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 differences (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] Estimating spillover effects is notoriously difficult. 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 the agent's payoffs depend on performance, making it extremely difficult to disentangle the spillover effects from agent' 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.

Elite sport tournaments offer three important advantages for the study of spillover effects.[2] First, elite sports tournaments sharply increase exposure to elite peers, providing a valuable laboratory to measure the casual impact of exposure to high quality peers. In this paper, we use a regression discontinuity (RD) design that exploits eligibility cutoffs for participation in the most prestigious football tournament in Europe to identify the spillover effect on team performance. 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) from England, La Liga from Spain, Bundesliga from Germany, Serie A from Italy, and Ligue 1 from France, from 2000 through 2019. We have collected match-level data on betting odds and match scores, and team-level data on end of the season points and rankings. We have

[1]Among others, 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).

also collected exhaustive data on salaries of football players, transfer fees and managerial changes. Third, a unique feature of our 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 the 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 size of the goal difference, independent of the magnitude of the goal difference, one might argue that teams might not exert costly effort to improve their 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 the betting odds to construct an *ex-ante* measure of performance at the match level. Analogues to stock prices, 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 it. From the betting odds, we extract the

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

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

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.

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, 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 composition do not account for the improved

[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.

performance of the UCL participant teams. More precisely, we use the same regression discontinuity idea to show that narrowly qualified teams do not pay higher wages to their players, compared to the teams that narrowly miss the opportunity to play in the UCL. Therefore, our findings suggest that the improved performance is not due to teams employing better players. 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. Moreover, the improvement in team performance persists even when we account for managerial changes before the start of the season, so managerial changes cannot explain the jump in team performance at the eligibility cutoff. The evidence thus rules out changes in 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), sport (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 depend 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 the 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. 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.

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, 39 out of 40 finalists of the UCL in the last 20 years 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 prestige and financial incentives of this tournament, 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.

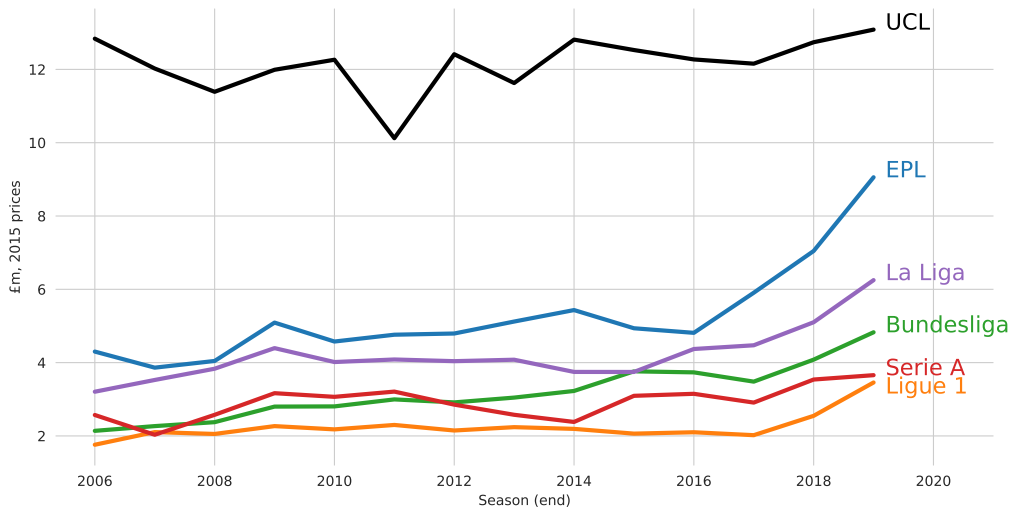
Eligibility is mostly determined by the team's performance in its national league. Each national league is contested by N teams, playing twice (i.e. home and away) against each opponent. The result of each match is decided by the goal difference, defined as goals scored minus goals conceded. A positive 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 Champions League. In reality, however, eligibility does not necessarily

[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.

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.

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 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 player valuations

[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.

[11] Teams that narrowly miss the opportunity to play in the UCL, most likely participate in the less prominent Europa League (UEL). In our analysis, we only focus on the UCL cutoffs since the eligibility for the Europa league was partly based on applications, and not role-based cutoffs. Moreover, clubs that are knocked out of the qualifying round and the group stage of the Champions League join the Europa League, at different stages, which makes the peer definition more difficult.

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 the UCL is a competition in which only elite teams with top players can participate.

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 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.

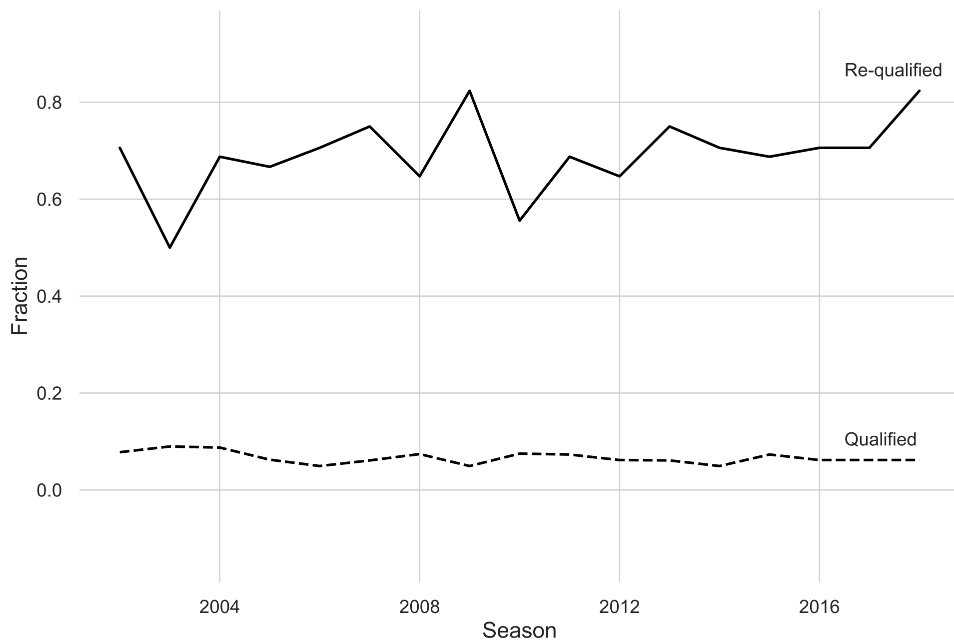
3 Data Description

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. That's because standard aggregate end-of-season measures (e.g. total points) might not accurately reflect teams' performance. To see this point, consider two teams: Team A wins some games by

[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 seaosn $t+1$, 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.

+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. Consider a match between two teams, say Team A vs Team B. If Team A were to score 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. 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 27461 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 team's 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 the Team A to win, the odds will shift. If another trader believes that the odds are now mispriced and that there is value on the other side, they might place \$100 on the 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

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

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

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 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

[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.

[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.

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:

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

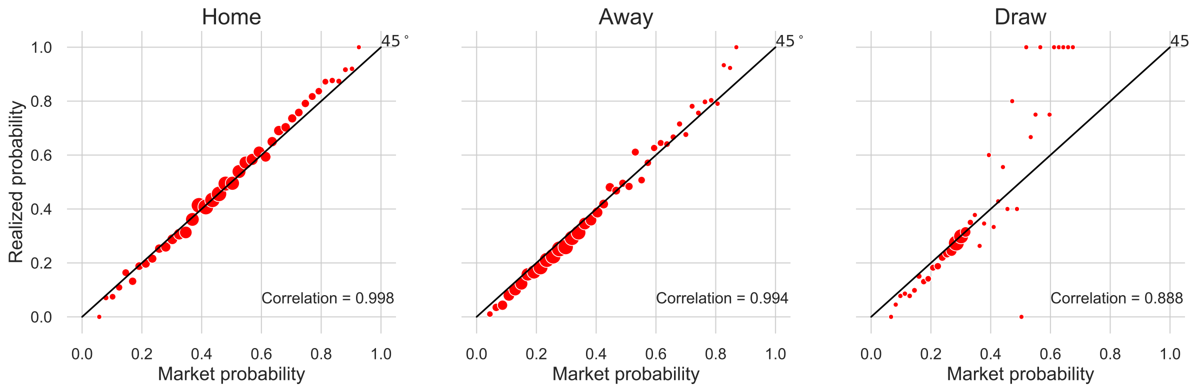
where $\mathrm{P}_{i,j,h,l,t}^*$ denotes the fair probability that team i wins against team j, $h \in \{0, 1\}$ indicates whether the game is played at home or away, in league l and season t.

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

The betting markets are doing a remarkable job at predicting actual results. To see this, we compare the market predictions with the actual outcomes in Figure 3. Remember that for each match we have home team winning, away team winning, and draw proba-

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

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.

bilities 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 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 and managerial changes from `https://www.transfermarkt.com` for the full sample. Finally, we obtain 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.

4 Identification Strategy

We are interested in whether and how participation in the UCL might affect team 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

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

[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.

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 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 $\text{Pts}^{5th}_{l,t}$ denotes 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 variable is then defined as

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

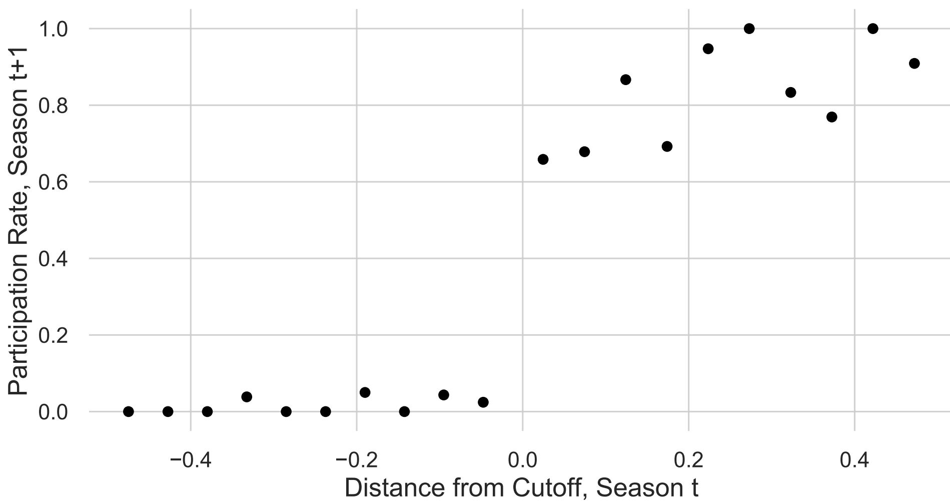
where $\text{Pts}_{i,l,t}$ denote team i's points and $\text{Std}(\text{Pts}_{l,t})$ is the standard deviation of the league-season total points. These standardized league-season-specific points equal zero at the cutoff, with nonnegative values indicating teams who are eligible to play in the UCL in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

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

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. Figure 4 gives a graphical representation of the participation rate in the UCL as a function of the standardized running variable. The plot clearly shows that less than 5% of teams that were not eligible, 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

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.

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

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

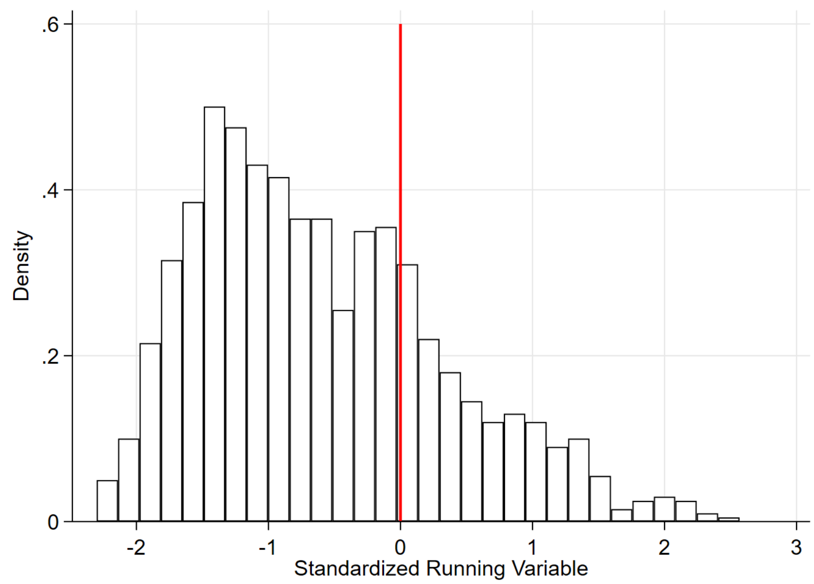
where the dummy variable $\mathrm{Elig}_{i,l,t+1}$ is used as an instrument for $\mathrm{UCL}_{i,l,t+1}$.

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

[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.

Figure 5: Density of Running Variable



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

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]

Inspecting the 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 0.3 (p-value is 0.76), 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 baseline wage bills. Seeing no discontinuity in the wage bills at the cutoff would suggest toward the validity of our RD design.[23] Figure 6 plots the balance of individual player wages (million GBP, 2015

[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 observation from 2007-08 season, since in 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.

[23]Lee (2008) argues that the validity of RD design can be tested by examining whether or not there is

prices). We report the results for both gross and net real wages to take into account tax differentials in different countries. Each dot in the figure indicate local averages, and the lines are fitted values from a quadratic polynomial fit, which is allowed to be different on either side of the discontinuity.

Figure 6 shows a positive relationship between the running variable and the wages: teams that rank better pay higher wages. However, the plots indicate no significant discontinuity in wages at the threshold, pointing towards local random assignment. Discontinuity estimates, reported in Table 1, confirm these findings, where 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. As Table 1 clearly shows, all point estimates are small economically and statistically insignificant. We also experimented with different bandwidth and polynomial orders, but the results (see Appendix C) were not particularly sensitive to the bandwidth and polynomial order choice.

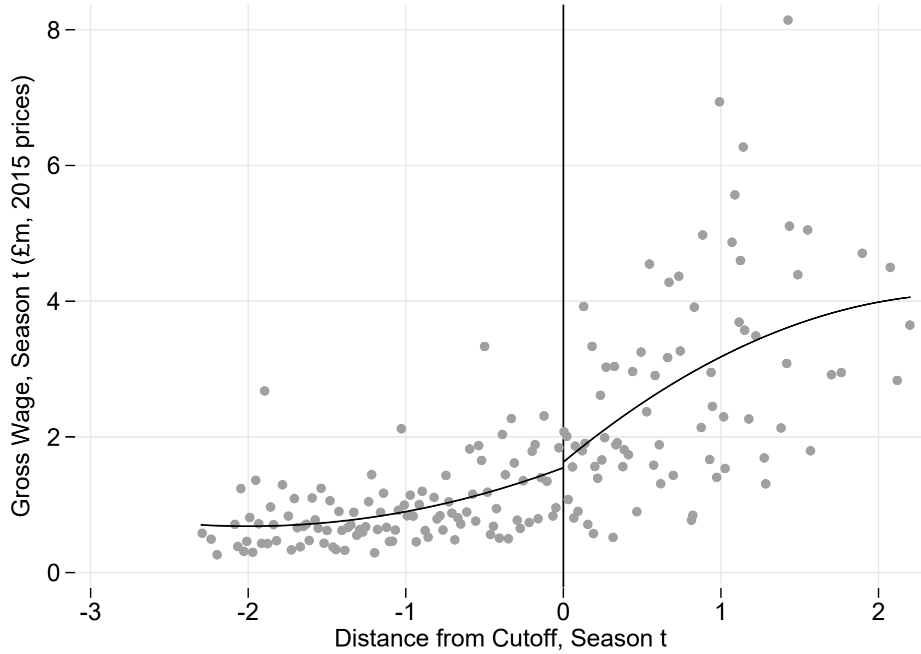
A practically relevant issue in our setting is that each team plays multiple games in a given season; as a result, the running variable contains "mass points".[24] If the running variable has mass points, the local polynomial methods will behave essentially as if each mass point is a single observation. Thus, 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 checks and adjusts for mass points in the running variable.

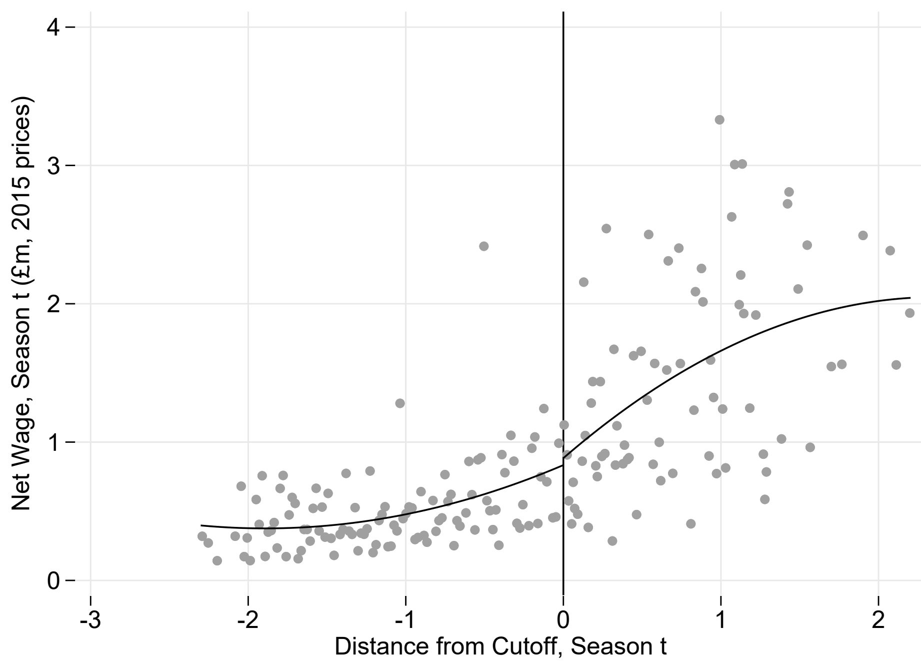
To further ensure that our design is valid, we check the continuity of the goal difference and probability margin of winning at time $t-1$. A key practical issue here is that these predetermined variables might be actually treated, because some teams that participate in the UCL season $t+1$ might have also participated in the UCL in season $t-1$. For

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.

Figure 6: Discontinuity in Real Wage





Notes: Gross player wages (top) and net player wages (bottom) 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 Real Wage (£m, 2015 prices)

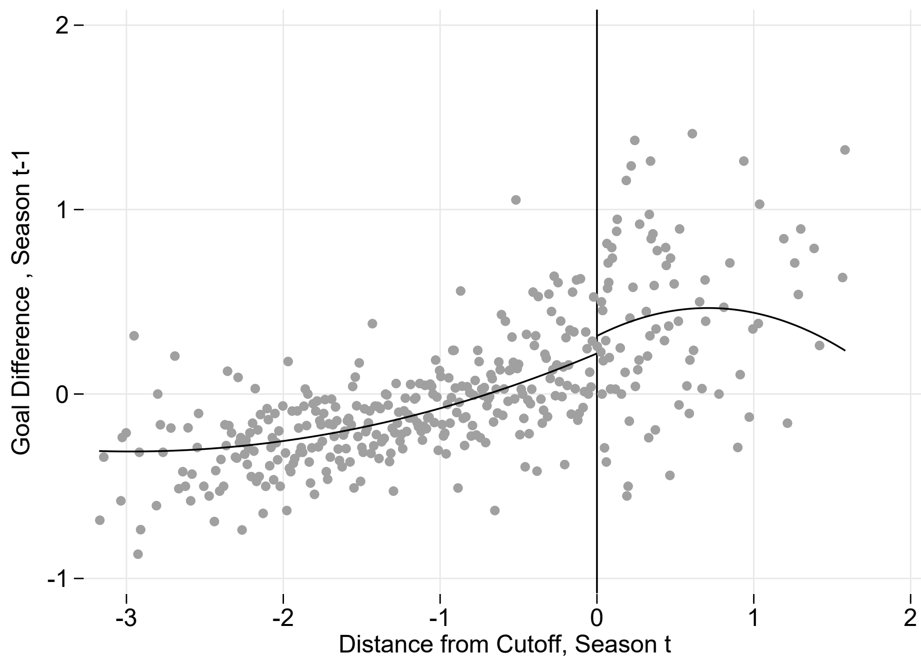
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	GW(t)	GW(t)	NW(t)	NW(t)	GW(t)	GW(t)	NW(t)	NW(t)
Estimate	0.357	-.245	0.184	-.151	0.306	-.003	0.161	-.016
Std. Error	0.381	0.621	0.204	0.331	0.328	0.542	0.187	0.289
Bandwidth	0.558	0.642	0.556	0.644	0.558	0.642	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

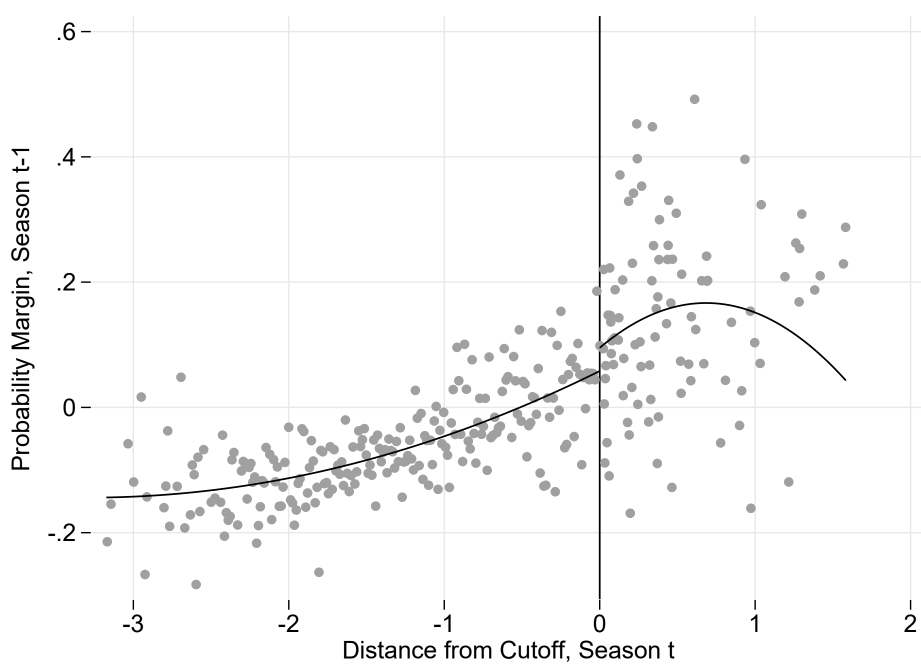
Notes: Discontinuity estimates in outcome variables in season t: GW:=Gross Wage and NW:=Net Wage. Estimates are based on linear and quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way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

this reason, when analyzing the balance of the predetermined variables, we restrict the sample to the teams that did not play in the UCL in season $t-1$. This is necessary to ensure that predetermined variables are not treated at time $t-1$.

Figure 7 shows that eligible teams had somewhat better performance in season $t-1$. Table 2, columns (1)-(4), presents corresponding discontinuity estimates using the bias-corrected procedure proposed by Calonico, Cattaneo, and Titiunik (2014). The discontinuity estimates are all positive, but not statistically significant at the 10% level. 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 throughout the paper. All specifications include league fixed effects and seasons fixed effects to control for differences across leagues and seasons. Table 2, columns (5)-(8), presents corresponding discontinuity estimates from conventional methods. These estimates are slightly larger in magnitude and statistically significant at the 10% level for local linear specifications. However, as the Figure 7 suggests, the linear specification seems inadequate, particularly on the treatment side.

Figure 7: Discontinuity in Predetermined Variable





Notes: Team's goal difference (top) and probability margin of winning (bottom) 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 2: 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	0.117	0.089	0.038	0.042	0.153	0.112	0.053	0.060
Std. Error	0.145	0.186	0.048	0.056	0.129	0.170	0.042	0.050
Bandwidth	0.925	1.008	0.818	1.410	0.925	1.008	0.818	1.410
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	16,476	18,380	14,529	27,540	16,476	18,380	14,529	27,540

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 8 illustrates the discontinuity in the performance of the teams right at the cutoff point. As Figure 8 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, reported in Table 3, confirm these findings, where 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 0.30 goals per game in the linear specification and 0.29 goals per game in the quadratic specification. The estimates are statistically significant at the 5% level, and robust to the polynomial order and bandwidth choice. Columns (3)-(4) of Table 3 present analogous estimates for the probability margin of winning in season $t+1$. The causal effects are 0.089 in the linear specification and 0.099 in the quadratic specification, 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 3 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 25% 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 0.24 goal difference per game in season $t+1$, whereas 4th and 3rd ranked teams have 0.37 and 0.68 goal differences. An increase of 0.3 goal difference per game would make a 5th ranked team to perform better 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

Table 3: 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	0.300**	0.274	0.089***	0.10**	0.290***	0.284*	0.089***	0.097***
Std. Error	0.127	0.169	0.031	0.040	0.110	0.151	0.027	0.036
Bandwidth	0.792	0.882	0.925	1.107	0.792	0.882	0.925	1.107
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	20,611	23,417	24,469	29,887	20,611	23,417	24,469	29,887

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.

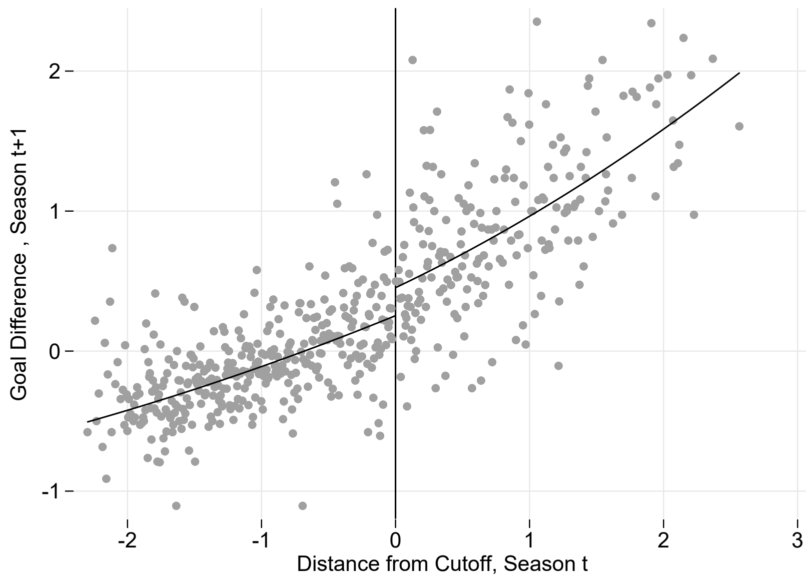
points increase in the probability margin of a 5th ranked team would potentially make the team perform better than the 4th ranked team in the following season. Thus, the economic magnitude of our discontinuity estimates is large.

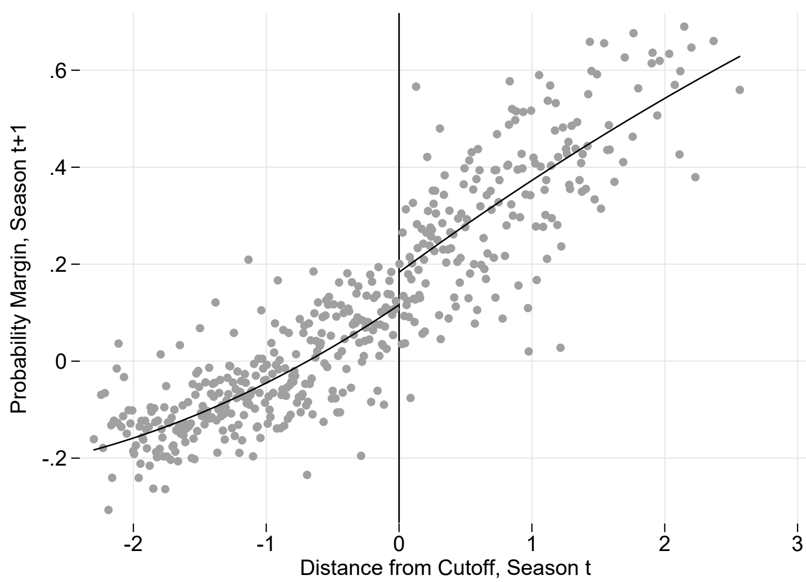
6.2 Investigating Causal Channels

The results presented in Table 3 indicate that participation in the UCL significantly improves team performance. There are at least two reasons that UCL participation might 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".[25] While our identification strategy does not allow us to directly measure the spillover effects, we can provide credible evidence that the composition channel does not account for the improved performance of the UCL participant

[25] 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.

Figure 8: Discontinuity in Outcome Variables





Notes: Team's goal difference (top) and probability margin of winning (bottom) 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 Wages

	(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	-.197	0.114	-.112	0.180	-.039	0.099	-.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

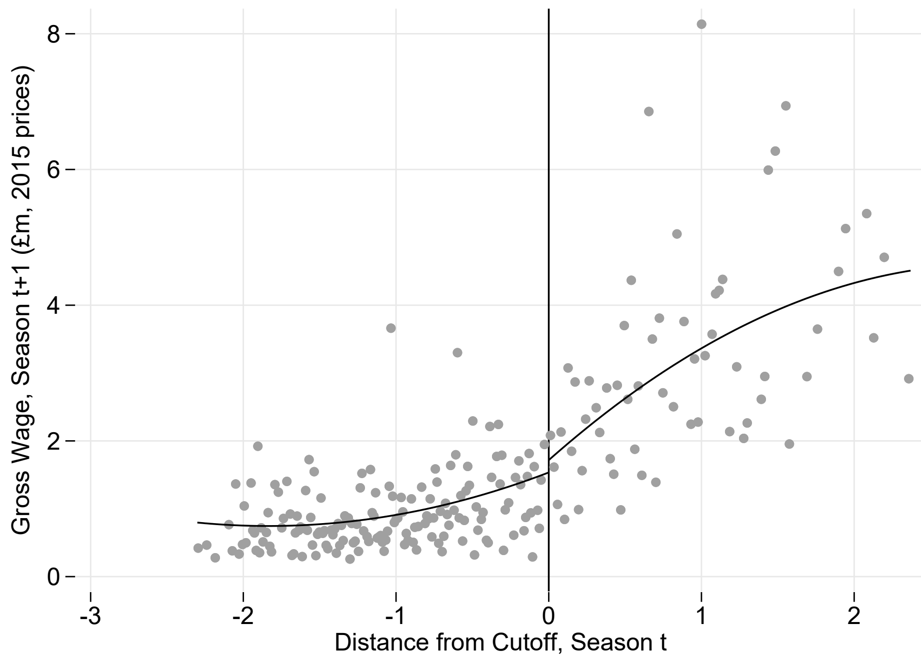
Notes: Discontinuity estimates in outcome variables in season $t+1$: GW:=Gross Wage and NW:=Net Wage. Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and league fixed effects. Estimated standard errors are two-way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

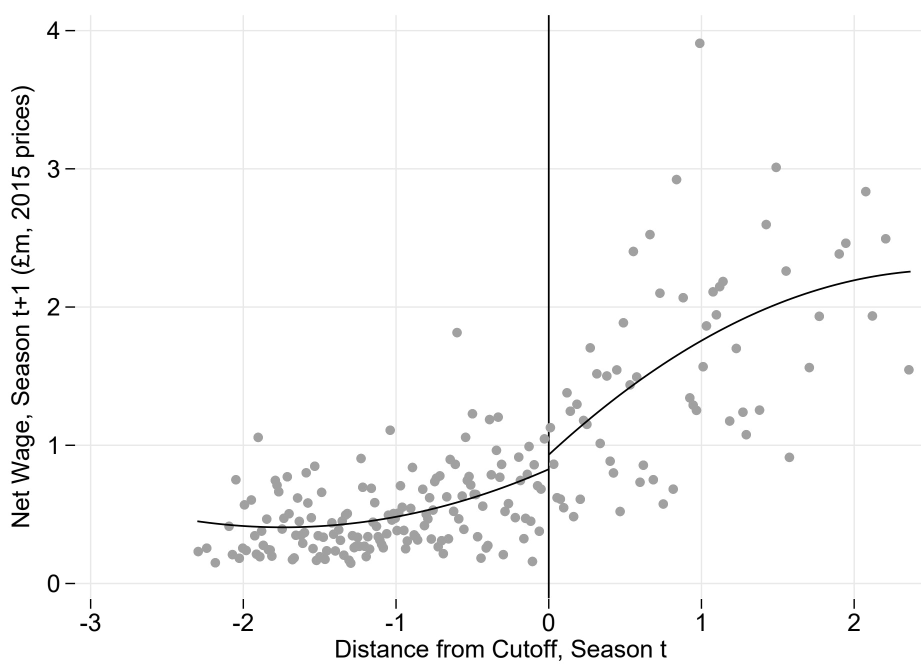
teams.

As discussed earlier, UCL participation is associated with huge financial rewards. 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. Similarly, higher wages might incentivize players to perform better, again resulting in better performance. To investigate these hypotheses, 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. As Figure 9 clearly shows, we find no jump in wages in season $t+1$, suggesting that the improved performance is not due to teams having better players, as proxied by player salaries, or players' response to higher wages. Table 4 reports the estimated effect and corroborate our findings that wages are unlikely to explain the improved performance reported in Table 3.

Similarly, clubs that participate in the UCL may use the financial rewards to strengthen their teams by changing their team composition with (a) Player transfers, that is teams that qualify to play in the UCL may sign better players; and (b) Managerial changes, that is teams on two sides of the threshold may decide to change their managers, which

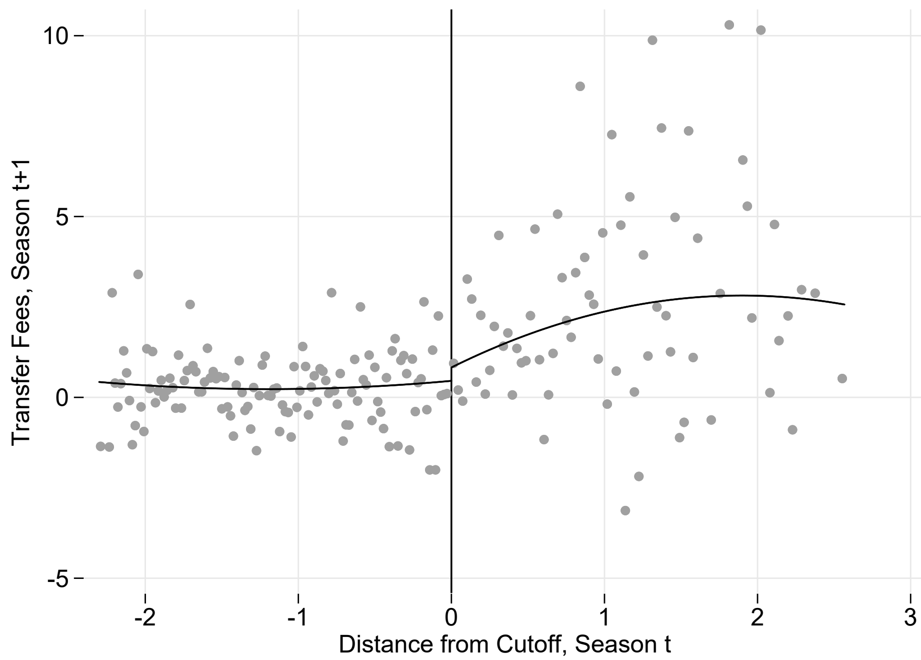
Figure 9: Discontinuity in Wages





Notes: Team's goal difference (top) and probability margin of winning (bottom) in season $t+1$, by distance from the cutoff in season t. The sample is restricted to no managerial changes at the end of 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.

Figure 10: Discontinuity in Transfer Fees



Notes: Transfer fees 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 5: Discontinuity Estimates in Transfer Fees

	(1)	(2)	(3)	(4)
	Robust Bias-corrected		Conventional Method	
Dep. variable	TF(t+1)	TF(t+1)	TF(t+1)	TF(t+1)
Estimate	1.025	1.214	0.803	1.008
Std. Error	0.937	1.080	0.829	0.982
Bandwidth	0.772	1.200	0.772	1.200
Polynomial	1	2	1	2
Eff. Sample Size	5,565	8,660	5,565	8,660

Notes: Discontinuity estimates in outcome variables in season $t+1$: TF:=Transfer Fees. 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 6: Discontinuity Estimates 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	0.318**	0.308*	0.097***	0.109***	0.305***	0.314**	0.096***	0.105***
Std. Error	0.126	0.170	0.031	0.040	0.109	0.151	0.027	0.036
Bandwidth	0.821	0.895	0.912	1.155	0.821	0.895	0.912	1.155
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	21,351	23,789	24,241	31,526	21,351	23,789	24,241	31,526

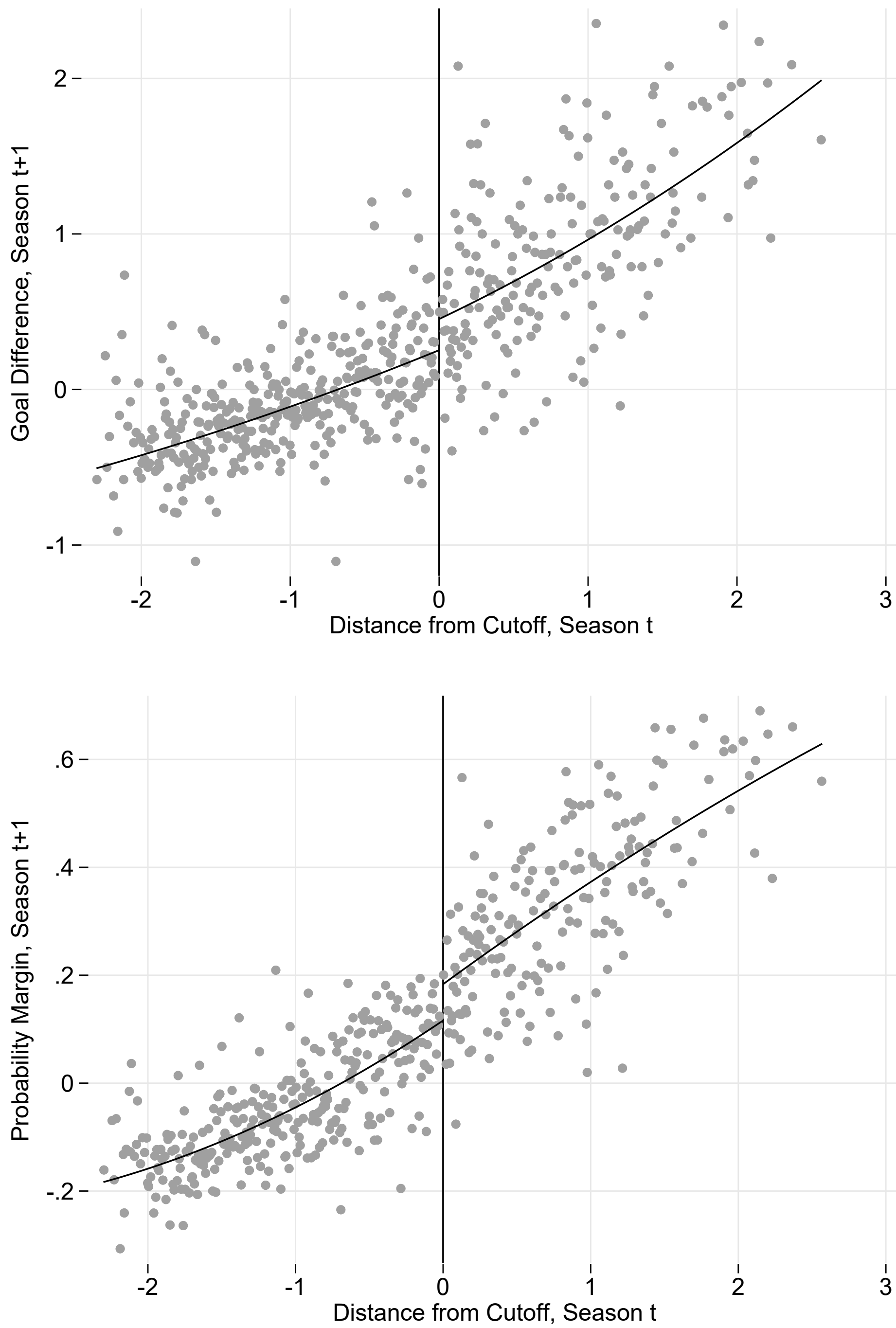
Notes: Discontinuity estimates in outcome variables in season $t+1$: GD:=Goal Difference and PM:=Probability Margin of Winning, controlling for managerial changes. Estimates are based on a quadratic polynomial within a MSE-optimal bandwidth and triangular kernel. All specifications include a season and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

might affect their performance.

To rule out players transfer as a causal channel, we look at the balance of transfer fees on the two sides of the cutoff. Figures 10 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. 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.[26] 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 5 reports the estimated discontinuities. 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.

[26]Our results are both qualitatively and quantitatively very similar when we use all transfers.

Figure 11: Discontinuity in Outcome Variables (Controlling for Managerial Changes)



Notes: Team's goal difference (top) and probability margin of winning (bottom) in season $t+1$, by distance from the cutoff in season t. The sample is restricted to no managerial changes at the end of 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.

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 6 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 3. 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.[27] 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 11, 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 3.

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.

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 our research 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

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

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 wages and transfer spending of UCL participants are not statistically higher than the non-participant teams close to the cutoff. 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,[28] 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.

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

Table 7: 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)	20 (4,2,2)	18 (3,2,1)	18 (3,2,1)
2002-2003	20 (4,2,2)	20 (4,2,2)	20 (4,3,1)	18 (3,2,1)	20 (3,2,1)
2003-2004	20 (4,2,2)	20 (4,2,2)	20 (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 the League 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

This section 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 in Table 9 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 8: Descriptive Statistics

	Obs	Mean	SD	Percentile 10th	25th	50th	75th	90th
			All leagues					
GD(t+1)	53630	0.08	1.79	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	53630	0.03	0.34	-0.42	-0.20	0.04	0.28	0.49
Fees(t+1)	13482	0.66	10.24	-6.49	-1.52	0.32	2.83	8.33
GW(t+1)	17159	1.34	2.08	0.05	0.28	0.65	1.61	3.28
NW(t+1)	17159	0.71	1.08	0.02	0.15	0.35	0.86	1.74
			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
Fees(t+1)	2797	0.33	6.52	-3.38	-0.51	0.19	1.70	4.88
GW(t+1)	2802	1.15	1.54	0.05	0.26	0.63	1.50	2.48
NW(t+1)	2802	0.61	0.82	0.03	0.14	0.34	0.79	1.32
			EPL					
GD(t+1)	11362	0.10	1.82	-2.00	-1.00	0.00	1.00	2.00
PM(t+1)	11362	0.04	0.36	-0.46	-0.22	0.05	0.31	0.53
Fees(t+1)	2963	2.16	12.51	-7.38	-1.97	0.83	5.76	14.04
GW(t+1)	3127	2.21	2.16	0.07	0.78	1.69	2.94	4.91
NW(t+1)	3127	1.22	1.19	0.04	0.43	0.93	1.62	2.70
			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
Fees(t+1)	1989	0.73	13.10	-8.46	-2.48	0.45	3.40	10.19
GW(t+1)	2687	1.55	3.16	0.07	0.29	0.63	1.41	3.41
NW(t+1)	2687	0.74	1.51	0.03	0.14	0.30	0.68	1.63
			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
Fees(t+1)	2168	-0.22	9.37	-7.14	-2.16	0.36	2.21	5.52
GW(t+1)	2989	0.73	1.53	0.05	0.17	0.37	0.67	1.50
NW(t+1)	2989	0.40	0.84	0.03	0.09	0.20	0.37	0.82
			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
Fees(t+1)	3565	0.18	9.02	-6.28	-1.44	0.26	2.41	6.95
GW(t+1)	5554	1.17	1.65	0.02	0.30	0.66	1.38	2.84
NW(t+1)	5554	0.63	0.89	0.01	0.16	0.36	0.74	1.53

Notes: This table shows descriptive statistics on the main outcome variables GD:Goal Difference, PM: Probability Margin of Winning, TF: Transfer Fees, GW: Gross wages, NW: Net Wages. Positive values for Transfe Fees represent incoming transfers, whereas negative values represent outgoing transfers.

C Robustness Checks

Table 9: 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	0.371***	0.283*	0.117***	0.107***	0.269***	0.380***	0.093***	0.119***
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	53,630	53,630	53,630	53,630	53,630	53,630	53,630	53,630

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 10: 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	0.386***	0.313**	0.122***	0.117***	0.276***	0.397***	0.096***	0.125***
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	53,630	53,630	53,630	53,630	53,630	53,630	53,630	53,630

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. The sample includes the observations with no managerial changes at the end of season t. 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 11-12 shows, the gain in away games is larger, suggesting that UCL gains is not related to the home support.

Table 11: 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	0.260*	0.224	0.080***	0.088**	0.245*	0.244	0.082***	0.086**
Std. Error	0.158	0.200	0.029	0.039	0.136	0.178	0.025	0.034
Bandwidth	0.774	0.991	0.956	1.106	0.774	0.991	0.956	1.106
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	10,062	13,336	12,703	14,945	10,062	13,336	12,703	14,945

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 12: 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	0.319**	0.388*	0.098***	0.111***	0.318***	0.364**	0.097***	0.107***
Std. Error	0.142	0.208	0.033	0.043	0.121	0.184	0.029	0.038
Bandwidth	0.901	0.873	0.902	1.107	0.901	0.873	0.902	1.107
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	11,986	11,443	12,024	14,942	11,986	11,443	12,024	14,942

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 Total Wages

Table 13: Discontinuity Estimates in Total Wages (£m, 2015 prices)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	TGW(t)	TGW(t)	TNW(t)	TNW(t)	TGW(t)	TGW(t)	TNW(t)	TNW(t)
Estimate	16.847	0.128	9.015	-0.400	13.430	6.978	7.254	3.409
Std. Error	12.00	24.54	6.466	13.18	10.124	20.72	5.477	11.15
Bandwidth	0.519	0.595	0.515	0.596	0.519	0.595	0.515	0.596
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	122	136	122	136	122	136	122	136

Notes: Discontinuity estimates in outcome variables in season t: TGW:= Total Gross Wage and TNW:=Total Net Wage. 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 clustered at the season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.

Table 14: Discontinuity Estimates in Total Wages (£m, 2015 prices)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robust Bias-corrected				Conventional Method			
Dep. variable	TGW(t+1)	TGW(t+1)	TNW(t+1)	TNW(t+1)	TGW(t+1)	TGW(t+1)	TNW(t+1)	TNW(t+1)
Estimate	3.86	-17.76	2.077	-9.794	2.86	-10.61	1.603	-5.871
Std. Error	13.67	24.40	7.485	13.20	11.80	21.59	6.479	11.74
Bandwidth	0.542	0.638	0.539	0.641	0.542	0.638	0.539	0.641
Polynomial	1	2	1	2	1	2	1	2
Eff. Sample Size	151	172	151	172	151	172	151	172

Notes: Discontinuity estimates in outcome variables in season t: TGW:= Total Gross Wage and TNW:=Total Net Wage. 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 clustered at the season levels. ***,**,* indicate significance at 1%, 5% and 10% level, respectively.