Serie A), and France (Ligue 1), and will refer to these top divisions as *domestic national leagues*. These football leagues are commonly regarded as the top 5 football leagues in Europe. In fact, 35 out of 36 finalists of the UCL in our sample (2000/2001-2017/2018) are from these leagues.

Union of European Football Associations (UEFA) is an umbrella organization of national football associations. Besides overseeing national football associations, UEFA organizes two big club competitions: UEFA Champions League (UCL) and UEFA Europa League (UEL). The UCL is the most prestigious club competition in European football, contested by 32 clubs from the strongest UEFA members. Participating teams play both in UEFA competitions and in their national leagues. Due to the financial incentives of this tournament and its prestige, every club wants to play in the UCL. In its present format, less than 20% of teams from each national league are *eligible* to play in the UCL.

Eligibility is mostly determined by the team's performance in its national league. Each national league is contested by N teams, playing twice (i.e. home and away) against each opponent. The result of each match is decided by the goal difference, defined as goals scored minus goals conceded. A positive goal difference within a match indicates a win, a zero goal difference indicates a draw, and a negative goal difference indicates a loss. Accordingly, in each match a team earns 3 points for a win, 1 point for a draw, 0 points for a loss. The ranking of the teams at the end of the season is a deterministic function of the total number of points collected by each team during that season. In case two teams have the same number of points, then the better placed team will be the team with better total goal difference,[7] or better goal difference in direct games amongst the tied teams.

Eligibility is determined at the end of each season, with the winner and 2-3 runners up are eligible for playing in the UCL the next season. The number of teams from each member association entering the UCL is based on the UEFA coefficients of the member associations.[8] The higher an association's coefficient, the more teams represent the association in the UCL. In reality, however, eligibility does not necessarily imply playing in the UCL.[9] More precisely, the UEFA coefficient indicates the number of teams that directly play in the UCL, and the number of teams that must go through playoff-rounds, with some small chance of elimination.[10] For instance, a total of 4 teams out of

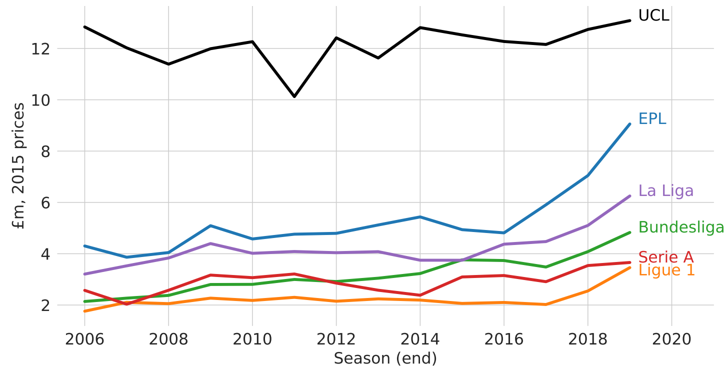
[7] Total goal difference is calculated as the sum of within game goal differences in a given season.

[8] UEFA calculates these coefficients based on the results of clubs representing each association during the previous five Champions League and UEFA Europa League seasons. See `https://www.uefa.com/memberassociations/uefarankings/club` for more information.

[9] Appendix A provides more information on the UCL eligibility and participation.

[10] It is a small chance because the teams from top 5 European countries usually face teams from countries with lower UEFA coefficients (i.e. weaker). See UEFA Article 3 for more information about entries for the competition.

Figure 1: Average Market Value of Players



Notes: Unweighted means of valuations of players registered in each league. UCL average includes players from all the participating teams, not just players from the top 5 European national leagues. Authors own calculations using data from `https://www.transfermarkt.com`.

20 teams in the English Premier League (EPL) were eligible for the 2015-16 UCL season, with the top 3 teams from 2014-15 EPL final table qualifying automatically, and the 4th team going to a playoff round.

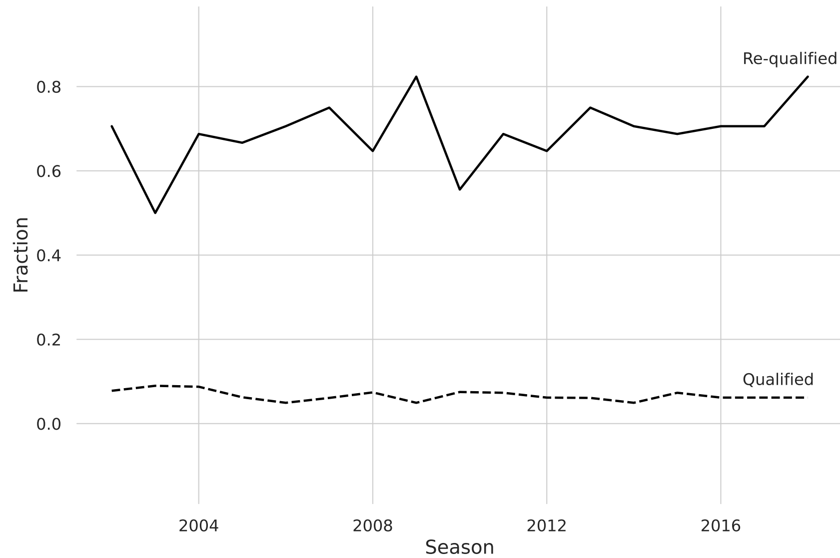
Teams who qualify to play in the UCL see a dramatic change in their peer quality compared to the teams that narrowly miss this opportunity.[11] Figure 1 shows player valuations in 5 European football leagues and in the UCL.[12] We see that average valuation of players in the UCL is consistently higher than average valuation of players in other leagues. This is not surprising since only elite teams with top players can participate in the UCL.

One of the striking facts of European football is the consistently high rate of success among the top teams. Figure 2 shows that the teams that participate in the current UCL season have about 70% chance to participate in the next UCL season. By contrast, the

[11]Teams that narrowly miss the opportunity to play in the UCL, most likely participate in the less prominent Europa League (UEL). We investigate the impact of Europa League participation on teams' performance in Appendix F.

[12]Player valuations are taken from `https://www.transfermarkt.co.uk`. Average player value is mean value of all the registered players in a league.

Figure 2: Persistence of Participation in UCL



Notes: This figure plots the UCL participation rates in season $t + 1$, conditional on participation status in season t. Solid line show the re-qualification rate, i.e. teams that participate at both season t and $t + 1$, while the dashed lines show the fraction of teams that play in the UCL in season $t+1$, but did not play in the UCL in season t. The sample used to construct this figure consists of teams from top 5 European national leagues from 2000 to 2019. Authors own calculations using information from Wikipedia.

teams that do not participate in the current UCL season have less than 10% chance to participate in the next UCL season. These rates have been fairly stable over the last two decades. Therefore, higher ranked teams tend to do well in the next season and participate in the UCL in the following season. Such persistence in the UCL participation can be the result of two factors: i) participating teams are inherently better than others and ii) by participating in the UCL, teams improve their domestic league performance. In this study, we examine whether and how the second factor might have played a role.

3 Data Description

To answer our research questions, we compile a new data set of European football at the match level. Our dataset contains information on the universe of matches across top 5 European football leagues, namely EPL (England), La Liga (Spain), Bundesliga (Germany), Serie A (Italy), and Ligue 1 (France), from 2000 to 2019. We collected information on betting odds and match scores (goals scored and goals conceded) from `https://www.football-data.co.uk`.

One key issue in our study is to accurately measure team performance because standard aggregate end-of-season measures (e.g. total points) might not accurately reflect teams' performance. To see this point, consider a match between two teams (say Team A vs Team B): Team A wins some games by +5 goal difference and loses some games by -1 goal difference. Team B on the other hand, win/lose same number of games as Team A, but with reverse goal difference (i.e, +1, and -5). These two teams end up with identical total points at the end of the season, but with a measure that captures performance at the match level, Team A has better performance than Team B.

We construct two measures of a team performance in a match. First measure is an ex-post measure, *goal difference* within a match, which is the number of goals scored by a team minus the number of goals conceded by the team in the same match. Using our example where Team A scores six goals but concede one goal (i.e. Team B scores one goal), the goal difference would be +5. More specifically, we define the goal difference as

$$\mathrm{GD}_{i,j,h,l,t} = \mathrm{GS}_{i,j,h,l,t} - \mathrm{GS}_{j,i,h,l,t},$$

where $\mathrm{GS}_{i,j,h,l,t}$ denotes the goals that team i scores against team j, $h \in \{0, 1\}$ indicates whether the game is played at home or away, l is the league and t is the season.

A problem regarding the goal difference, and other *ex-post* measures of performance, is that it depends on the dynamics of the match. To use the Team A vs Team B example above, suppose that Team A is significantly stronger than Team B, and would normally win the match with +5 goal difference if they exert full effort. However, since the outcome of a match is only determined by the sign of the goal difference, after achieving a comfortable lead over Team B (e.g. +3 goals), Team A might reduce their efforts to preserve energy for the next match or to reduce the risk of injuries. Thus, while we would expect that Team A to win, we do not expect the goal difference to precisely reflect the difference in quality of the two teams.

To avoid this problem, we exploit information contained in betting odds to construct *probability margin of winning*, defined as the probability of winning a game minus the probability of losing. To construct probability margins, we obtain betting odds from 13 major online bookmakers: Bet365, Blue Square, BWin, Gamebookers, Interwetten, Ladbrokes, Pinnacle, Sporting Odds, Sportingbet, Stan James, Stanleybet, VC Bet, and William Hill.[13] The data is obtained from `https://www.football-data.co.uk`, which is unique with respect to its size and the information it contains: The dataset spans the period 2000-2019 containing information about 27,461 unique football matches. For our purposes, the variables of interests are: draw, home win, and away win odds. The odds are kick-off time odds (also known as *closing odds*), i.e. those that were quoted when bookmakers stopped accepting new bets before the matches.

The odds represent the current balance of opinions about the likelihood of a team winning as expressed by the amounts of money wagered for and against it. To fix ideas, let's think of a game between Team A and Team B. Typically, bookmakers determine their odds based on a statistical model, which takes all the available information into consideration, including the teams' lineup, injuries, location (home or away), current form and historical performance. Once the initial odds have been set, the odds will be adjusted based on the amount of money put on the different outcomes by traders. If a bookmaker underpriced the odds of a particular outcome, let's say Team A win, then traders will put money on this outcome until it is priced at a fair value. For instance, if a trader places, say, \$100 on Team A to win, the odds will shift. If another trader

[13] For each match, we have betting data from most of these bookmakers, but not necessarily from all bookmakers.

believes that the odds are now mispriced and that there is value on the other side, they might place \$100 on Team B to win and the odds will shift again and thus eliminating the mispricing.

Typically, sports betting odds are expressed as decimal odds.[14] Decimal odds describe the total return, including both stake and profit, if the bet wins. For instance, odds of 1.25 would imply that a \$100 winning stake will return \$125 in total (including the original stake of \$100).[15] Consequently, we can obtain the implied (observed) probabilities from decimal odds, using the equation

$$\text{Implied probability} = \frac{1}{\text{Odds}}$$

For example, a home-draw-away book with odds of $\mathrm{O}_h = 1.53$, $\mathrm{O}_d = 3.5$, and $\mathrm{O}_a = 5.5$ implies probabilities

$$\mathrm{P}_h = \frac{1}{\mathrm{O}_h} = 0.654,\ \mathrm{P}_d = \frac{1}{\mathrm{O}_d} = 0.286,\ \mathrm{P}_a = \frac{1}{\mathrm{O}_a} = 0.182$$

where O_h, O_d, and O_a are the home team win, draw, and away team win odds and P_h, P_d, and P_a denotes the home team win, draw, and away team implied probabilities.

These probabilities, however, do not reflect the "fair" odds.[16] More precisely, the sum of the probabilities exceeds 1, and equals 1.121 in the above example. Mathematically, of course, the sum of probabilities for all possibilities must be 1. The excess 0.121 in our example determines the bookmaker's profit margin. Thus, the bookmaker's odds do not reflect the fair (true) probabilities. To obtain the fair probabilities, we first need to remove

[14] See Buchdahl (2016) for more information on betting odds.

[15] Fractional odds simply describe the potential profit that can be won from a unit stake. Consequently, odds of 1/4 (one-to-four) would imply that the bettor with a winning stake of \$100 will make a profit of \$25. It is straightforward to convert fractional odds into decimal odds, using the equation

$$\text{Decimal odds} = \text{Fractional odds} + 1$$

[16] If the odds are equal to the true odds that an event will occur, then they are said to be "fair" odds.

the margins that bookmakers apply to their odds. Since bookmakers usually do not reveal how they apply the margins to their odds, we are forced to guess how they might do it. The common method to obtain the fair odds is to assume that the margin applied to each outcome is proportional to the outcome probability.[17] Thus, the fair probability for the i-th outcome, P_i, is

$$\mathrm{P}_i^* = \frac{\mathrm{P}_i}{\sum_i \mathrm{P}_i},\ i \in \{h, d, a\}.$$

To use the example above, the fair probabilities the home team win, draw, and away team win odds are given by

$$\mathrm{P}_h^* = \frac{0.654}{1.121} = 0.58,\ \mathrm{P}_d^* = \frac{0.286}{1.121} = 0.25,\ \mathrm{P}_a^* = \frac{0.182}{1.121} = 0.16$$

To calculate our ex-ante measure of team performance, probability margin, we use fair probabilities of home team and away team winning for each match and from each bookmaker. More specifically, the probability margin of home team against away team is calculated as follows:

$$\mathrm{PM}_{i,j,h,l,t} = \mathrm{P}^*_{i,j,h,l,t} - \mathrm{P}^*_{j,i,h,l,t},$$

where $\mathrm{P}^*_{i,j,h,l,t}$ denotes the fair probability that team i wins against team j, $h \in \{0, 1\}$ indicates whether the game is played at home or away, in league l and season t.

For the purpose of our analysis, probability margins from all bookmakers with available data have been combined into a single probability by taking cross-sectional average of probability margins over bookmakers.[18] For a few matches, we don't have betting odds from any bookmaker. When no betting information is available, we remove that observation from our sample even if we have information about the goal difference. Notice that

[17]Our results are both qualitatively and quantitatively very similar when we use other methods (e.g. additive method or logarithmic method) to remove the markups.

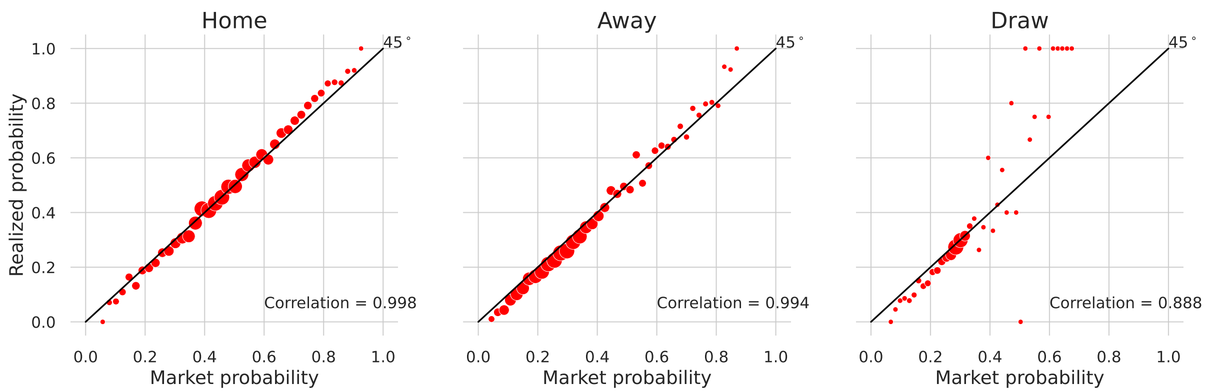
[18]Bürgi and Sinclair (2017) show that it is difficult to improve upon the simple cross-sectional average.

for each match we construct two probability margins, one for the home team and one for the away team.

A typical league consists of 20 teams and each team plays 38 games (2 games with each opponent). In most cases, the last 3 teams at the end of the season are relegated to a lower division. Therefore, in our data set we have 646 (17 non-relegated teams $\times$ 38 games) game level observations for the league l in season $t+1$. Notice that the number of teams and the number of relegated teams vary across leagues and seasons. Hence, the 646 number does not apply to all the league-season pairs. For more information about the distribution of observations to leagues and seasons, see Table 10 in the Appendix. In total, our data set in the main specification contains 53,896 observations. However, RDD regressions are run on a bandwidth around the cutoff. The number of observations that are actually used in the regressions are listed on Effective Sample Size row of each regression table.

The betting markets are doing a remarkable job at predicting actual results. Figure 3 compares the market predictions with the actual outcomes. Remember that for each match we have home team winning, away team winning, and draw probabilities constructed from corresponding odds. For each probability, we split matches into 40 bins with a bin size equal to 1.6 percentage points. Then we calculate the ratio of the matches in each bin that is in accordance of the market prediction. For instance, we take all games for which the market predicts that the probability of the home team beating the away team is between 5.4 percent to 7 percent. We then report the proportion of the games where the home team beats the away team. From Figure 3 it is clear that the market probabilities correspond quite closely to the actual results: When the market predicts that the probability of home team win is 5.4-7 percent, the home team wins about 5.4-7 percent of the time. It is only for the case of draws that the market and the actual probabilities are not closely aligned. In this case, however, the sample size is relatively small as represented by the sizes of the dots in the figure; there are relatively few games which

Figure 3: Market Prediction and Actual Results



Notes: Market Probability refers to the probability that the market predicts a team will beat the other team (Home or Away team winning probabilities) or the game will result in a draw, and Realized Probability refers to actual success rates in the sample. The sample used to construct this figure consists of all games from top 5 European countries from 2000 to 2019. The dots in the figure are averages of the probabilities of different events calculated in bins 1.6 points wide, while the line through the dots shows a perfect fit. The size of a dot is proportional to the number of matches in the bin corresponding to the dot. Authors own calculations using data from `https://www.football-data.co.uk`.

the market predicts to be a draw with probability greater than 50 percent.

Our analysis combines match level data with team level data from various sources. League tables are collected from Wikipedia and provide end-of-season information about total points earned and ranking of each team. UCL quotas are collected from Wikipedia and specify the number of teams from each league at each season that can directly play in the UCL group stage and the number of teams that need to play in the playoff-rounds to qualify for the UCL group stage.[19] We obtain the data on transfer fees, player valuations and managerial changes from `https://www.transfermarkt.com` for the full sample. Finally, we use the wage bill data of Hoey, Peeters, and Principe (2021). We also provide results with the wage data (gross and net) from Capology which covers the EPL, La Liga, Ligue 1, and Bundesliga since 2013-14 season, and Serie A since 2009-10.

[19]We classify teams as the UCL participants if they played at least in the group stage. Teams knocked out during the play-off rounds are not classified as the UCL participants.

4 Identification Strategy

We are interested in whether and how participation in the UCL might affect a team's performance. Any strategy that aims at identifying such causal effects needs to address the endogeneity in the UCL participation status. In practice, football teams differ along many dimensions, and certain teams may be more likely to participate in the UCL (e.g. those with better organizational structure). Our empirical approach overcomes the endogeneity problem by focusing on the jump in performance among teams at the eligibility threshold. We do this using a fuzzy regression discontinuity design that compares performance among teams that narrowly played in the UCL and narrowly did not.

Our econometric strategy therefore begins by constructing a running variable that determines treatment assignment. As we discussed in Section 2, eligibility depends on the ranking at the end of the season, which itself is a function of total points. Thus, we construct our running variable as a function of total points.[20] More precisely, we first calculate the league-season-specific cutoff point as the average of total points of the worst eligible teams and best ineligible team. For instance, if 4 teams from league l are eligible to participate in the UCL in season $t+1$, the league-season-specific cutoff ($\text{Pts}^*_{l,t}$) is defined as

$$\text{Pts}^*_{l,t} = \frac{\text{Pts}^{4th}_{l,t} + \text{Pts}^{5th}_{l,t}}{2}$$

where $\text{Pts}^{4th}_{l,t}$ and $\text{Pts}^{5th}_{l,t}$ denote the total points of the $4th$ team and the $5th$ team from league l in season t, respectively.

To account for the difference in cutoff points across leagues and seasons, we center and scale the running variable around the cutoff value. Precisely, our standardized running

[20]We don't define our running variable based on team ranks because proximity in ranking does not imply proximity in performance before treatment. Intuitively, by defining the running variable according to team ranks, we might compare $4th$ team against the $5th$, while they are very different from each other based on their total points.

variable is then defined as

$$\mathrm{S}_{i,l,t} = \frac{\mathrm{Pts}_{i,l,t} - \mathrm{Pts}^{*}_{l,t}}{\mathrm{Std}(\mathrm{Pts}_{l,t})},$$

where $\mathrm{Pts}_{i,l,t}$ denote team i's points and $\mathrm{Std}(\mathrm{Pts}_{l,t})$ is the standard deviation of the league-season total points. These standardized league-season-specific points equal zero at the cutoff, with nonnegative values indicating teams who are eligible to play in the UCL in the next season. Thus, the eligibility is a deterministic function of the standardized points

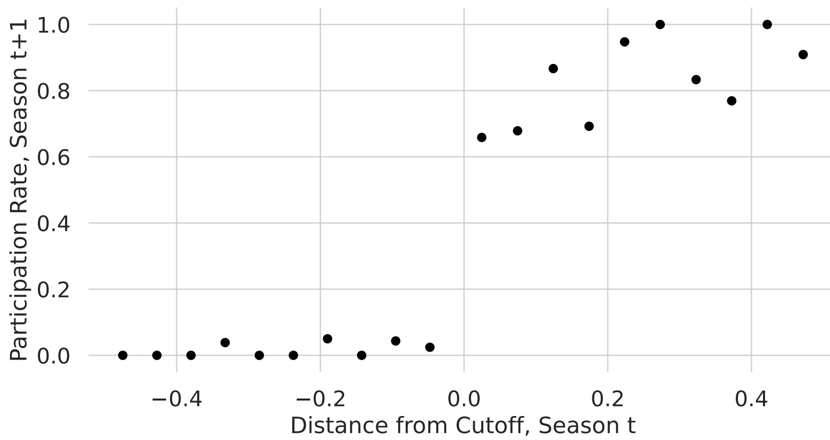
$$\mathrm{Elig}_{i,l,t} = \mathbb{1}(\mathrm{S}_{i,l,t} \geq 0),$$

which assigns all teams whose score are below the zero cutoff to the control group, and all teams whose score is above zero to the treatment group.

Although eligibility is a deterministic function of standardized points, participation in the UCL remains probabilistic. Specifically, not all eligible teams play in the UCL and some ineligible teams play in the UCL. Figure 4 gives a graphical representation of the participation rate in the UCL as a function of the standardized running variable, where participation rate is defined as the number of teams participating in next year's UCL as a fraction of total number of teams in a bin of standardized running variable. The plot clearly shows that less than 5% of ineligible teams participated in the UCL. The ineligible teams that participate in the UCL are the UEFA Champions League and UEFA Europa League titleholders. For instance, Liverpool FC ranked 5th in the 2004-05 EPL season, so not eligible based on standardized points, but actually played in the 2005-06 UCL season since they won the UCL in the 2004-05 season. Above the threshold, the probability of participating in the UCL increases rapidly: More than 70% of the eligible teams participate in the UCL. Teams that were eligible but did not play in the UCL were those teams that lost the playoff rounds.

This setup naturally leads to a fuzzy RD design, where standardized points ($\mathrm{S}_{i,l,t}$) is

Figure 4: Discontinuity in Probability of Participation in the UCL



Notes: This figure plots participation in the UCL group stage, plotted against league-season-specific standardized running variable.

the running variable that partially determines participation in the UCL. As discussed in Hahn, Todd, and Van der Klaauw (2001), estimation of the UCL treatment essentially amounts to a simple 2SLS estimation strategy, using the discontinuity in the eligibility as an instrumental variable for the UCL participation status. More precisely, let $\mathrm{Y}_{i,j,h,l,t+1}$ be an outcome variable of team i against team j, $h \in \{0, 1\}$ indicates whether the game is played at home or away, from league l in season $t+1$. To obtain the causal impact of the UCL participation, we estimate variants of the following parametric regression model:

$$\mathrm{Y}_{i,j,h,l,t+1} = \alpha + \tau \ \mathrm{UCL}_{i,l,t+1} + f(\mathrm{S}_{i,l,t}) + \epsilon_{i,j,h,l,t+1}, \tag{1}$$

where $\mathrm{UCL}_{i,l,t+1}$ is the indicator for participation in the UCL (i.e. treatment status), and $f(\mathrm{S}_{i,l,t})$ is a flexible function of the standardized points, which is allowed to differ on each side of the discontinuity. We follow the common practice in the literature, and assume that $f(.)$ can be described by a low-order polynomial.[21]

The parameter of interest is τ, which captures the causal impact of participation in the

[21] Gelman and Imbens (2019) argue that including high-order polynomials of the running variable may lead to noisy estimates and poor coverage of confidence intervals.

UCL. A consistent estimate of τ can be obtained by estimating (1) with the instrumental variable estimator, where $\text{Elig}_{i,l,t} = \mathbb{1}(\text{S}_{i,l,t} \geq 0)$ is used as instrument. The corresponding first-stage in this case is

$$\text{UCL}_{i,l,t+1} = \gamma_0 + \gamma_1 \text{ Elig}_{i,l,t+1} + f(\text{S}_{i,l,t}) + \nu_{i,l,t+1}, \tag{2}$$

where the dummy variable $\text{Elig}_{i,l,t+1}$ is used as an instrument for $\text{UCL}_{i,l,t+1}$.

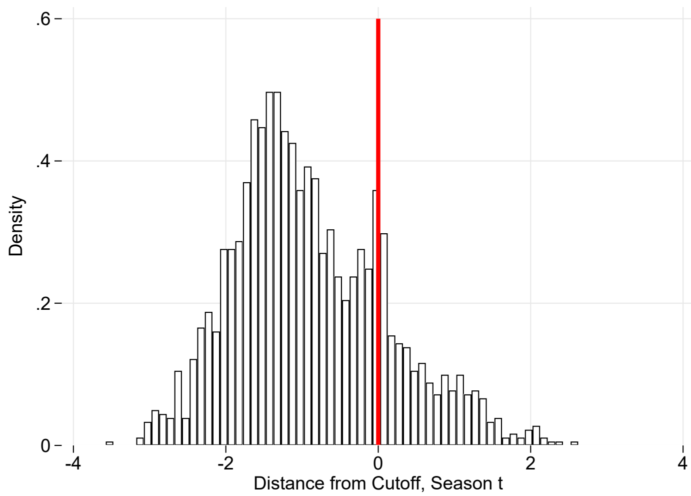
5 RD Validity Checks

Before presenting our results, we conduct several checks to ensure the validity of our RD strategy. The key identifying assumption in our RD design is the inability of teams to precisely control treatment status. In our case, local random assignment would be violated if teams just below the cutoff could influence their total number of points to be eligible for the UCL in the next year. Violation of local random assignment requires some teams to be able to precisely control the outcome of the games they play against their opponents. However, in our setting, points are gained (and lost) against direct opponents, who also want to rank as high as possible in their domestic league and play in the UCL. Furthermore, there is also some element of chance involved in a match outcome, which can influence the total number of points and eligibility at the end of the season. This supports our RD design from the outset, since it is unlikely that some teams could precisely control the assignment variable.[22]

Density tests, first proposed by McCrary (2008), seek to formally determine whether there is evidence of manipulation of the running variable at the cutoff. Inspecting the

[22]The 2006 Italian football scandal, or Calciopoli, where a number teams tried to influence referee appointments, is a valid concern. Thus, in our analysis, we drop observations from Italian Serie A for season 2006-07. In addition, we drop observations from the 2007-08 season, since in the 2006-07 season, Fiorentina were punished with a penalty of 15 points, Reggina 11 points, Milan 8 points and Lazio 3 points. These point deductions might bring some teams artificially close to the cutoff. The result are qualitatively and quantitatively very similar when we include these observations in our sample.

Figure 5: Density of Running Variable



Notes: Density of the standardized points within bins of width 0.10.

density of the running variable, shown in Figure 5, suggests no manipulation of the assignment variable. The Cattaneo, Jansson, and Ma (2019) density test confirms this point. The test statistic is -0.001 (p-value is 0.999), and therefore, we fail to reject the null hypothesis of no difference in the density of running variable at the cutoff.

As a second validity test, we check the continuity of the baseline covariates. Seeing no discontinuity at the cutoff would suggest the validity of our RD design.[23] A practically relevant issue in our setting is that there are several observations (e.g. games played, transfers made) for each team; as a result, the running variable contains "mass points".[24] If the running variable has mass points, the total number of observations in the RD analysis is essentially equal to the number of mass points in the running variable. Throughout this paper, we use the Calonico, Cattaneo, and Titiunik (2014) method that automatically adjusts for mass points in the running variable.

Throughout the paper, we present RD plots using several baseline and outcome vari-

[23]Lee (2008) argues that the validity of RD design can be tested by examining whether or not there is a discontinuity in any baseline covariate at the RD threshold.

[24]See Cattaneo, Idrobo, and Titiunik (2018) for more discussion on RD design with mass points.

ables. In these plots, each dot in indicates local averages, calculating the mean of the outcome for observations falling within each bin, and then plotting the average outcome in each bin against the mid point of the bin. The bin's length is selected using the optimal data driven method of Calonico et al. (2015). The lines are fitted values from a quadratic polynomial fit, which is allowed to be different on either side of the discontinuity.

Figures 6 and Table 1 show the validity tests with transfer fees (million GBP, 2015 prices). The sample includes all transfers since 2005 for all teams.[25] Figures 6 plots transfer fees against the running variable, where positive values represent incoming signings and negative values represent outgoing transfers. The plot clearly shows that the transfer fees do not jump at the threshold. Table 1 reports the estimated discontinuities (i.e., second-stage), where columns (1)-(2) are estimates obtained using the robust method of Calonico, Cattaneo, and Titiunik (2014), and columns (3)-(4) present analogous estimates using the conventional method.[26] Given the potential for error correlation across transfers by teams in a given team and season, we cluster standard errors two-ways, at the team-season level. Perhaps surprisingly, the discontinuity estimates are negative (although economically small), but statistically insignificant. So it is not the case that teams can manipulate their qualification by signing better quality players.

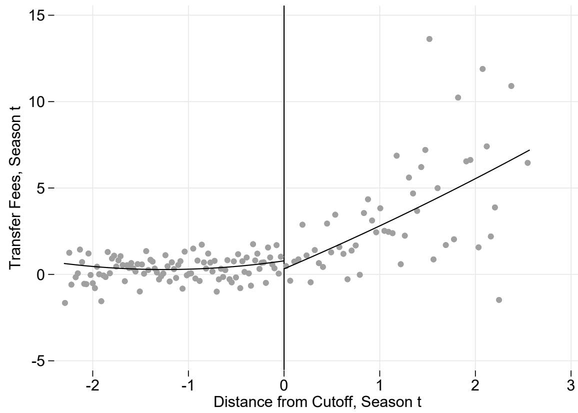
To further investigate the validity of our RD design, we check the continuity in wages using a dataset from Hoey, Peeters, and Principe (2021), who construct their data from administrative records.[27] This dataset cover 2000-2019 period for all top five leagues that we consider in this study. However, for some league-season pairs this dataset has many missing data. This is particularly severe for Bundesliga in the entire sample, Serie A in 2001, and Ligue 1 before 2005. Therefore, we drop observations belonging to these league-

[25]For this exercise, we only consider player transfers that involve some fees. That is we remove free (or loan) transfers, or youth transfers that involve no fees from the sample. Our results are both qualitatively and quantitatively very similar when we use all transfers.

[26]The first-stage estimate are 0.64 using the robust method and 0.66 using the conventional method, both statistically significant at 1% level. Full results are available upon request from the authors.

[27]We thank Thomas Peeters for kindly sharing this dataset with us.

Figure 6: Discontinuity in Transfer Fees



Notes: Transfer fees (£m, 2015 prices) in season t, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 1: Discontinuity Estimates in Transfer Fees

	(1)	(2)	(3)	(3)	(4)	(3)
	Robust Bias-corrected			Conventional Method		
Dep. variable	TF(t)	TF(t)	TF(t)	TF(t)	TF(t)	TF(t)
Estimate	-0.812	-1.086	-1.151	-0.685	-0.884	-1.056
Std. Error	0.793	1.007	1.694	0.674	0.889	1.532
Bandwidth	0.983	1.278	0.891	0.983	1.278	0.891
Polynomial	1	2	3	1	2	3
Eff. Sample Size	6,760	8,739	6,147	6,760	8,739	6,147

Notes: Discontinuity estimates in outcome variables in season t: TF:=Transfer Fees (£m, 2015 prices). Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

Table 2: Discontinuity Estimates in Total Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	Robust Bias-corrected			Conventional Method		
Dep. variable	TW(t)	TW(t)	TW(t)	TW(t)	TW(t)	TW(t)
Estimate	17.46	18.85	17.04	17.64	18.35	18.26
Std. Error	12.86	16.82	22.92	11.41	15.25	20.45
Bandwidth	0.822	1.038	1.146	0.822	1.038	1.146
Polynomial	1	2	3	1	2	3
Eff. Sample Size	416	563	632	416	563	632

Notes: Discontinuity estimates in outcome variables in season t: TW:=Total Wages (£m, 2015 prices). All specifications include a season and league fixed effects. Estimated standard errors are clustered at the league-season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.

season pairs from our sample. As Table 2 clearly shows, all point estimates are positive, but not statistically significant, pointing towards local random assignment. In Appendix E, we confirm the results in Table 2 using player-level salary data from Capology.

Lastly, we check the continuity of the goal difference and probability margin of winning at time $t-1$. Table 3 presents corresponding discontinuity estimates. As before, given the potential for error correlation across games played by a team in a given season, we cluster standard errors two-ways, at the team-season level. All specifications include league fixed effects and seasons fixed effects to control for differences across leagues and seasons. The discontinuity estimates are all positive and mostly statistically significant at the 10% level.

The results in Table 3 suggests that our RD design may not be valid.[28] Based on the above validity checks in favor of our research design and especially on the nature of competition in European football leagues, we believe that our forward-looking regressions contain causal effects. However, we would like to acknowledge the possibility of some selection into treatment and the results we will show in the next section could be biased

[28]We further investigate the validity checks with predetermined performance measures in Appendix G. As Table 20 shows, when we control for the UCL participation in season $t-1$, the parameter estimates are both economically and statistically less significant.

upward.

Table 3: Discontinuity Estimates in Predetermined Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t-1)	GD(t-1)	PM(t-1)	PM(t-1)	GD(t-1)	GD(t-1)	PM(t-1)	PM(t-1)
Estimate	0.211**	0.197	0.104***	0.106**	0.217**	0.208*	0.103***	0.107**
Std. Error	0.101	0.138	0.039	0.047	0.087	0.123	0.034	0.041
Bandwidth	1.231	1.285	0.835	1.141	1.231	1.285	0.835	1.141
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	31,502	33,013	20,955	34,837	31,502	33,013	20,955	34,837

Notes: Discontinuity estimates in outcome variables in season $t-1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

6 Empirical Results

In the first part of this section, we estimate the effect of participation in the UCL on team performance in their domestic leagues. We do this using a regression discontinuity design that compares performance among teams that narrowly qualified to play in the UCL and teams that narrowly missed this opportunity. In the second part of this section, we investigate the causal channels through which participation in UCL might have affected performance.

6.1 The Effects of the UCL Participation

Figure 7 illustrates the discontinuity in the performance of the teams right at the cutoff point. As Figure 7 clearly shows, teams who narrowly qualified to play in the UCL are much more likely to have a better goal difference and more likely to win their games next season, compared to teams who narrowly did not qualify. Discontinuity estimates from the variants of regression model (1), reported in Table 4, confirm these findings.

For ease of expositions, we do not report the first-stage estimates here but could be seen in Appendix H.[29] In Table 4, columns (1)-(4) are estimates obtained using the robust method of Calonico, Cattaneo, and Titiunik (2014), and columns (5)-(8) present analogous estimates using the conventional method. The causal effects of playing in the UCL are approximately 0.30 goals per game. The estimates are statistically significant at the 5% level, and robust to the polynomial order and bandwidth choice.

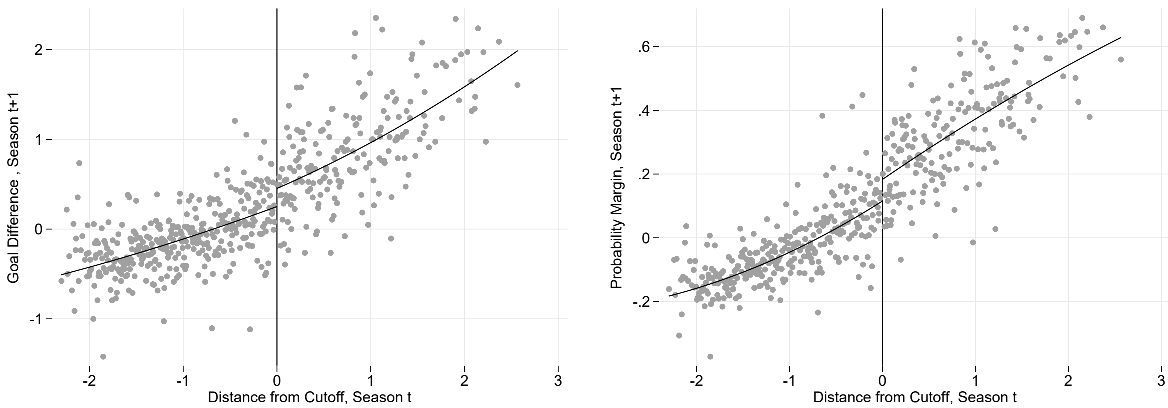
Columns (3)-(4) of Table 4 present analogous estimates for the probability margin of winning in season $t+1$. The causal effects are approximately 0.1, which indicates that playing in the UCL increases the winning probability by about 10 percentage points per game. These estimates are statistically significant at the 5% level, and robust to different specifications and bandwidth choice (See Appendix C). Columns (5)-(8) of Table 4 present analogous estimates using the conventional method. These estimates are similar in size and significance to the discontinuity estimates obtained using the robust method, reported in columns (1)-(4).

One way to quantify the magnitude of the discontinuity estimates is to consider how they scale relative to the national leagues champions. The discontinuity estimates of 0.3 in the goal difference corresponds to about 27% of the average goal difference that national league champions in season t achieve in season $t+1$. For the probability margin of winning, 10 percentage points improvement corresponds to approximately 24% of the average probability margin that national league winners achieve in season $t+1$.

A second approach to quantify the economic magnitude of the discontinuity estimates is to consider how causal effects may have affected the rankings of the teams close to the cutoff. In our sample, 5th ranked teams in season t have 0.25 goal difference per game in season $t+1$, whereas 4th and 3rd ranked teams have 0.37 and 0.69 goal differences. An increase of 0.3 goal difference per game would make a 5th ranked team to perform better

[29]The first-stage estimate of the discontinutity in the assignment probability is 0.62 using the robust method and 0.65 using the conventional method, both statistically significant at the 1% level.

Figure 7: Discontinuity in Outcome Variables



Notes: Goal difference (left) and probability margin of winning (right) in season $t+1$, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 4: Discontinuity Estimates in Outcome Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.304^{**}	0.296^{*}	0.090^{***}	0.099^{**}	0.294^{***}	0.302^{**}	0.090^{***}	0.097^{***}
Std. Error	0.128	0.163	0.031	0.040	0.111	0.146	0.027	0.035
Bandwidth	0.770	0.954	0.919	1.131	0.770	0.954	0.919	1.131
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	20,197	25,289	24,431	30,964	20,197	25,289	24,431	30,964

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.

than a 4th ranked team, but not better than a 3rd ranked team. Therefore, our coefficient estimate is economically significant as it alters the rankings of the teams meaningfully but it is not drastic as it pushes the 5th team (the team barely lost a UCL spot) by just 1 rank. For probability margin of winning, 5th, 4th, and 3rd ranked teams in season t have on average 0.11, 0.16, 0.26 probability margins in season $t+1$. Hence, a 10 percentage points increase in the probability margin of a 5th ranked team would potentially make the team perform better than the 4th ranked team in the following season. Thus, the economic magnitude of our discontinuity estimates is relatively large.

Some caution is warranted when interpreting these results because the effect of UCL participation on team performance might go beyond the contemporaneous season. If this is the case, our estimates will capture the composite effect of two (or potentially more) UCL participations.[30] To shed more light on this issue, we re-estimate equation (1) while controlling for $\mathrm{UCL}_{i,l,t}$. More precisely, we estimate variants of the following regression model:

$$\mathrm{Y}_{i,j,h,l,t+1} = \alpha + \tau\ \mathrm{UCL}_{i,l,t+1} + \gamma \mathrm{UCL}_{i,l,t} + f(\mathrm{S}_{i,l,t}) + \epsilon_{i,j,h,l,t+1},$$

where $\mathrm{UCL}_{i,l,t}$ is the indicator for participation in the UCL in season t, and $\mathrm{Y}_{i,j,h,l,t+1}$ is the outcome variable of interest. We caution that this analysis does not necessarily warrant a causal interpretation since $\mathrm{UCL}_{i,l,t}$ is likely endogenous. As Table 5 shows, controlling for lagged UCL reduces the point estimates by about 30%, suggesting that the contemporaneous impact of UCL participation is about twice the lagged impact.

6.2 Investigating Causal Channels

The results presented in Table 4 indicate that participation in the UCL significantly improves team performance. There are at least two reasons that UCL participation might

[30] We thank an anonymous referee for pointing out this issue to us.

Table 5: Discontinuity Estimates in Outcome Variables (Controlling for Lagged UCL Participation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.229*	0.236	0.056**	0.072**	0.206*	0.224*	0.054**	0.066**
Std. Error	0.127	0.148	0.028	0.035	0.110	0.133	0.024	0.031
Bandwidth	0.713	1.072	1.000	1.204	0.713	1.072	1.000	1.204
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	20,197	25,289	24,431	30,964	20,197	25,289	24,431	30,964

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. $^{***},^{**},^{*}$ indicate significance at 1%, 5% and 10% level, respectively.

affect performance. First, participants might learn from their peers or be motivated to play better or practice harder, a mechanism we refer to as "spillover effects". Second, monetary benefits from the UCL might enable participating clubs to keep more productive players in their rosters, sign better players, and hire new managers, a mechanism we refer to as "composition channel".[31] While our identification strategy does not allow us to directly measure the spillover effects,[32] we will argue that the composition channel does not account for the improved performance of the UCL participant teams.

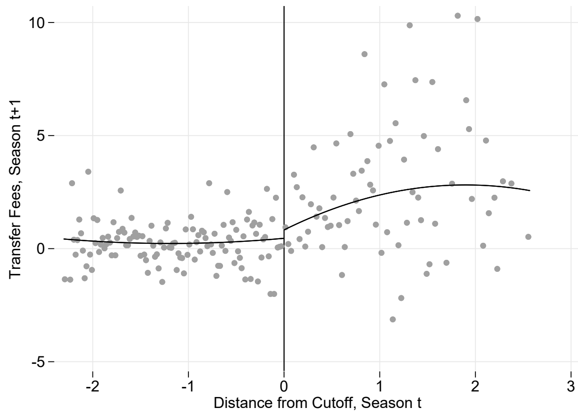
As discussed earlier, UCL participation is associated with huge financial rewards. Clubs that participate in the UCL may use the financial rewards to strengthen their teams by changing their team composition. Teams that qualify to play in the UCL may sign better players. Furthermore, teams on the two sides of the threshold may decide to change their managers, which might affect their performance.

To rule out players transfer as a causal channel, we look at the balance of transfer

[31]One other possible explanation for our main results is that teams might play a different number of games, which somehow might affect their performance. However, we don't think this is an important channel in our setting, given that most of the teams in our control group play in the Europa league. So they play a similar number of games and travel a similar distance.

[32]That's because we have a valid instrument that provides exogenous variation in UCL participation, but we do not have an instrument for the peers composition per se.

Figure 8: Discontinuity in Transfer Fees



Notes: Transfer fees (£m, 2015 prices) in season $t+1$, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

fees on the two sides of the cutoff. Figures 8 plots transfer fees against the running variable. Each dot in the figure indicate local averages of transfer fees, where transfer ins (purchases) are recorded as positive and transfer outs (sales) are recorded as negative. As before, we only consider player transfers that involve some fees. The plot shows a clear positive relationship between the running variable and the transfer fees: teams that rank higher in season t make more expensive purchases in season $t+1$. The plot also shows that the transfer fees do not jump at the threshold, so it is not the case that the teams that narrowly qualify sign better quality players, or the teams that narrowly miss the UCL lose their top players. Table 6 reports the estimation results. Compared to the teams that do not participate in the UCL, teams that play in the UCL spend about £1 million (in 2015 prices) more on each transfer. However, these estimates are not statistically significant at the 10% level.

Similarly, clubs participating in the UCL may use these resources to employ more productive (higher quality) players compared to the clubs not playing in the UCL, which might result in better performance. Moreover, higher wages might incentivize players to perform better, again resulting in better performance. To investigate these hypotheses,

Table 6: Discontinuity Estimates in Transfer Fees

	(1)	(2)	(3)	(3)	(4)	(6)
	Robust Bias-corrected			Conventional Method		
Dep. variable	TF(t+1)	TF(t+1)	TF(t+1)	TF(t+1)	TF(t+1)	TF(t+1)
Estimate	1.021	1.217	0.494	0.793	1.007	0.759
Std. Error	0.934	1.080	1.484	0.827	0.982	1.357
Bandwidth	0.778	1.199	1.038	0.778	1.199	1.038
Polynomial	1	2	3	1	2	3
Eff. Sample Size	5,609	8,690	7,577	5,609	8,690	7,577

Notes: Discontinuity estimates in outcome variables in season $t+1$: TF:=Transfer Fees (£m, 2015 prices). Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

we use the same regression discontinuity idea to investigate whether teams that narrowly participate in the UCL pay higher wages to their players, compared to the teams that narrowly miss this opportunity.

Table 7 provides mixed evidence that participation in the UCL at time $t+1$ increases total personnel expenses at time $t+1$. One possible explanation for this finding is that Hoey et al. (2021) wage data includes expenses of all departments of the club (i.e., non-football teams, women teams, museum, etc), and therefore we cannot be sure on how much of the wage bill goes to the football team. We do not find any significant effect of UCL participation on total player salaries using a different wage dataset that includes only football players' salaries.[33] Another explanation for the positive and significant estimates in Table 7 is the automatic increase in wages and bonuses following qualification for the UCL. Options and bonuses tied specifically to performance in the UCL is standard practice in football players' contracts. Because Table 6 shows that UCL teams did not sign better players and there is no discontinuity on player salaries in the UCL participation threshold (Appendix E), we can argue that higher wage bills observed in the UCL teams

[33]See Appendix E.

Table 7: Discontinuity Estimates in Total Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	Robust Bias-corrected			Conventional Method		
Dep. variable	TW(t+1)	TW(t+1)	TW(t+1)	TW(t+1)	TW(t+1)	TW(t+1)
Estimate	30.82**	30.36	31.06	28.58**	30.50*	32.41
Std. Error	14.01	20.78	25.57	12.27	18.25	22.53
Bandwidth	0.884	0.980	1.264	0.884	0.980	1.264
Polynomial	1	2	3	1	2	3
Eff. Sample Size	469	530	713	469	530	713

Notes: All specifications include a season and league fixed effects. Estimated standard errors are clustered at the league-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

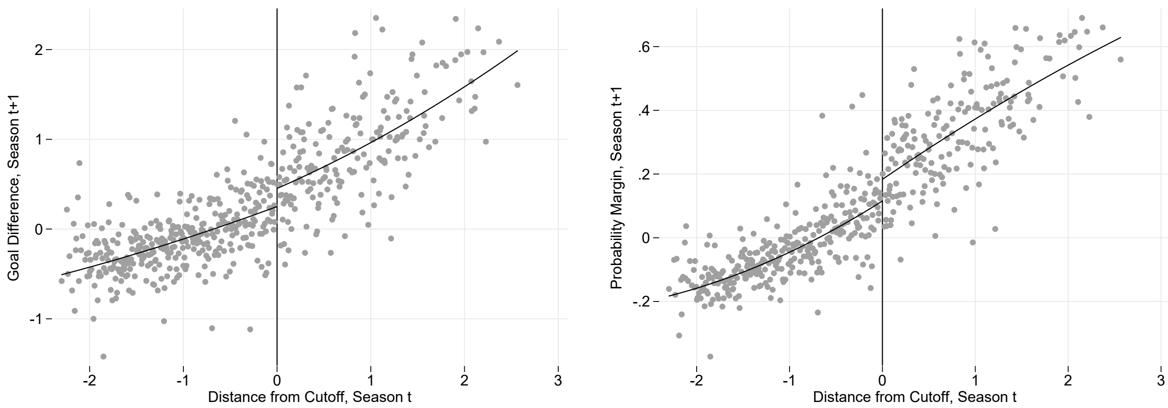
are probably due to bonuses and salaries of other employees of the clubs.

Could managerial changes explain our results? A simple way to answer this question is to control for managerial changes by including a dummy variable in our model. From Table 8 we see that the estimated effect is 0.32 for the goal difference and 0.10 for the probability margin of winning, both statistically significant at the 1% level. These estimates are very similar to the results reported in Table 4. However, we caution that this analysis does not necessarily warrant a causal interpretation. That's because some teams might decide to change their managers based on the results in season t, making managerial changes a "bad control", which might bias our estimates.[34] Nevertheless, we believe that these results are suggestive, especially because they are very close to the results without controlling for managerial changes. A visual representation of these estimates is in Figure 9, which shows a jump in the goal difference and the probability margin of winning at the threshold. These results suggest that managerial changes are unlikely to explain the improved performance reported in Table 4.

Overall, the causal impact of the UCL participation cannot be explained by player transfers, managerial changes, or wages. These results suggest the importance of spillover effect in sport as a result of social interaction, in contrast to economic incentives.

[34] See Angrist and Pischke (2008), page 64.

Figure 9: Discontinuity in Outcome Variables (Controlling for Managerial Changes)



Notes: Goal difference (left) and probability margin of winning (right) in season $t+1$, by distance from the cutoff in season t. We control for managerial changes by including a dummy variable in our model for the teams that changed their manager in the summer before the $t+1$ season. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 8: Discontinuity Estimates in Outcome Variables (Controlling for Managerial Changes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.323**	0.323**	0.099***	0.109***	0.310***	0.327**	0.098***	0.105***
Std. Error	0.127	0.164	0.031	0.040	0.110	0.146	0.027	0.035
Bandwidth	0.801	0.968	0.904	1.176	0.801	0.968	0.904	1.176
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	20,911	25,927	24,165	32,193	20,911	25,927	24,165	32,193

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning, controlling for managerial changes. Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

7 Conclusion

This paper analyzes whether and how participation in an elite sport tournament affects participating teams' performance. We ask whether competing against the best of other leagues improves performance of teams in their domestic leagues and if so how. To answer these questions, we compile a novel dataset of match level betting odds and goals scored. Using the betting odds, we construct an ex-ante measure of team performance at the match level, probability margin of winning: the extra probability betting market assigns for a team's win over its opponent's winning probability. Using goals scored information, we construct an ex-post measure of team performance at the match level, goal difference: the number of goals a team scored minus the number of goals it conceded. We link match level team performance measures with information on total points of teams at the end of season, eligibility and participation in the UCL.

We show causal effects of participation in the UCL on teams' performance in their domestic leagues with a fuzzy regression discontinuity design that exploits eligibility cutoffs. We identify a large and significant increase in the subsequent performance of the UCL participants. More specifically, teams that played in the UCL score about 0.3 goals per match more than teams that missed a UCL spot. Similarly, market assigns 10 percentage points more chance for the UCL teams to win a game than the teams that do not play in the UCL in that season.

The results we observe could be due to i) spillover effects: teams getting better by competing against the best teams in Europe, ii) team composition changes: financial rewards of the UCL enabling teams to keep better players in their rosters (higher wages), sign better players (higher transfer fees), and hire better managers. Higher wages can also serve as incentive to players for better performance. We show that transfer spending of UCL participants is not statistically higher than the non-participant teams close to the cutoff, while the results with wage bills are mixed. Moreover, we still find positive and statistically significant effects even when we control for managerial changes over the summer. Therefore, our findings suggest the importance of spillover effects.

We consider any change in performance as a result of a social interaction (in contrast to economic incentives) as a spillover effect. Spillovers can arise in many forms. First, competing against the best requires every player in the team to be physically fit, the team to be well organized on the pitch, every player to be focused on and off the pitch. Physical fitness and team organization on the pitch are developed through training sessions throughout the season. Therefore, our hypothesis is that as teams prepare for tough competition in Europe, they take their training sessions throughout the season more seriously and build up their physical and mental fitness and learn the team tactics. Enhanced physical and mental fitness, and adoption of team tactics helps team not just in the UCL but in their domestic leagues as well. Second, being part of an elite group can bring joy to the participating teams, which motivates them to play better in both domestic and international leagues. Third, teams might learn football skills and team tactics from their European counterparts by playing against European teams. Such learning will then be carried out to the domestic league games, improving performance. Therefore, UCL participants achieve better outcomes in their domestic competitions than UCL non-participants.

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A Entries for the UEFA Champions League

In what follows we provide a brief overview of the national leagues from 2000 to 2019.

England: English Premier League (EPL) is the top level of the English football league, and contested by 20 clubs (380 matches per-season). The three lowest placed teams in the Premier League are relegated to the Championship, and the top two teams from the Championship promoted to the Premier League, with an additional team promoted after a series of play-offs involving the third, fourth, fifth and sixth placed clubs. During our sample period, the top 3-4 teams in EPL qualify for the UEFA Champions League (UCL).

Spain: La Liga is the top level of the Spanish football league, and is contested by 20 teams, with the three lowest-placed teams at the end of each season relegated to the Segunda División and replaced by the top three teams in that division. The top four teams in La Liga qualify for the UCL.

Italy: Serie A is the top level of the Italian football league, and is contested by 20 teams, with the three lowest-placed teams at the end of each season relegated to the Serie B and replaced by the top three teams in that division. During our sample period, the top 3-4 teams in Serie A qualify for the UCL.

Germany: Bundesliga is Germany's primary football competition and is contested by 18 teams, with the three lowest-placed teams at the end of each season relegated to the 2. Bundesliga and replaced by the top three teams in that division. During our sample period, the top 3-4 teams qualified for the UCL.

France: Ligue 1 is France's top division football competition and is contested by 20 teams,[35] with the three lowest-ranked teams at the end of each season relegated to the Ligue 2, and replaced by the top three teams in that division. During our sample period, the top 3 teams qualified for the UCL.

[35]Except for 2000-01 season where 18 teams were present.

Table 9: Entries for the UEFA Champions League Competition

	Football League				
Season	EPL	La Liga	Serie A	Bundesliga	League 1
2001-2002	20 (4,2,2)	20 (4,3,1)	18 (4,2,2)	18 (3,2,1)	18 (3,2,1)
2002-2003	20 (4,2,2)	20 (4,2,2)	18 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2003-2004	20 (4,2,2)	20 (4,2,2)	18 (4,2,2)	18 (3,2,1)	20 (3,2,1)
2004-2005	20 (4,2,2)	20 (4,2,2)	20 (4,2,2)	18 (3,2,1)	20 (3,2,1)
2005-2006	20 (4,2,2)	20 (4,2,2)	20 (4,2,2)	18 (3,2,1)	20 (3,2,1)
2006-2007	20 (4,2,2)	20 (4,2,2)	20 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2007-2008	20 (4,2,2)	20 (4,2,2)	20 (4,2,2)	18 (3,2,1)	20 (3,2,1)
2008-2009	20 (4,3,1)	20 (4,3,1)	20 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2009-2010	20 (4,3,1)	20 (4,3,1)	20 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2010-2011	20 (4,3,1)	20 (4,3,1)	20 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2011-2012	20 (4,4,0)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2012-2013	20 (4,3,1)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2013-2014	20 (4,3,1)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2014-2015	20 (4,3,1)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2015-2016	20 (4,3,1)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2016-2017	20 (4,3,1)	20 (4,3,1)	20 (3,2,1)	18 (4,3,1)	20 (3,2,1)
2017-2018	20 (4,4,0)	20 (4,4,0)	20 (4,4,0)	18 (4,4,0)	20 (3,3,0)
2018-2019	20 (4,4,0)	20 (4,4,0)	20 (4,4,0)	18 (4,4,0)	20 (3,3,0)

Notes: Each entry indicates the number of teams in a season from a specific league. The numbers in the paranthesis indicate the number of teams that are eligible, the number of eligible teams that directly participate in the UCL group stage, and the number of teams that play in the play-off rounds to qualify for the group stage, respectively. *Source: Wikipedia.*

B Descriptive Statistics

Table 10 shows the number of observations in each season-league.

- In many season-league pairs, there are 646 observations. Recall that in each season-league, end of the season league tables are matched with game level performance measures in the following year. Therefore, in leagues with 20 teams and 3 relegation spots, 17 teams of season t play 38 games each in season $t+1$. Therefore, 17 teams $\times$ 38 games each makes 646 observations. This calculation applies to EPL, La Liga, Ligue 1 from 2003-2004 on, and Serie A from 2005-2006 on.

- 18 teams compete in Bundesliga. Depending on the outcome of the relegation play-off, 15 or 16 teams of season t play 34 games each in season $t+1$ making 510 or 544 observations.

- In season $t+1 = 2002-2003$ of French top division, 16 non-relegated teams of season t played 38 games each, making 608 observations. In season $t+1 = 2001-2002$, 15 non-relegated teams of season t played 34 games each, making 510 observations. Here, we have one missing observation.

- In Serie A, we drop observations from seasons $t+1 = 2006-2007$ and $2007-2008$ due to the 2006 Italian football scandal, Calciopoli. In season $t+1 = 2004-2005$, 14 non-relegated teams (18 teams - 4 relegated teams), played 38 games each, making 532 observations. Recall that in Serie A, the number of teams increased from 18 to 20 in season $t+1 = 2004-2005$, similarly number of relegating teams went down to 3 from 4. In seasons $t+1 = 2001-2002, 2002-2003,$ and $2003-2004$, 14 non-relegated teams played 34 games each, making 476 observations. Therefore we have 4 missing observations in season $t+1 = 2001-2002$ and 9 missing observations in season $t+1 = 2003-2004$.

Table 10: Number of observations by league and season

	Football League				
Season $(t+1)$	Bundesliga	EPL	La Liga	Ligue 1	Serie A
2001-2002	510	646	646	509	472
2002-2003	510	646	644	608	476
2003-2004	510	646	646	646	467
2004-2005	510	646	646	646	532
2005-2006	510	646	646	646	646
2006-2007	510	646	646	646	646
2007-2008	510	646	646	646	646
2008-2009	510	646	646	646	646
2009-2010	510	646	646	646	646
2010-2011	544	646	646	646	646
2011-2012	544	646	646	646	646
2012-2013	510	646	646	646	646
2013-2014	544	646	646	646	646
2014-2015	544	646	646	646	646
2015-2016	544	646	646	646	646
2016-2017	544	646	646	646	646
2017-2018	544	646	646	646	646
2018-2019	544	646	646	684	646

Notes: Each entry indicates the number of observations in our data set in a season from a specific league. We drop observations from seasons 2006−2007 and 2007−2008 due to the 2006 Italian football scandal, Calciopoli.

Table 11 provides descriptive statistics on our outcome variables in the entire sample and in each league separately. Distributions of goal difference and probability margin are similar across leagues. Mean probability margin in each league is close the mean probability margin in the entire dataset, 0.03. Mean goal difference in each league is also close to the mean goal difference in the entire sample, 0.08. Due to the discrete nature of goal difference, the percentiles recorded are identical across leagues. Distribution of transfer fees differ across leagues with EPL teams spending considerably higher per each signing than the other leagues. League 1 teams, on the other hand, receive more transfer fees than they pay.

Table 11: Descriptive Statistics

				Percentile				
	Obs	Mean	SD	10th	25th	50th	75th	90th
				All leagues				
GD(t+1)	53896	0.08	1.79	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	53896	0.03	0.34	-0.42	-0.20	0.04	0.28	0.49
TF(t+1)	13529	0.67	10.23	-6.48	-1.51	0.32	2.87	8.35
TW(t+1)	1083	57.45	54.79	14.67	21.89	38.51	70.92	127.72
				Bundesliga				
GD(t+1)	9452	0.07	1.91	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	9452	0.03	0.33	-0.41	-0.20	0.03	0.26	0.47
TF(t+1)	2797	0.33	6.52	-3.38	-0.51	0.19	1.70	4.88
				EPL				
GD(t+1)	11628	0.10	1.82	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	11628	0.04	0.36	-0.46	-0.22	0.04	0.31	0.53
TF(t+1)	3010	2.15	12.43	-7.31	-1.92	0.83	5.73	13.92
TW(t+1)	305	82.82	54.77	34.66	43.95	64.01	98.35	178.83
				La Liga				
GD(t+1)	11626	0.08	1.84	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	11626	0.03	0.36	-0.45	-0.21	0.03	0.28	0.51
TF(t+1)	1989	0.73	13.10	-8.46	-2.48	0.45	3.40	10.19
TW(t+1)	298	48.10	63.00	11.14	15.08	24.39	50.44	113.99
				Ligue 1				
GD(t+1)	11491	0.07	1.67	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	11491	0.03	0.30	-0.36	-0.18	0.02	0.24	0.41
TF(t+1)	2168	-0.22	9.37	-7.14	-2.16	0.36	2.21	5.52
TW(t+1)	239	38.82	36.41	15.08	20.08	27.34	41.98	75.37
				Serie A				
GD(t+1)	9699	0.10	1.68	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	9699	0.04	0.35	-0.43	-0.21	0.05	0.30	0.52
TF(t+1)	3565	0.18	9.02	-6.28	-1.44	0.26	2.41	6.95
TW(t+1)	241	55.38	47.27	15.80	22.61	35.46	80.88	126.88

Notes: This table shows descriptive statistics on the main outcome variables GD:Goal Difference, PM: Probability Margin of Winning, TF: Transfer Fees, TW: Total wages (wage bill). Positive values for Transfer Fees represent incoming transfers, whereas negative values represent outgoing transfers.

C Robustness Checks

Table 12: Discontinuity Estimates in Outcome Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.374***	0.285*	0.118***	0.108***	0.270***	0.384***	0.094***	0.120***
Std. Error	0.122	0.153	0.032	0.041	0.101	0.132	0.026	0.035
Bandwidth	∞	∞	∞	∞	∞	∞	∞	∞
Polynomial	2	3	2	3	2	3	2	3
Eff. Sample Size	53,896	53,896	53,896	53,896	53,896	53,896	53,896	53,896

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on a global polynomial approach ($h = \infty$) on each side of the cutoff. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

Table 13: Discontinuity Estimates in Outcome variables (Controlling for Managerial Changes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.390***	0.316**	0.123***	0.118***	0.277***	0.400***	0.096***	0.126***
Std. Error	0.121	0.153	0.032	0.041	0.101	0.132	0.026	0.035
Bandwidth	∞	∞	∞	∞	∞	∞	∞	∞
Polynomial	2	3	2	3	2	3	2	3
Eff. Sample Size	53,896	53,896	53,896	53,896	53,896	53,896	53,896	53,896

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning, controlling for managerial changes. Estimates are based on a global polynomial approach ($h = \infty$) on each side of the cutoff. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

D Home Games vs Away Games

In this section we investigate the causal effect of UCL participation on home and away games separately. If UCL effect works through supporters channel, then the gain in the away games must be smaller than the gains in home games. We can partially test this hypothesis by looking at the home games and away games separately. However, what we see in the data is the opposite. As Table 14-15 shows, the gain in away games is larger, suggesting that UCL gains is not related to the home support.

Table 14: Discontinuity Estimates in Outcome Variables (Home Games Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.261	0.237	0.081^{***}	0.087^{**}	0.249^{*}	0.248	0.083^{***}	0.086^{**}
Std. Error	0.159	0.195	0.029	0.038	0.137	0.174	0.025	0.034
Bandwidth	0.757	1.038	0.946	1.130	0.757	1.038	0.946	1.130
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	10,028	14,078	12,572	15,464	10,028	14,078	12,572	15,464

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,**,* indicate significance at 1%, 5% and 10% level.

Table 15: Discontinuity Estimates in Outcome Variables (Away Games Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.329^{**}	0.388^{*}	0.099^{***}	0.111^{***}	0.327^{***}	0.366^{**}	0.098^{***}	0.107^{***}
Std. Error	0.145	0.199	0.033	0.042	0.124	0.176	0.029	0.037
Bandwidth	0.850	0.946	0.899	1.1029	0.850	0.946	0.899	1.129
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	11,278	12,569	12,005	15,462	11,278	12,569	12,005	15,462

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,**,* indicate significance at 1%, 5% and 10% level.

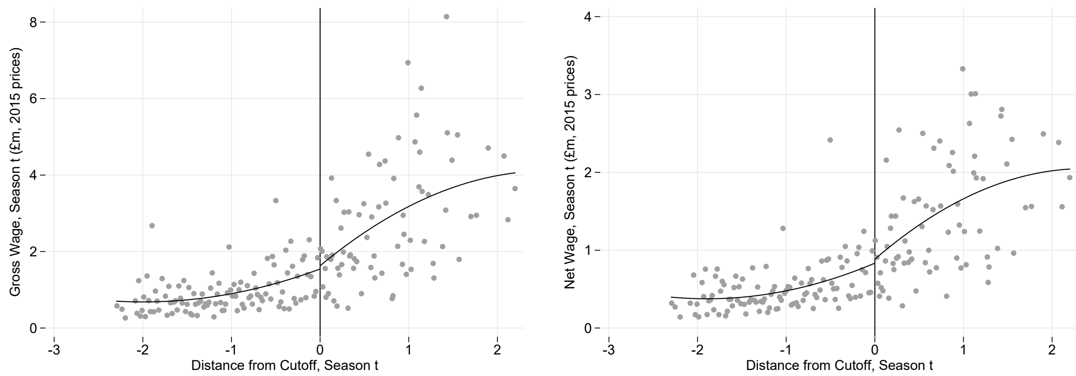
E Discontinuity in Player Wages

In this section we further investigate the validity of our design and causal channels with a different wage dataset. The dataset includes wage data (gross and net) from Capology, which covers the EPL, La Liga, Ligue 1, and Bundesliga since 2013-14 season, and Serie A since 2009-10. Unlike Hoey et al. (2021) dataset in which the wage series is defined as the total wages and bonuses payed to all club's employees (i.e., non-football teams, women teams, museum, etc), the Capology dataset includes only wages of football players of the first team. Since larger clubs are more likely to have several teams participating in different sports and infrastructures that require more paid staff, we expect the point estimate to be smaller with the Capology datasets compared to the estimates on Hoey et al. (2021) wage dataset. The disadvantage of the Capology dataset is that it covers fewer seasons than Hoey et al. (2021) dataset.

Figures 10 plots the current-season player-level wages against the running variable. We report the results for both gross and net to take into account tax differentials in different countries. The plot clearly shows that the wages do not jump at the threshold. Table 16 confirms these findings: all point estimates are economically small and statistically insignificant. So teams close to the cutoff are similar regarding average wages they pay to their players when they qualify to play in the UCL next season.

To rule out wages as a causal channel that explains the improvement in performance, we look at the balance of player wages on the two sides of the cutoff. Figures 11 plots player wages against the running variable. The plot shows a clear positive relationship between the running variable and the wages: teams that rank higher in season t pay higher wages in season $t + 1$. The plot also shows that wages do not jump at the threshold. Table 17 reports the estimation results. All point estimates are small and statistically insignificant. So teams close to the cutoff are similar regarding total wages they pay to their players in season $t + 1$.

Figure 10: Discontinuity Estimates in Real Wage (Player-Level)



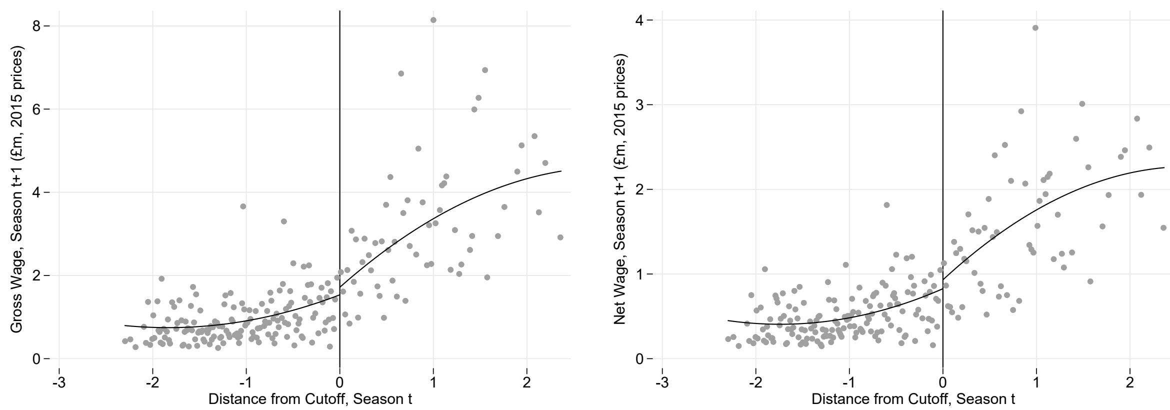
Notes: Gross player wages (left) and net player wages (right) in season t, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 16: Discontinuity Estimates in Real Wage (Player-Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GW(t)	GW(t)	NW(t)	NW(t)	GW(t)	GW(t)	NW(t)	NW(t)
Estimate	0.357	-0.245	0.184	-0.151	0.306	-0.003	0.161	-0.016
Std. Error	0.381	0.621	0.204	0.331	0.328	0.542	0.176	0.289
Bandwidth	0.558	0.642	0.556	0.644	0.558	0.642	0.556	0.644
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	3,785	4,176	3,753	4,176	3,785	4,176	3,753	4,176

Notes: Discontinuity estimates in outcome variables in season t: GW:=Gross Wage and NW:=Net Wage (£m, 2015 prices). Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.

Figure 11: Discontinuity Estimates in Future Real Wages (Player-Level)



Notes: Gross player wages (left) and net player wages (right) in season $t+1$, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 17: Discontinuity Estimates in Future Real Wages (Player-Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GW(t+1)	GW(t+1)	NW(t+1)	NW(t+1)	GW(t+1)	GW(t+1)	NW(t+1)	NW(t+1)
Estimate	0.211	-0.197	0.114	-0.112	0.180	-0.039	0.099	-0.023
Std. Error	0.376	0.581	0.203	0.315	0.320	0.510	0.174	0.276
Bandwidth	0.660	0.735	0.655	0.737	0.660	0.735	0.655	0.737
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	5,425	5,971	5,375	5,971	5,425	5,971	5,375	5,971

Notes: Discontinuity estimates in outcome variables in season $t+1$: GW:=Gross Wage and NW:=Net Wage (£m, 2015 prices). Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.

F Europa League Analysis

In this section, we investigate whether participation in the Europa League affects teams' performance. A potential problem is that the eligibility and participation in the Europa League (previously called the UEFA Cup), is not as straightforward as the UCL. For most of our sample, each association has three quotas, two of which are awarded to the runner-ups to the Champions League. The last quota, is usually awarded to the cup competition (winner or the runner-up if the winner qualified to play in the UCL).[36] To be precise, if four teams from league l are eligible to participate in the UCL and two teams are eligible to play in the Europa League in season $t+1$, the league-season-specific Europa League cutoff ($\text{Pts}^*_{l,t}$) is defined as

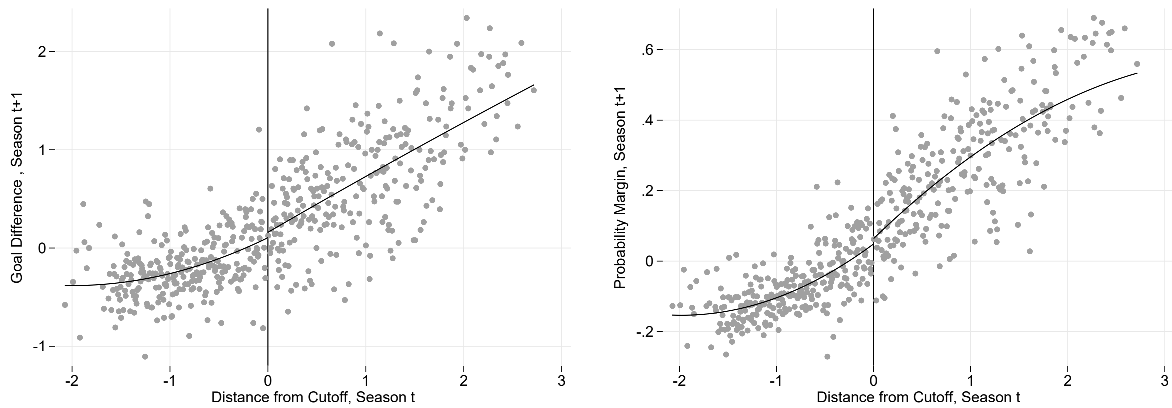
$$\text{Pts}^*_{l,t} = \frac{\text{Pts}^{6th}_{l,t} + \text{Pts}^{7th}_{l,t}}{2}$$

where $\text{Pts}^{6th}_{l,t}$ and $\text{Pts}^{7th}_{l,t}$ denotes the total points of the $6th$ team and the $7th$ team from league l in season t, respectively.

Inspecting Figure (12) we see no discontinuity in the outcome variables at the cutoff. The RD estimates, reported in Table (18), confirms this point. The parameter estimates are positive (about half the size of the UCL estimates), but none is statistically significant at the 10% level. These estimates suggest that there is no significant impact of playing in Europa League on teams' performance.

[36] In the beginning of our sample, however, teams qualified to play in the Europa League based on their ranking in the UEFA Fair Play ranking, or winning UEFA Intertoto Cup.

Figure 12: Discontinuity in Outcome Variables (Europa League)



Notes: Team's goal difference (left) and probability margin of winning (right) in season $t+1$, by distance from the cutoff in season t. Vertical lines indicate the cutoff, and dots indicate local averages. The solid lines are predicted values from quadratic polynomial on either sides of the cutoff.

Table 18: Discontinuity Estimates in Outcome Variables (Europa League)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.169	0.253	0.056	0.077	0.153	0.203	0.053	0.066
Std. Error	0.213	0.309	0.059	0.088	0.179	0.277	0.050	0.079
Bandwidth	0.744	0.922	0.701	0.839	0.744	0.922	0.701	0.839
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	26,356	33,357	24,860	30,226	26,356	33,357	24,860	30,226

Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

G Predetermined Variables Analysis

Table 3 of Section 5 showed that performance measures at $t-1$ exhibit discontinuity at UCL_{t+1} participation cutoff. To better understand this issue, we run the following regression to check whether UCL participants at $t+1$ are more like to have played in UCL in $t-1$ even after controlling for the running variable:

$$\text{UCL}_{i,l,t-1} = \alpha + \tau \ \text{UCL}_{i,l,t+1} + f(\text{S}_{i,l,t}) + \epsilon_{i,t-1}, \tag{3}$$

where $\text{Elig}_{i,l,t}$ is used as instrument for $\text{UCL}_{i,l,t+1}$. Table 19 presents corresponding discontinuity estimates in regression (3). As Table 19 shows, the discontinuity estimates are all positive and statistically significant at the 10% level, suggesting that the teams which barely made it to the UCL at $t+1$ are more likely to have played in the UCL at $t-1$ than the teams which barely lost a spot in UCL of season $t+1$.

To further investigate this issue, we re-estimate pre-determined performance measure equations while controlling for $\text{UCL}_{i,l,t-1}$. More precisely, we estimate variants of the following regression model:

$$\text{Y}_{i,j,h,l,t-1} = \alpha + \tau \ \text{UCL}_{i,l,t+1} + \gamma \text{UCL}_{i,l,t-1} + f(\text{S}_{i,l,t}) + \epsilon_{i,j,h,l,t+1}, \tag{4}$$

where $\text{UCL}_{i,l,t}$ is the indicator for participation in the UCL in season t, and $\text{Y}_{i,j,h,l,t-1}$ is the outcome variable of interest. Because we do not have instruments for $\text{UCL}_{i,l,t-1}$ in regression 4, we caution that this analysis does not necessarily warrant a causal interpretation. As Table 20 shows, the point estimates are about 0.13 for the goal difference and about 0.06 for probability margin of winning, and mostly statistically insignificant at 10% level, suggesting toward the validity of our RD design.

Table 19: Discontinuity Estimates in Lag UCL Participation

	(1)	(2)	(3)	(4)	(5)	(6)
	Robust Bias-corrected			Conventional Method		
Dep. variable	UCL(t-1)	UCL(t-1)	UCL(t-1)	UCL(t-1)	UCL(t-1)	UCL(t-1)
Estimate	0.303**	0.286**	0.121	0.286***	0.286**	0.187
Std. Error	0.118	0.144	0.187	0.100	0.128	0.170
Bandwidth	0.867	1.240	1.226	0.867	1.240	1.226
Polynomial	1	2	3	1	2	3
Eff. Sample Size	620	922	911	620	922	911

Notes: All specifications include a season and league fixed effects. Estimated standard errors are clustered at the league-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

Table 20: Discontinuity Estimates in Predetermined Variables (Controlling for Lagged UCL Participation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t-1)	GD(t-1)	PM(t-1)	PM(t-1)	GD(t-1)	GD(t-1)	PM(t-1)	PM(t-1)
Estimate	0.136	0.114	0.062*	0.065	0.136	0.126	0.062**	0.067*
Std. Error	0.099	0.134	0.033	0.040	0.084	0.119	0.028	0.035
Bandwidth	1.200	1.326	0.872	1.325	1.200	1.326	0.872	1.325
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	30,602	34,137	21,699	34,137	30,602	34,137	21,699	34,137

Notes: Discontinuity estimates in outcome variables in season $t-1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. ***,** ,* indicate significance at 1%, 5% and 10% level, respectively.

H First-stage regressions

As explained in section 4, in our fuzzy RD analysis we use UCL eligibility, $\text{Elig}_{i,l,t} = \mathbb{1}(\text{S}_{i,l,t} \geq 0)$, as an instrumental variable for the UCL participation status, $\text{UCL}_{i,l,t+1}$. In all regressions, first-stage coefficient estimates of discontinuity in the assignment probability are statistically significant at the 1 percent level. Table 21 shows detailed results of first-stage regressions in our main specification (which are reported in section 6). In

Table 21: Discontinuity Estimates in the First-Stage Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)	GD(t+1)	GD(t+1)	PM(t+1)	PM(t+1)
Estimate	0.623***	0.582***	0.634***	0.597***	0.653***	0.603***	0.666***	0.617***
Std. Error	0.065	0.078	0.061	0.074	0.057	0.071	0.053	0.066
Bandwidth	0.770	0.954	0.919	1.131	0.770	0.954	0.919	1.131
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	20197	25289	24431	30964	20197	25289	24431	30964

Notes: Discontinuity estimates in the first-stage regression. Dep. variable represents the ultimate outcome (2SLS) variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way clustered at the team-season levels. *** indicate signifiance at 1% level.

order to avoid cluttering of the paper, we are not reporting first-stage results from other regressions, but we will happily provide such results upon request.